M A R K E T I N G S C I E N C E I N S T I T U T E

The Short- and Long-run Category Demand Effects of Price Promotions

Vincent R. Nijs, Marnik G. Dekimpe, Jan-Benedict E.M. Steenkamp,
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While the commercial use of price promotions has increased over the last decade, attention has primarily focused on their effects on brand choice and brand sales. Little is known about the conditions under which price promotions expand short-run and long-run category demand, even though the benefits of category expansion can be substantial to manufacturers and retailers alike.

In this report, the authors investigate the category-demand effects of consumer price promotions. Using a dataset of 560 consumer product categories over a four-year period, they examine the main effects of price promotions on consumer demand in the product category in the short and the long run, as well as how these effects change with marketing intensity and competition.

The results, based on market-level data, generate an overall picture of the power and limitations of consumer price promotions in expanding category demand.

Findings and Implications

Short- and Long-run Effects. Price promotions have a significant short-term impact on category demand: they significantly expand category demand in 58 percent of cases. In addition, the more frequently price promotions are used, the stronger is the short-run consumer sensitivity.

However, this strong short-term effect weakens over time, and only rarely (in 2 percent of cases) does it result in permanent shifts in category demand. Promotion-intensive product categories in general tend to follow stationary demand patterns over time, except when trend-setting new products are introduced.

This result offers a caution to brand managers who see the large, immediate effect of price promotions on sales, and may divert resources to support price promotional efforts. This study suggests that such actions do not help enhance the brand's long-run position.

Effects of Marketing Intensity and Competition. The most influential moderator of price promotion effectiveness is the use of nonprice advertising by incumbents. Advertising creates differentiation among brands in the category, which reduces consumers' price promotion sensitivity at the category level. In other words, heavy advertising may make it easier for a firm to implement a strategy of reduced price promotional spending.

Short-run promotional effectiveness is also determined by competitive structure: the fewer industry members, the stronger the promotional effectiveness of its participants. However, price promotional effectiveness is shaped to a greater extent by the behavior of firms within the category (i.e., marketing intensity and competitive reactivity). Even so, the dominant form of reactivity found in this study is nonreaction. This could be attributable to budget limitations (consider the expense of prolonged price promotion or advertising wars), and the difficulty in sustaining cooperative behavior/agreements over long time periods.

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Introduction

Managers in consumer and industrial sectors alike seek long-term profitable growth for their products and services. Such growth can be found in three sources: growth in category demand, in market share, or in profit margin. Competitive conditions largely dictate which sources of growth can realistically be pursued and for how long. While much of the market response literature has focused on the effects of various marketing resource allocations on *brand* sales, the implications for identifying the best sources of profitable growth are not yet well understood, even less so in the long run.

Our research examines the first source of profitable growth, *category demand*. Achieving growth in category demand can be attractive for several reasons. First, the base for the growth is large, as it involves all industry participants. Second, harmful competitive reaction may be limited because competitive share losses may be hidden in sales gains, and therefore attract less retaliatory action. Third, category demand growth leaves room for price and profit margin increases, as there is tangible evidence that consumers have an increasing utility for category consumption. Last, but not least, retailer revenues are more closely related to the sales of a product category than to the sales of any one brand. Brand managers are more likely to receive the needed cooperation of retailers, if retailers can be convinced that the proposed marketing programs increase category sales. These four benefits should be offset against two drawbacks: an individual brand may be financing the growth of the category (i.e., competitors enjoy free-rider effects), and growth may attract new entrants.

The strategic importance of category demand along with the relative paucity of existing research motivates our large-scale empirical investigation of marketing determinants of category demand. We question to what extent marketers' actions—in particular consumer price promotions—are related to short-term and long-term changes in the consumer demand of a product category. We study moderators of these promotional effects that are very relevant to marketing managers in a given category, i.e., the state of competition and the intensity of competitors' actions and reactions in the market.

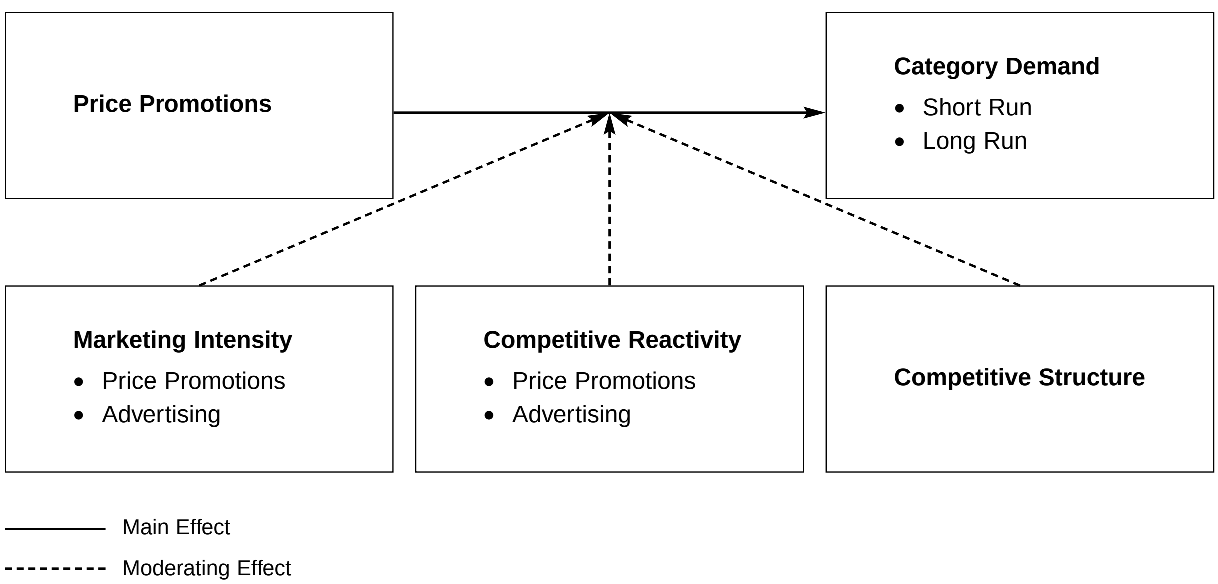
Our framework is one of literature-based hypothesis generation, followed by empirical testing based on a "full marketing-mix" scanner database of 560 product categories over a four-year period. We apply a consistent measurement scheme across categories and derive generalizations directly from the data, unlike previous empirical generalizations' studies that use meta-analysis and necessitate additional corrections for study design and measurement differences. To the best of our knowledge, the size and scope of the database are unique in the literature to date.

Our study of the determinants of price promotional effectiveness focuses upon the intensity of marketing use (i.e., the measured behavior of all market participants) and two distinct dimensions of competition: (1) competitive structure, i.e., the competitive landscape in the category, and (2) competitive conduct or reactivity, i.e., the extent to which any marketing action is matched by competitors. The latter distinction is strategically important because the stronger the effects of competitive structure, the more static and predetermined a brand's promotional effectiveness is likely to be, and vice versa.

Finally, we make the distinction between price promotional effectiveness in the short run and the long run. Most previous research on the effectiveness of price promotions has had a short-run focus. Recently, however, we see a growing interest in long-term effectiveness, though insights into the determinants or drivers of long-run effectiveness are still lacking. Thus, a key contribution of our work is that it provides insights on the evolution of promotional impact from the short to the long run.

Figure 1 provides a schematic overview of the major aspects of our study of price promotion effects on category demand. Taken in combination, we provide marketing scholars and managers with tools and insights to (1) assess the category promotional effectiveness for any brand, given its competitive setting, (2) estimate how this category-level price promotional effectiveness changes over time and in function of marketing intensity, competitive behavior, and competitive structure, and (3) generate guidelines on how environments can be selected or shaped to enhance the long-term category effects of promotions. Note that in this paper, we focus on *consumer* price promotions which may originate with the retailer or the manufacturer. Trade promotions, in contrast, are not considered in our study.

Figure 1. Research Overview



The paper begins with a comprehensive literature review leading to the formulation of several hypotheses on the category-expansive power of price promotions. We then introduce the measurement methods, describe the database, and operationalize the variables. The empirical results are summarized and discussed in the context of our hypotheses. Various validation exercises are subsequently carried out to assess the robustness of our findings. We formulate overall conclusions, and end with recommendations for future research.

Research Hypotheses

The Main Effects of Price Promotions on Category Demand in the Short and Long Run

The Short-run Effect

A vast body of literature has established the empirical generalization that price promotions result in a substantial initial sales increase at the brand level (see Blattberg, Briesch, and Fox [1995] or Van Heerde [1999] for extensive reviews). This immediate sales increase may be due to within-category brand switching (see, for example, Gupta 1988; Totten and Block 1987), as well as to a category-expansion effect of price promotions (Chintagunta 1993; Van Heerde 1999; Vilcassim and Chintagunta 1992). The size of the latter effect, which can be driven by a variety of sources, such as quantity acceleration, increased consumption, and category switching (Ailawadi and Neslin 1998; Van Heerde 1999), is the main focus of the current research.

Part of the initial sales peak, however, may be negated in subsequent periods. Purchase acceleration, for example, may cause a post-promotion through, i.e., additional sales now come at the expense of future purchases (see Blattberg and Neslin 1990). To obtain an accurate estimate of the *net* short-run effect of price promotions, we will consider the immediate sales effect as well as possible changes in the weeks following the initial price promotion.

The Long-run Effect

No conclusive findings are currently available on the long-run effectiveness of promotions at the brand level, let alone at the category level. Blattberg, Briesch, and Fox (1995) even call this "the most debated issue in the promotional literature" (p. G127). Negative, positive, and nonsignificant long-run effects have been reported, but one should keep in mind that the comparability of findings is hampered by the variety of performance measures and research settings used in previous studies. Jedidi, Mela, and Gupta (1999), for example, report a negative long-run impact of (repeated) promotions on a brand's equity and intrinsic utility, while Shoemaker and Shoaf (1977) and Strang (1975) observe a negative impact on repeat purchase probabilities and brand loyalty/differentiation, respectively. Others, in contrast, have failed to observe a long-run effect. Examples include Dekimpe, Hanssens, and Silva-Risso (1999), who do not find a long-run effect on brand and category sales in three different product categories, and Neslin and Shoemaker (1989), who do not observe any effect on brand-level repeat purchase probabilities. Finally, some studies have found a positive long-run impact. Dekimpe, Hanssens, and Silva-Risso (1999) report one instance where long-run brand and category sales are positively impacted by price promotions, while both Franses, Kloek, and Lucas (1999) and Srinivasan, Popkowski Leszczyc, and Bass (1999) report a similar impact on market shares. In our study, category sales (in units) is used as the measure of performance. The large scale of our empirical analysis (560 categories) will enable us to derive firm empirical generalizations on the sign and size of the long-run impact of price promotions on this measure.

