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# The Category-Demand Effects of Price Promotions

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## Abstract

Although price promotions have increased in both commercial use and quantity of academic research over the last decade, most of the attention has been focused on their effects on brand choice and brand sales. By contrast, 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.

This paper studies the category-demand effects of consumer price promotions across 560 consumer product categories over a 4-year period. The data describe national sales in Dutch supermarkets and cover virtually the entire marketing mix, i.e., prices, promotions, advertising, distribution, and new-product activity. We focus on the estimation of main effects (i.e., the dynamic category expansive impact of price promotions) as well as the moderating effects of marketing intensity and competition (both conduct and structure) on short- and long-run promotional effectiveness.

The research design uses modern multivariate time-series analysis to disentangle short-run and long-run effects. First, we conduct a series of unit-root tests to determine whether or not category demand is stationary or evolving over time. The results are incorporated in the specification of vector-autoregressive models with exogenous variables (VARX models). The impulse-response functions derived from these VARX models provide estimates of the short- and long-term effects of price promotions on category demand. These estimates, in turn, are used as dependent variables in a series of second-stage regressions that assess the explanatory power of marketing intensity and competition. Several model validation tests support the robustness of the empirical findings.

We present our results in the form of empirical generalizations on the main effects of price promotions on category demand in the short and the long run and through statistical

tests on how these effects change with marketing intensity and competition. The findings generate an overall picture of the power and limitations of consumer price promotions in expanding category demand, as follows.

Category demand is found to be predominantly stationary, either around a fixed mean or a deterministic trend. Although the total net short-term effects of price promotions are generally strong, with an average elasticity of 2.21 and a more conservative median elasticity of 1.75, they rarely exhibit persistent effects. Instead, the effects dissipate over a time period lasting approximately 10 weeks on average, and their long-term impact is essentially zero. By contrast, the successful introduction of new products into a category is more frequently associated with a permanent category-demand increase.

Several moderating effects on price-promotion effectiveness exist. More frequent promotions increase their effectiveness, but only in the short run. The use of nonprice advertising reduces the category-demand effects of price promotions, both in the short run and in the long run. Competitive structure matters as well: The less oligopolistic the category, the smaller the short-run effectiveness of price promotions. At the same time, we find that the dominant form of competitive reaction, either in price promotion or in advertising, is no reaction. Short-run category-demand effectiveness of price promotions is lower in categories experiencing major new-product introductions. Finally, both the short- and long-run price promotion effectiveness is higher in perishable product categories.

The paper discusses several managerial implications of these empirical findings and suggests various avenues for future research. Overall, we conclude that the power of price promotions lies primarily in the preservation of the status quo in the category.

*(Category Demand; Empirical Generalizations; Long-Term Promotion Effects; Competitive Strategy; Marketing Mix; Econometric Models; Time-Series Analysis)*

## 1. Introduction

Managers in consumer and industrial sectors alike seek long-term profitable growth for their products and services. Such growth can be found from three sources: growth in category demand, in market share, or in profit margins. Competitive conditions largely dictate which sources of growth can be pursued realistically and for how long. Although 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 may attract less retaliatory action. Third, growing category demand signals that consumer preferences and willingness to pay may be rising, which may create opportunities for price and profit margin increases. Last, but not least, retailer revenues are more closely related to category demand than to the sales of any one brand. Brand managers are more likely to receive needed retailer cooperation when retailers can be convinced that the proposed marketing programs increase category sales. These four benefits should be offset against two potential 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 on 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. 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.

We study moderators of these consumer price promotional effects that are 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, while at the same time controlling for a variety of other category characteristics. Furthermore, 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, although 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.

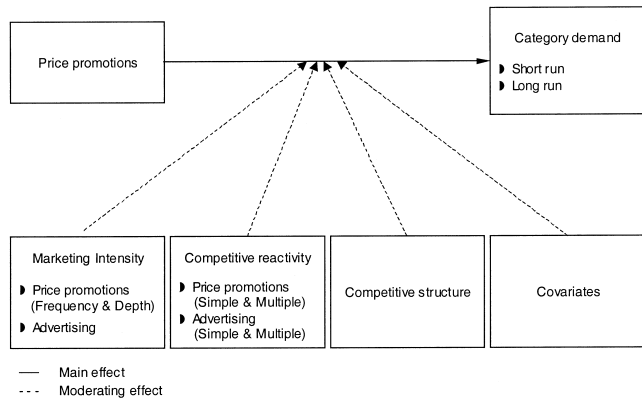
We examine the short- and long-run category-demand effects of price promotions on a "full marketing-mix" scanner database of 560 product categories over a 4-year period. We apply a consistent measurement scheme across categories and derive generalizations directly from the data, unlike previous empirical 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.

The paper first briefly discusses the framework underlying our research. We then introduce the measurement methods, describe the database, and operationalize the variables. The empirical results are summarized and discussed, and various validation tests are carried out to assess the robustness of our findings. We formulate overall conclusions and end with recommendations for future research.

## 2. Research Framework

The focus of our study is on the effect of price promotions on short- and long-run category demand. We further investigate whether, and to what extent, 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 ac-

**Figure 1** Research Overview



tions: the use of price promotions and advertising. We further examine two distinct dimensions of competition: (1) competitive conduct or reactivity, i.e., the extent to which any marketing action is matched by competitors and (2) competitive structure of the category. This distinction is strategically important, because the stronger the effects of competitive structure, the more predetermined a brand's category-level promotional effectiveness is likely to be, and vice versa.

Figure 1 provides a schematic overview of the major aspects of our study. 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.

We begin by describing the main and moderating effects of price promotions. Given the paucity of conceptual and empirical research on the potential of price promotions to expand category demand, our discussion is exploratory and does not develop formal hypotheses. Our large data set allows us to derive *empirical generalizations* that can subsequently be used to develop *generalized explanations*. This is in line with the ETET (Empirical-Theoretical-Empirical-Theoretical) model of scientific evolution described by Bass (1995).

## 2.1. The Main Effect of Price Promotions on Category Demand in the Short and Long Run

Price promotions are temporary price reductions offered to the consumer (Blattberg et al. 1995). 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 et al. 1995 or Van Heerde 1999 for extensive reviews). This immediate sales increase may be attributable to within-category brand switching (see, e.g., Gupta 1988), as well as to a category-expansion effect of price promotions (Chintagunta 1993, Van Heerde 1999). The size of the category-expansion effect, which is 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.

The impact of a price promotion need not be limited to its immediate effect. Purchase acceleration, for example, may cause a postpromotion dip, i.e., additional sales come at the expense of future purchases (Blattberg and Neslin 1990). Dynamic effects can also enhance the initial impact of a price promotion through different forces at the level of the consumer, the promoting brand, and its competition. Consumer purchase reinforcement can stimulate subsequent category demand induced by the promotion of one brand. Competitive reactions and feedback loops can stimulate new promotions, either by the promoting brand or its competition. Company decision rules can stimulate spending in other parts of the marketing mix, causing further demand increases (Dekimpe and Hanssens 1995a). 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 after the initial price promotion.

