Do promotions benefit manufacturers, retailers, or both?

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Abstract

While there has been strong managerial and academic interest in price promotions, much of the focus has been on the impact of such promotions on category sales, brand sales and brand choice. In contrast, little is known about the long-run impact of price promotions on manufacturer and retailer revenues and margins, although both marketing researchers and practitioners consider this a priority area (Marketing Science Institute 2000). Do promotions generate additional revenue and for whom? Which brand, category and market conditions influence promotional benefits and their allocation across manufacturers and retailers?

To answer these questions, we conduct a large-scale econometric investigation of the effects of price promotions on manufacturer revenues, retailer revenues and total profits (margins). This investigation proceeds in two steps. First, persistence modeling reveals the short- and long-run effects of price promotions on these performance measures. Second, weighted least-squares analysis shows to what extent brand characteristics and promotional policies, as well as market-structure and category characteristics, influence promotional impact.

A first major finding of our analyses is that a price promotion typically does not have permanent monetary effects for either party. Second, in terms of the cumulative, over-time, promotional impact on their revenues, we find significant differences between the manufacturer and retailer. Price promotions have a predominantly *positive* impact on manufacturer revenues, but their effects on retailer revenues are *mixed*. Moreover, retailer category margins are typically *reduced* by price promotions. Even when accounting for cross-category and store-traffic effects, we still find evidence that price promotions are typically not beneficial to the retailer. Third, our results indicate that manufacturer revenue elasticities are higher for promotions of small-share brands, for national brands and for frequently promoted brands. Moreover, they are higher for impulse products and in categories with a low degree of brand proliferation and low private-label shares. Retailer revenue elasticities, in turn, are higher for brands with frequent and shallow promotions, for impulse products and in categories with a low degree of brand proliferation. As such, from a revenue-generating point of view, manufacturer and retailer interests are often aligned in terms of which categories and brands to promote. Finally, retailer margin elasticities are higher for promotions of small-share brands and for brands with infrequent and shallow promotions. Thus, the implications with respect to the frequency of promotions depend upon the performance measure the retailer chooses to emphasize. The paper discusses the managerial implications of our results for both manufacturers and retailers, and suggests various avenues for future research.

Key words: Long-term profitability, sales promotions, category management, manufacturers versus retailers, empirical generalizations, vector-autoregressive models.

1. INTRODUCTION

Since the early seventies, price promotions have emerged as an important part of the marketing mix. Increasingly, they represent the main share of the marketing budget for most consumer-packaged goods. An extensive body of academic research has established that temporary price reductions substantially increase short-term brand sales (see e.g. Blattberg et al. 1995; Neslin 2002), which may explain their intensity of use by manufacturers and retailers alike. However, the long-term effects of price promotions tend to be much weaker. Recent research consistently finds that short-term promotion effects die out in subsequent weeks or months - a period referred to as dust settling - leaving very few, if any, permanent gains to the promoting brand. This pattern has been shown to hold for the market shares of promoting brands (Srinivasan et al. 2000), for category demand (Nijs et al. 2001), as well as for consumers' purchase incidence, brand choice and purchase quantity (Pauwels et al. 2002).

From a strategic perspective, these findings imply that promotions generally do not generate long-term benefits to the promoting brand beyond those accrued during the dust-settling period. By the same token, brands do not suffer permanent damage to their market position from competitive promotions either. Therefore, in order to be economically viable, promotional actions should be held accountable for net positive results during the dust-settling period. This accountability has two components. First, a promotion *must not* initiate a permanent price or margin drop. After the promotion period, prices must return to their normal levels lest they cause permanent erosion of profit margins without offsetting volume increases. Second, a promotion *must* generate a net surplus (incremental revenue and profit over baseline) for the promoter over the dust-settling period. These conditions motivate a fresh look at the economics of promotions using metrics such as revenue and margins (total profits). Indeed, the focus of past empirical research on promotions has been on their *volume* impact, due to both data limitations and marketing’s interest in consumer decision-making. However, for managers, volume is just part of the equation. The more relevant business goal is *incremental revenue and profit (margin) generation*, i.e. the question is whether or not promotions are attractive in financial terms.

In addition, promotions typically involve two parties whose interests need not necessarily be aligned: the manufacturer and the retailer. To the *manufacturer*, volume gains may come from two sources: primary-demand expansion and brand switching. The relevant question then becomes whether the added revenues from these incremental sales are large enough to compensate for the margin loss on the brand's baseline volume. To the *retailer*, the financial attractiveness of price promotions is more intricate to assess. Not only is the retailer's performance linked to all brands in the category rather than the sales of any one brand (Raju 1992), it also depends on category interdependencies and on the store-traffic implications of promotions (Walters and Rinne 1986). As for volume, retailers can benefit from promotions because of primary-demand effects in both the focal and complementary categories, while an opposite effect may be observed for substitute categories. As for margin, price promotions may have a dual impact: the per-unit margin of the promoted brand is affected, and there may be an increased switching from higher to lower-margin brands (or vice versa). Moreover, the revenue and margin implications may well vary *across* different categories or even across brands within the category on promotion.

There is only limited empirical evidence on the *overall* profitability of a given price promotion and its *division* across manufacturers and retailers (Ailawadi 2001, p. 313). Some researchers argue that, while manufacturer profits from promotions have increased at a steady rate, retailers have been earning lower profits (Farris and Ailawadi 1992; Ailawadi, Farris and Shames 1999). Likewise, competition among stores may prevent retailers from translating trade allowances into profits (Kim and Staelin 1999). In contrast, some believe that power in the channel has shifted toward the retailers, so their share of promotion profits should be on the rise (Kadiyali, Chintagunta and Vilcassim 2000; see Ailawadi 2001 for an extensive review on this issue). In fact, the proliferation of price promotions at the expense of advertising budgets has been attributed to the increasing power of retailers (Achenbaum and Mitchel 1987; Olver and Farris 1989). Similarly, Nijs et al. (2001) argue that many leading manufacturers would like to reduce their excessive reliance on price promotions but are reluctant to do so, lest they lose the support of retailers who still appreciate the market expansive power of price promotions.

Interestingly, other sources (see e.g. Urbany, Dickson and Sawyer 2000) have reported a similar discontent with price promotions on the part of retail executives.

To summarize, price promotions may impact primary demand, selective demand and per-unit margins, and their combined or *net* financial effect for both manufacturers and retailers depends on their relative impact on these three performance dimensions. Unfortunately, no empirical literature to date has systematically assessed these net effects over time. The research questions we want to address are therefore: (i) are promotions financially attractive, (ii) for whom, and (iii) what accounts for the variation in promotional benefits across categories and brands?

To answer these questions, we conduct a large-scale econometric investigation of the effects of price promotions on manufacturer revenues, retailer revenues and retailer margins.[1] Given the well-established dynamic nature of promotion response, we adopt the time-series framework used in Dekimpe and Hanssens (1995, 1999). Following Nijs et al. (2001), our research proceeds in two stages. First, we *quantify* the promotion impact on the relevant dependent variables for a large number of brands and product categories over a long time period. Unlike previous studies, we do not limit ourselves to the manufacturer (volume) sales, either in relative or absolute terms, but we consider manufacturer revenues as well. For the retailer, five performance variables are considered: (i) category sales, (ii) category revenue, (iii) category margin, (iv) store traffic, and (v) overall store revenues. Second, we *explain* the observed differences in revenue effects for both manufacturers and retailers. As such, our paper provides new insights into the over-time financial effects of price promotions, and how they may differ between manufacturers and retailers.

The paper is organized as follows. In section 2, we describe Vector AutoRegressive (VAR) modeling, and the associated impulse-response functions, as a suitable method for quantifying the cumulative promotion effects on manufacturer and retailer performance. We then introduce an extensive multi-category scanner database covering 265 weeks of promotional activity in a regional market (section 3). In section 4, we report and interpret the results of our first-stage estimation for both manufacturers and retailers. These results are extensively validated in section 5.

Having quantified the cumulative promotion effects on performance, we introduce in Section 6 the second-stage analysis to examine how brand and category characteristics influence the promotional impact on, respectively, manufacturer revenue, retailer revenue and retailer margins. Finally, we formulate overall conclusions and suggest limitations and proposed areas for future research in section 7.

2. MODELING LONG-TERM PROMOTIONAL IMPACT ON PERFORMANCE

Price promotions are commonly defined as temporary price reductions offered to the consumer (Blattberg et al. 1995, Neslin 2002). Previous work has operationalized price promotions in two ways (see Pauwels et al. 2002 for a recent review): (i) in absolute, nominal numbers (e.g. 10 cents off), or (ii) relative to a benchmark or baseline. The former approach is adopted in most individual-choice models (see e.g. Chintagunta 1993 or Bucklin, Gupta and Siddarth 1998), while the latter is reflected in PROMOCAST (Abraham and Lodish 1987), SCAN*PRO (Foekens et al. 1999) and recent VAR-based studies (e.g. Bronnenberg et al. 2000; Srinivasan et al. 2000; Nijs et al. 2001). The VAR approach, which is used in this paper, is most explicit in defining the benchmark: a price promotion is defined as an unexpected price shock, relative to the expected price as predicted through the dynamic structure of the VAR model. Underlying this specification is the idea that consumers (managers) incorporate price expectations in their buying (reaction) behavior, and respond to the unanticipated part of a given price reduction (Helson 1964; Kalyanaram and Winer 1995; Raman and Bass 2002). Given the focus of this paper on the market performance impact of promotions, we model market-level performance and price series rather than individual-level purchases (see Pauwels et al. 2002 for an in-depth comparison). The parameters of this aggregate model reflect the combined response of all players, and the forecasts derived from the model reflect the anticipated (combined) consumer response, as well as the extrapolated reactions or decision rules of the market players. These forecasts can therefore be interpreted as aggregate expectations, conditional on the information set at hand.[2]

Previous VAR-based studies have focused on distinguishing between the short-term and long-term effects of price promotions on different levels of consumer demand of frequently purchased consumer goods, and two major findings emerge from this research stream. First, permanent effects are the exception rather than the rule for category sales, brand sales (or share) and their components (category incidence, brand choice and purchase quantity). While promotions almost always have substantial effects on immediate sales, these effects tend to die out over a finite number of weeks (the "dust-settling period"), leaving very few, if any, permanent gains to the promoting brand. Second, the total sales impact of a price promotion (immediate and dust-settling effects) is typically *positive* for all sales components. These papers therefore conclude that negative dust-settling effects such as post-promotion dips do *not* offset the immediate gains of price promotions. However, because promotions reduce the unit profit margin, increased sales over the total effect horizon are only a necessary, not a sufficient, condition for promotional profitability (Dekimpe and Hanssens 1999; Kopalle et al. 1999). Indeed, the net effect of volume increase and price reduction has not been examined to date, nor have the margin implications to the retailer of switching among promoted and non-promoted brands.