While there is little consensus on the long-run effectiveness of price promotions, there is a general belief that its magnitude is reduced relative to the short-run effect. This evolution is intrinsically present in studies that find negative long-run effects as well as in those studies that fail to observe any such effects. Also, the studies that do find a positive long-run impact typically report its size to be a fraction of the short-run effect. We therefore hypothesize:

H_1: The price promotion elasticity of category demand declines as one goes from short to long run.[1]

The Moderating Impact of Marketing Intensity and Competition on the Market-expansive Power of Price Promotions

Some authors have claimed that the majority of promotional sales volume comes from within-category brand switching (see, for example, Gupta 1988), while others have attributed a major effect to the category-expansion effect of price promotions (Chintagunta 1993; Van Heerde 1999; Vilcassim and Chintagunta 1992). Part of these conflicting findings on the sources of promotional volume may be due to the fact that the potential for category expansion differs across categories (Blattberg, Briesch, and Fox 1995). In this paper, we investigate whether, and to what extent, the marketing actions of the industry participants and the competitive environment they operate in moderate the market-expansive capabilities of price promotions. We consider two key types of marketing actions: the use of price promotions and advertising. For each instrument, we examine not only the *intensity of use* of the instrument, but also the nature and extent of the *competitive reactions*, if any, to an aggressive move by an incumbent with that instrument. Further, we investigate whether the *competitive structure* in the category has an effect over and above the effect of the firms' conduct. Hypotheses 2 -7 reflect the expected sign of the effect at the two considered time horizons. Subsequently, we formulate a hypothesis on the evolution in *effect size* when moving from short to long run (H_8).

Price Promotion Intensity

Following Raju (1992), we distinguish two components of promotional intensity in a product category: promotional frequency and promotional depth. Promotional frequency reflects the extent to which consumers are exposed to price promotions (e.g., the percentage of weeks with a price promotion), while promotional depth specifies the average size of the promotions to which consumers are exposed (e.g., cents off). Previous research suggests that depth and frequency have a distinct effect on promotional effectiveness (see, for example, Jedidi, Mela, and Gupta 1999; Raju 1992).

Promotional Frequency. Frequent use of price promotions makes them a more important component in consumers' motivation to buy from a category, as they are conditioned to look for, and rely on, future promotions for a product purchase (Mela, Gupta, and Lehmann 1997). This will decrease the consumers' purchase quantity in the absence of price promotions, while increasing the quantity purchased in promotional weeks. Indeed, current users of the category may learn to “lie in wait” for deals (Bell and Bucklin 1999; Jedidi, Mela, and Gupta 1999; Mela, Jedidi, and Bowman 1998). The combined impact of increased consumer promotional sensitivity and reduced purchase quantity under regular conditions may enlarge the overall effect of a particular price promotion relative to an environment where consumers are offered fewer deals. Based on the above argumentation, we hypothesize:

H_2: Price promotional frequency has a positive impact on the price promotion elasticity of category demand.

Promotional Depth. Deep discounts may drop price levels below the reservation price of current nonbuyers (Dekimpe, Hanssens, and Silva-Risso 1999; Raju 1992). This is one reason why deeper discounts result in larger category demand effects. The question at hand, however, is whether a price promotion of *given* depth is more effective in an environment where the average depth is higher or lower. Adaptation theory and reference price theory predict that, in product environments where deep discounts occur, consumers come to expect such discounts and may be less sensitive to price promotions of more limited depth (Jedidi, Mela, and Gupta 1999; Kalyanaram and Winer 1995). We therefore hypothesize:

H_3: Price promotion depth decreases the price promotion elasticity of category demand.

Price Promotion Reactivity

For any given level of price promotional intensity, the effect of price promotions will also depend on competitive reactions (Putsis and Dhar 1998). If a competitor initiates a price promotion, this will have limited impact on the purchase quantities or usage rates of consumers loyal to other brands, unless its rivals reciprocate with price promotions of their own. In addition, if some of the cheaper brands react with a promotion of their own, some customers who otherwise found the category too expensive might enter the market (Dekimpe, Hanssens, and Silva-Risso 1999; Raju 1992). Thus:

H_4: Greater price promotion competitive reactivity increases the price promotion elasticity of category demand.

Advertising Intensity

It is important to distinguish between price-oriented and nonprice-oriented advertising (Boulding, Lee, and Staelin 1994; Kaul and Wittink 1995). Our data are mostly national brand advertising, as confirmed by industry experts. This type of advertising typically consists of nonprice-oriented, brand-differentiating messages, emphasizing nonprice motivations to buy a brand (Alsem, Leeflang, and Reuyl 1989; Kaul and Wittink 1995; Mela, Gupta, and Jedidi 1998). Such information should lead to increased product differentiation and reduced price (promotion) sensitivity (Boulding, Lee, and Staelin 1994; Kaul and Wittink 1995; Mela, Jedidi, and Bowman 1998). Although previous studies typically deal with price sensitivity at the brand level, these results also suggest that *categories* characterized by high advertising intensity will exhibit a lesser degree of price promotion sensitivity than categories with low advertising intensity. Bolton (1989) and Pagoulatos and Sorensen (1986) provided some empirical support for this. We therefore hypothesize:

H_5: The greater the advertising intensity in a product category, the lower the price promotion elasticity of category demand.

Advertising Reactivity

As argued before, nonprice-oriented advertising tends to reduce price sensitivity. What happens if competitors react to such advertising by increasing their own nonprice advertising? Such a competitive response, which is referred to as a "simple" competitive reaction since it involves the same instrument as the one that triggered the reaction (see, for example, Hanssens 1980; Leeflang and Wittink 1992, 1996), should lead to a still greater degree of brand differentiation, which is expected to further reduce price promotion elasticities in the category (Mitra and Lynch 1995; see also Chamberlin 1962).

H_6: A greater "simple" advertising reactivity decreases the price promotion elasticity of category demand.

Competitive Structure

Finally, we study whether the competitive structure in a category has an effect on price promotion effectiveness over and above the strategic actions of the respective brands.[2] Following previous work in industrial organization and marketing, competitive structure in the category is measured by the number of brands in a market (Bell, Chiang, and Padmanabhan 1999; Narasimhan, Neslin, and Sen 1996; Reddy and Holak 1991; Scherer 1980), whereby the structure is considered more competitive in markets with more brands.

Becker (1971) has argued that the price elasticity of demand should be greater in markets characterized by a limited number of brands as they can engage more easily in cooperative activities that attempt to restrict output and raise prices to reach a more elastic portion of the industry demand curve. As such, price promotion effectiveness is expected to be higher (lower) in less (more) competitive environments. A similar effect is hypothesized based on the information-search literature. Indeed, in order for consumers to be informed about the price and quality of the different brands in a category, they must engage in search activities. A given level of information requires higher search costs as the number of brands to be evaluated increases (Pagoulatos and Sorensen 1986; Ratchford 1980). Also, the probability of information overload increases, leading to a greater likelihood of random decision making (Jacoby, Speller, and Kohn 1974). Some empirical support for the hypothesized effect of competitive structure is provided in Pagoulatos and Sorensen (1986). Hence, we hypothesize:

H_7: The more competitive the structure of a category, the lower the price promotion elasticity of category demand.

Evolution in the Moderating Role of Marketing Intensity and Competition

While a substantial body of literature deals with the impact of both marketing intensity and various competitive factors on the effectiveness of price promotions (see hypotheses 2-7), there is a paucity of research on the relative size of their moderating effect in the short versus long run. We therefore conduct an exploratory investigation on the evolution in their effect size as moderators of promotional effectiveness. While detailed hypotheses concerning this evolution for each of the different dimensions cannot be developed, our general expectation is that the effect of intensity and competition will attenuate over time. There are some indications in the literature, related to both conduct and structure, that support this generalized expectation. Over time, any positive effects of price promotion intensity and reactivity (cf. H_2, H_4) on promotional effectiveness might be attenuated by negative side effects of price promotions. The "lie in wait" heuristic described previously (see, for example, Jedidi, Mela, and Gupta 1999) suggests a consumer purchase strategy whereby sales under regular price conditions are sacrificed for additional units purchased under promotion. In such situations, the effects of price promotions favor deal-to-deal buying rather than long-run category expansion (Blattberg and Neslin 1990).

With respect to advertising (cf. H_5, H_6), consumers (independent of their purchase history) may remember past advertising, which may continue to contribute to the perception of increased differentiation, and hence, reduced price promotion effectiveness (Givon and Horsky 1990). Still, it is well known that this carryover is typically less than 100 percent (see, for example, Leone 1995) and that quite some advertising expenditures do not have a long-term effect (Lodish, Abraham, Linvelberger, Lubetkin, Richardson, and Stevens 1995). Another indication relates to competitive structure (H_7). Even in very competitive categories characterized by a large number of brands, over time, consumers will learn more about unknown brands through, for example, word-of-mouth and vicarious consumption (Assael 1998). Consequently, the negative effect of competitive structure on price promotion effectiveness (H_7) is expected to attenuate over time. In sum, we hypothesize that:

H_8: The effect of marketing intensity and competition on price promotion elasticity of demand will attenuate over time.

Covariates

Our focus is on the moderating role of marketing intensity, competitive reactivity, and competitive structure. Several other variables may, however, also have an impact on the effectiveness of price promotions. For example, traditional meta-analyses (e.g., Tellis 1988) have shown that parameter estimates may be sensitive to model specification issues. Two such issues that may be relevant in the context of this research are the inclusion of a deterministic trend component, and the addition of a dummy variable to capture the impact of a new product introduction in a specific category (see Appendix A and the methodology section for details on model specification). Furthermore, product perishability has been shown to impact the elasticity estimates of price promotions (see Bell, Chiang, and Padmanabhan

1999; Narasimhan, Neslin, and Sen 1996). Also, our data cover sales in supermarkets, but other outlet types may also sell some of the same products. If consumers switch outlet types due to promotional activity, this may impact our elasticity estimates. Finally, while previous research has indicated that “simple” competitive reactions (i.e., a reaction with the same instrument as the initiating brand) are the most common (see, for example, Leeflang and Wittink 1992), we need to ensure that our analyses are not affected by the omission of measures capturing “multiple” competitive reactions (i.e., a reaction with an instrument other than that used by the initiating brand). Including these covariates should yield more precise estimates of the moderating impact of our focal constructs, while generating additional insights into other relevant market factors that may affect price promotion effectiveness.