No conclusive findings are currently available on the long-run effectiveness of promotions at the brand level, let alone at the category level. Blattberg et al. (1995) even call this "the most debated issue in the promotional literature" (p. G127). However, it is plausible that the magnitude of the long-run impact is reduced relative to the short-run effect, given that

most effects of marketing actions tend to dissipate over time (Hanssens et al. 2000).<sup>1</sup>

## 2.2. The Moderating Impact of Marketing Intensity, Competitive Reactivity, and Competitive Structure on the Market-Expansive Power of Price Promotions

**Price Promotion Intensity.** In the manner of 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), whereas promotional depth specifies the average size of the promotions to which consumers are exposed (e.g., cents off). Research at the brand level suggests that depth and frequency may have a distinct effect on promotional effectiveness (see, e.g., Jedidi et al. 1999, Raju 1992), but the direction of each of these effects is not established unequivocally (Assunção and Meyer 1993, Jedidi et al. 1999, Raju 1992).

**Advertising Intensity.** Our data cover 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 within a particular category (Mela et al. 1998). Such information has been found to increase product differentiation and reduce price (promotion) sensitivity of brands (Kaul and Wittink 1995, Mela et al. 1998). Although previous studies typically dealt with the brand level, Pagoulatos and Sorensen (1986) studied demand at the industry level and found that advertising intensity reduced price sensitivity.

**Price Promotion and Advertising Reactivity.** For any given level of price-promotional intensity, the effect of price promotions may depend on competitive

reactions (cf. Putsis and Dhar 1998). Competitors may react with the same weapon ("simple" competitive response) or with another marketing instrument ("multiple" competitive response) (Hanssens 1980).

**Competitive Structure.** The competitive structure in a category may have an impact on price-promotion effectiveness above and beyond the strategic actions of the individual brands.<sup>2</sup> As with previous work in industrial organization and marketing, competitive structure is measured by the number of brands in a category (Bell et al. 1999, Hay and Morris 1991, Narasimhan et al. 1996, Scherer 1980): the more brands, the more competitive the category.

Becker (1971) has argued that the price elasticity of demand should be greater in markets characterized by a limited number of brands, because 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 expected based on the information-search literature. For consumers to be informed about the price and quality of the different brands in a category, they must engage in search activities. Consumers' search costs will naturally increase with the number of brands to be evaluated (Pagoulatos and Sorensen 1986, Ratchford 1980).

## 2.3 Covariates

Our main interest is in the moderating role of marketing intensity, competitive reactivity, and competitive structure. However, several other variables may have an impact on price-promotional effectiveness as well. We include five covariates in our moderator analyses. Product perishability is included as a covariate, because the results of Ailawadi and Neslin (1998) indicate that the category-demand effect of

<sup>1</sup>Positive numbers will be used to describe instances in which 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.

<sup>2</sup>It is not claimed that structure is exogenous to conduct, as in the long run conduct may well affect structure and vice versa (see, 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 while estimating the effect of the other, thus arriving at more accurate parameter estimates.

price promotions is larger for perishable than for non-perishable products. This is because of a larger increase in the consumers' usage rate of the perishable category.

We include private-label share as a covariate, because private-label success may indicate consumer price and promotion sensitivity in a product category (Narasimhan et al. 1996, Steenkamp and Dekimpe 1997). The introduction of a new product is accounted for, as it can enhance the overall attractiveness of the category and change the behavior of consumers (e.g., Dekimpe et al. 1997, Mason 1990). A relevant issue related to model specification is the inclusion of a deterministic-trend component (see Appendix A and § 3 below, for details on model specification). Finally, our data cover sales in supermarkets, but other outlet types may also sell some of the same products. When consumers switch outlet types because of promotional activity, this may impact our effectiveness estimates. We therefore control for the market coverage of supermarkets in a given category. 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.

### 3. Methodology

#### 3.1. Measuring Price-Promotion Effectiveness

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 et al. 1999). In the manner of Dekimpe et al. (1999), we operationalize price promotions and baseline performance levels in the context of a VARX model. Specifically, a three-equation model is used with the logarithm of 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. However, this would cause extreme overparameterization. Price and category de-

mand were specified as endogenous, because their dynamic interrelationships are at the core of our research. Given our interest in the moderating impact of advertising intensity and reactivity, advertising is included as a third endogenous variable. This specification also helps ensure that the estimates of price-promotion effectiveness 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 logarithms in periods  $t$ ,  $t + 1$ ,  $t + 2$ , ... that would be expected based on the available information up to period  $t - 1$  (Dekimpe and Hanssens 1995a). Promotions are operationalized as one-time, hence temporary, deviations from the expected price level in period  $t$ .<sup>3</sup> 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 (in logarithms), but now based on the extended information set that includes the promotion. For a given endogenous variable, the difference between both forecast series measures the incremental effect in period  $t + i$  ( $i = 0, 1, 2, \dots$ ) of the promotional shock in period  $t$ .<sup>4</sup> These incremental effects, taken in combination, form the promotion's impulse-response functions (Bronnenberg et al. 2000). The impulse-response function (IRF) tracing the incremental impact of the price-promotion shock on the logarithm of category demand (i.e., the incremental effect in period  $t$ ,  $t + 1$ ,  $t + 2$ , ...), is our basic mea-

<sup>3</sup>A similar baseline and shock operationalization has recently been used to quantify the over-time effectiveness of distribution changes in Bronnenberg et al. (2000), of advertising shocks in Dekimpe and Hanssens (1995a, 1999), and of price promotions in Dekimpe et al. (1999) and Srinivasan et al. (2000).

<sup>4</sup>The information set used to derive these two forecasts is the same up to the point in time at which the price-promotional shock occurs. This implies that any specific history before such a shock does not influence the shock's estimated incremental performance impact, as it is cancelled out when one takes the difference of the forecasts. As a consequence, the impulse-response functions derived from this study are "starting-point invariant," i.e., regardless of starting point in time, the same incremental effects are always obtained (see also Pesaran and Shin 1998).

sure of promotional effectiveness. By working in logarithms, the impulse-response estimates can be shown to be elasticities at the unit-shock level, making the results comparable across categories.<sup>5</sup>

We derive two summary statistics from each IRF, to be used in cross-category comparisons:

- its asymptotic value (for  $t \rightarrow \infty$ ), 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, capturing the promotion's short-run effectiveness. We compute this net effect as the sum of the individual IRF coefficients over the dust-settling period. The resulting value corresponds to the change in category demand over the dust-settling period expressed relative to the sample mean and can again be interpreted as an elasticity (cf. Baumol 1977).<sup>6</sup>

Bronnenberg et al. (2000) and Dekimpe and Hanssens (1995a, 1999) illustrate how impulse-response functions can either converge to zero (as occurs by definition in stationary markets) or stabilize at a non-zero level (as is possible in evolving markets). Both scenarios are illustrated in Figure 2.