VAR models of promotional response are well suited to measure these total or net revenue and profit effects. In a VAR model, we assess the net result of a chain of reactions initiated by a single promotion. Specifically, VAR models are designed to not only measure direct (immediate and/or lagged) promotional response, but to also capture the performance implications of complex feedback loops. For instance, a promotional shock may generate higher retailer revenue, which may induce the retailer to promote that brand again in subsequent periods. As a result, other brands may engage in their own promotions that influence the over-time effectiveness of the initial promotion. Because of all these reactions, the total performance implications of the initiating promotional shock may extend well beyond the typical instantaneous and post-promotional dip effects. Similarly, the *effective* time span that elapses before all prices in the market return to their pre-shock level could exceed the initial *nominal* promotional period of one to two weeks. Our main interest lies in the net (total) result of all these actions and reactions, which can be derived from a VAR model through its associated impulse-response functions, as discussed in more detail below.

In this paper, we estimate a sequence of four-equation VAR models per product category, where the endogenous variables are the prices for the three major brands (P_i, i=1,2,3) and one of the performance measures (PERF). This setting allows us to capture (i) the dynamic interrelationships between the considered performance measure and the three price (promotion) variables, and (ii) the reaction patterns among the latter. One could argue that a more extensive VAR model might be more appropriate, e.g. to simultaneously include multiple performance measures, or to also include other promotional variables such as feature and display activity as endogenous variables. However, this would put considerable strain on an already heavily parameterized model (see Pesaran and Smith 1998, pp. 78-79, for a discussion on the influence of VAR dimensionality on parameter biases). The current four–equation model tries to balance completeness and parsimony, while we refer to Section 5 for various sensitivity analyses with higher-order models.

Apart from the four selected endogenous variables, the focal model also includes different sets of exogenous control variables. In addition to an intercept (a_0), we add five sets of exogenous control variables: (i) feature (FT) and display (DP) variables for each of the three major brands; (ii) a step dummy variable for the impact of new-product introductions (NP), as these have been shown to potentially increase category sales (Nijs et al. 2001) and market shares (Kornelis et al. 2001); (iii) four-weekly seasonal dummy variables (SD) to account for seasonal fluctuations in performance and/or marketing spending; (iv) a set of dummy variables (HD) that equal one in the shopping periods around major holidays, given empirical evidence that the total demand at most retail chains is quite volatile around these days (Chevalier et al. 2000); and (v) a deterministic-trend variable *t* to capture the impact of omitted, gradually-changing variables (see Nijs et al. 2001 for a similar approach).

VAR models can be written in levels, differences or error-correction format, depending on the outcome of preliminary unit-root and cointegration tests (Powers et al. 1991). As for the unit-root tests, Augmented Dickey Fuller (ADF) tests are performed for each series. With respect to deterministic components, seasonal dummy variables and holiday dummy variables are included in all instances (Ghysels, Lee and Noh 1994). There is no need to adjust the critical values for the unit-root tests because of their inclusion, since neither interferes with the zero frequency of the test given that they are fixed from the outset (Ghysels and Perron 1996). Finally, the inclusion of a deterministic trend is based on the procedure described in Enders (1995). Since unit-root tests are known to be biased towards finding a unit root when there is a structural break (Perron 1989, 1990), we subject all series that are found to have a unit root to the innovational-outlier structural break test of Perron (see Nijs et al. 2001 for a similar approach). In our context, a candidate for such an event is the introduction of a new brand into the market (Bronnenberg et al. 2000).[3] It is important to note that in the Perron test, the exogenous entry date of the new brand is the only candidate for a structural break in the price and/or performance variables. Therefore, we also perform the endogenous break test (Zivot and Andrews 1992), which endogenously determines the most likely breakpoint over the data period. The unit-root specifications allow for a maximum of 8 lags, and we select the best model based on the SBC criterion (Hall 1994). In case more than one endogenous variable in our four-equation model is found to have a unit root (i.e. to be evolving in the terminology of Dekimpe and Hanssens 1995),[4] we apply Johansen's cointegration test for co-evolution. Specifically, we will use the extension advocated in Johansen et al. (2000), because cointegration tests have also been shown to be sensitive to potential structural breaks, as caused by, for example, a major new-product introduction.

Assuming, for ease of exposition, that all variables are found to be level or trend stationary, the following model is specified for each performance variable:

$$\begin{bmatrix} PERF_t \\ P_{1,t} \\ P_{2,t} \\ P_{3,t} \end{bmatrix} = \begin{bmatrix} a_{0,PERF} + \sum_{S=2}^{13} a_{s,PERF} SD_{st} + \sum_{h=1}^{11} a_{h,PERF} HD_{ht} + \delta_{PERF} t + \eta_{PERF} NP_t \\ a_{0,P1} + \sum_{S=2}^{13} a_{s,P1} SD_{st} + \sum_{h=1}^{11} a_{h,P1} HD_{ht} + \delta_{P1} t + \eta_{P1} NP_t \\ a_{0,P2} + \sum_{S=2}^{13} a_{s,P2} SD_{st} + \sum_{h=1}^{11} a_{h,P2} HD_{ht} + \delta_{P2} t + \eta_{P2} NP_t \\ a_{0,P3} + \sum_{S=2}^{13} a_{s,P3} SD_{st} + \sum_{h=1}^{11} a_{h,P3} HD_{ht} + \delta_{P3} t + \eta_{P3} NP_t \end{bmatrix} +$$

$$\sum_{i=1}^{k} \begin{bmatrix} \beta_{11}^i & \beta_{12}^i & \beta_{13}^i & \beta_{14}^i \\ \beta_{21}^i & \beta_{22}^i & \beta_{23}^i & \beta_{24}^i \\ \beta_{31}^i & \beta_{32}^i & \beta_{33}^i & \beta_{34}^i \\ \beta_{41}^i & \beta_{42}^i & \beta_{43}^i & \beta_{44}^i \end{bmatrix} \begin{bmatrix} PERF_{t-i} \\ P_{1,t-i} \\ P_{2,t-i} \\ P_{3,t-i} \end{bmatrix} + \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} & \gamma_{14} & \gamma_{15} & \gamma_{16} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} & \gamma_{24} & \gamma_{25} & \gamma_{26} \\ \gamma_{31} & \gamma_{32} & \gamma_{33} & \gamma_{34} & \gamma_{35} & \gamma_{36} \\ \gamma_{41} & \gamma_{42} & \gamma_{43} & \gamma_{44} & \gamma_{45} & \gamma_{46} \end{bmatrix} \begin{bmatrix} FT_{1,t} \\ FT_{2,t} \\ FT_{3,t} \\ DP_{1,t} \\ DP_{2,t} \\ DP_{3,t} \end{bmatrix} + \begin{bmatrix} \varepsilon_{PERF,t} \\ \varepsilon_{P1,t} \\ \varepsilon_{P2,t} \\ \varepsilon_{P3,t} \end{bmatrix} \quad (1)$$

where $PERF_t$ refers to the performance variable of interest, $P_{1,t}$, $P_{2,t}$ and $P_{3,t}$ to the prices of the 3 major brands, and $[\varepsilon_{PERF,t}, \varepsilon_{P1,t}, \varepsilon_{P2,t}, \varepsilon_{P3,t}]' \sim N(0,\Sigma)$. In case of level stationary series, the δ parameters become zero. In case of unit-root series (as determined on the basis of regular and structural-break unit-root tests), the model is estimated in first differences, i.e. X_t is replaced by $\Delta X_t = X_t - X_{t-1}$. When different unit-root series are found to be cointegrated, the model in differences is augmented with an error-correction term that captures the system's gradual adjustment towards a long-run equilibrium (see Powers et al. 1991 for a detailed technical exposition). In case the break date is endogenously determined (cf. supra), we add additional dummy variables in the VAR model corresponding to this break date.

In the above model, feature and display are included as exogenous variables with no direct lags; hence, their dynamic effects are captured indirectly through the lagged endogenous variables (Pesaran and Shin 1998). No direct lags are included (i) to save degrees of freedom, and (ii) since it has been argued that the added benefits of allowing more intricate dynamics for feature and display are limited, given that consumers are less likely to accelerate their purchases as a result of these activities (Van Heerde et al. 2000). We validate this argument in Section 5. For the order of the VAR model (k), we set the maximum number of lags to 8 and select the best model based on the Schwarz Bayesian Criterion (SBC). For the manufacturer, brand sales (S) and manufacturer revenue (MR) are used as performance measures, while the five retailer performance measures are category sales (CS), total retailer revenue (RR), total retailer margins (RM), store revenue (SR) and store traffic (ST).

In a VAR framework, price promotions are operationalized as temporary price shocks whose over-time impact is quantified through the corresponding impulse-response functions (see e.g. Dekimpe et al. 1999; Srinivasan et al. 2000 or Nijs et al. 2001 for technical details). 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 an extended information set that takes the promotion into account. The difference between both forecasts measures the incremental effect of the price promotion. The impulse-response function (IRF), tracing the incremental impact of the price-promotion shock, is our basic measure of promotional effectiveness.

A critical issue in the derivation of impulse-response functions is the temporal ordering between the different endogenous variables. As is often the case in marketing applications, a priori insights on the leader-follower roles between the different brands are unavailable. We therefore adopt the approach developed in Evans and Wells (1983) and Buckle and Meads (1991), and recently applied in a marketing setting by Dekimpe and Hanssens (1999) and Pauwels et al. (2002) in which the information in the residual variance-covariance matrix Σ of Equation (1) is used to derive a vector of *expected* instantaneous shock values. In so doing, we assumed that the shocked variable (the price series of brand i) is ordered first in the sequence, i.e. we allow the *initiating* price promotion to elicit an instantaneous reaction in all other endogenous variables. We subsequently vary the price variable ordered first in the sequence, depending on which brand is considered to initiate the promotion. This procedure is in line with the general idea behind IRF simulations, i.e. *we assume that competitors will react to the "new" price promotion according to the same decision rules that governed their historical reactions,* as reflected in (i) the autoregressive coefficients for delayed reactions, and (ii) the correlations between the initiating promotion and the other price residuals for instantaneous reactions.

As for the standard errors of the IRF estimates, these are derived using a bootstrap procedure similar to the one described in Dekimpe and Hanssens (1999, p. 404). Such a bootstrap procedure works as follows: using the sampled residuals and the estimated equations, one creates new (artificial) performance and price series. With these artificial data as input, one reestimates the VAR model and derives the associated IRFs. This procedure is repeated 250 times, and the sample standard error of the resulting 250 IRF coefficients gives an indication of their accuracy. Note that all parameters of the estimated VAR model are used in the computation of the new artificial data. Therefore, the estimated error for each parameter contributes to the estimated error of the impulse response function. As is common practice in economics (see e.g. Mark 1990, footnote 6; Lütkepohl 1993) and marketing (see e.g. Dekimpe and Hanssens 1999; Nijs et al. 2001), we applied the same VAR specification in all 250 runs, i.e. no separate unit-root and cointegration tests are performed on the respective artificial data series.

We summarize the different options taken in the various steps of the specification and estimation procedure in Table 1.