Methodology

Measuring Price Promotion Effectiveness

Price promotions are temporary price reductions offered to the consumer (Blattberg, Briesch, and Fox 1995). To assess the effectiveness of price promotions, one typically evaluates the performance of a brand or category relative to its baseline performance (Abraham and Lodish 1993; Kopalle, Mela, and Marsh 1999). Following Dekimpe, Hanssens, and Silva-Risso (1999), we operationalize price promotions and baseline performance levels in the context of a VARX model. Specifically, a three-equation model is used with category demand, category price, and total advertising spending in the category as endogenous variables, and distribution coverage, feature and display, feature only, and display only as exogenous variables. Ideally, all available marketing mix variables would be incorporated as endogenous in the VARX model. This would, however, lead to extreme over-parameterization. Price and category demand were specified as endogenous as their dynamic interrelationships are at the core of our research. Given the focus of H_5 and H_6, advertising is included as a third endogenous variable in an attempt to ensure estimates of price promotion effectiveness that are not confounded with dynamic effects attributable to advertising (see Appendix A for further details on model specification).

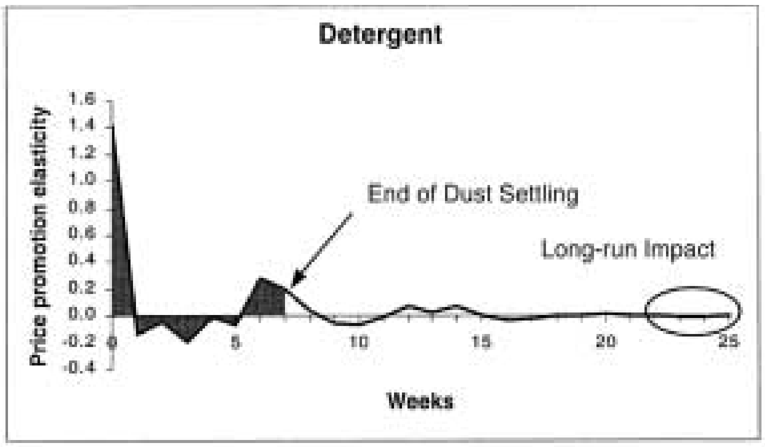
The unconditional forecasts (extrapolations) from the VARX system reflect the levels of the performance and control variables in periods t, t + 1, t + 2, ... that would be expected based on the available information up to period t - 1 (Darnell and Evans 1990; Dekimpe and Hanssens 1995a). Promotions are operationalized as one-time (hence temporary) deviations from the expected price level in period t.[3] As discussed in Appendix B, deviations from the base level are implemented through a shock to the residual vector of the VARX model. Given a price promotion in period t, one can again forecast the future levels of the performance and control variables, but now based on the extended information set that includes the promotion. The difference between both forecast series gives, for a given endogenous variable, the incremental effect in period $t + i$ (i = 0, 1, 2, ...) of the promotional shock in period t. These incremental effects, taken in combination, form the promotion's impulse-response functions (Bronnenberg, Mahajan, and Vanhonacker 2000; Judge, Hill, Griffiths, Lütkepohl, and Lee 1988). The impulse-response function (IRF) tracing the incremental impact of the price promotion shock on category demand (i.e., the incremental effect in period t, t + 1, t + 2, ...), is our basic measure of promotional effectiveness. To allow for the cross-category comparisons needed to formally test our hypotheses, we propose to derive two summary statistics from each IRF:

- its asymptotic value (for $t \to \infty$), which measures the persistent or long-run effect, and
- the *net* effect over the dust-settling period, which is defined as the time needed for the IRF to stabilize. As argued below, this measure quantifies the promotion's short-run effectiveness.

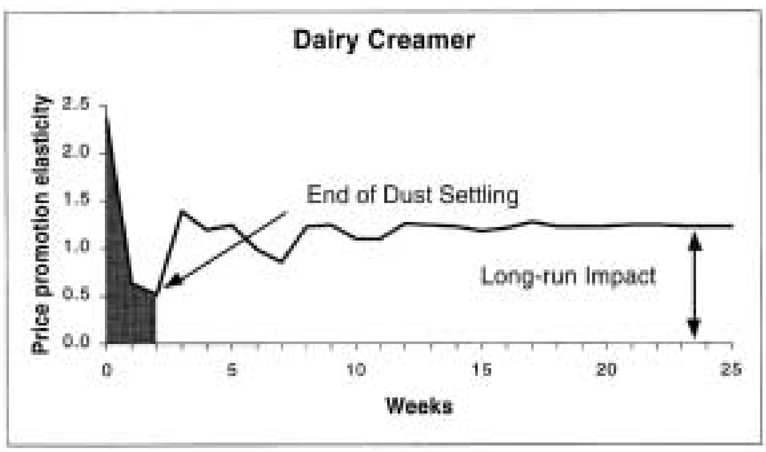
Bronnenberg, Mahajan, and Vanhonacker (2000) and Dekimpe and Hanssens (1995a, 1999), illustrate how impulse-response functions can either converge to zero (in case of stationary markets), or stabilize at a nonzero level (as is possible in evolving markets). Both scenarios are illustrated in Figure 2.

Figure 2. Impulse-response Functions

A. Impulse-response function for a stationary market



B. Impulse-response function for an evolving market



Note: The shaded area marks the duration of the dust-settling period. Short-run elasticities are operationalized as the *net* percentage change in sales over this period, normalized by the size of the initial price cut.

Panel A depicts the impulse-response function for the *stationary* Dutch all-purpose detergent market, in which the solid line represents the impulse response function of a price promotion on category sales. More specifically, the impulse response function shows the incremental impact (relative to the baseline forecast) on category demand in period t, $t + 1$, $t + 2$, ... of a price promotion in $t = 0$. The contemporaneous promotional elasticity is found to equal 1.41, while subsequent periods show a post-promotional dip (Blattberg, Briesch, and Fox 1995). Eventually, the graph converges to zero, indicating that any incremental effect disappears over time, and no long-run effect is observed.

When interested in the net short-run effect of promotions, attention should not be limited to the instantaneous effect alone (see Van Heerde, Leeflang, and Wittink 2000). Fluctuations in subsequent periods should also be taken into account. Critical in this decision is how many periods to consider. Following Dekimpe and Hanssens (1999) we consider how many periods it takes for the IRF to stabilize, and refer to the fluctuations during this dust-settling period as short-run fluctuations. The dust-settling period in this graph lasts for seven periods after the initial pulse. Formally, the end of this period is marked by a sequence of four consecutive nonsignificant effects in the impulse-response function. Significance for stationary series is determined relative to the (zero) convergence value (i.e., the impulse-response parameters in periods 8-11 were no longer significantly different from the convergence value, while the impact in period 7 was). The total elasticity over the dust-settling period was found to equal .18 (i.e., the percentage change in sales over the dust-settling period, normalized by the size of the initial price cut [%] at the time *t*). As indicated before, we report elasticity estimates as positive numbers to reflect their positive impact on performance. As such, a more effective response is reflected by a higher (i.e., more positive or less negative) number.

Panel B gives the corresponding impulse-response function for an evolving market. Contrary to the previous graph, this impulse-response function does not converge to zero, but stabilizes at a nonzero level of 1.23. This is called the long-run or persistent effect (Dekimpe and Hanssens 1995a, 1999). The dust-settling period is defined in a similar way as before, but we now look for the last period that has an impact significantly different from the (nonzero) asymptotic value.

In Appendix A, we elaborate on issues involved in estimating the VARX models, while Appendix B considers the shock operationalization of price promotions and the derivation of impulse-response functions from the VARX model.

Assessing the Moderating Effect of Competition

For each individual product category i (i = 1, .., M), a three-equation VARX model, described in Appendix A, was estimated. From these VARX models we derived the impulse-response functions corresponding to a price promotional shock. The two summary statistics described above (along with their associated standard errors) were derived from these impulse-response functions, resulting in 2 ($M\times1$) vectors of elasticity estimates. These vectors subsequently became the dependent variable in a regression model linking price promotion effectiveness to the different dimensions of competition and marketing intensity. As the dependent variables are estimated parameters, characterized by differing degrees of estimation accuracy, OLS may yield biased estimates of the standard errors if the model residuals exhibit heteroscedasticity. White's (1980) test indicated that our model of persistence elasticities was not affected by heteroscedasticity ($p > .65$). For the short-term elasticity model, however, the hypothesis of no heteroscedasticity was rejected ($p < .001$). Consequently, OLS is applied to our model of persistence elasticities, while Weighted Least Squares (WLS) is used in our analysis concerning the short-term effectiveness of price promotions (see Narasimhan, Neslin, and Sen 1996 for a similar approach). In WLS, both dependent and independent variables are weighted by the inverse of the standard error of the former (Bolton 1989).

Data Description and Measurement

Description of the Data

Data were available on 560 different frequently purchased consumer goods (FPCG) categories in the Netherlands. Product categories were delineated based on IRI/GfK's classification in product types, and offered a quasi-complete coverage of all goods found in a typical supermarket. To illustrate the range of products available in our dataset, we have grouped them into broader product *fields*. Table 1 shows some illustrative examples and frequency counts.

Table 1. Data Coverage

Product fields	Examples	Number of categories
Assorted foods	cereals, rice, croissants, pretzels	74
Assorted nonfood products	magazines, lighters, paper plates, greeting cards	23
Beverages	cola, wine, mineral water, coffee	46
Cakes	cookies, cake, waffles	26
Candy	mints, chocolate, chewing gum, toffee	46
Canned/bottled foods	tuna fish, hot dogs, peaches, olives	72
Care products	toilet tissue, perfume, shampoo, band-aids	50
Cleaning products	bleach, floor cleaners, detergents, shoe polish	19
Dairy products	ice cream, skimmed milk, eggs	48
Frozen foods	pizza, chicken, puff pastry, french fries	52
Household supplies	air fresheners, candles, sponges, bug-spray	35
Pet products	fish feed, frozen dog food, animal toys	15
Taste enhancers	vinegar, powdered sugar, pesto, salt	54
Total		560

Our database originated from two sources. First, IRI/GfK Benelux provided data on volume sales, price, feature and display activity, and distribution coverage. From the sales data at the brand level, we were able to establish the impact of major new product introductions, that occurred in 496 out of 560 categories.[4] Two hundred and eight weekly observations were available on each category. All scanner data were collected and processed using standard IRI procedures. Specifically, IRI collects data from a representative sample of over 350 Dutch supermarkets using a stratified sampling procedure where chains (or clusters of chains) are used as strata. Second, corresponding advertising data were obtained from the BBC research agency. This combination resulted in two unique features of our dataset: (1) the wide coverage of product categories, allowing us to establish empirical generalizations, and (2) the simultaneous inclusion of virtually the entire marketing mix, i.e., price, advertising, feature and display, distribution, and new-product activity.