Panel A depicts the impulse-response function for the *stationary* all-purpose detergent market, in which the solid line represents the impulse-response function of a price promotion on the logarithm of 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 be 1.41, whereas subsequent periods show a post-promotion dip.<sup>7</sup> Eventually, the graph converges to

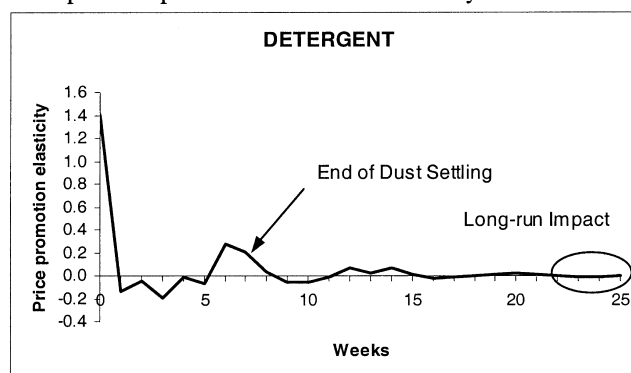
<sup>5</sup>Details are available from the first author upon request.

<sup>6</sup>For the stochastically and deterministically trending series, we also computed a weighted sum of the IRF coefficients, with weights based on the average growth rate of category demand. All substantive results were the same, and numerical differences were negligible.

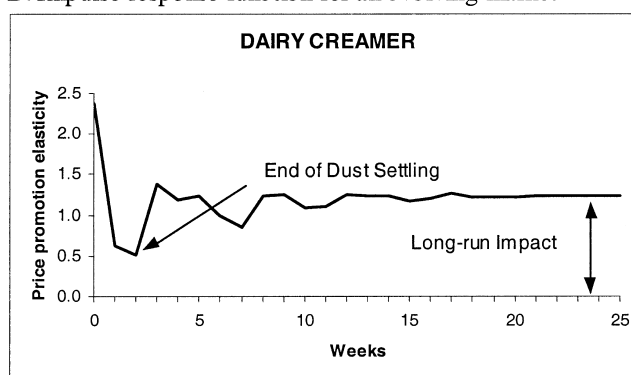
<sup>7</sup>Our measure of net short-run price-promotion effectiveness accounts for regular stockpiling effects but does not explicitly measure reduced demand attributable to consumer anticipation of price promotions. We operationalize price promotions as unanticipated price shocks. Given a certain price movement, the VARX model disentangles what fraction of such a shock was anticipated and what fraction was not. It is the over-time impact of the unanticipated part (the shock) that is subsequently traced.

Figure 2 Impulse-Response Functions\*

A: Impulse response function for a stationary market



B: Impulse response function for an evolving market



zero, indicating that any incremental effect disappears over time, and no long-run impact is observed.

Our interest in the net short-run effect of promotions should not be limited to the instantaneous effect (see Van Heerde et al. 2000). Fluctuations in subsequent periods should also be taken into account, and the question arises as to how many periods to consider. In the manner of Dekimpe and Hanssens (1999), we consider how many periods it takes for the IRF to stabilize, and we 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. We determined significance for stationary series relative to the (zero) convergence value, i.e., the impulse-response parameters in periods 8–11 were no longer significantly different ( $|t - value| < 1$ ) from

the convergence value, whereas the impact in period 7 was. The short-run elasticity, obtained as the sum of the individual IRF coefficients over the dust-settling period, was found to equal 1.43, i.e., the total estimated incremental effect over the dust-settling period of an initial 1% price promotion is 1.43% of the category's average period (e.g., weekly) sales.

Panel B shows 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, indicating that an initial 1% price promotion enduringly enhances sales levels by 1.23% after the dust-settling period ends. This is called the long-run or persistent effect (Dekimpe and Hanssens 1995a, 1999). The dust-settling period is defined in a manner similar to that used earlier, but we now look for the last period that has an impact significantly different from the nonzero asymptotic value.

Appendix A elaborates on technical 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.<sup>8</sup>

### 3.2. Assessing the Moderating Impact of Marketing Intensity, Competitive Reactivity, Competitive Structure, and Covariates

For each individual product category  $i$  ( $i = 1, \dots, M$ ), a three-equation VARX model, as 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 two ( $M \times 1$ ) vectors of elasticity estimates. These vectors subsequently became the dependent variable in a second-stage regression model linking price-promotion effec-

tiveness to the different dimensions of competition and marketing intensity.<sup>9</sup> Because the dependent variables are estimated parameters, characterized by differing degrees of estimation accuracy, ordinary least squares (OLS) may yield biased estimates of the standard errors if the model residuals exhibit heteroscedasticity. White's test indicated that our model of long-run elasticities was not affected by heteroscedasticity ( $p < 0.40$ ). For the short-term elasticity model, however, the hypothesis of no heteroscedasticity was rejected ( $p < 0.001$ ). Consequently, OLS is applied to our model of long-run elasticities, whereas weighted least squares (WLS) is used in our analysis of the short-term effectiveness of price promotions (see Narasimhan et al. 1996 for a similar approach). In WLS, both dependent and independent variables are weighted by the inverse of the standard error of the dependent variable.

## 4. Data Description and Measurement

### 4.1. 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's classification of product types and offered a quasicomplete coverage of all goods found in a typical supermarket. To illustrate the range of products available in our data set, we have grouped them into broader product *fields*. Table 1 shows the frequency counts of these product fields and some illustrative examples.

Our database originated from two sources. First, IRI/Europanel provided data on volume sales, price, feature and display activity, new-product introductions, and distribution coverage. Two hundred and eight weekly observations were available on each cat-

<sup>8</sup>Given the marketing reality of multiple price promotions offered by different brands in different time periods, we can expect that the consumer response and competitive reaction times to these promotions will be overlapping. The VARX method is designed to measure the incremental effect of each price promotion shock separately, so that the cumulative effect of overlapping promotions would be derived by summing the individual impulse-response weights.

<sup>9</sup>This design implies that we make cross-sectional inferences on the parameters of longitudinal models, based on a sample of 4 years. The parameters (dependent variables in the second stage) are category summaries of the over-time magnitudes of promotional response, and the covariates (independent variables in the second stage) are various category descriptors.