--- Insert Table 1 about here---

While impulse-response functions are useful summary devices, the multitude of numbers (periods) involved makes them awkward to compare (i) across manufacturers and retailers, and (ii) across different brands and product categories. To reduce this set of numbers to a manageable size, we derive the following three summary statistics from each IRF:

(i) the immediate performance impact of a price promotion, which is readily observable to managers, and may therefore receive considerable managerial scrutiny,

(ii) the long-run or permanent impact, i.e. the value to which the impulse-response function converges, and

(iii) the total or cumulative impact, which combines the immediate effect with all effects over the dust-settling period. In the absence of a permanent impact, this statistic becomes the relevant metric to evaluate a promotion's performance. For level- and trend-stationary series with zero convergence value, this effect is computed as the sum of all significant impulse response coefficients.[5] For unit-root series, we follow Nijs et al. (2001), and derive the total sum until four consecutive IRF estimates are encountered not significantly different from the IRF's asymptotic value.

Figure 1 shows a plot of prices, manufacturer revenue, retailer revenue and retailer margin for a brand in the stationary canned-tuna market. Figure 2 shows an example of the incremental effect over time of a price promotion of one cent per ounce for one of the leading brands in that market on the manufacturer's (Panel A) and the retailer's (Panel B) revenues. Both parties experience a significant and immediate revenue increase in the promotional period, and a post-promotional dip around period 2. However, given the level/trend stationarity of the performance series, neither player experiences a permanent or enduring revenue gain (i.e. the incremental revenue impact converges to zero). Furthermore, both the immediate effect ($5,790 versus $4,400) and the cumulative impact ($5,180 versus $4,030) prior to convergence are more pronounced for the manufacturer than for the retailer. This is also the case in Panel C and Panel D, which trace the over-time impact of a one-cent price promotion in the stationary cheese market, where only the manufacturer (Panel C) enjoys an immediate revenue increase ($8,200), while both the immediate and cumulative effects (-$10,430 and –$18,010, respectively) for the retailer are negative (Panel D). Hence, in the former case, the retailer's and the manufacturer's financial interests are aligned, while this is clearly not the case in the latter example. The relevant question then becomes whether these examples are the rule, or whether scenarios where the retailer is the main beneficiary, or even where both lose revenues are more prevalent. A large-scale empirical analysis on this issue is presented in section 4.

--- Insert Figures 1 and 2 about here ---

The summary statistics depict the performance effects in additional (incremental) units or ounces sold (brand and category sales), customers (store traffic) or dollars (manufacturer revenues, retailer revenues and margins). The common dollar metric is especially useful to assess the relative financial benefits to, respectively, the retailer and the manufacturer for a *given* price promotion. When making comparisons across brands and product categories, however, one may want to control for scale differences, and convert the respective summary statistics to unit-free elasticities. We derive the elasticities at the mean by normalizing the incremental performance by the ratio of the sample performance mean to the sample price mean. For the tuna brand in Figure 2, the immediate (cumulative) increase in manufacturer revenue of $5,790 ($5,180) is transformed into an elasticity of 3.38 (3.02) by normalizing the incremental performance by the ratio of $25,530 (sample mean of weekly manufacturer revenue) to 14.8 cents (sample mean of weekly price per ounce of the brand). Similarly, the immediate (cumulative) increase in retailer revenue of $4,400 ($4,030) is transformed into an elasticity of 0.47 (0.43) by normalizing the incremental performance by the ratio of $138,540 (sample mean of weekly retailer revenue in the category) to 14.8 cents (sample mean of weekly price per ounce of the brand). Using a similar calculation for the cheese category, the immediate (cumulative) manufacturer revenue elasticity is 0.81 (0.44) while the immediate (cumulative) retailer revenue elasticity is –0.34 (–0.58).

3. DATA DESCRIPTION AND VARIABLE OPERATIONALIZATION

The database consists of scanner records for twenty-five product categories from a large mid-western supermarket chain, Dominick's Finer Foods (DFF). With 96 stores in and around Chicago, this chain is one of the two largest in the area. Relevant variables include unit sales at the SKU level, retail and wholesale price (appropriately deflated using the Consumer Price Index for the area), feature and display,[6] and information on new-product introductions. Sales are aggregated from the SKU to the brand level, and we follow Pauwels et al. (2002) in adopting static weights (i.e. average share across the sample) to compute the weighted prices, rather than dynamic (current-period) weights. We use data from September 1989 to September 1994, a total of 265 weeks.[7] We terminated the sample period in 1994 because in subsequent years, manufacturers made extensive use of "pay-for-performance" price promotions, which are not fully reflected in the Dominick's wholesale price data (Chintagunta 2002, Peltzman 2000). All data are given at the weekly level. Our impulse-response functions will therefore trace the over-time impact of weekly price promotions, which is by far the most frequently occurring promotional length (Cooper et al. 1999). Finally, we control for major new-product introductions in several product categories by both national brands and private labels.[8]

Beyond the richness in performance and control variables, this data set is also very broad as it covers non-food (e.g. detergents and toothbrushes) and food products, both storable (e.g. canned tuna and canned soup) and perishable (e.g. cheese and refrigerated juice). Research problems previously addressed using the Dominick's data set include store-level differences in price sensitivity (Hoch et al. 1995), the customization of marketing-mix variables at the store level (Montgomery 1997), the power division between manufacturers and retailers (Kadiyali et al. 2000), the retail pass-through for competing brands (Besanko et al. 2001), the relationship between prices and peak demand (Chevalier et al. 2000), asymmetric price response to costs (Peltzman 2000), brand and category pricing behavior at a retail chain (Chintagunta 2000; Chintagunta 2002), and the impact of price discrimination (Chintagunta et al. 2001).

To the best of our knowledge, this is the first data set that documents weekly manufacturer and retailer prices for a large number of products. Focusing on the top-three brands in each category, we analyze a total of 75 brands.

Manufacturer performance measures

For the top-three brands in a category, we consider brand sales as well as manufacturer revenues, defined as:

$$MR_{i,t} = MS_{i,t} \times Q_t \times WP_{i,t}$$

where $MS_{i,t}$ refers to market share of brand i at time t, Q_t is the category sales and $WP_{i,t}$ is the wholesale price of brand i at time t.

Retailer performance measures

For the retailer, a more extensive set of performance measures is considered. In addition to category sales, we also derive the total category revenue for the retailer as:

$$RR_t = \sum_{i=1}^{n} MS_{i,t} \times Q_t \times P_{i,t}$$

where $P_{i,t}$ refers to the price of brand i at time t and n is the total number of brands in a category. As both retailer and manufacturer revenues are expressed in dollars, the relative changes in $MR_{i,t}$ and RR_t due to a given price promotion will yield insights into the division of promotional benefits between manufacturer and retailer. Additionally, we compute the retailer's total category margins (defined in dollars) as:

$$RM_t = \sum_{i=1}^{n} MS_{i,t} \times Q_t \times (P_{i,t} - WP_{i,t})$$

We note that the wholesale-price measure $WP_{i,t}$ does not capture the replacement cost of the item in a given week, but rather the average acquisition cost ($AAC_{i,t}$) of all items in inventory in that week. $AAC_{i,t}$ is obtained as a weighted average of the price paid by the retailer for brand i in week t and the retailer's average acquisition cost in t-1 (for a description, see http://gsbwww.uchicago.edu/research/mkt/Databases/DFF/W.html). Even though this measure has been used repeatedly in the marketing literature (e.g. Besanko et al. 2001; Chevalier et al. 2000; Chintagunta 2002; Chintagunta et al. 2001; Kadiyali et al. 2000; Peltzman 2000), there has been some concern that it may be sensitive to both sluggish adjustment and forward buying practices of the retailer. Moreover, we acknowledge that our manufacturer revenue measure for a given week does not perfectly reflect true manufacturer revenue for that same week since the timing of manufacturer trade deals and retail price discounts need not coincide. Still, manufacturer shipments ultimately increase to the extent that a consumer promotion is more or less successful in increasing end-user demand for the brand. Similarly, changes in the retailer average acquisition cost do reflect changes in manufacturer revenue per unit. Therefore, the average acquisition cost seems an appropriate measure to study the total effects of price promotions on manufacturer revenues and retailer margins. We will nevertheless extensively validate our substantive findings with respect to these issues in Section 5.

Finally, we investigate two store-level performance variables of relevance to the retailer. Store revenue is captured by the total dollar sales summed over all Dominick's-defined departments for a given week. Store traffic is defined as the total number of customers visiting the store and buying at least one item in a given week.

Holiday dummy variables

The total demand at most retail chains is volatile around major holidays. Hence, following Chevalier et al. (2000), we incorporate dummy variables that equal one in the shopping periods around the following holidays: Lent, Easter, Memorial Day, July 4th, Labor Day, Thanksgiving, the week following Thanksgiving, Christmas and the Superbowl. The database contains weekly data in which the weeks start on Thursday and end on Wednesday. We generate a set of dummy variables, one for each holiday. For Thursday holidays, the corresponding dummy variable is set to 1 for the two weeks prior to the holiday, but zero for the week including the holiday. For holidays taking place on all other days, the dummy variable is set to 1 for the week before the holiday and the week including the holiday. The Lent dummy variable takes the value one for the four weeks prior to the 2-week Easter shopping period (as e.g. tuna demand may increase during, and drop after Lent), the post-Thanksgiving variable has the value one for the week following Thanksgiving and the Christmas dummy is set to one for the week following Christmas to capture the shopping in anticipation of New Year's as in Chevalier et al. (2000). We incorporate a dummy variable corresponding to Halloween, since the demand for one of the categories we analyze -- front-end candies -- is likely to be much higher around this holiday. Since little candy is likely to be bought immediately after Halloween, we add an additional dummy variable that is set equal to 1 for the week following the holiday. For consistency, these eleven holiday dummy variables are incorporated in all 25 categories analyzed.

Brand characteristics

A dummy variable indicates whether the promoting brand is a national brand (=1) or a private label (=0). The promoting brand's share is operationalized as the average volume-based share of the brand. Private-label share is measured as the average volume-based market share for all private labels in the category combined. Finally, promotional frequency and depth (Jedidi et al. 1999) are defined consistently with the impulse response functions that estimate the incremental effect of a 'shock' to price: a promotion week is defined as a week in which the price shock is at least two standard deviations below the mean shock. In line with Rao, Arjunji and Murthi (1995) and Nijs et al. (2001), we define the brand's price promotion frequency as the proportion of promotion weeks (as defined above) for the brand and the brand's price-promotion depth as the (percentage) difference between a brand's promotional price shock (in a promotion week) and the brand's average price averaged across all non-promotion weeks. Summary information on the average promotional frequency and depth in each of the categories in the data set is provided in Table 2.

--- Insert Table 2 about here ---

Market and category characteristics

We measure the competitive structure in a given category by the variance in shares across brands. The number of SKUs in the category (Narasimhan et al. 1996) is included to capture the extent of brand proliferation. We use the Narasimhan et al. (1996) storability and impulse-buy scales to construct dummy variables indicating whether the product category is considered perishable or storable (=1), and whether or not it is an impulse good (=1).[9]

4. DO PROMOTIONS INCREASE REVENUES AND MARGINS?

We first review our results on the temporal behavior of manufacturer sales, category sales, manufacturer revenues, retailer revenues, retailer margins, and store revenue and store traffic. We then discuss our main findings concerning the magnitude of the immediate and total price-promotion effects.[10]

4.1 Stationarity of the time series

Table 3 shows the results of the unit-root tests.