Variable Operationalization

The operationalization of the two price promotion effectiveness measures was discussed in the previous section, i.e., the value to which the impulse-response function converges (long run), and the cumulative incremental impact on demand (%) normalized by the size of the initial price cut (%) (short run). We now discuss the operationalization of the different measures of marketing intensity, competitive reactivity, and competitive structure. The former two reflect the actions taken by industry participants. Marketing intensity reflects the degree to which a given marketing mix instrument is used, while competitive reactivity describes the extent to which marketing behavior is either aggressive, independent, or cooperative (see, for example, Putsis and Dhar 1998; Raju and Roy 1997). To determine the dominant form of action taken by competitors in response to an "aggressive competitive move" (either a price promotion or an advertising increase), we first consider all pairwise reactions between the top five brands, and subsequently combine the respective outcomes into aggregate, category-wide measures of advertising and price promotion reactivity. Finally, we describe our measure of competitive market structure.

Price Promotion Intensity

Price promotion frequency is defined as the number of weeks in which the price of one or more of the top five brands in a market was at least two standard deviations below its average price level. As such, it reflects the number of weeks where the consumer had the opportunity to buy one of the best-selling brands in a product category on promotion.

A brand's *price promotion depth* is defined in terms of the (percentage) difference between a promotional price (as defined for the frequency count) and the brand's average price level. By averaging this value across all five top brands and all promotional weeks, an overall category measure for promotional depth is obtained. These measures are conceptually similar to the ones adopted in Raju (1992), Raju, Srinivasan, and Lal (1990), and Rao, Arjunji, and Murthi (1995), among others.

Price Promotion Reactivity

For each brand pair, we first estimate a bivariate VAR model with their respective price series as endogenous variables. To enhance the ability of VAR models to capture lagged reactions, we include up to eight lags in the model specification. From these VAR models, we derive impulse-response functions which track the over-time reaction by brand *j (i)* to a price promotion implemented by brand *i (j)* at time t = 0. We use these impulse response functions to derive the magnitude of the short- and long-run reactivity to a competitive price promotion. Specifically, we determine the extent to which the initial impulse generated by brand *i (j)* at $t = 0$ impacts brand *j*'s (*i*'s) promotional tactics (1) during the dust-settling period observed in model A5 (short-run reactivity), and (2) in the long run (long-run reactivity).[5] In doing so, we make an explicit link between the time frame during which the reaction to the promotion is implemented and the net category demand effect of that promotion.

If an estimated effect is not significantly different from zero, this is equivalent to the case where, over the considered time frame, no reaction takes place, and where price promotional calendars and budgets are set independently. Effects in the same direction as the initial price promotion are evidence of a competitive reaction, while effects in the opposite direction reflect cooperative behavior (Gatignon 1984).[6] Moreover, the magnitude of the effect indicates the extent of matching or cooperating.

It is important to note that VAR models are flexible enough to capture asymmetric reaction patterns, which implies that different outcomes may be obtained depending on whether brand *i* or brand *j* was responsible for the initial promotional effort. Focusing on the top-five brands, 10 bivariate VAR models are estimated per category, resulting in 20 impulse-response functions from which the time-dependent reaction intensities are determined. An aggregate measure for the nature of competitive reactivity in a given industry and time frame is then obtained by averaging over elasticities, weighted by both the accuracy of their estimation and the size of the reacting firm. The former weighting is similar in spirit to the WLS procedure discussed previously, while the latter is similar to Gatignon (1984) who weights the estimated elasticities to account for the fact that the reactions of larger firms contribute more to the perceived extent of competitive interaction (see also Reddy and Holak 1991).

In total, more than 4,200 bivariate VAR models were estimated, resulting in over 8,400 impulse-response evaluations.[7] The significance of the different reaction elasticities is derived using Monte-Carlo simulations, each involving 250 runs (see Dekimpe and Hanssens [1999] for a formal discussion).

Advertising Intensity

Advertising intensity is captured by the advertising-to-sales ratio, both measured at the category level (cf. Lambin 1976; Tellis 1998).

Advertising Reactivity

Advertising reactivity reflects the extent of observed advertising changes that are triggered by competitive advertising changes. Aggregate measures for advertising reactivity are derived using a similar procedure as described above for price promotion reactivity, but with the two advertising series as endogenous variables in the bivariate VAR models.

For advertising reactivity, no explicit link with an initiating promotion is present. We therefore add one overall measure of advertising reactivity between each pair of brands to the second-stage regression. We quantify this measure as the cumulative incremental impact on demand (%) over a one-year period (52 weeks), again normalized by the size of the initial price cut (%). If this metric is not significantly different from zero, the net outcome (after all instantaneous and lagged reactions and counter-reactions have been taken into account) is equivalent to the case where no reaction takes place, and where advertising budgets are set independently.[8] Net effects in the same direction as the initial advertising change are evidence of a competitive reaction, while net effects in the opposite direction reflect cooperative behavior (Gatignon 1984, Note 4). The magnitude of the net effect again indicates the extent of matching or cooperating. For advertising, over 700 bivariate VAR models were estimated to measure the extent of reactivity in the different industries.[9] Brand-level estimates were subsequently combined into aggregate reactivity measures weighted by the size of the reacting firm and the accuracy of estimation (cf. above).

Competitive Structure

Competitive structure was measured by the number of brands in a category. It is one of the best-known measures of competitive market structure (Hay and Morris 1991; Scherer 1980) and was computed for each product category based on all brands whose market share exceeded 1 percent.

Covariates

The covariates considered in this study are (1) VARX specification characteristics, (2) product perishability, (3) the extent to which supermarkets capture national sales of a category, and (4) "multiple" competitive reactions.

Two dummy variables were specified to capture VARX specification characteristics. The first dummy variable indicates whether a dummy variable for a major new product introduction was added to the VARX model (see Note 4). The second dummy variable takes on a value of one, when the VARX model included a deterministic trend as a regressor. An additional dummy variable indicates whether products belonging to a specific category can be considered perishable (= 0) or nonperishable (= 1). A variable measuring the percentage of category volume sold through supermarkets (i.e., supermarket coverage) was also included. Two measures of "multiple" competitive reaction were included, one capturing the extent of reactivity of advertising to price promotions, and one pertaining to the extent of reactivity of price promotions to advertising. These reactivity covariates were calculated for brand pairs and subsequently aggregated to obtain a category-level indicator of reactivity, using a similar procedure as before.

Results[10]

Given the substantial size of our database, we begin with a discussion of important descriptive findings on (1) the temporal behavior of category demand, (2) the short- and (3) long-run magnitudes of price promotion effects, and (4) the nature of the competitive reactions. These results set the stage for a review of the empirical support for our hypotheses on both the main effects of price promotions and the identified moderators of these effects. We conclude with a discussion of the substantive implications of our findings.

Overall Descriptive Findings

Data Stationarity

Based on the ADF unit root test, we find that only 54 out of 560 markets studied are evolving, and this figure drops even further when a correction is made for structural breaks due to new product introductions (see Table 2). The overwhelming majority of category demand patterns is stationary over our four-year period, either around a fixed mean (38 percent) or around a deterministic trend (36 percent positive trend, 26 percent negative trend). This predominance of stationarity had previously been reported on several fast-moving consumer good categories by Dekimpe, Hanssens, and Silva-Risso (1999) and Srinivasan, Popkowski Leszczyc, and Bass (1999).[11]

Table 2. Unit Root Test Results

	Stationary	Evolving
ADF unit root test	506	54
Perron's structural-break unit root test	518	42

We therefore derive the empirical generalization that long-run category demand effects of promotions are the exception rather than the rule, since evolutionary behavior is a necessary condition for the occurrence of persistent effects. When apparent evolution is found, it can be traced to the introduction of new products in approximately 22 percent of the cases (12 out of 54). The importance of new product introductions in revitalizing markets is not only evident in this subset of categories, however. More broadly, we found that in 496 of the 560 categories, a major new product was introduced (see Note 4), and that in 30 percent of those categories (i.e., 147/496), the introduction had a significant expansive impact on category demand. Finally, while most markets are found not to be evolving, there are many cases of gradual change in category demand. The resulting trends are, however, deterministic in nature, resulting from exogenous factors outside the realm of brand-level marketing.

Magnitude of Short-run Promotion Effects

Descriptives on the distribution of the estimated category-demand elasticities of price promotions are given in Table 3 and Figure 3. In the short run, price promotions significantly expand category demand in 58 percent of cases. The estimated mean short-run price promotion elasticity is equal to .44. This value is *below* the brand-level price elasticities of 3.45 and 2.5 reported by, respectively, Bell, Chiang, and Padmanabhan. (1999), and Tellis (1988), substantiating the belief that brand-level elasticities exceed category elasticities (Hanssens, Parsons, and Schultz 2000). On the other hand, our price promotion elasticity *exceeds* the average category price elasticity of .24 found by Pagoulatos and Sorensen (1986). Thus, more so than regular price actions, price promotions lead consumers to increase category purchase levels (Blattberg, Briesch, and Fox 1995).

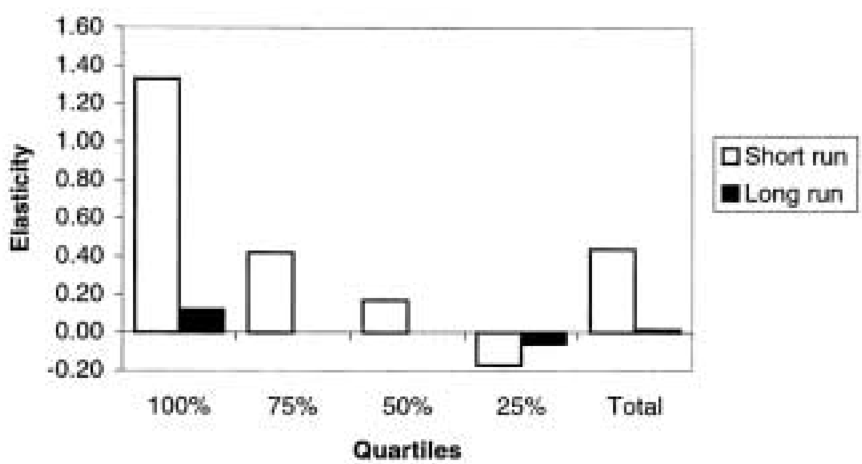
Magnitude of Long-run Promotion Effects

Table 3 also shows the over-time distribution of positive, negative, and zero elasticities. The incidence of positive price promotion effects declines significantly, and becomes a rare occurrence in the long run (2 percent). Figure 3 presents a graphical summary, where the mean price promotion elasticities for the different time horizons are depicted by quartile.