**Table 1 Data Coverage**

Product Fields	Examples	No. of Categories
Assorted foods	Cereals, croissants, pretzels, rice	74
Assorted nonfood products	Greeting cards, lighters, magazines, paper plates	23
Beverages	Coffee, cola, mineral water, wine	46
Cakes	Cake, cookies, waffles	26
Candy	Chewing gum, chocolate, mints, toffee	46
Canned/bottled foods	Hotdogs, olives, peaches, tuna fish	72
Care products	Band-aids, perfume, shampoo, toilet tissue	50
Cleaning products	Bleach, detergents, floor cleaners, shoe polish	19
Dairy products	Eggs, ice cream, skimmed milk	48
Frozen foods	Chicken, french fries, pizza, puff pastry	52
Household supplies	Air fresheners, bug-spray, candles, sponges	35
Pet products	Animal toys, fish food, frozen dog food	15
Taste enhancers	Pesto, powdered sugar, salt, vinegar	54
<i>Total</i>		<u>560</u>

egory. 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. The information obtained from this sample is then extrapolated to the market level. Second, corresponding advertising data were obtained from the BBC research agency. This combination resulted in two unique features of our data set: (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. All price and advertising data were inflation adjusted, using the consumer price index.

#### 4.2. Variable Operationalization

Below, we discuss the operationalization of the different measures of marketing intensity, competitive reactivity, and competitive structure. The former two describe the actions taken by industry participants. Marketing intensity reflects the degree to which a given marketing-mix instrument is used, whereas competitive reactivity describes the extent to which marketing behavior is either aggressive, independent, or cooperative (see, e.g., Putsis and Dhar 1998). To determine the dominant form of action taken by com-

petitors 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 categorywide measures of average advertising and price-promotion reactivity (simple and multiple). Finally, we describe our measure of competitive structure and the operationalization of several control variables.

**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 in which 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, a measure of average promotional depth in the category is obtained. These measures are conceptually similar to the ones adopted in Raju (1992) and Rao et al. (1995), among others.

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

**Simple Price-Promotion Reactivity.** For each brand pair, we first estimate a bivariate VAR model with their respective price series, expressed in log terms, 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 that track the reaction over time 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). 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.

When an estimated effect is not significantly different from zero, it is equivalent to the case in which no reaction takes place over the considered time frame and in which price-promotional calendars and budgets are set independently. Effects in the same direction as the initial price promotion are evidence of a competitive reaction, whereas effects in the opposite direction reflect cooperative behavior (Gatignon 1984).<sup>10</sup> Moreover, the magnitude of the effect indicates the extent of matching or cooperation.

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, ten bivariate VAR models are estimated per category, resulting in twenty im-

pulse-response functions from which the time-dependent reaction intensities are determined. A measure of the extent of competitive reactivity in a given industry and time frame is then obtained by averaging over elasticities, weighted both by the accuracy of their estimation and the size of the reacting brand. The former weighting is similar in spirit to the WLS procedure discussed previously, whereas the latter is similar to that of 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).<sup>11</sup>

In total, more than 4,200 bivariate VAR models were estimated, resulting in over 8,400 impulse-response evaluations.<sup>12</sup> 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).

**Simple 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. Therefore, we use one overall measure of advertising reactivity between each pair of brands in the second-stage regression. We quantify this measure as the sum of 52 weekly IRF coefficients. When this metric is not significantly different from zero, the net outcome (after all instantaneous and lagged reactions and counterreactions have been taken into account) is equivalent to the case in which no reaction takes place and advertising bud-

<sup>10</sup>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," because of the category-demand expansion effects of these actions. Also, these reactions reflect adjustments in the prices consumers observe and may be initiated by the manufacturer and/or the retailer.

<sup>11</sup>All reactivity variables used in this study (simple/multiple price-promotion reactivity and simple/multiple advertising reactivity) are coded so that a higher score implies a stronger competitive response.

<sup>12</sup>This number is smaller than the maximum of 5,600 (i.e.,  $560 \times 10$ ) one would expect, because 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.

gets are set independently.<sup>13</sup> Net effects in the same direction as the initial advertising change are evidence of a competitive reaction, whereas net effects in the opposite direction reflect cooperative behavior (Gatignon 1984, Footnote 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.<sup>14</sup> Brand-level estimates were subsequently combined into an average reactivity measure through a weighting scheme similar to that described above.

**Multiple Competitive Reactivity.** Multiple competitive reactions are responses with one type of marketing instrument to an initial effort in which another marketing instrument was used. We define these reactions with respect to advertising and price promotions. Specifically, two measures are derived, using the same VARX-based approach as was used for the simple competitive responses: one capturing the extent of reactivity with advertising to a price promotion (i.e., multiple advertising reactivity) and one pertaining to the extent of reactivity with price promotions to advertising (i.e., multiple price promotion reactivity). These metrics of reactivity were calculated for all possible brand pairs and subsequently combined to obtain category-level indicators of average multiple reactivity in each category, using the weighting procedures described above.

**Competitive Structure.** Competitive structure is measured by the number of brands in a category. This 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% over a period of at least 3 consecutive months.

<sup>13</sup>By focusing on the *net* effect, we take a more conservative view than that of traditional Granger-causality tests (see, e.g., Leeflang and Wittink 1992).

<sup>14</sup>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.

**Table 2 Unit-Root Test Results**

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

**Covariates.** A dummy variable indicates whether products belonging to a specific category can be considered perishable (= 1) or nonperishable (= 0). Private-label share was operationalized as the average volume-based market share in a category for all private labels combined. Another dummy variable was created, indicating whether a major new-product introduction had taken place in the category.<sup>15</sup> A third dummy variable takes on the value of one when a deterministic trend was included in the VARX model. A variable measuring the percentage of category volume sold through supermarkets (i.e., supermarket coverage) was included as well.

## 5. Results<sup>16</sup>

We first discuss descriptive findings on the temporal behavior of category demand and the nature of the competitive reactions. This sets the stage for our main findings concerning the short- and long-run magnitudes of price-promotion effects and the moderating effects of marketing intensity and competition. We conclude with a discussion of the substantive implications of our findings.

### 5.1. Overall Descriptive Findings

**Data Stationarity.** Based on the ADF unit-root test, we find that only 54 out of 560 markets studied are evolving. Perron's structural break-test, however, indicates that the observed evolution is spurious in approximately 22% of these cases (see Table 2). The overwhelming majority of category-demand patterns is stationary over our 4-year period, either around a

<sup>15</sup>Product categories in which the most successful new-product introduction was able to capture a market share in excess of 1% during at least 3 consecutive months were labelled as having witnessed a "major new-product introduction."