--- Insert Table 3 about here ---

For manufacturer performance, we find that three of the 75 sales series and five of the 75 revenue series are classified as evolving. However, when a correction is made for structural breaks due to new-product introductions, all these series are re-classified as stationary. Second, three of the 25 series are evolving for each of the retailer category performance measures. Once again, all these series are re-classified as stationary after controlling for a new-product introduction in the category. Third, the store revenue and store traffic series are all (level or trend) stationary. Finally, eleven out of the 75 retail price series and nine out of the 75 wholesale price series are classified as evolving. All these price series are re-classified as stationary after we account for new-product introductions using the Perron and/or Zivot and Andrews structural break test.[11]

This prevalence of stationarity of marketing series for frequently purchased consumer good categories has been reported in previous literature (Dekimpe et al. 1999; Srinivasan and Bass 2000, Nijs et al. 2001, Pauwels et al. 2002). In the terminology of Dekimpe & Hanssens (1999), we are observing predominantly "business-as-usual" scenarios. Thus, our evidence supports the existing empirical generalization that there are no permanent effects of price promotions on volume, i.e. brand sales and category sales. *Additionally, we offer a new generalization that a price promotion has no long-term effects on financial performance (manufacturer and retailer revenues, and retailer margins) and on store performance (store revenues and store traffic).* By contrast, new-product introductions can clearly affect long-term financial performance. Specifically, the apparent evolution in revenues and margins found in 25 cases is consistently related to major new-product introductions, a finding that also extends volume results in prior literature (Nijs et al. 2001).

4.2 First-stage results on the over-time effects of price promotions

4.2.1 Manufacturer performance: brand sales and brand revenues

A summary of the number of lags in the respective VAR models is shown in Table 4. The maximum number of lags is three, and the majority of estimated models (over 90%) has one lag, similar to other recent VAR-based studies (e.g. Dekimpe and Hanssens 1999). Our first-stage analysis reveals a predominantly positive impact of promotions on both brand sales and manufacturer revenues (Table 5).

--- Insert Tables 4 and 5 here ---

For brand sales, 63 out of the 75 brands (84%) obtain significant total positive effects. To assess the size of this effect, we subsequently calculated price-promotion elasticities at the mean following the method outlined in section 2. The average (median) immediate price-promotion elasticity in Table 6 is 3.56 (3.20), while the average (median) cumulative price promotion elasticity is 3.83 (3.65). This average total elasticity is similar to the average value of 3.94 reported in Steenkamp et al. (2001) in their large-scale analysis on promotional effectiveness in the Netherlands.

--- Insert Table 6 about here ---

With regard to manufacturer revenue, 62 out of 75 brands (83%) obtain significant total effects, which are positive in 54 cases (72%) and negative in 8 cases (11%). Thus, the predominant finding is that *promotions generate incremental manufacturer sales and revenue by the end of the dust-settling period.* The average (median) immediate price promotion elasticity in Table 5 is 2.58 (2.35) while the average (median) cumulative price-promotion elasticity is 1.87 (2.27).

4.2.2 Retailer performance: category sales and category revenues

For the retailer's category sales, we observe significant total effects for 44 out of the 75 brands, as seen in Table 5. Compared to 40 brands (53%) with a positive impact, only 4 brands (5%) have a negative impact. The average (median) elasticity is 0.55 (0.38) for the immediate impact, and 0.66 (0.50) for the total impact.

Thus, promotions generate incremental category sales for the retailer by the end of the dust-settling period, a finding that is consistent with Nijs et al. (2001). Their study finds positive total effects in 58% of all cases, versus only 5% with negative effects. Their average (median) elasticity equals 2.21 (1.75) for the log-log model and 1.98 (1.44) for the linear model. The difference in these estimates may be due to country-specific differences between the U.S. and the Netherlands, or could be due to the fact that Nijs et al. (2001) examine category demand at the national level, while we study category sales for one large chain in a regional market. We also note that the brand-level sales elasticity and the category-level sales elasticity are positive for both the manufacturer and the retailer; hence, *from a volume perspective, price promotions are attractive for both manufacturers and retailers.* The results change substantially when focusing on category revenue as opposed to volume sales. Indeed, while we observe significant total revenue effects for 29 out of 75 brands (39%), only 14 (19%) of those are positive, while 15 (20%) have a negative total impact. In contrast to manufacturer revenue, the average (median) immediate price-promotion elasticity is only 0.21 (0.10), and the total price-promotion elasticity is even smaller: –0.02 (–0.03). While the immediate price-promotion elasticity is still positive, the cumulative price promotion elasticity over the dust-settling period is negative, indicating that the immediate category-revenue expansive effect of a price promotion is negated in subsequent periods. A plausible explanation is that retailers' loss of revenue from non-promoted items is about the same or slightly higher than their revenue gains from promoted items. As a result, *price promotions are less financially attractive to retailers than they are to manufacturers.*

A common finding from Table 6 is that, for both market players, the total promotional elasticity exceeds the immediate elasticity for sales, but not for revenues. In other words, the additional effects in the post-promotion weeks tend to be positive for sales series, but negative for the revenue series. These findings suggest that, from a financial point of view, managers' well-documented focus on immediate results ignores an unexpected side effect of promotions. The danger is not so much that volume sales are borrowed from future periods (as we find that dust-settling volume effects are typically positive), but that prices tend to stay below baseline prices for some weeks before returning to their pre-promotion levels.

4.2.3 Retailer performance: margin, store revenue and store traffic

When focusing on *margin* implications, we find even stronger evidence that price promotions are typically not beneficial to retailers. Specifically, only 6 brands (8%) experience a positive total impact on category margins while 39 brands (52%) experience a negative total impact. The average (median) immediate price-promotion elasticity is –0.45 (-0.21) while the corresponding average (median) total price promotion elasticity is

–1.00 (-0.70). *Here too, there are strong negative post-promotion effects on retailer margins such that the initial negative impact is worsened.*

These unfavorable results to the retailer could, of course, be mitigated by beneficial store-traffic and store-revenue effects of promotions (Blattberg et al. 1995). For *store revenue*, we find that only 11 out of 75 brands (15%) experience a positive total impact, while 64 brands (85%) experience no significant total impact. The average (median) immediate price-promotion elasticity for store revenue is 0.01 (0.00) while the corresponding average (median) total price promotion elasticity is 0.01 (0.02). The results for *store traffic* are similar: only 12 out of the 75 brands (16%) experience a positive total impact, while 63 brands (84%) experience no significant total impact of price promotions on store traffic. All twelve brands with a positive impact on store traffic are national brands. This is line with the theoretical result in Lal and Narasimhan (1996) and the empirical generalization in Blattberg et al. (1995) that nationally-advertised brands are more effective in generating store traffic than private-label brands. Given this finding, it is not surprising that retailers typically use national brands as loss leaders to build store traffic (Drèze 1995). Our result on store traffic validates the finding in Hoch et al. (1994), based on data from field experiments conducted in the Dominick's chain, and other authors reporting only weak store-substitution effects of promotions (see, for example, Kumar and Leone 1988; Walters and Mackenzie 1988). Finally, only five of the twelve (42%) national brands with positive total impact on store traffic also experience a positive total impact on store revenue. Thus, while promotions on these national brands build store traffic, these promotions do not increase store revenue in more than half the cases. This could be due to the fact that the additional traffic generated by loss-leader promotions consists mainly of cherry-picking consumers (Walters and MacKenzie 1988).

Hence, the store traffic and revenue effects of retail promotions are typically insignificant, and do not compensate for the negative category-margin impact. Overall, our store impact findings are consistent with prior arguments that retail grocery managers overestimate the extent of cross-store shopping and the impact of price promotions on store traffic, thereby pricing more aggressively than warranted (Urbany et al. 2000).

In conclusion, after the dust settles, price promotions have a predominantly positive impact on manufacturer sales, manufacturer revenues and category sales, a small effect on store revenue and store traffic, a slightly negative effect on retailer revenues, and a decidedly negative effect on retailer margins. The opposite financial results for manufacturers versus retailers invite the question to what extent the retailer can extract a fixed compensation from the manufacturer, such that promotions have at least a neutral bottom-line effect for the retailer. Indeed, recent survey research has suggested that retailers make increasing use of promotional allowances (Bloom et al. 2000). In order to answer this question, we compare the magnitude of the positive manufacturer revenue impact with that of the negative retailer revenue impact due to promotions. In Table 5, out of the 12 (15) brands that had negative immediate (cumulative) retailer revenue impact, 8 (11) are national brands while the rest are private-label brands. Focusing on the immediate effects for these national brands, the compensation potential is weak, i.e. for only one of the 8 brands (12%) with negative retailer revenue impact does the promotion-generated financial gain for the manufacturer exceed the retailer's loss. Furthermore, when modeling total promotional impact, for none of the 11 national brands with negative revenue impact for the retailer is there sufficient potential for side payments. Obviously, these findings do not imply that it is impossible for the retailer to extract larger side payments from the manufacturer. However, in that case, the total *channel* gain from the promotion would become negative.

5. VALIDATION

To assess the robustness of the above findings, we conduct an extensive set of validation exercises. These focus on six main issues: (i) our treatment of feature and display activity as exogenous variables, (ii) the sensitivity of the results to aggregation across stores, (iii) the inclusion of only one performance variable at a time, (iv) our treatment of the retailer's price-setting process, (v) the sensitivity to (omitted) cross-category influences and, (vi) the appropriateness of the adopted wholesale-price operationalization. Table 7 presents the validation results.

--- Insert Table 7 about here ---

5.1 Sensitivity to the treatment of feature and display

The exogenous treatment of feature and display is relaxed in two ways. First, we extend our model by allowing for two lags of feature and display variables.[12] For all performance measures, the elasticity estimates closely match those obtained from the focal model (panel A1). Second, we treat the feature and display activity of the brand experiencing a price promotion as endogenous. This results in a model with six endogenous and four exogenous variables (the feature and display activity of the two competing brands). Again, results very similar to our focal model are obtained (panel A2).

5.2 Sensitivity to aggregation across stores

Our aggregation across stores with heterogeneous marketing-mix activities may have caused some biases (see Christen et al. 1997 for an in-depth discussion). Previous work has asserted that DFF aligns its promotions across stores (see e.g. Hoch et al. 1995); still, there may have been some deviations in terms of individual-store compliance. The linear (focal) model has been shown to be least sensitive to the store aggregation issue (Christen et al. 1997). In contrast, the log-log model is more susceptible to store aggregation bias, provided aggregation issues are a concern. If the results are very similar for the two specifications, this implies that the store aggregation bias is not a serious issue. Table 7 (panel B) shows that the log-log model indeed yields results that are very similar to those obtained with the linear model.