Table 3. Category Demand Effects of Price Promotions

	Short run	Long run
Positive	58%	2%
Negative	5%	0%
Zero	37%	98%

Figure 3. Average Price Promotion Elasticity per Quartile



The absence of long-run promotion effects is a logical consequence of our first result that category demand is predominantly stationary. Furthermore, even in the 7.5 percent (i.e., 42/560) cases where category demand is evolving, price promotions are often unrelated to that evolution as in less than one-third of the evolving cases a long-run price-promotion effect is actually observed. We believe that this is the first large-scale empirical evidence on the absence of long-run category demand effects of price promotions, and we hope it provides an important contribution to the "most debated issue in the promotional literature" (Blattberg, Briesch, and Fox 1995, p. G127).

Nature of Competitive Reactions

Brand reactivity was assessed using the VAR modeling approach outlined in the section on variable operationalization. Our findings concerning price promotion and advertising reactivity in the short run and long run are summarized in Table 4.

Table 4. Competitive Reactivity*

	Short run	Long run
Price promotion reactivity		
- Competitive	20%	9%
- Cooperative	13%	6%
- Independent	67%	85%
Advertising reactivity**		
- Competitive	5%	0%
- Cooperative	2%	0%
- Independent	93%	100%

* We report the percentage of significant (*t*-value > 1) competitive reactions.

** For reasons of comparability, we report the extent of short- (computed over the dust-settling period) and long-run (persistent) advertising reactivity, rather than the measure of advertising reactivity used in the second-stage regressions (i.e., the *net* reactivity over a 52-week period).

Based on the analysis of over 10,000 potential competitive reactions, we conclude that (1) the predominant form of competitive reaction is no reaction, and (2) if competitive reactions do occur, they do so more frequently in the short run than in the long run. This overall lack of reactivity is in line with findings by Brodie, Bonfrer, and Cutler (1996) and Leeflang and Wittink (1992, 1996) that, while (overly) intense reactivity may take place, it is a relatively rare occurrence (see also Rao, Arjunji, and Murthi 1995). The further reduction in reactivity in the long run could be attributable to budget limitations (consider the expense of prolonged price promotion or advertising wars), and the difficulty in sustaining cooperative behavior/agreements over long time periods.

Hypotheses Testing

Main Effect of Price Promotions

H_1 states that the impact of price promotions on category demand declines as one goes from short to long run. Consistent with this hypothesis, we find that the mean short- and long-run price-promotion elasticities are .44 and .02, respectively. The means are significantly different from one another (paired *t*-test, $p < .01$). Thus, H_1 is supported.

Moderating Role of Marketing Intensity and Competition

The results of the regression analyses of the short- and long-run price-promotion elasticities on promotional frequency, depth, and reactivity, advertising intensity and reactivity, and competitive structure are reported in Table 5.[12] Price promotion frequency has a positive impact on the short-run elasticity of category demand ($b = .863$, $p < .01$). This supports H_2. However, the effect on the long-run elasticity is negative ($b = -.134$, $p > .10$), albeit not significant. Our results indicate that over time, the positive effect of price promotional frequency on promotional effectiveness is offset by its negative side effects.

Consistent with H_3, promotional depth decreases the price promotion elasticity of category demand in the short run ($b = -.133$, $p < .10$). The effect on the long run elasticity is in the expected direction but is not significant ($b = -.006$, $p > .10$). Therefore, H_3 is partially supported. Price promotion reactivity does not have a significant effect on either the short- or long-run elasticity of category demand (*p*'s > .10). Therefore, H_4 is not supported. A possible explanation may be that while strong reactivity allows multiple market segments to benefit from a price promotion without the need for brand switching, it may also have a harmful influence on category image, thus reducing category demand effects (Brodie, Bonfrer, and Cutler 1996). If these opposing forces are of similar magnitude, cancellation may occur.

Greater advertising intensity in a category leads to a lower short-run ($b = -.011$, $p < .01$) and long-run ($b = -.029$, $p < .01$) elasticity of demand. Thus, H_5 is supported. In line with H_6, competitive advertising reactivity decreases the price promotion elasticity of category demand. This result is found for the short run ($b = -.060$, $p < .01$) and long run ($b = -.020$, $p < .10$). Thus, H_6 is supported for both time windows.

Finally, it was hypothesized that the more competitive the structure of a category, the lower the price elasticity of demand (H_7). This hypothesis is directionally supported for both time windows. The effect is significant for the short run ($b = -.003$, $p < .05$), but was not significant for the long-run elasticity ($b = -.000$, $p > .10$).

Evolution in the Moderating Role of Marketing Intensity and Competition

We posited as generalized expectation that the effect of moderators on the price promotion elasticity of category demand attenuates over time (H_8). H_8 predicts that the unstandardized regression coefficient for the long run is significantly smaller than the unstandardized regression coefficient for the short run. The magnitude of the effect of a moderator can only be meaningfully compared across time frames for those factors that are identically defined in each equation. This excludes price promotion reactivity. To test H_8, a meta-analysis was conducted on the *p*-values associated with the difference in magnitude of the regression coefficients across time frames for price promotion frequency, price promotion depth, advertising intensity, advertising reactivity, and competitive structure, using the method of adding *Z*s (Rosenthal 1991).[13] It revealed that the collective evidence across all moderators supports H_8 (Z = 2.29, p = .011). Moreover, H_8 was directionally supported at the level of the individual moderators for four out of five factors, while the difference was significant in the expected direction for price promotion frequency, advertising reactivity, and competitive structure (*p*-values range from .001 to .09). Thus, H_8 is supported.

Table 5. Moderating Role of Marketing Intensity, Competitive Reactivity, and Competitive Structure on Short- and Long-run Price Promotion Elasticities

		Price promotion elasticities			
		Short run		Long run	
Predictor variables	**Hypothesized sign**	***b***[1]	**β**[2]	***b***	**β**
Price promotion frequency	+ (H_2)	.863[a]	.231	-.134	-.040
Price promotion depth	- (H_3)	-.133[c]	-.085	-.006	-.003
Price promotion reactivity[3]	+ (H_4)	.100	.011	-.001	-.000
Advertising intensity	- (H_5)	-.011[a]	-.290	-.029[a]	-.119
Advertising reactivity	- (H_6)	-.060[a]	-.127	-.020[c]	-.058
Competitive structure	- (H_7)	-.003[b]	-.091	-.000	-.008

a $p < .01$

b $p < .05$

c $p < .10$

1 *b* represent the unstandardized regression coefficients.

2 β represent the standardized regression coefficients.

3 Measure specification for price promotion reactivity varies across equations. Details are provided in the section on data description and measurement.

Covariates

In the regressions linking the price promotion elasticities to our constructs of main interest, i.e., marketing intensity, competitive reactivity, and competitive structure, we controlled for several other factors (see previous section on covariates). Categories in which a major new product was introduced (i.e., for which a new product introduction dummy variable was included in the VARX specification) did not show different short- or long-run estimates of price promotion effectiveness than categories in which no such introduction occurred (*p*'s > .10).[14] Categories where one or more of the endogenous variables showed trending behavior (i.e., a deterministic trend was included in the VARX model) exhibited a significantly lower price promotion elasticity of category sales in the long run ($b = -.102$, $p < .01$), but not in the short run ($p > .10$). The long-run impact of this covariate can be explained by the fact that no series was found to contain both a deterministic and a stochastic trend.

The coverage variable had a significant negative impact on the long-run effectiveness of price promotions at the category level ($b = -.239$, $p < .05$). While a similar negative effect is found for the short run, it fails to reach significance ($b = -.233$, $p > .10$). We thus conclude that, when supermarkets have higher market coverage in a category, the extent to which sales can be drawn from other outlet types is reduced.

Previous research has indicated that nonperishable products facilitate stockpiling and inter-temporal sales displacement (see for example, Bell, Chiang, and Padmanabhan 1999; Narasimhan, Neslin, and Sen 1996). Our second-stage analysis shows that the effectiveness of price promotions is lower in categories of nonperishable products, in both the short run ($b = -.060$, $p < .10$) and the long run ($b = -.031$, $p < .10$). This indicates that sales-displacement effects (e.g., a post-promotion dip) may be more important in such categories. Finally, neither of the "multiple" reactivity measures showed a significant effect in either the short or the long run (p's > .10).

Discussion

We find support for H_1, H_5, H_6, and H_8. Further, H_2, H_3, and H_7 are supported for the short run, while the results are in the expected direction for H_4. Two other hypotheses (H_3, H_7) are directionally supported for the long run but their effects do not reach statistical significance. The somewhat weaker results for the long-run time window are actually not surprising, given that most long-run price-promotional elasticities are very small in the first place (see Table 3). Our results show that promotional and advertising intensity typically have a larger impact on elasticities than competitor reactivity variables in both the short and the long run.[15] This indicates that, overall, the general level of activity (promotions, advertising) is more important than what triggered this activity level.[16]

Our results further show that with respect to marketing intensity levels, promotion and advertising activities are approximately equally important in shaping the effectiveness of price promotions, but only in the short run. In the long run, advertising activities (intensity, reactivity) have a bigger impact than promotional activities on price promotion effectiveness.

We find that competitive structure has a significant effect on short-run promotional effectiveness. Thus, the structure of a category is a relevant factor to consider in evaluating the short-run effectiveness of price promotions. Price promotions tend to be more effective in stimulating category demand in markets with fewer brands. However, structure had no effect on long-run promotional effectiveness, and the effect of marketing actions was more important.[17] Of all drivers of price-promotion elasticity of category demand, the three most important effects that stand out are the large positive effect of promotional frequency on the short-run elasticity of demand and the large negative effect of advertising intensity on both the short- and the long-run effectiveness of price promotions. A higher price promotional frequency generates a large increase in price promotion effectiveness in the short run. However, this effect is completely dissipated in the long run, where price promotions are, if anything, less effective in a high-frequency scenario. This dissipation of the initial positive effect presents a potential trap to managers. They see the large, immediate effect of this driver on sales while the long-run effect is some time away. As a consequence, resources may be diverted to support price promotional efforts, which do not help enhance the long-run position. This myopic view may explain why price promotions are so attractive to brand managers who are often responsible for a brand only for a relatively short time (Abraham and Lodish 1993).