<sup>16</sup>All results are generated using Ox version 2.20 (see Doornik 1999).

fixed mean (38%) or around a deterministic trend (36% positive trend, 26% negative trend;  $p < 0.05$ ). This predominance of stationarity was previously reported on several frequently purchased consumer good categories by Dekimpe et al. (1999) and Srinivasan et al. (2000).<sup>17</sup>

We therefore derive the empirical generalization that long-run category-demand effects of promotions are the exception, rather than the rule, because evolutionary behavior is a necessary condition for the occurrence of persistent effects. In contrast, our empirical evidence highlights the importance of new-product introductions in revitalizing markets. Specifically, we found that in 496 of the 560 categories studied, a major new product was introduced, and that in 30% of those categories (i.e., 147/496), the introduction had a significant expansive impact on category demand. Finally, although most markets are found to be stationary, 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.

**Nature of Competitive Reactions.** The extent of reactivity was assessed using the VARX modeling approach outlined in § 4.2. Our findings concerning price-promotion reactivity in the short run and long run are summarized in Table 3.

Based on an analysis of more than 10,000 potential competitive reactions, we conclude that (1) the predominant form of competitive reaction is no reaction and (2) when competitive reactions do occur, they do so more frequently in the short run than in the long run. A similar predominance of independence (in more than 85% of cases) is found for advertising reactivity and both forms of multiple reactivity.

<sup>17</sup>The study of Dekimpe and Hanssens (1995b) inferred stationarity versus evolution from the use of levels versus differences in a number of previously published marketing time-series models. These studies typically did not distinguish between deterministic and stochastic trends. However, only stochastic trends can be linked to marketing actions, which are the focus of our paper. When we combine the incidence of stochastic evolution with the incidence of deterministic trends in our data, about 66% of the cases evolve. This percentage is very close to the 68% of evolution in market-performance variables reported by Dekimpe and Hanssens (1995b).

**Table 3 Price-Promotion Reactivity**

	Short Run	Long Run
Competitive*	20%	9%
Cooperative*	13%	6%
Independent	67%	85%

\*We report the number of significant ( $|t\text{-value}| > 1$ ) competitive reactions relative to the maximum number of possible reactions (20) between the top five brands in a category. Note that if the size of the competitive set is changed, the percentages may begin to differ.

**Table 4 Category-Demand Effects of Price Promotions**

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

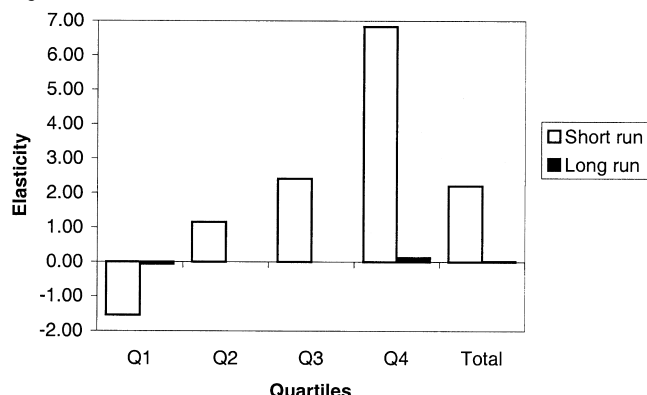
\*Percentages reflect the proportion of estimated elasticities that were found to differ significantly from zero ( $p < 0.05$ ).

This overall lack of reactivity is in line with findings by Brodie et al. (1996) and Leeflang and Wittink (1992, 1996) that, although (overly) intense reactivity may take place, it is a relatively rare occurrence (see also Rao et al. 1995). This may be attributable to managers and/or retailers focusing their attention on a very small set of competitors/brands, as recently deployed in Leeflang and Wittink (1996). The reduced extent of reactivity in the long run can be attributed to budget limitations, considering the expense of prolonged price promotion or advertising wars, and to the difficulty of sustaining cooperative behavior over long time periods.

## 5.2. Main Effect of Price Promotions

**Magnitude of Short-Run Promotion Effects.** Price-promotion elasticities were estimated using the models described in Appendix A. Table 4 and Figure 3 describe the distribution of the estimated category-demand elasticities of price promotions. In the short run, price promotions significantly expand category demand in 58% of the cases over a dust-settling period that lasts, on average, 10 weeks. The estimated mean (median) short-run price-promotion elasticity is equal to 2.21 (1.75). We find that in almost 40% of cases, the immediate category-expansive effect of a

**Figure 3** Mean Price-Promotion Elasticities Per Quartile



price promotion is partially negated in subsequent periods. For example, in the tuna fish and toilet tissue categories, we observe strong postpromotion cancellation effects, in line with findings by Van Heerde et al. (2000). In the remaining 60% of categories, the initial impact of a price promotion is either not negated or is enhanced. This finding can be attributed to different forces, such as purchase reinforcement, competitive reactions, feedback loops, and company decision rules (Dekimpe and Hanssens 1995a). In the VARX modeling approach used in this study, each of these effects is captured, even when they take some time to materialize. The overall impact of these dynamic forces is subsequently assigned to the initiating price promotion, without which the subsequent effects would not have occurred.

#### Magnitude of Long-Run Promotion Effects.

Table 4 also shows the distribution over time 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%). Figure 3 presents a graphical summary, where the mean price-promotion elasticities for the different time horizons are depicted by quartile. The mean long-run price-promotion elasticity is 0.02, which is significantly smaller than the short-run elasticity of 2.21 (paired  $t$ -test,  $p < 0.001$ ).

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% of cases (i.e., 42/560) in which category

demand is evolving, price promotions are often unrelated to that evolution. Indeed, a long-run price-promotion effect is observed in less than one-third of the evolving cases. 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 et al. 1995, p. G127).

#### 5.3. Moderators of Price-Promotion Effectiveness

The results of the second-stage regression analyses of the short- and long-run category-level price-promotion elasticities on marketing intensity, competitive reactivity, competitive structure, and covariates are reported in Table 5.

We find that the *short-run* price-promotion elasticity is higher in categories associated with high promotional frequency ( $b = 5.02$ ,  $p < 0.01$ ). On the other hand, advertising intensity ( $b = -0.14$ ,  $p < 0.01$ ) reduces the short-run price-promotion elasticity. The short-run price-promotion elasticity is also lower in more competitive categories ( $b = -0.02$ ,  $p < 0.10$ ). Finally, the short-run effectiveness of price promotions is higher in perishable product categories ( $b = 0.51$ ,  $p < 0.01$ ) and lower in categories in which a major new product was introduced ( $b = -0.67$ ,  $p < 0.01$ ).

As with the results obtained for the short run, the *long-run* price-promotion elasticity is lower in categories characterized by high advertising intensity ( $b = -0.03$ ,  $p < 0.01$ ). The long-run effectiveness of price promotions is higher in perishable product categories ( $b = 0.03$ ,  $p < 0.10$ ). The combined effects of product perishability on short- and long-run price-promotion elasticity provide strong support for the Monte Carlo simulation results of Ailawadi and Neslin (1998).