5.3 Sensitivity to inclusion of multiple performance measures

Simultaneous incorporation of all performance measures of both retailer and manufacturers into one giant VAR model would put too much strain on an already heavily parameterized model (see also Pesaran and Smith 1998). To examine whether incorporation of only one performance variable affects our substantive insights, four additional analyses are implemented. First, we incorporate simultaneously all three brand sales (manufacturer revenue) variables, along with their corresponding price variables, in a six-equation model. As shown in Panel C1, very similar elasticity estimates are again obtained for both performance indicators. Second, the financial metric of manufacturer revenue that is a focus of our research, is a composite of unit sales and prices. Therefore we conduct validation analyses by running separate models on unit sales and wholesale prices, and comparing the computed additional manufacturer revenues (evaluated at the series' sample mean) with the ones obtained through the focal model's IRFs. These new results (panel C2) confirm our findings on manufacturer revenue. Third, we capture retailer pricing considerations beyond the focal category by including the store-traffic variable as an additional endogenous variable in all model specifications, resulting in a set of five-equation VAR models (Chintagunta 2002).[13] Once more, comparable elasticity estimates are obtained (panel C3). Fourth, we verify whether the impulse responses for manufacturers and retailers are indeed statistically distinct by including manufacturer and retailer revenue, along with the three price variables, in the same VAR model. Using the aforementioned bootstrap procedure, we computed 250 times an estimate of the difference between the manufacturer and retailer elasticities. A subsequent test through the sample standard errors obtained from the empirical distribution on these elasticity differences revealed that in 95% (97%) of the cases, the immediate (cumulative) manufacturer revenue elasticity is significantly different from the immediate (cumulative) retailer revenue elasticity (Panel C4), indicating that our statistical inference is robust to this issue.

5.4 Sensitivity to the nature of the price-setting mechanism

The focal four-equation VAR model contains three price equations (see Equation 1), which capture previous research's arguments that retail prices are based on (1) the current prices of all (major) brands in the category (e.g. Zenor 1994), (2) past prices and performance (e.g. Pesendorfer 2001; Chintagunta 2002) and, (3) demand seasonality and special shopping periods (e.g. Chevalier et al. 2000). However, retail price setting considerations may also include (1) the wholesale price or acquisition cost (e.g. Choi 1991, Lee and Staelin 2000), (2) store-traffic implications (Drèze 1995), and (3) cross-category effects, if any (Pesendorfer 2001). As for the store traffic, we already demonstrated the robustness of the model with respect to this variable in Section 5.3. In addition, we estimated an augmented (5-equation) model, in which we add the wholesale price of the shocked brand (panel D1); the summary statistics are very similar to the ones derived from our focal model. Next, the store-traffic model is augmented with a weighted price variable for the other categories, resulting in a five-equation model with the store-traffic variable, three price series from category i and a weighted price for the j

other categories ($i \neq j$) as endogenous variables (panel D2). No substantial differences in the summary statistics for store traffic are observed.

5.5 Sensitivity to potential cross-category influences

Previous research has also suggested that price changes in one category typically do not affect demand in other categories (e.g. Pesendorfer 2001), *unless* these categories are obvious demand complements/substitutes (Manchanda, Ansari and Gupta 2001). Our dataset contains a number of such obvious candidates: fabric softener and laundry detergents, cereal and oatmeal, toothbrushes and toothpaste, crackers, snack crackers and cheese, bottled, refrigerated and frozen juice, shampoo and soap. For those category pairs, we estimate an augmented model, in which the market-share weighted price of the top 3 brands in category *j* is added as an endogenous variable to the focal model in category *i* (rotating *i* and *j*, 20 such analyses are performed, resulting in the additional estimation of 220 VAR models. Similar summary statistics on these analyses are presented in Table 7 (panel E). Once again, no substantial differences in results are observed.

5.6 Sensitivity to the adopted wholesale price operationalization

Two of our performance measures, manufacturer revenue and retailer margin, depend on the adopted wholesale price (WP) definition. This measure is used by the retailer herself as the relevant acquisition cost to compute profit margins, and has been applied in previous literature (see e.g. Kadiyali et al. 2000; Peltzman 2000; Besanko et al. 2001; Chevalier et al. 2001; Chintagunta 2002; Chintagunta et al. 2001). However, the operationalization has been criticized on two grounds: (i) it may be subject to sluggish adjustment, as the older, higher-priced inventory needs to be sold off first (Peltzman 2000, Besanko et al. 2001), and (ii) it may be affected by forward-buying practices on the part of the retailer (Besanko et al. 2001). Therefore, we obtained an additional dataset that features the base manufacturer wholesale price to the retailer and the starting and ending date of manufacturer promotions to retailers for a period from 1991 to 1994.[14] This data allows us to compute an alternative wholesale price measure for a subset of three categories also present in the Dominick's data: paper towels, toothpaste and toothbrushes. Because it records the period in which manufacturer trade deals are offered, this measure is not affected by retailer inventory management and thus not subject to sluggish adjustment nor forward buying. The alternative wholesale price measure is, however, subject to some other issues: it only features a subset of SKUs per brand and a subset of the Dominick's product categories, and it only informs us whether a manufacturer offered a deal, not whether the retailer accepted it. Despite these differences between the two wholesale price measures, they lead to similar time series of manufacturer revenue and retailer margin and result in comparable IRFs and elasticity estimates (Table 7, Panel F).[15]

6. DRIVERS OF PROMOTIONAL PERFORMANCE

6.1 Second-stage analysis: moderators and methodology

Our first-stage results reveal that, on average, price promotions are not financially advantageous to the retailer. However, we expect that this general finding is moderated by several characteristics of the brand and the category. The second stage of our research explores several drivers of promotional impact on financial performance variables. As such, we try to take maximum advantage of both the temporal (exploited in the first-stage VAR models) and cross-sectional richness of the data. While the first stage is more data-driven, in that we impose very little a priori structure, prior marketing theory will drive our selection of second-stage covariates. Specifically, we consider two categories of variables: *brand* characteristics (market share, private label versus national brand, promotional depth, promotional frequency) and *category* characteristics (market concentration, SKU proliferation, private-label share, ability to stockpile and whether or not the category is typically bought on impulse). Previous literature on these characteristics (e.g. Blattberg et al. 1995; Narasimhan et al. 1996; Bell et al. 1999; Nijs et al. 2001) are helpful in formulating expectations for their moderating effect on total promotional elasticity. However, most of these references consider the volume impact of promotions, whereas we focus on the revenue impact. Some of the moderating factors may impact price as well (e.g. Narasimhan 1988; Blattberg et al. 1995), and we have little knowledge on their combined impact on financial performance variables. As such, while previous literature is helpful in identifying factors that may moderate the total promotional impact, our second stage analysis is mostly explorative in nature. Econometrically, this stage uses weighted least-squares estimation on three second-stage equations, using the promotional impact on manufacturer revenues, retailer revenues and retailer margins as the dependent variables. The weights are the inverse of the standard errors of the dependent variables, and account for the bias caused by statistical error around our first-stage estimates. Because of the potential endogeneity of some independent variables, we tested for the presence of an endogeneity bias. For example, the market share of brands may be influenced by the promotional response elasticities of the brands. As such, unobserved determinants of the promotional response elasticities may not be independent of market share, causing a correlation between the latter and the error term of the estimation equation. In such a situation, market share should be treated as endogenous rather than exogenous, as it will otherwise lead to biased estimates. Following Davidson and MacKinnon (1993), we tested for the presence of endogeneity using the Hausman-Wu test (for a marketing application, see Gielens and Dekimpe 2001). Specifically, in the test equation, we included both the potentially endogenous variable (market share) and instruments for these variables, where the latter are derived as the forecasts from an auxiliary regression linking market share to the other control variables. A χ^2-test on the significance of these instruments then constitutes the exogeneity test. This test was implemented in turn (e.g. market share, category frequency, category depth, …). None of these tests revealed any violation of the assumed exogeneity of the RHS variables (using a significance level of $p < 0.05$), indicating that our specification is robust to this issue.

6.2 Results of second-stage analysis

The findings of our second-stage analysis are presented in Table 8. In our discussion, we focus on the moderating effect of the brand and category characteristics at hand on the total promotional impact on our three financial measures: (i) manufacturer revenue, (ii) retailer revenue, and (iii) retailer category margin.

--- Insert Table 8 about here ---

6.2.1 Manufacturer revenue

Table 8 shows that the total promotional impact on manufacturer revenue is moderated by brand ownership, the market share and the promotional frequency of the promoting brand, as well as the extent of SKU proliferation, the impulse-buying nature and the private-label share in the category. We elaborate on these results below.

For brand ownership, national brands generate higher total promotional impact on manufacturer revenue than private-label brands (Sivakumar and Raj 1997). This result is consistent with the empirical generalization that promoting high-equity (national) brands generates more switching than does promoting low-equity (private label) brands (Blattberg et al. 1995). The higher the market share of the promoting brand, the lower the total promotional elasticity impact on manufacturer revenue (Bolton 1989). This result extends previous findings on the immediate effects (Blattberg et al. 1995; Bell et al. 1999) and on the total effects (Pauwels 1999) of promotions on selective demand. High-share brands are likely to operate on the flat portion of their sales response functions.[16] These brands therefore experience 'excess' loyalty and lower selective demand effects (Fader and Schmittlein 1993). Moreover, high-share brands lose more money on subsidized baseline sales, i.e. sales that would have occurred even in the absence of a price promotion (Narasimhan 1988).

The higher the promotional frequency, the higher the promotional impact on manufacturer revenue. This result extends recent findings that the total promotional impact on selective demand increases with promotional frequency (Pauwels 1999). Frequent promotions may make promotions salient to the consumer, and thus increase promotional response (Dickson and Sawyer 1990). Moreover, they may raise the awareness of the brand so that consumers consider it for future purchase (Siddarth et al. 1995).

As for category characteristics, the extent of SKU proliferation has a significant negative effect on the total promotional impact on manufacturer revenue. This result extends the findings by Narasimhan et al. (1996) that categories with many brands obtain a lower immediate promotional response. There are two behavioral explanations for these findings (Narasimhan et al. 1996). First, brand proliferation within a category may imply that there are several market segments in the category, and hence ample room for product differentiation. This differentiation leads to less brand switching by consumers, and thus a lower promotional impact on selective demand. Our alternative explanation is a promotion crowding effect, similar to clutter in advertising: the smaller the number of

SKUs in the category, the more an individual promotion can stand out and influence consumer category incidence and brand choice. In contrast, the promotional impact may be diluted in crowded categories with a large number of competing SKUs.

The higher the private-label share in a category, the lower the promotional impact on manufacturer revenue. An explanation for this finding is that the characteristics of promotion buyers differ from those of consumers in categories with large private-label share (Ailawadi et al. 2001). These consumers tend to stockpile less and to be less impulsive than consumers in categories with a small private- label share. Thus, promotions may have less impact in such categories. Additionally, impulse goods obtain higher promotional effects on manufacturer revenue since promotions are likely to stimulate the impulse to buy the brand (Narasimhan et al. 1996).

6.2.2 Retailer category revenue and category margin

Table 8 shows that the total promotional impact on category revenue is moderated by the promotional frequency and promotional depth of the promoting brand as well as by the impulse-buying nature and SKU proliferation of the category. In contrast, category margin elasticities are moderated by the market share, promotional frequency and promotional depth of the promoting brand.