Overall, advertising conduct (own conduct and competitive reactivity) emerges as a key driver affecting both short- and long-run price-promotion elasticities of category demand. Consistent with H_5 and H_6, the effect of advertising is negative, i.e., the higher the advertising intensity and the greater the advertising reactivity, the more the effectiveness of price promotions is diminished. This offers an interesting opportunity for companies like Colgate-Palmolive, Quaker Oats, and Procter & Gamble that want to reduce the reliance on price promotions in their categories (*Wall Street Journal* 1996). As long as price promotions remain effective to increase category demand, competitors of these companies will remain tempted to use them, and retailers may insist on high consumer promotional spending to stimulate category demand. In such a situation, de-emphasizing price promotions may weaken the market position of these companies not only vis-à-vis its competitors but also in the distribution channel. Heavy advertising is a good strategy to reduce the category-level price-promotion effectiveness, which will make it easier for the firm to implement a strategy of reduced price-promotional spending.

Validation

To assess the robustness of our empirical findings, a number of validation analyses were conducted. Specifically, we assess the sensitivity of the results to the choice of endogenous variables in the VARX models, and the potentially confounding impact of aggregation bias on effect size estimates. We further establish to what extent our effectiveness estimates might be affected by the level of temporal aggregation of the data, the static/dynamic specification of the exogenous variables, and the order specification of the VARX. Finally, we determine the sensitivity of our competitive reactivity measures to alternative model specifications.

Endogenous Variables

The impulse-response function tracing the incremental impact of a price promotion shock on category demand is our basic measure of promotional effectiveness (see the methodology section). To assess the robustness of our findings, we determine to what extent these impulse-response functions are sensitive to the manner in which various regressors enter the VARX models. As discussed in the methodology section, we specify VARX models with sales, price, and advertising as endogenous variables, while allowing other variables to enter as exogenous regressors. The choice of sales, price, and advertising as endogenous variables is directly in line with our research objectives to (1) assess the dynamic interrelationships between price promotions and category demand, and (2) assess the moderating role of advertising with respect to price-promotional effectiveness. Ideally, we would like to specify more elaborate VARX models with additional endogenous variables. This would, however, add strain to an already heavily parameterized model. To ensure that our substantive results are not sensitive to the specific selection of endogenous variables, four alternative VARX specifications were implemented. In each specification, sales and price are selected as endogenous as they are the core variables of the study, while we rotate which other variable is entered as endogenous: feature and display, feature only, display only, or distribution coverage. For each alternative VARX, IRFs were calculated over a period of 52 weeks, and compared with the IRFs derived from the focal model discussed in Appendix A. First, we examined to what extent these IRFs were correlated by calculating 560 correlation estimates per specification, i.e., one for each category and each alternative model specification. The average correlation, over the 560 categories, was very high for each of the alternative specifications, varying between .94 and .98.[18] A second comparison was based on the average short- and long-run elasticity estimates for each of the different model specifications. The magnitudes of the elasticity estimates were found to be very similar. Overall, these results indicate that our main findings are not sensitive to the choice of the third endogenous variable (detailed results are given in Table 6 below).

Table 6. Average Correlations of IRFs and Average Short- and Long-run Elasticities, Derived from Alternative Specifications of the VARX Models

Validation issue	*Average correlation of IRFs*	*Average short-run elasticity*	*Average long-run elasticity*
Focal model	1	.44	.02
Specification of third endogenous variable			
Feature and Display	.95	.46	.03
Feature only	.96	.45	.02
Display only	.96	.46	.02
Distribution	.94	.40	.02*
Aggregation bias			
Linear model	.83	×	×
# of lags of exogenous variables			
1 lag	.98	.43	.01
2 lags	.97	.43	.02*
3 lags	.96	.40	.02*
VARX order			
6 lags	.93	.45	.02
4 lags	.87	.46	.02

* One outlying observation was removed before calculating this value.

Aggregation Bias

Christen, Gupta, Porter, Staelin, and Wittink (1997) have shown that when working with arithmetically-averaged data, models estimated in log-log form may be sensitive to an aggregation bias if there is heterogeneity in marketing activities across stores. As it has been shown that linear models do not exhibit this bias, we reestimated all VARX models using a linear specification, and determined the corresponding IRFs. Using the procedure detailed above, we then compared the results from the log-log and the linear model, and obtained an average correlation of .83.[19] While this value is still fairly high, it is somewhat lower than the correlation values reported above. We see two possible explanations for this. First, both the linear and the log-log model may be subject to some misspecification bias (see Leeflang, Wittink, Wedel, and Naert 2000). As a consequence, if this bias does not work in exactly the same direction for both model specifications, the size of the correlation coefficient is reduced (Nunnally 1978). Second, we noticed that the linear model gave rise to some outlying estimates. The median correlation, which is more robust to outliers, was found to equal .93.

We further calculated the percentage of cases in which unit root tests on linear and log-transformed data lead to the same conclusion. In 96 percent of cases the classification was identical. Based on the above findings we conclude that the possible bias due to arithmetic averaging of the variables in our log-log model is minimal.

Temporal Aggregation of Data

As shown in Cogger (1981), temporal aggregation of the data does *not* affect the level of integration of an ARIMA model, and hence should not affect the classification of a series as either evolving or stationary. Empirical testing procedures, on the other hand, may be sensitive to such aggregation, as found by Dekimpe and Hanssens (1995b). We were able to determine that the percentage of markets classified as evolving was minimally affected by aggregating our weekly data to the bi-weekly level (7.5 percent versus 7.1 percent, based on original and aggregated data respectively). Furthermore, over 93 percent of all category sales series were equally classified as either stationary or evolving based on the weekly and bi-weekly data.

Exogenous Variables

In our VARX specification, we allow for implicit dynamic effects of the exogenous variables (distribution and feature/display variables) through the inclusion of lagged endogenous variables (e.g., lagged sales). This approach is conceptually similar to the partial adjustment model (see Hanssens, Parsons, and Schultz 2000). By not incorporating lagged exogenous effects directly, the parameterization level of our models is reduced at the expense of some flexibility. To assess the invariance of our results to the manner in which exogenous variables are incorporated in the VARX models, we compared our results to those obtained from models with varying dynamic specifications of these variables. Specifically, we compare the results from the focal model, which does not allow for lags of the exogenous variables, with estimates derived from models in which respectively 1, 2, and 3 lags of the exogenous variables are incorporated. Similar to the validation exercises detailed above, we calculate the average correlation between IRFs derived from the various VARX models, and establish the size of the average short- and long-run elasticities. Again, the correlations were very large, ranging from a low of .96 to a high of .98, while the magnitudes of the elasticity estimates were almost identical. We conclude that the imposed restrictions do not substantially affect our findings.

VARX Order

As detailed in Appendix A, we specify VARX models with eight lags. To establish that our findings are robust to the lag order chosen, VARX models with four and six lags have also been estimated. The size of the elasticity estimates was, again, very comparable. Also, the average correlations between the IRFs derived from the different models are .87 and .93 for the comparison with the four and six lag models, respectively. As expected, the correlation between results from the eight lag and four lag model is somewhat lower, as the later is less flexible in capturing dynamic effects, and as such tends to smooth the IRF.

Competitive Reactivity

Our measure of competitive reactivity draws upon previous work on reaction functions (as pioneered by Lambin, Naert, and Bultez 1975) and Granger-causality testing (see Leeflang and Wittink 1992 for a recent marketing application). It has been shown, however, that both approaches are sensitive to the information set that is considered (see, for example, Bult, Leeflang, and Wittink 1997; Hanssens, Parsons, and Schultz 2000, chapter 7). Our reactivity operationalization is based on bivariate specifications, which can be extended along multiple dimensions. When looking at, for example, the price reactivity between brand *i* and brand *j*, one could add (a) other marketing mix variables of brand *i* and brand *j* (e.g., A_i and A_j), (b) other price series (P_k, P_l, $k, l \neq i, j$), or (c) the sales series of the two brands at hand (i.e., S_i and S_j), as it has been argued that market interactions may be a function of demand considerations (see, for example, Vilcassim, Kadiyali, and Chintagunta 1999). Each of these extensions was considered (resulting in the estimation of over 10,000 additional VARX systems). Using a similar approach as before, we derived the average correlation between the IRFs of the bivariate specifications with the corresponding IRFs from the extended, four-variable models. These correlations were high overall, indicating that our findings are not significantly affected by the information set considered in estimating competitive reactivity. Detailed results are provided in Table 7 below.

Table 7. Average IRF Correlations for Competitive Reactivity Measures

	Variables added to bivariate base model		
Bivariate base model	(A_i, A_j)	(P_k, P_l, $k, l \neq i, j$)	(S_i, S_j)
Price promotion reactivity (P_i, P_j)	.86	.81	.77
	(P_i, P_j)	(A_k, A_l, $k, l \neq i, j$)	(S_i, S_j)
Advertising reactivity (A_i, A_j)	.90	.94	.90

P_i = price for brand *i;* A_i = advertising for brand *i;* S_i = sales for brand *i.*

Conclusions

This paper has investigated the category demand effects of consumer price promotions in 560 consumer product categories over four years. The wide range of our cross-sectional and time-series data allows us to make empirical generalizations that include competitive as well as over-time drivers of promotional effectiveness.

Price promotions have a significant short-term impact on category demand. They stimulate consumers to concentrate purchases in promotional periods, to “lie in wait,” to accelerate purchase decisions, and/or to increase category consumption. This strong short-term effect generally weakens over time, and only rarely does it result in permanent shifts in category demand. Indeed, promotion-intensive product categories in general tend to follow stationary demand patterns over time, except when trend-setting new products are introduced. Our results, based on market-level data, should also provide valuable benchmarks for practitioners, as in the vast majority of cases they, too, only have access to market-level data (Bucklin and Gupta 1999; Christen et al. 1997).

The effectiveness of price promotions is partially determined by the manner in which the participants in the category use them. The more frequently price promotions are used, the stronger is the short-run consumer sensitivity to them. This positive effect of price promotions is, however, dissipated in the long run. The most influential moderator of price promotion effectiveness found in this study is the use of nonprice advertising by incumbents (intensity and reactivity). Advertising creates differentiation among brands in the category, which reduces consumers’ price promotion sensitivity at the category level. This finding offers valuable insights to both brand managers and retail managers interested in reducing their dependence on price promotions in specific categories.