Two other covariates exhibit significant effects on long-run price-promotion elasticity. Categories in which a deterministic trend was included in the VARX model exhibit a significantly lower long-run price-promotion elasticity of category sales ( $b = -0.10$ ,  $p < 0.001$ ). This result is not surprising, given that there were no series that contained both a deterministic and

**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	
	<i>b</i>	<i>t</i> -value	<i>b</i>	<i>t</i> -value
♦ Marketing intensity				
Price-promotion frequency	5.02	5.00***	−0.13	−0.86
Price-promotion depth	−0.81	−1.46	−0.01	−0.07
Advertising intensity	−0.14	−2.77***	−0.03	−2.89***
♦ Competitive reactivity				
Simple price-promotion reactivity	−0.27	−0.95	−0.00	−0.02
Simple advertising reactivity	0.03	0.24	−0.02	−1.41
Multiple price-promotion reactivity	0.00	0.34	−0.00	−0.03
Multiple advertising reactivity	−1.60	−0.68	−0.26	−0.32
♦ Competitive structure	−0.02	−1.92*	−0.00	−0.16
♦ Covariates				
Perishability	0.51	3.30***	0.03	1.70*
Private-label share	−0.31	−1.12	−0.02	−0.45
New-product dummy	−0.67	−3.26***	−0.01	−0.61
Deterministic trend dummy	0.02	0.12	−0.10	−4.63***
Supermarket coverage	−0.52	−0.55	−0.24	−2.07**

\* =  $p < 0.10$ .

\*\* =  $p < 0.05$ .

\*\*\* =  $p < 0.01$ .

a stochastic trend. The *coverage* variable has a significant negative impact on the long-run effectiveness of price promotions at the category level ( $b = -0.24$ ,  $p < 0.05$ ). When supermarkets have higher market coverage in a category, the extent to which sales can be drawn from other outlet types is reduced.

When comparing the moderator results across the two time windows, the findings for the long-run time window are typically weaker. This is to be expected, given that most long-run price-promotional elasticities are small in the first place (see Figure 3).

**Discussion.** The key driver of short-term price-promotion elasticity of category demand is the large positive effect of promotional frequency. A higher price-promotional frequency generates a large increase in price-promotion effectiveness in the short run. The 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 et al. 1997). However, this effect is completely dissipated in the long run. This indicates that, over time, the positive effect of price-promotional frequency on promotion effectiveness is offset by its negative side effects (see, e.g., Jedidi et al. 1999 for an elaboration at the brand level). The dissipation of the initial positive effect presents a potential trap to managers. They witness the large, short-run effect of frequent promotions 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 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 for only a relatively short period of time (Abraham and Lodish 1993).

Advertising intensity emerges as another key driver, affecting both short- and long-run price-promotion elasticities of category demand. The effect of advertising is negative, i.e., the higher the advertising

intensity, the more the effectiveness of price promotions is diminished. Advertising emphasizes nonprice purchase motivations, increases brand differentiation, and reduces price sensitivity in the category (Mela et al. 1998). Furthermore, we find that short-run price-promotion effectiveness is lower in categories experiencing major new-product introductions. The negative effects of advertising and new-product introductions on price-promotion effectiveness are consistent with previous arguments by Steenkamp and Dekimpe (1997) that companies can get out of price wars by increasing advertising and new-product introduction activity. Our findings offer an interesting opportunity for companies such as 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 in increasing category demand, these companies' competitors will be tempted to use them, and retailers may insist on high consumer promotional spending to stimulate category demand. In such a situation, deemphasizing price promotions may weaken these companies' market position, not only vis-à-vis their competitors but also in the distribution channel. Increasing advertising and new-product introduction activity are effective strategies to reduce category-level price-promotion effectiveness. This makes it easier for the firm to engage in price-promotional spending reductions, and the savings on these expenditures might be used to pay for increased investment in advertising and new-product development.

We find that marketing (promotional and advertising) intensity typically has a larger impact on elasticities than competitor reactivity variables in both the short and the long run. This indicates that, overall, the general level of activity (promotions, advertising) is more important than what triggered this activity level.<sup>18</sup>

<sup>18</sup>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, may influence each other. The same applies to the interplay between some category characteristics and marketing intensity.

Competitive structure has a significant negative effect on short-run promotional effectiveness, which is consistent with the arguments of Becker (1971) and Pagoulatos and Sorensen (1986). 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 has no effect on long-run promotional effectiveness, and the explanatory effect of marketing conduct is larger.<sup>19</sup>

## 6. 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 (§ 6.1), and the potentially confounding impact of aggregation bias on effect-size estimates (§ 6.2). We further establish to what extent our effectiveness estimates may be affected by the level of temporal aggregation of the data (§ 6.3), the static/dynamic specification of the exogenous variables (§ 6.4), and the order specification of the VARX (§ 6.5). Finally, we determine the sensitivity of our competitive reactivity measures to alternative model specifications (§ 6.6).

### 6.1. Endogenous Variables

The impulse-response function tracing the incremental impact of a price-promotion shock on the logarithm of category demand is our basic measure of promotional effectiveness (see § 3.1). 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 § 3.1, we specify VARX models with sales, price, and advertising as endogenous

<sup>19</sup>We control for marketing conduct when estimating the effect of competitive structure and vice versa. As such, apart from the non-significant direct effect of structure on long-run promotional effectiveness, it may still exert a long-run, indirect effect through marketing conduct. The explicit study of these interrelationships is, however, beyond the scope of this study.

variables, while allowing other variables to enter as exogenous regressors. To ensure that our substantive results are not sensitive to the choice of endogenous variables, four alternative VARX specifications are implemented. In each specification, sales and price are selected as endogenous, because they are the core variables of the study, whereas we rotate which other variable is entered as endogenous: feature and display, feature only, display only, or distribution coverage. For each alternative VARX, IRFs are calculated over a period of 52 weeks, and compared with the IRFs derived from the focal model discussed in Appendix A. First, we examine to what extent these IRFs are 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 is very high, varying between 0.94 and 0.96.<sup>20</sup> A second comparison is based on the average (median) short- and long-run elasticity estimates for each of the different model specifications. The magnitudes of the elasticity estimates are 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 provided in Table 6.

## 6.2. Aggregation Bias

Christen et al. (1997) have shown that when working with arithmetically averaged data, models estimated in log-log form may be sensitive to an aggregation bias when there is heterogeneity in marketing activities across stores. Because it has been shown that linear models do not exhibit this bias, we reestimate all VARX models, using a linear specification, and determine the corresponding IRFs. Using the procedure detailed in § 6.1, we then compare the results from the log-log and the linear model and obtain an average correlation of 0.83. While this value is high, it is somewhat lower than the correlation values reported in § 6.1. We see two possible explanations for this. First, both the linear and the log-log model may be subject to some misspecification bias (see Leeftang et al. 2000). As a consequence, when this bias does not

<sup>20</sup>Similar results were obtained when working with IRFs computed over 26 weeks.