The higher the brand's market share, the lower the total promotional impact on the retailer category margin. This finding is important because retailers typically promote high-share brands in order to draw consumers to the category (Bronnenberg and Mahajan 2001). Our results imply that, even though high-share brands may have a stronger category drawing power (Bell et al. 1999; Krishnamurthi and Raj 1991), this advantage is offset by the margin loss on subsidized baseline sales. The latter explanation is consistent with the negative effect of market share on manufacturer revenue elasticity. In other words, both retailers and manufacturers obtain a higher promotional impact on financial performance if small-share brands are promoted.

The higher the brand's promotional frequency (Mela et al. 1997; 1998), the higher the promotional impact on retailer revenue, but the lower the promotional impact on retailer margin. The first finding extends recent volume-based category demand results (Nijs et al. 2001). Behavioral explanations are similar to those for manufacturer revenue. In contrast, retail margin effects (which are already negative on average) are further reduced for brands with high promotional frequency. This finding may indicate that frequent use of promotions erodes unit margins because consumers learn to expect them (Assunçao and Meyer 1993). Jedidi et al. (1999, p.18) conclude that “promotions make it more difficult to increase regular prices and increasingly greater discounts need to be offered to have the same effect on consumers' choice.” Our findings contrast the revenue and margin effects of promotions, and may imply potential conflicts. From the manager's standpoint, revenue effects (typically positive) of price promotions are easier to assess while the margin effects (typically negative) are harder to assess. In fact, based on a survey of practitioners, Bucklin and Gupta (1999, p. 269) state that “marketing managers seldom evaluate profit impact.” As a result, marketing managers find promotions attractive and allocate resources to them. Financial performance may get hurt in the process, however, as evidenced by their negative impact on retailer margins.

Promotional depth has a negative impact on the total promotional elasticity on *both* retailer revenues and margins, extending previous literature on demand effects. Decreasing returns to deal depth are intuitive given limitations to increases in selective and primary demand. Category demand gains are limited by consumers' ability to transport and stockpile products. Selective demand gains are limited by the existence of loyal segments for non-promoted brands (Colombo and Morrison 1989).

The extent of brand proliferation has a significant negative impact on the promotional revenue elasticity, but not on the promotional margin elasticity. The finding for retailer revenue elasticity is consistent with that for manufacturer revenue elasticity. Moreover, the same behavioral explanations apply (Narasimhan et al. 1996).

Finally, impulse goods obtain higher promotional effects on category revenues. Promotions for such goods are more likely to attract the consumer to the category and stimulate the impulse to buy the promoted brand (Narasimhan et al. 1996). Similar to our findings for market share, manufacturer and retailer interests are aligned. As a result, promoting small brands in impulse-buying categories is more likely to maximize promotional revenue response for both manufacturers and retailers.

7. CONCLUSIONS

In this paper, we have investigated the manufacturer revenue, the retailer revenue and the retailer margin effects of price promotions for twenty-five categories over 265 weeks. The breadth of the sample allows us to derive empirical generalizations on price-promotion effectiveness and its drivers. To the best of our knowledge, this research is the first large-scale empirical investigation of the revenue and margin effects of promotions for manufacturers versus retailers. We group our findings on duration, magnitude and moderators of promotional revenue effect, and summarize as follows:

(i) Revenue effects materialize over the promotional dust-settling period, but they are not permanent. Manufacturer revenue, retailer revenue and retailer margins are stationary, i.e. when shocked by promotion or other events, they revert to their mean or deterministic trend. Consequently, promotional planning is more tactical than strategic. As such, each promotion should be evaluated based on its own financial impact over the dust-settling period.

(ii) Over the dust-settling period, a consumer price promotion has positive effects on our measure of manufacturer revenue in almost all cases. In contrast, a consumer price promotion is sometimes beneficial in terms of retailer revenues, and typically not beneficial in terms of retailer margin. Even though this latter finding may be subject to data limitations on our wholesale price series, it reflects and strengthens the conclusion from an extensive review of previous literature that "promotions are just as beneficial for manufacturers as for retailers, if not more so" (Ailawadi 2001, p. 299). Consequently, manufacturer side payments are needed in order to offset retailer losses. However, only in a very small fraction of the cases is there sufficient manufacturer surplus to allow for such side payments without making the combined channel impact negative. Thus, the financial interests of manufacturers and retailers are not guaranteed to be aligned in the promotional game.

(iii) There are significant moderators of promotional effectiveness. First, manufacturer revenue elasticities are higher for national brands, for low-share brands, for brands with high promotional frequency, in categories with lower private-label share, for impulse buying products, and in categories with few SKUs. Similarly, retailer revenue elasticities are higher for brands with frequent and shallow promotions, for impulse buying products and in categories with few SKUs. From a revenue perspective, manufacturer and retailer interests are therefore often aligned in terms of what categories and brands to promote. Third, retailer margin elasticities are higher for small-share brands with shallow promotions, but lower for brands with frequent promotions. Whether or not promotional frequency is beneficial therefore depends on the performance measure that retailers choose to emphasize.

Our study has several limitations, which offer useful avenues for future research. First, we had access to data from one supermarket chain only, Dominick's, in one geographic region (the Chicago area). While Dominick's is one of the largest chains in the area, some store switching might take place as a result of competitive price promotions that is not captured in our study. Moreover, our results may depend on both the pass-through strategy of this specific retailer and on the competitive landscape in which it operates. Depending on the relative power of other retailers (relative to their suppliers but also to their local competition), some of our findings may be affected, necessitating further research that allows for variation along this dimension. Second, we had information on margins and wholesale prices, but there are other promotional expenses the manufacturer may incur on which no information was available, such as slotting allowances, buy-back charges, failure fees, etc… Our result that in about ninety percent of the cases, the extra revenues generated for the manufacturer are insufficient to cover the retailer's revenue loss is therefore a conservative benchmark, and more detailed analyses would be advisable once the necessary data are available. Moreover, our results do not apply to a major policy change, such as dropping all consumer price promotions, since we have studied the marginal effect of a single consumer promotion on performance. Such a drastic shift could cause considerable demand and supply reactions, and change the data generating process. Future research may address the impact of such a retailer policy change, similar to the manufacturer policy change studied in Ailawadi, Lehmann and Neslin (2001). Third, our analysis aggregates sales data across the different stores of the supermarket chain, which may have caused some aggregation bias (Allenby and Rossi 1991). However, our model estimations on the more sensitive log-log model show that aggregation bias is not likely to be a major issue in our study. Fourth, we could expand our framework to explicitly account for the impact of changes in other marketing-mix variables, such as advertising, in response to the initial price promotion. Moreover, future research could allow for non-linear relations between promotional impact and the second-stage characteristics. Fifth, our findings are based on data from well-established, mature product categories. Since promotions often work better for new products, more research is needed on whether these findings can be generalized to new product categories. Sixth, several observations in our second-stage regression may violate the independence assumption, as they belong to the same product category. While Sethuraman et al. (1999) apply a generalized least-squares procedure to unweighted observations to account for such dependencies, more research is needed to extend their approach to the weighted least-squares procedure used here. Finally, our results allow for a direct revenue comparison between manufacturers and retailers. Margin implications, in contrast, could only be derived for the retailer. Data on manufacturer margins would be highly desirable for a direct assessment of promotional profitability for manufacturers, and consequently, for their latitude in using incentive payments to retailers.

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Table 1 Empirical specification of the focal VAR models

Modeling step	Empirical options	Decisions
Unit root test	ADF unit root test	Maximum 8 lags; SBC criterion; deterministic holiday dummies; deterministic seasonal dummies; inclusion of trend based on Enders (1995).
	Exogenous structural-break unit-root test	Perron (1989, 1990) procedure to control for new product introductions.
	Endogenous structural-break unit-root test	Zivot and Andrews (1992) procedure.
Cointegration test	Johansen's FIML procedure (Johansen et al. 2000)	Trend and intercept in the cointegrating relationship.
Focal VAR model	Endogenous variables	Performance measure (brand sales, manufacturer revenue, category sales, total retailer revenue, retailer margins, store revenue and store traffic), prices of the three major brands.
	Exogenous marketing-mix variables	Feature and display variables for the three major brands for a total of six exogenous variables.
	Parameterization	Order=8; SBC criterion; no lagged effects for exogenous variables.
	Deterministic components	Deterministic holiday dummies; seasonal dummies, deterministic trend based on the unit-root tests, step dummy for new product introductions.
Impulse response functions	Variable shocked	Price of each of the major brands.
	Derivation of the shock vector	Simultaneous shocking approach described in Dekimpe and Hanssens (1999).
	Determination of standard errors	Monte Carlo simulations, 250 iterations.
	Derived summary statistics	Immediate performance impact; long-run impact; combined or total impact. In case of evolving performance, the dust-settling period is defined based on four consecutive IRF estimates that are not significantly different from their convergence value.

Table 2 Dominick's Database

Category	Promotional depth	Promotional frequency
Analgesics	25%	23%
Beer	19%	25%
Bottled juice	25%	19%
Cereal	25%	19%
Cheese	17%	13%
Cookies	21%	12%
Crackers	21%	13%
Canned soup	25%	17%
Dish detergent	27%	21%
Front-end candies	22%	6%
Frozen dinner	26%	15%
Frozen juice	23%	15%
Fabric softener	25%	21%
Laundry detergent	24%	19%
Oatmeal	7%	4%
Paper towel	12%	10%
Refrigerated juice	23%	19%
Soft drinks	24%	23%
Shampoo	19%	25%
Snack crackers	19%	13%
Soap	26%	22%
Toothbrush	6%	3%
Canned tuna	17%	15%
Toothpaste	18%	17%
Bathroom tissue	17%	15%

Table 3 **Unit-root tests[a]**

	ADF unit root test		Evolving after exogenous break test[b]	Evolving after endogenous break test[c]
	Stationary	**Evolving**		
Manufacturer Performance				
Brand sales	71	3	1	-
Manufacturer revenue	70	5	-	-
Retailer Performance				
Category sales	22	3	-	-
Retailer revenue	22	3	-	-
Retailer margins	22	3	-	-
Store revenue	1	0	-	-
Store traffic	1	0	-	-
Price Series				
Retail price	64	11	-	-
Wholesale price	63	9	3	-

a- All the series in the table are stationary at the 5% levels.

b- Perron break test (1989, 1990).

c- Zivot and Andrews break test (1992).