Promotional effectiveness is also determined by competitive structure and competitive behavior. The fewer industry members, i.e., the more oligopolistic, the stronger the promotional effectiveness of its participants. However, the relative importance of competitive conduct is greater than that of competitive structure in impacting promotional elasticities. Price promotional effectiveness is shaped to a large extent by the strategic behavior of firms within the category. Furthermore, while competitive advertising reactivity in a market is found to be a main driver of price-promotional effectiveness, the dominant form of reactivity found in this study is *nonreaction*.

Our study has various limitations. First, more detailed insights into the category expansive effects of price promotions could be gained by differentiating their impact with respect to the initiating brand (e.g., market leader versus private label) (see Dekimpe, Hanssens, and Silva-Risso 1999). Second, we could expand our framework to other marketing-mix variables, and derive empirical generalizations and moderators of, for example, advertising effectiveness. Third, our analysis of competitive reactivity is conducted at the brand rather than the SKU level, and as a consequence does not provide insight with respect to within-brand cannibalization issues (see Fader and Hardie 1996). Fourth, we only had access to data from supermarkets. While supermarkets cover the majority of sales in most product categories used in our study, there is some cross-store substitutability that was not covered in our database. Fifth, due to data limitations, we were unable to establish elasticity estimates at the store level. These limitations offer areas for extending/improving upon our study.

Other areas for future research are open as well. First, our aggregate data do not provide direct information about the individual-level processes underlying the results. A detailed investigation at the consumer level may uncover the mechanisms underlying the aggregate market behavior analyzed in our study. Second, the VARX models we advocate are fixed-parameter models, and individual promotional shocks are assumed not to affect the structure of the data-generating process (Dekimpe, Hanssens, and Silva-Risso 1999; Pesaran and Samiei 1991). It would be useful to relax this assumption, using either an explicit varying-parameter specification (as recently used by Foekens, Leeflang, and Wittink 1999 in a single-equation setting) or by adopting a moving-window operationalization, as implemented by Bronnenberg, Mahajan, and Vanhonacker (2000). Third, our approach to quantifying competitive reactivity, while very flexible in capturing dynamics, does not provide insights into *why* competitors act the way they do. Models derived in the tradition of NEIO are better suited to this end (see, for example, Vilcassim, Kadiyali, and Chintagunta 1999; Roy, Hanssens, and Raju 1994). Future work could attempt to integrate the two traditions. Fourth, our findings are based on data from the Netherlands. The Netherlands are a highly industrialized country with few restrictions on sales promotions and a competitive retail trade, and it was shown that our findings on price promotional effectiveness and promotional reactivity are consistent with other research. Still, it is important to investigate whether these findings can be generalized to other countries.

Fifth, it has been argued that, with the increased reliance on price promotions by manufacturers, the "center of marketing gravity" has shifted to retailers (Berthon, Hulbert, and Pitt 1999). Retailers are now demanding that manufacturers demonstrate the role their brands play in the overall performance of product categories (Kumar 1997). In the current paper, we have shown that price promotions have a significant impact on sales at the category level. Sales of different categories, however, need not occur in isolation. To get a strategically even more complete picture, future research should attempt to also gain insights into the cross-category effect of price promotions. Such insights should enhance the effectiveness of merchandising strategies of both retailers and manufacturers active in multiple categories. Finally, if margin data are available, empirical generalizations could be developed that focus on category profitability as opposed to category demand. Indeed, our results have established that consumer price promotions generally do not create long-run market expansion. Coupled with the fact that market shares are known to be predominantly stationary, this leaves only one major source of long-run profitable growth from the use of price promotions, profit margins. Herein lies an opportunity for established brands in oligopolistic categories. Promotions' high short-run effects and zero long-run category demand effects make such categories costly to enter and thus less attractive for new competitors. Smaller existing competitors may also be enticed to leave the market for the same reasons. These conditions keep the category in a "business as usual" condition that is profitable to its major participants. As such, the power of price promotions lies primarily in the preservation of the status quo in the category.

Appendix A. VARX Specification

When specifying a VARX model, several issues need to be decided upon, such as whether to include the variables in level or difference form, which variables to treat as endogenous/exogenous, and whether the model should be augmented with lagged error-correction terms.

Unit Root Tests

To determine whether the different variables should enter the VARX model in level or difference form, preliminary unit root tests were conducted. Specifically, we applied the Augmented Dickey Fuller (ADF) test to each individual series. The general form of the test equation is given by:

$$\Delta y_t = \alpha_0 + \alpha_1 t + \gamma y_{t-1} + \sum_{i=1}^{k} \beta_i \Delta y_{t-i} + \sum_{s=2}^{13} \theta_s SD_{st} + \varepsilon_t , \tag{A1}$$

in which y_t is the variable of interest, t a deterministic trend variable, and the *SD*s a set of four-weekly seasonal dummy variables. When implementing the ADF test, two decisions must be made: (1) which deterministic components to include in the test equation, and (2) the number of lagged difference terms to include. As for the deterministic components, seasonal dummy variables were added in all instances, as Ghysels, Lee, and Noh (1994) have shown this to lead to a favorable bias-power trade-off. The iterative procedure advocated in Enders (1995, pp. 256-258) was used to empirically decide on the need to include a deterministic-trend component. The only modification to the Enders procedure was that we always incorporated an intercept term to account for the fact that y_0 will, in general, not be equal to zero (see Franses [1998] for a formal motivation). To determine the number of lagged difference terms (which are needed to ensure that the residuals are white noise), we varied k from 0 to 8, and selected the one with the best value of the SBC criterion (cf. Hall [1994]; see Bronnenberg, Mahajan, and Vanhonacker [2000] or Dekimpe and Hanssens [1999] for marketing applications).

Unit root tests are known to be biased towards finding a unit root when some "extraordinary" event caused a structural break in the intercept α_0 (Perron 1989, 1990). In our context, a prime candidate for such an event is the introduction of a new product, as discussed in Bronnenberg, Mahajan, and Vanhonacker (2000) and by Dekimpe, Steenkamp, Mellens, and Vanden Abeele (1997). To avoid the spurious classification of a series as evolving, all endogenous series that were found to have a unit root according to Equation A1, were subjected to the innovational-outlier structural-break test of Perron, with test equation:

$$\Delta y_t = \alpha_0 + \theta_1 DU_t + \theta_2 D(TB)_t + \alpha_1 t + \gamma y_{t-1} + \sum_{i=1}^{k} \beta_i \Delta y_{t-i} + \sum_{s=2}^{13} \theta_s SD_{st} + \varepsilon_t , \tag{A2}$$

which is equivalent to Equation A1 augmented with two terms: DU_t, a step dummy variable taking the value of one if $t \geq TB$ (i.e., the potential break date) and zero otherwise, and $D(TB)_t$ which is equal to one at $t = TB$ and zero otherwise. Through the inclusion of DU_t, one allows for a break in the intercept, while $D(TB)_t$ is added to make the test statistic for $\gamma = 0$ invariant in finite samples to the value of the change in the intercept under the null hypothesis of a unit root (cf. Perron 1994). Critical values for the test statistic are listed in Perron (1989) in case $\alpha_1 t$ is included, and Perron (1990) if not.

VARX Specification

Three-equation VARX models were estimated, with category demand (CD), the market-share weighted average price (P), and total advertising spending (A) as endogenous variables, and four exogenous variables: distribution coverage ($Dist$) and three nonprice promotional variables, feature only (F), display only (D), and feature and display (FD). In addition, we added the following deterministic components: an intercept ($c_{0,..}$), four-weekly seasonal dummy variables ($c_{s,..}$), a deterministic-trend variable (t) anytime an endogenous variable was found to have a deterministic trend in the data-generating process (based on the unit root testing procedure of Enders), and a step dummy variable for the potential impact of new product introductions (NP). One such step dummy variable was added for the most successful new product entry in the category, provided it achieved an average market share exceeding one percent over three consecutive months.

In the absence of unit roots, variables were written in levels form, while unit root series were incorporated in first-difference form. Assuming, for ease of exposition and without loss of generality, that all series have a unit root (but are not cointegrated, cf. below), the following model was obtained:

$$\begin{bmatrix} \Delta CD_t \\ \Delta P_t \\ \Delta A_t \end{bmatrix} = \begin{bmatrix} c_{0,CD} + \sum_{s=2}^{13} c_{s,CD} SD_{st} + \delta_{CD}\, t + \eta_{CD} NP_t \\ c_{0,P} + \sum_{s=2}^{13} c_{s,P} SD_{st} + \delta_P\, t + \eta_P NP_t \\ c_{0,A} + \sum_{s=2}^{13} c_{s,A} SD_{st} + \delta_A\, t + \eta_A NP_t \end{bmatrix} + \sum_{i=1}^{8} \begin{bmatrix} \phi_{11}^i & \phi_{12}^i & \phi_{13}^i \\ \phi_{21}^i & \phi_{22}^i & \phi_{23}^i \\ \phi_{31}^i & \phi_{32}^i & \phi_{33}^i \end{bmatrix} \begin{bmatrix} \Delta CD_{t-i} \\ \Delta P_{t-i} \\ \Delta A_{t-i} \end{bmatrix}$$
$$+ \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} & \gamma_{14} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} & \gamma_{24} \\ \gamma_{31} & \gamma_{32} & \gamma_{33} & \gamma_{34} \end{bmatrix} \begin{bmatrix} \Delta Dist_t \\ \Delta F_t \\ \Delta D_t \\ \Delta FD_t \end{bmatrix} + \begin{bmatrix} \mu_{CD,t} \\ \mu_{P,t} \\ \mu_{A,t} \end{bmatrix}, \quad \text{(A3)}$$

where $[\mu_{CD,t}\ \mu_{P,t}\ \mu_{A,t}]' \sim N(0, \Sigma)$. Two issues deserve further attention. First, given the high frequency of our data, and in order to capture dynamic effects that take some time to materialize (which may be the case for advertising), we use a VAR model of fairly high order (8) to derive the impulse-response functions. Second, anytime one of the endogenous variables had a deterministic trend in the data-generating process, we included a trend variable in all three equations. This may have caused a (small) loss in power if some of these parameters turned out to be insignificant, but resulted in significant computational gains (given the number of analyses to be performed), as OLS rather than iterative SUR can be used when all equations have the same regressors. When none of the endogenous variables had a trend in the data-generating process, we set δ_i (i = CD, P, A) equal to zero.