**Table 6 Average Correlations of IRFs and Average/Median Short- and Long-Run Elasticities, Derived from Alternative Specifications of the VARX Models**

Validation Issue	Average Correlation of IRFs	Average/Median Short-Run Elasticity	Average/Median Long-Run Elasticity
♦ Focal model	1	2.21/1.75	0.02/0.00
♦ Specification of third endogenous variable			
Feature and display	0.95	2.53/1.79	0.03/0.00
Feature only	0.96	2.26/1.68	0.02/0.00
Display only	0.96	2.44/1.77	0.02/0.00
Distribution	0.94	2.04/1.68	0.02*/0.00
♦ Aggregation bias			
Linear model	0.83	1.98/1.44	0.01/0.00
♦ No. of lags of exogenous variables			
1 lag	0.98	2.22/1.77	0.01/0.00
2 lags	0.97	2.40/1.71	0.02*/0.00
3 lags	0.96	2.55/1.71	0.02*/0.00
♦ VARX order			
6 lags	0.93	2.28/1.59	0.02/0.00
4 lags	0.87	2.07/1.62	0.02/0.00

\*One outlying observation was removed before calculating this value.

work in exactly the same direction for both model specifications, the size of the correlation coefficient is reduced (Nunnally 1978). Second, we notice that the linear model gives rise to some outlier estimates. The median correlation, which is more robust to outliers, is 0.93. As for the mean/median effect size, we find values of 1.98/1.44 (short run) and 0.01/0.00 (long run), which are comparable to the mean/median values in the logarithmic model of 2.21/1.75 and 0.02/0.00, respectively.

We further calculate the percentage of cases in which unit-root tests on linear and log-transformed data lead to the same conclusion. In 96% of cases the classification is identical.

Finally, we compare our estimates of the contemporaneous effect of price promotions on category demand with those reported in Bell et al. (1999), as these are derived from individual-level models that are unaffected by aggregation bias. A direct comparison was possible for ten of their 14 categories. Across those categories, our immediate elasticity averaged



1.01, which is very close to the value of 0.91 found by Bell et al. (1999).

Based on the above findings, we conclude that the possible bias attributable to arithmetic averaging of the variables in our log-log model is minimal.

### 6.3. 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 are able to determine that the percentage of markets classified as evolving is minimally affected by aggregating our weekly data to the biweekly level (7.5% versus 7.1%, based on original versus aggregated data, respectively). Furthermore, more than 93% of all category sales series are equally classified as either stationary or evolving, based on the weekly and biweekly data.

### 6.4. 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 et al. 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 compare 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. As with the validation exercises detailed in § 6.1, we calculate the average correlation between IRFs derived from the various VARX models and establish the size of the average (median) short- and long-run elasticities. Again, the correlations

are very large, ranging from a low of 0.96 to a high of 0.98, while the magnitudes of the elasticity estimates are very similar. We conclude that the imposed restrictions do not substantially affect our findings.

### 6.5. 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 4 and 6 lags are estimated as well. The size of the elasticity estimates is, again, very comparable. Also, the average correlations between the IRFs derived from the different models are 0.87 and 0.93 for the comparison with the 4 and 6 lag models, respectively. As expected, the correlation between results from the 8-lag and 4-lag model is somewhat lower, as the latter is less flexible in capturing dynamic effects and, as such, tends to smooth the IRF.

### 6.6. Competitive Reactivity

Our measure of competitive reactivity draws upon previous work on reaction functions and Granger-causality testing (see Leeflang and Wittink 1992 for a marketing application). It has been shown, however, that both approaches are sensitive to the information set that is considered (see, e.g., Hanssens et al. 2000, Chap. 7). Our reactivity operationalization is based on bivariate specifications, which can be extended along multiple dimensions. When looking at the price reactivity between brand  $i$  and brand  $j$ , for example, 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, e.g., Vilcassim et al. 1999). Each of these extensions is considered, resulting in the estimation of more than 10,000 additional VARX systems. Using an approach similar to that used earlier, we derive the average correlation between the IRFs of the bivariate specifications with the corresponding IRFs from the extended, four-variable models. These correlations are 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		
	$(A_i, A_j)$	$(P_i, P_j)$ $k, l \neq i, j$	$(S_i, S_j)$
Bivariate Base Model			
◆ Simple price-promotion reactivity $(P_i, P_j)$	0.86	0.81	0.77
	$(P_i, P_j)$	$(A_i, A_j)$ $k, l \neq i, j$	$(S_i, S_j)$
◆ Simple advertising reactivity $(A_i, A_j)$	0.90	0.94	0.90

$P_i$  = log of price brand  $i$ ;  $A_i$  = log of advertising of brand  $i$ ;  $S_i$  = log of sales of brand  $i$ .

## 7. Conclusions

This paper has investigated the category-demand effects of consumer price promotions in 560 consumer product categories over 4 years. The wide range of our cross-sectional and time-series data allows us to derive empirical generalizations that include competitive as well as over-time moderators of promotional effectiveness. Our results, based on market-level data, should provide valuable benchmarks for practitioners, as in the vast majority of cases they, too, only have access to market-level data (Christen et al. 1997).

Category demand is found to be predominantly stationary, either around a fixed mean or a deterministic trend. Although the short-term effects of price promotions are generally strong, with an average elasticity of 2.21 and a median elasticity of 1.75, they rarely exhibit persistent effects. Instead, price-promotion effects typically last for around 10 weeks, and their long-term impact converges to zero in 98% of the 560 product categories investigated. The successful introduction of new products is more frequently associated with a permanent category-demand increase.

The frequent use of price promotions has a strong effect on the short-run consumer sensitivity to them. This positive effect of price-promotion frequency is, however, dissipated in the long run. Another influential moderator of both short- and long-run price-promotion effectiveness found in this study is the use of nonprice advertising. 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 and retail managers interested in reducing their dependence on price promotions in specific categories. No significant effects were found for any of the competitive reactivity measures. Indeed, the dominant form of reactivity found in this study was no reaction.

Promotional effectiveness is also affected by competitive structure. The fewer industry members, i.e., the more oligopolistic, the stronger the promotional effectiveness of its participants. Furthermore, price-promotion effectiveness is lower in categories experiencing major new-product introductions and higher in perishable categories.