Table 4 Summary of number of lags in the VAR model

	1 lag	**2 lags**	**3 lags**
Manufacturer Performance			
Brand sales	91%	8%	1%
Manufacturer revenue	91%	8%	1%
Retailer performance			
Category sales	92%	8%	0%
Retailer revenue	92%	8%	0%
Retailer margins	92%	8%	0%
Store revenue	92%	8%	0%
Store traffic	92%	8%	0%

Table 5 **Total promotional impact for manufacturers and the retailer**

	Immediate promotional effects			**Total (cumulative) promotional effects**		
	Positive effect*	**No significant effect**	**Negative effect***	**Positive effect***	**No significant effect**	**Negative effect***
Manufacturer Performance						
Brand sales (units, pounds…)	73 (98%)	1 (1%)	1 (1%)	63 (84%)	10 (13%)	2 (3%)
Manufacturer revenue (dollars)	66 (88%)	7 (9%)	2 (3%)	54 (72%)	13 (17%)	8 (11%)
Retailer performance						
Category sales (units, pounds…)	46 (61%)	25 (33%)	4 (5%)	40 (53%)	31 (41%)	4 (5%)
Retailer revenue (dollars)	28 (37%)	35 (47%)	12 (16%)	14 (19%)	46 (61%)	15 (20%)
Retailer margins (dollars)	12 (16%)	29 (39%)	34 (45%)	6 (8%)	30 (40%)	39 (52%)
Store revenue (dollars)	22 (29%)	53 (71%)	0 (0%)	11 (15%)	64 (85%)	0 (0%)
Store traffic (customers)	12 (16%)	63 (84%)	0 (0%)	12 (16%)	63 (84%)	0 (0%)

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

Table 6 **Descriptive statistics for immediate and total price-promotion elasticities for the different performance series**

	Immediate promotional effects	**Total (cumulative) promotional effects**
	Mean (Median)	**Mean (Median)**
Manufacturer Performance		
Brand sales	3.56 (3.20)	3.83 (3.65)
Manufacturer revenue	2.58 (2.35)	1.87 (2.27)
Retailer performance		
Category sales	0.55 (0.38)	0.66 (0.50)
Retailer revenue	0.21 (0.10)	-0.02 (-0.03)
Retailer margins	-0.45 (-0.21)	-1.00 (-0.70)
Store revenue	0.01 (0.00)	0.01 (0.02)
Store traffic	0.01 (0.01)	0.01 (0.00)

Table 7 Comparison of median elasticities derived from alternative specifications of the VAR Models

	Focal model		Extended model	
	Median immediate elasticity	**Median total (cumulative) elasticity**	**Median immediate elasticity**	**Median total (cumulative) elasticity**
A1. Sensitivity to treatment of feature and display -- Added dynamics for exogenous feature and display				
Manufacturer performance				
Brand sales	3.20	3.65	3.12	3.54
Manufacturer revenue	2.35	2.27	2.22	2.16
Retailer performance				
Category sales	0.38	0.50	0.37	0.49
Retailer revenue	0.10	-0.03	0.12	-0.02
Retailer margin	-0.21	-0.70	-0.19	-0.72
Store revenue	0.00	0.02	0.00	0.01
Store traffic	0.01	0.00	0.01	0.00
A2. Sensitivity to treatment of feature and display -- Feature and display of promoted brand are treated as endogenous				
Manufacturer performance				
Brand sales	3.20	3.65	3.17	3.68
Manufacturer revenue	2.35	2.27	2.28	2.40
Retailer performance				
Category sales	0.38	0.50	0.32	0.48
Retailer revenue	0.10	-0.03	0.12	-0.04
Retailer margin	-0.21	-0.70	-0.24	-0.74
Store revenue	0.00	0.02	0.01	0.02
Store traffic	0.01	0.00	0.01	0.00
B. Sensitivity to aggregation across stores -- Log-log model				
Manufacturer performance				
Brand sales	3.20	3.65	3.07	3.36
Manufacturer revenue	2.35	2.27	2.11	2.06
Retailer performance				
Category sales	0.38	0.50	0.36	0.50
Retailer revenue	0.10	-0.03	0.12	-0.03
Retailer margin	-0.21	-0.70	-0.24	-0.82
Store revenue	0.00	0.02	0.02	0.01
Store traffic	0.01	0.00	0.01	0.00
C1. Sensitivity to inclusion of multiple performance measures -- Simultaneous inclusion of multiple sales or revenue variables				
Manufacturer performance				
Brand sales	3.20	3.65	3.18	3.89
Manufacturer revenue	2.35	2.27	2.38	2.15
C2. Sensitivity to inclusion of multiple performance measures -- Separate models on brand sales and wholesale price				
Manufacturer performance				
Manufacturer revenue	2.35	2.27	2.31	2.22
C3. Sensitivity to inclusion of multiple performance measures -- Store traffic as additional endogenous variable				
Manufacturer performance				
Brand sales	3.20	3.65	3.31	3.99
Manufacturer revenue	2.35	2.27	2.38	2.41
Retailer performance				
Category sales	0.38	0.50	0.42	0.59
Retailer revenue	0.10	-0.03	0.09	-0.04
Retailer margin	-0.21	-0.70	-0.27	-0.81
Store revenue	0.00	0.02	0.00	0.01

Table 7 (continued) Comparison of median elasticities derived from alternative specifications of the VAR Models

	Focal model		Extended model	
	Median immediate elasticity	**Median total (cumulative) elasticity**	**Median immediate elasticity**	**Median total (cumulative) elasticity**
C4. Sensitivity to inclusion of multiple performance measures -- Simultaneous inclusion of both manufacturer and retailer revenue				
Manufacturer revenue - retailer revenue (significant instances)	--	--	95%	97%
Manufacturer revenue - retailer revenue (mean estimate)	2.37	1.89	2.42	1.97
D1. Sensitivity to the nature of the price-setting mechanism -- WP of the promoted brand as an additional endogenous variables				
Manufacturer performance				
Brand sales	3.20	3.65	3.13	3.78
Manufacturer revenue	2.35	2.27	2.29	2.42
Retailer performance				
Category sales	0.38	0.50	0.33	0.52
Retailer revenue	0.10	-0.03	0.10	-0.06
Retailer margin	-0.21	-0.70	-0.23	-0.69
Store revenue	0.00	0.02	0.00	0.03
Store traffic	0.01	0.00	0.01	0.01
D2. Sensitivity to the nature of the price-setting mechanism -- Weighted price for other categories as additional endogenous variable in store-traffic model				
Retailer performance				
Store traffic	0.01	0.00	0.01	0.00
E. Sensitivity to potential cross-category influence -- Price in complementary/substitute category as additional endogenous variable*				
Manufacturer performance				
Brand sales	3.19	3.62	3.10	3.58
Manufacturer revenue	2.29	2.19	2.23	2.22
Retailer performance				
Category sales	0.50	0.58	0.51	0.61
Retailer revenue	0.10	-0.03	0.09	-0.05
Retailer margin	-0.23	-0.45	-0.26	-0.49
Store revenue	0.02	0.01	0.02	0.01
Store traffic	0.00	0.01	0.00	0.01
F. Sensitivity to the adopted wholesale price operationalization -- Alternative wholesale price measure**				
Manufacturer revenue	2.05	1.63	2.14	1.84
Retailer margin	-0.21	-0.78	-0.30	-0.88

* Computed on the following subset of categories: cereal, oatmeal, fabric softener, laundry detergent, toothbrush, toothpaste, snack crackers, crackers, cheese, bottled juice, frozen juice, refrigerated juice, shampoo and soap.

** Computed on the following subset of categories: paper towels, toothbrush and toothpaste.

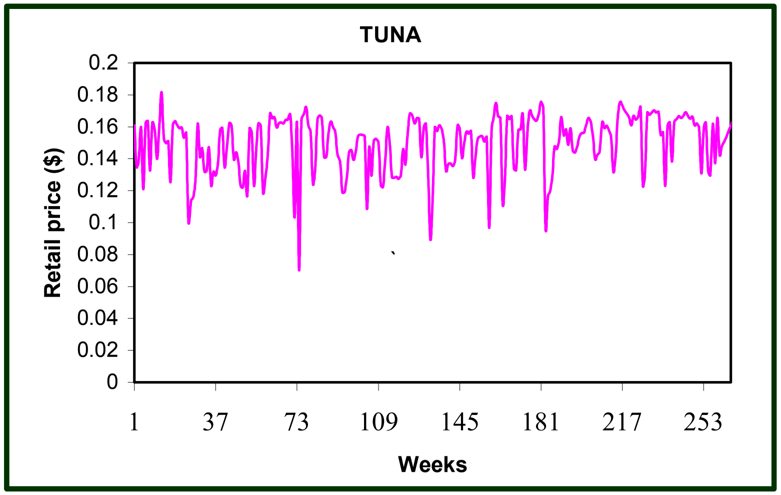
Table 8 Moderating role of brand, market and category characteristics on total price-promotion elasticities (standardized coefficients with standard errors in parentheses)

Promotional Impact Drivers	Manufacturer revenue	Retailer revenue	Retailer margin
Brand characteristics			
National brands	0.103 (0.058)*	0.044 (0.110)	-0.067 (0.087)
Market share	-0.122 (0.069)*	0.033 (0.053)	-0.203 (0.066)***
Promotional frequency	0.124 (0.063)**	0.133 (0.051)***	-0.067 (0.028)***
Promotional depth	0.016 (0.073)	-0.136 (0.059)**	-0.107 (0.056)*
Market and category characteristics			
Variance of shares	0.060 (0.083)	0.034 (0.069)	-0.016 (0.078)
Number of SKUs	-0.175 (0.075)***	-0.095 (0.055)*	-0.590 (0.750)
Private-label share	-0.213 (0.112)*	-0.040 (0.047)	0.098 (0.066)
Storability	0.040 (0.057)	-0.060 (0.054)	-0.064 (0.048)
Impulse	0.092 (0.054)*	0.042 (0.023)*	0.046 (0.061)

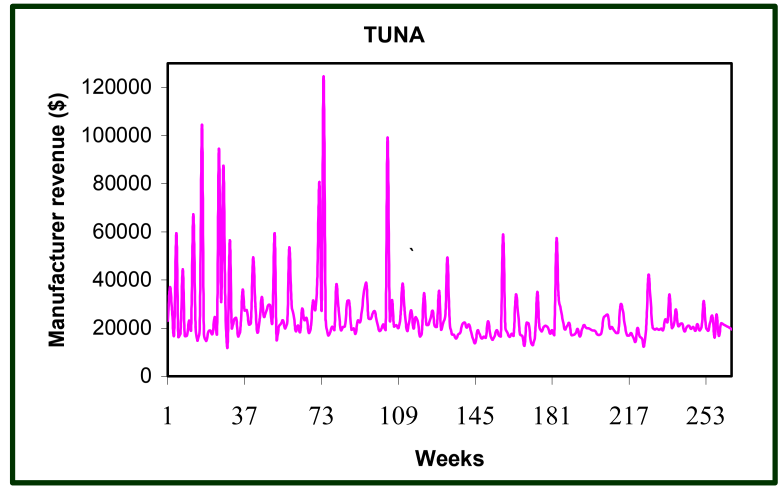
*** = $p < 0.01$
** = $p<0.05$
* = $p < 0.10$