Cointegration and Error-correction Models

VARX models specified in the first difference of evolving endogenous variables may result in a loss of relevant long-run information when two or more of them are cointegrated, in which case the included parameters, the impulse-response functions derived from them, and the resulting short- and long-run promotional elasticities would be biased. In those instances, the VARX model in Equation A3 should be augmented with lagged error-correction terms (see Johansen [1988] for a formal discussion, and Bronnenberg, Mahajan, and Vanhonacker [2000] or Dekimpe and Hanssens [1999] for recent marketing applications).

Still assuming, without loss of generality, that all three endogenous variables are evolving, we wish to test whether the residuals from the following equation,

$$CD_t = \beta_0 + \beta_1 t + \beta_2 P_t + \beta_3 A_t + e_{CD,t} \quad , \tag{A4}$$

have stationary residuals. If so, a long-run equilibrium relationship exists between the different evolving series from which the system can only temporarily deviate (as the deviations are mean-reverting to zero when $e_{CD,t}$ does not have a unit root). Some choices need to be made in the context of cointegration modeling. First, a procedure to test for the existence of such a long-run equilibrium needs to be selected. The current standard for cointegration testing was used, i.e., Johansen's Full Information Maximum Likelihood (FIML) procedure (Johansen 1988, 1995). Second, we allowed for both an intercept and a deterministic trend in the equilibrium relationship. The former is added to allow for a level difference between the respective endogenous variables, and a trend is added following the recent recommendations in Doornik, Hendry, and Nielsen (1998) and Franses (1999). Depending on the presence of deterministic trends in the VARX described above, the critical values in tables 15.4 or 15.5 of Johansen (1995) were used to test for cointegration. Third, when dealing with N evolving endogenous variables, N-1 such cointegrating or long-run equilibrium relationships may exist. As this may lead to interpretational problems (e.g., when opposite signs emerge in the different equilibria), we focused on the cointegration vector associated with the highest eigenvalue in Johansen's procedure, as this vector is the most highly correlated with the stationary part of the underlying data-generating process, and hence, of most interest (cf. Johansen and Juselius 1990, p. 192). If cointegration is found, the VARX model in Equation A3 is augmented with the lagged residuals from A4, also called error-correction terms, as described in Harris (1995) and Dekimpe and Hanssens (1999).[20]

$$\begin{bmatrix} \Delta CD_t \\ \Delta P_t \\ \Delta A_t \end{bmatrix} = \begin{bmatrix} c_{0,CD} + \sum_{s=2}^{13} c_{s,CD} SD_{st} + \delta_{CD}\, t + \eta_{CD} NP_t \\ c_{0,P} + \sum_{s=2}^{13} c_{s,P} SD_{st} + \delta_{P}\, t + \eta_{P} NP_t \\ c_{0,A} + \sum_{s=2}^{13} c_{s,A} SD_{st} + \delta_{A}\, t + \eta_{A} NP_t \end{bmatrix} + \sum_{i=1}^{8} \begin{bmatrix} \phi_{11}^i & \phi_{12}^i & \phi_{13}^i \\ \phi_{21}^i & \phi_{22}^i & \phi_{23}^i \\ \phi_{31}^i & \phi_{32}^i & \phi_{33}^i \end{bmatrix} \begin{bmatrix} \Delta CD_{t-i} \\ \Delta P_{t-i} \\ \Delta A_{t-i} \end{bmatrix}$$

$$+ \begin{bmatrix} \alpha_{CD} & 0 & 0 \\ 0 & \alpha_P & 0 \\ 0 & 0 & \alpha_A \end{bmatrix} \begin{bmatrix} e_{CD,t-1} \\ e_{P,t-1} \\ e_{A,t-1} \end{bmatrix} + \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} & \gamma_{14} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} & \gamma_{24} \\ \gamma_{31} & \gamma_{32} & \gamma_{33} & \gamma_{34} \end{bmatrix} \begin{bmatrix} \Delta Dist_t \\ \Delta F_t \\ \Delta D_t \\ \Delta FD_t \end{bmatrix} + \begin{bmatrix} \mu_{CD,t} \\ \mu_{P,t} \\ \mu_{A,t} \end{bmatrix}, \quad \text{(A5)}$$

Equation A5 is the most general form of the VARX model. If no cointegration is found, the model reduces to A3. If Enders' procedure indicated that none of the endogenous variables had a deterministic trend in the data-generating process, the δ_i parameters were set to zero, and if some of the variables did not have a unit root, the difference operator was omitted and the variable entered in levels form.

Appendix B. Promotional Shocks and Impulse Response Functions

Price promotions are operationalized as one-time unit shocks to the VARX model described in Appendix A. To derive the impulse-response functions (IRFs), we compute two forecasts, one based on an information set that does not take the promotion into account and one based on the extended information set that incorporates the promotion at time *t*, and we compute the difference between the two. This procedure is mathematically equivalent to simulating the over-time impact of a shock to the price residual in Equation A5; see, for example, Bronnenberg, Mahajan, and Vanhonacker (2000) or Dekimpe and Hanssens (1995a, 1999). Formally, one assumes $[\mu_{CD,t+i}\ \mu_{Pt+i}\ \mu_{A,t+i}]' = [0\ 0\ 0]'$ for $i = ..., -2, -1, +1, +2, ...$, while $\mu_{P,t}$ is set to -1. Under these assumptions, we compute $[CD_t\ P_t\ A_t]'$ for $t = 0, 1, 2, ...$. In order to make these computations, one still has to specify the values for $\mu_{CD,t}$ and $\mu_{A,t}$. Setting them equal to zero would imply that price promotions cannot have an instantaneous category-demand effect, while joint promotional-advertising decisions in period *t* would be excluded as well. Indeed, the VARX model, while extremely flexible in terms of the lagged dynamic effects, does not offer direct estimates of the instantaneous effects. To allow for these instantaneous effects, we follow Dekimpe and Hanssens (1999), and use the multivariate-normality property of the residual vector to derive the expected value of $\mu_{CD,t}$ and $\mu_{A,t}$ given the one-unit shock to $\mu_{P,t}$ as $-\sigma_{P,CD}/\sigma_{P,P}$ and $-\sigma_{P,A}/\sigma_{P,P}$, with $\sigma_{i,j}$ the corresponding element in the residual variance-covariance matrix Σ. We then simulate the over-time impact of the shock vector $[-\sigma_{P,CD}/\sigma_{P,P}\ -1.0\ -\sigma_{P,A}/\sigma_{P,P}]'$. In doing so, we capture both a wide variety of lagged effects (through the ϕ parameters in A5) and the expected instantaneous effects.

Standard errors for the IRFs and/or the summary statistics described in the methodology section were subsequently derived using the Monte-Carlo simulation approach introduced in Dekimpe and Hanssens (1999), with 250 runs in each case.

Notes

1. Positive numbers will be used to describe instances where a (larger) price promotion has a (more) positive category demand effect. A decline in elasticity therefore reflects a transition from more to less positive, or from positive to zero/negative.

2. It is not claimed that structure is exogenous to conduct, as in the long run, conduct may well affect structure and vice versa (e.g., Scherer 1980). However, the dynamic relations between structure and conduct in a category are outside the scope of this paper. By simultaneously including them in our analyses, we control for one when estimating the effect of the other, thus arriving at more accurate parameter estimates.

3. A similar baseline and shock operationalization has recently been used to quantify the over-time effectiveness of distribution changes in Bronnenberg, Mahajan, and Vanhonacker (2000), of advertising shocks in Dekimpe and Hanssens (1995a, 1999) and of price-promotions in Dekimpe, Hanssens, and Silva-Risso (1999) and Srinivasan, Popkowski Leszczyc, and Bass (1999).

4. Product categories in which the most successful new product introduction was able to capture a market share in excess of 1 percent during at least three consecutive months were labelled as having witnessed a "major new product introduction."

5. Further details on the derivation of short- and long-run impact estimates from IRFs are given in the methodology section and Appendix B.

6. Note that we define the terms *competitive* and *cooperative* at the brand level, which is the common interpretation. However, it may well be that competitor actions that are intended to be competitive (e.g., a price cut or an advertising increase that is matched), turn out to be "beneficial" due to the category demand expansion effects of these actions.

7. This number is smaller than the maximum of 5,600 (i.e., 560 x 10) one would expect, as some industries had less than five brands. Also, some brands that entered a market "late" offered insufficient data to estimate the extent of reactivity accurately.

8. By focusing on the *net* effect, we take a more conservative view than traditional Granger-causality tests (see, e.g., Hanssens 1980; Leeflang and Wittink 1992).

9. This reduced number of reactivity estimates can be attributed to the fact that many products are not advertised. As there can be no "reaction" if no "action" can be observed, we take a lack of action as a sign of independence of marketing tactics.

10. All results are generated using Ox version 2.20 (see Doornik 1999).

11. It should be noted that the predominant finding of stationarity contrasts to some extent with findings by Dekimpe and Hanssens (1995b). These differences may be due to a variety of factors, such as (1) differences in the nature of the considered products (durables versus FPCG), (2) differences in geographic region (predominantly U.S. and Canada versus Europe), (3) differences in temporal aggregation, and (4) differences in sample length (sometimes multiple decades versus four years of data in the current application).

12. Hypothesis tests are one-sided unless explicitly stated otherwise.

13. These comparisons are based on the absolute magnitude of the effect as H_8 deals with attenuation. Note that this renders the test more conservative.

14. The impact of covariates was evaluated using two-sided tests of significance.

15. Comparison of effect sizes between different competitive factors is based on standardized regression coefficients.

16. In our analysis, we include both intensity and reactivity variables in the same equation. Thus, we control for intensity (reactivity) when estimating the effect of reactivity (intensity). Note also that marketing intensity and reactivity are conceptually not independent, and as such, over time, will influence each other.

17. Note that we control for marketing conduct when estimating the effect of competitive structure and vice versa. As such, apart from the nonsignificant direct effect of structure on long-run promotional effectiveness, it may still exert a long-run, indirect effect through marketing conduct.

18. Similar results were obtained when working with IRFs computed over 26 weeks.

19. Elasticity estimates for the linear model were not computed, neither at the mean nor at the value of the last observation, as the former are not defined for nonstationary series (i.e., trend-stationary or evolving) (Granger and Newbold 1986) and estimates based on the latter depend heavily on one datapoint, and are therefore known to be highly sensitive to outlying observations.

20. Note that, as mentioned previously, A4 is estimated using Johansen's FIML approach.

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