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, for example, market leader versus private label. Second, we could expand our framework to other marketing-mix variables, and derive empirical generalizations and study 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, our findings are based on data from the Netherlands. It remains to be seen whether these findings can be generalized to other countries. Sixth, because of data limitations, we were unable to establish elasticity estimates at the store level. These limitations offer areas for extending and 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 et al. 1999). It would be

useful to relax this assumption, using either an explicit varying-parameter specification (as recently used by Foekens et al. (1999) in a single-equation setting) or by adopting a moving-window operationalization, as implemented by Bronnenberg et al. (2000). Third, our approach to quantifying competitive reactivity, although 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, e.g., Vilcassim et al. 1999 and Roy et al. 1994). Future work could detail the relative merits of the two traditions and attempt to combine their strengths. Also, more research is needed that disentangles retailer-versus-manufacturer-induced marketing actions and determines the relative influence and interdependence of these parties. Our database lacks sufficient detail for these purposes.

Finally, when margin data are available, empirical generalizations can 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.<sup>21</sup>

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## Appendix A: VARX Specification

When specifying a VARX model (i.e., a vector-autoregressive model with exogenous variables), several issues need to be decided on, such as whether to include the variables in level or difference form (§ A.1), which variables to treat as endogenous/exogenous (§ A.2), and whether the model should be augmented with lagged error-correction terms (§ A.3).

### A.1. 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:

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

in which  $y_t$  is the variable of interest,  $t$  is a deterministic trend variable, and the  $SD$ s are a set of 4-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 et al. (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 model specification with the best value of the SBC criterion (cf. Hall 1994; see Bronnenberg et al. 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  $\alpha_0$  (Perron 1989, 1990). In our context, a prime candidate for such an event is the introduction of a new product, as discussed in Bronnenberg et al. (2000) and Dekimpe et al. (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:

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

which is equivalent to Equation (A1) augmented with two terms:  $DU_t$ , a step dummy variable taking the value of one when  $t \geq TB$

(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 in Perron (1990) if not.

## A.2. VARX Specification

Three-equation VARX models were estimated in log-log form, with category demand ( $CD$ ), 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 ( $c_{0,\cdot}$ ), 4-weekly seasonal dummy variables ( $SD_{st}$ ), a deterministic-trend variable ( $t$ ) anytime an endogenous variable was found to have a deterministic trend in the data-generating process (based on Enders' unit-root testing procedure), and a step dummy variable for the potential impact of new-product introductions ( $NP$ ). One such step dummy variable was added when a major new product was introduced into the category.

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:

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

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 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 equa-

tions. This may have caused a (small) loss in power if some of these parameters turned out to be insignificant, but it 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  $\delta_i$  ( $i = CD, P, A$ ) equal to zero.

## A.3. 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 these variables 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 1995 for a formal discussion and Bronnenberg et al. 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,

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

are stationary. 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 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 et al. (1998) and Franses (1999). Depending on the presence of deterministic trends in Equation (A2), the critical values in Tables 15.4 and 15.5 of Johansen (1995) were used to test for cointegration. Third, when dealing with  $N$  evolving endogenous variables,  $N-1$  cointegrating or long-run equilibrium relationships may exist. Given that interpretational problems may occur when evaluating multiple cointegration equations (e.g., when opposite signs emerge in the different equilibria), we focused on the cointegrating 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). When 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).<sup>22</sup>

<sup>22</sup>As mentioned before, Equation (A4) is estimated using Johansen's FIML approach.

$$\begin{bmatrix} \Delta \ln(CD_t) \\ \Delta \ln(P_t) \\ \Delta \ln(A_t) \end{bmatrix} = \begin{bmatrix} c_{0,CD} + \sum_{s=2}^{13} c_{s,CD} SD_{st} + \delta_{CD}t + \eta_{CD}NP_t \\ c_{0,P} + \sum_{s=2}^{13} c_{s,P} SD_{st} + \delta_Pt + \eta_PNP_t \\ c_{0,A} + \sum_{s=2}^{13} c_{s,A} SD_{st} + \delta_At + \eta_ANP_t \end{bmatrix} + \sum_{i=1}^8 \begin{bmatrix} \phi_{11}^i & \phi_{12}^i & \phi_{13}^i \\ \phi_{21}^i & \phi_{22}^i & \phi_{23}^i \\ \phi_{31}^i & \phi_{32}^i & \phi_{33}^i \end{bmatrix} \begin{bmatrix} \Delta \ln(CD_{t-i}) \\ \Delta \ln(P_{t-i}) \\ \Delta \ln(A_{t-i}) \end{bmatrix} + \begin{bmatrix} \alpha_{CD} & 0 & 0 \\ 0 & \alpha_P & 0 \\ 0 & 0 & \alpha_A \end{bmatrix} \begin{bmatrix} e_{CD,t-1} \\ e_{P,t-1} \\ e_{A,t-1} \end{bmatrix} + \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} & \gamma_{14} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} & \gamma_{24} \\ \gamma_{31} & \gamma_{32} & \gamma_{33} & \gamma_{34} \end{bmatrix} \begin{bmatrix} \Delta \ln(Dist_t) \\ \Delta \ln(F_t) \\ \Delta \ln(D_t) \\ \Delta \ln(FD_t) \end{bmatrix} + \begin{bmatrix} \mu_{CD,t} \\ \mu_{P,t} \\ \mu_{A,t} \end{bmatrix}, \quad (A5)$$

Equation (A5) is the most general form of the VARX model. When no cointegration is found, the model reduces to (A3). When Enders' procedure indicated that none of the endogenous variables had a deterministic trend in the data-generating process, the  $\delta_i$  parameters were set to zero, and when some of the variables did not have a unit root, the difference operator was omitted and the variable was 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  $t$ , then 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, e.g., Bronnenberg et al. (2000) or Dekimpe and Hanssens (1995a, 1999). Formally, one assumes  $[\mu_{CD,t+i} \ \mu_{P,t+i} \ \mu_{A,t+i}]' = [0 \ 0 \ 0]'$  for  $i = \dots, -2, -1, +1, +2, \dots$ , whereas  $\mu_{P,t}$  is set to  $-1$ . Under these assumptions, we compute a vector of incremental effects on the endogenous variables,  $[\ln(CD_t^*) \ \ln(P_t^*) \ \ln(A_t^*)]'$  for  $t = 0, 1, 2, \dots$ . 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, although 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  $-\sigma_{PCD}/\sigma_{PP}$  and  $-\sigma_{PA}/\sigma_{PP}$ , with  $\sigma_{ij}$  the corresponding element in the residual variance-covariance matrix  $\Sigma$ . We then simulate the over-time impact of the shock vector  $[-\sigma_{PCD}/\sigma_{PP} \ -1.0 \ -\sigma_{PA}/\sigma_{PP}]'$ . In doing so, we capture both a wide variety of lagged effects (through the  $\phi$  parameters in Equation (A5)) and the expected instantaneous effects.

Standard errors for the IRFs and/or the summary statistics described in § 3.1 were subsequently derived using the Monte Carlo simulation approach introduced in Dekimpe and Hanssens (1999), with 250 runs in each case.

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