Figure 1 Plot of performance and price series for a leading brand

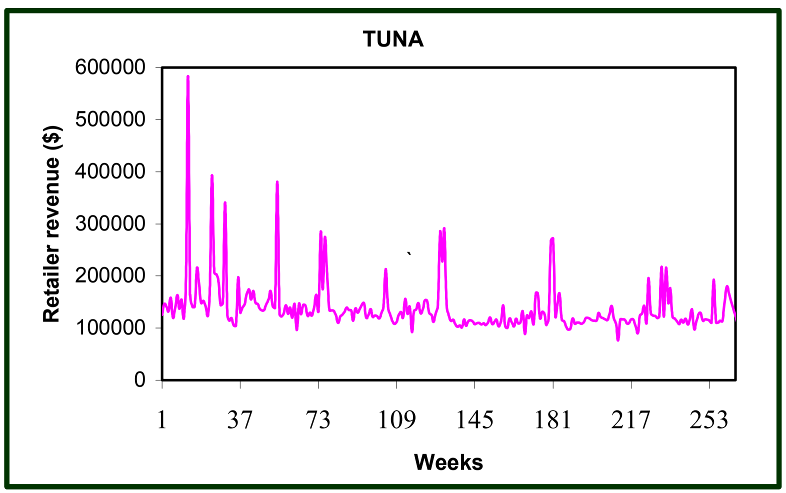
A: Plot of price series



B: Plot of manufacturer revenue series



C: Plot of retailer revenue series



D: Plot of retailer margin series

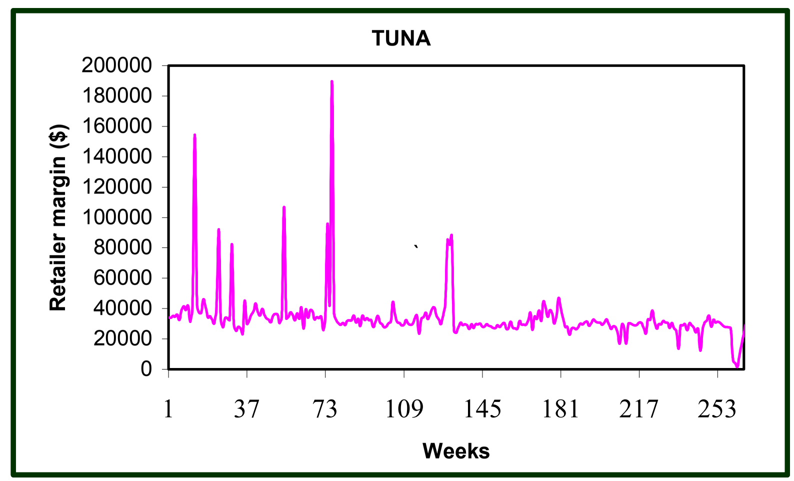
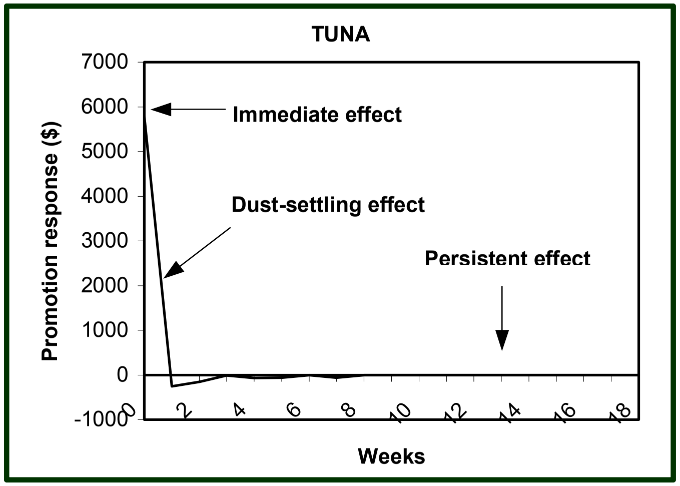
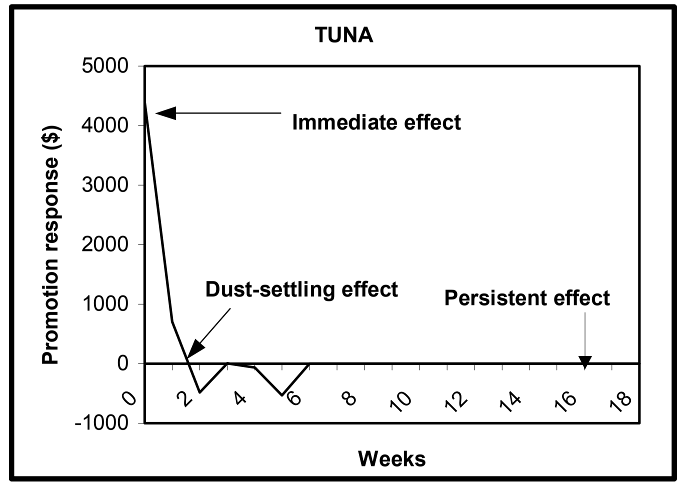


Fig. 2 Impulse-Response functions

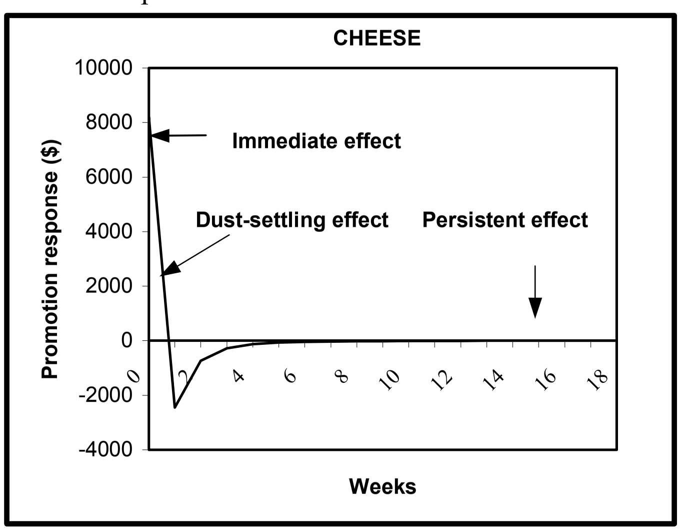
A: Impulse response function of a price promotion of one cent per ounce on manufacturer revenue



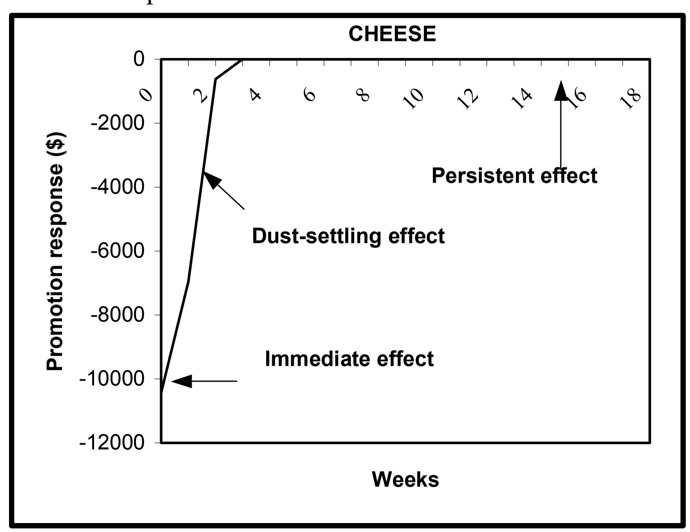
B: Impulse response function of a price promotion of one cent per ounce on retailer revenue



C: Impulse response function of a price promotion of one cent per ounce on manufacturer revenue



D: Impulse response function of a price promotion of one cent per ounce on retailer revenue



Footnotes

[1]Henceforth, we will use the term "retailer margin" to refer to the *total* dollar margin (gross profit) of the retailer for all the brands in the category, while the term "per-unit margin" refers to the *percentage* gross margin for a particular brand.

[2]Evidently, not all consumers and market players need to have the same information set. As such, the expected or base price may differ across different consumers and managers, implying that also the shock value of a given promotion could differ. As with any aggregate model, we therefore have to assume that our parameter estimates (and subsequently, our impulse response functions) adequately describe the behavior of a "representative" market participant (see Raman and Bass 2002, pp. 209-211 for a recent discussion on the issue in the context of price expectations). Further research is needed to assess whether this "representative-player" assumption is justified, i.e. to what extent our findings may be affected by aggregation bias (see e.g. Pesaran and Smith (1995) or Lim et al. (2003) for recent research).

[3]As is common in the structural-break literature (see e.g. Ben-David & Papell 1995, 1998), we allow for the new-product introduction to cause a structural change in the trend function of the data-generating process, but do not allow for additional changes in the model's autoregressive parameters or error variance. This approach is in line with the intervention-analysis approach of Box and Tiao (1975), in that extraordinary events are separated from the regular noise function, and modeled as a change (intervention) in the deterministic part of the time-series model. A similar approach was adopted in Bronnenberg et al. (2000) and Deleersnyder et al. (2002), among others.

[4]Following Dekimpe and Hanssens (1995), we use the term "evolves" to refer to the presence of a unit root.

[5]In our empirical application, up to 26 periods of impulse response coefficients are included when significant.

[6]Feature and display indicators are called price specials and bonus buys in the Dominick's data description (http://gsbwww.uchicago.edu/research/mkt/Databases/DFF/W.html). Following Chintagunta et al. (2001), we refer to these marketing activities through the more common labels of "feature" and "display". We operationalize the variables as the percentage of SKUs of the brand that are promoted in a given week.

[7]Five categories (beer, frozen dinner, oatmeal, shampoo and soap) had fewer than 265 weeks of data due to missing observations.

[8]Product categories in which the most successful new-product introduction is able to capture a market share in excess of 5% during at least 3 consecutive months were labeled as having witnessed a "major new-product introduction."

[9]We are grateful to S. Neslin for making the storability and impulse-purchase scales available to us.

[10]All results are generated using EViews 4.1 software.

[11]In the cases where the break dates are identified by the Zivot and Andrews (1992) test, the break dates are close enough to the new product introduction -- plus or minus 4 weeks -- that we can still attribute the break in the price series to the new product introduction. Furthermore, while most theoretical pricing models would require consistency conditions (e.g. common stationarity or cointegration between evolving wholesale and evolving retail prices), our empirical examination reveals that these are not violated here, given the stationarity of all these prices.

[12]Comparable results were obtained for one and three lags.

[13]Chintagunta (2002) finds that lower store traffic in one week (presumably because of retail competition), decreases retailer prices on some national brands in the next week (presumably to respond to this lower performance).

[14]We are indebted to K. Ailawadi, S. Neslin and P. Kopalle for making these data available to us.

[15]Finally, given the potential for conditional heteroskedasticity of the VAR model wherein normal prices could potentially have a smaller conditional variance compared to prices when there is price promotion, we tested for this issue by regressing the squared residuals on an intercept and price. For the two categories (i.e. for the price series' in two categories, of which we have 3 per category) that tested positive for conditional heteroskedasticity, we re-estimated the VAR models using the White heteroskedasticity-consistent approach (White 1980), resulting in the additional estimation of 22 VAR models; once again, no substantial differences in results are observed.

[16]Evidently, the lower *elasticity* (i.e. relative to mean performance) impact of high share brands does not necessarily imply they have lower *absolute* impact on performance (see Van Heerde et al. 2002).