

Do Promotions Benefit Manufacturers, Retailers, or Both?

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Do price 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).

A first major finding is that a price promotion typically does not have permanent monetary effects for either party. Second, 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 frequently promoted brands and for national brands in impulse product categories with a low degree of brand proliferation and low private-label shares. Retailer revenue elasticities are higher for brands with frequent and shallow promotions, for impulse products, and in categories with a low degree of brand proliferation. Finally, retailer margin elasticities are higher for promotions of small-share brands and for brands with infrequent and shallow promotions. We discuss the managerial implications of our results for both manufacturers and retailers.

Key words: long-term profitability; sales promotions; category management; manufacturers versus retailers; empirical generalizations; vector autoregressive models

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1. Introduction

Since the early 1970s, 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 (Blattberg et al. 1995), 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 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, to be economically viable, promotional actions should be held accountable for positive financial results during the dust-settling period. This motivates 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, because of 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 (Ailawadi 2001). 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 (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 (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 et al. 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 financial effect for both manufacturers and retailers depends on their relative impact on these three dimensions. Unfortunately, no empirical literature to date has systematically assessed these financial effects over time; therefore, we address the following research questions: (i) are promotions financially attractive and (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 (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, this paper provides new insights into the over-time financial effects of price promotions, and how they may differ between manufacturers and retailers.

This paper is organized as follows. In §2, we describe vector autoregressive (VAR) modeling and the associated impulse-response functions (IRFs) as a suitable method for quantifying the cumulative promotion effects on manufacturer and retailer performance. We then introduce an extensive multicategory scanner database covering 265 weeks of promotional activity in a regional market (§3). In §4, we report and interpret the results of our first-stage estimation for both manufacturers and retailers. Having quantified the cumulative promotion effects on performance, we introduce in §5, the second-stage analysis to examine how brand and category characteristics influence the promotional impact on manufacturer revenue, retailer revenue, and retailer margins, respectively. Finally, we formulate overall conclusions and suggest limitations and proposed areas for future research in §6.

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. Modeling Long-Term Promotions Impact on Performance

In this paper, price promotions are defined as temporary price reductions offered to the consumer, as is common in the marketing literature (e.g., Blattberg et al. 1995). 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., Bucklin et al. 1998), while the latter is reflected in PROMOCAST (Cooper et al. 1999), SCAN*PRO (Foekens et al. 1999), and recent VAR-based studies (e.g., Bronnenberg 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 (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

In covariance-stationary environments, VAR models of promotional response are well suited to measure promotions' total or combined revenue and profit effects. In a VAR model, we assess the combined 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 also to capture the performance implications of complex feedback loops.

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 1998).

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 postpromotional dip effects. Similarly, the *effective* time span that elapses before all prices in the market return to their preshock level could exceed the initial *nominal* promotional period of one to two weeks. Our main interest lies in the combined (total) result of all these actions and reactions, which can be derived from a VAR model through its associated IRFs.

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. We refer to the online appendix (available at mancipubs.informs.org/ecompanion.html) 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) four weekly seasonal dummy variables (SD) to account for seasonal fluctuations in performance and/or marketing spending; (iii) 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 (iv) 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 (Dekimpe et al. 1999). 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:

$$\begin{aligned}
 & \begin{bmatrix} \text{PERF}_t \\ P_{1,t} \\ P_{2,t} \\ P_{3,t} \end{bmatrix} \\
 &= \begin{bmatrix} a_{0,\text{PERF}} + \sum_{s=2}^{13} a_{s,\text{PERF}} \text{SD}_{st} + \sum_{h=1}^{11} a_{h,\text{PERF}} \text{HD}_{ht} + \delta_{\text{PERF}} t \\ a_{0,P1} + \sum_{s=2}^{13} a_{s,P1} \text{SD}_{st} + \sum_{h=1}^{11} a_{h,P1} \text{HD}_{ht} + \delta_{P1} t \\ a_{0,P2} + \sum_{s=2}^{13} a_{s,P2} \text{SD}_{st} + \sum_{h=1}^{11} a_{h,P2} \text{HD}_{ht} + \delta_{P2} t \\ a_{0,P3} + \sum_{s=2}^{13} a_{s,P3} \text{SD}_{st} + \sum_{h=1}^{11} a_{h,P3} \text{HD}_{ht} + \delta_{P3} t \end{bmatrix} \\
 &+ \sum_{i=1}^k \begin{bmatrix} \beta_{11}^i & \beta_{12}^i & \beta_{13}^i & \beta_{14}^i \\ \beta_{21}^i & \beta_{22}^i & \beta_{23}^i & \beta_{24}^i \\ \beta_{31}^i & \beta_{32}^i & \beta_{33}^i & \beta_{34}^i \\ \beta_{41}^i & \beta_{42}^i & \beta_{43}^i & \beta_{44}^i \end{bmatrix} \begin{bmatrix} \text{PERF}_{t-i} \\ P_{1,t-i} \\ P_{2,t-i} \\ P_{3,t-i} \end{bmatrix} \\
 &+ \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} & \gamma_{14} & \gamma_{15} & \gamma_{16} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} & \gamma_{24} & \gamma_{25} & \gamma_{26} \\ \gamma_{31} & \gamma_{32} & \gamma_{33} & \gamma_{34} & \gamma_{35} & \gamma_{36} \\ \gamma_{41} & \gamma_{42} & \gamma_{43} & \gamma_{44} & \gamma_{45} & \gamma_{46} \end{bmatrix} \begin{bmatrix} \text{FT}_{1,t} \\ \text{FT}_{2,t} \\ \text{FT}_{3,t} \\ \text{DP}_{1,t} \\ \text{DP}_{2,t} \\ \text{DP}_{3,t} \end{bmatrix} \\
 &+ \begin{bmatrix} \varepsilon_{\text{PERF},t} \\ \varepsilon_{P1,t} \\ \varepsilon_{P2,t} \\ \varepsilon_{P3,t} \end{bmatrix}, \tag{1}
 \end{aligned}$$

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 three major brands; and $[\varepsilon_{\text{PERF},t}, \varepsilon_{P1,t}, \varepsilon_{P2,t}, \varepsilon_{P3,t}]' \sim N(0, \Sigma)$. 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 $\Delta X_t = X_t - X_{t-1}$.³

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). For the order of the VAR model (k), we set the maximum number of lags to eight and select the best model based on the Schwarz Bayesian Criterion. For the manufacturer, brand sales and manufacturer revenue are used as performance measures, while the five retailer performance measures are category sales, total retailer revenue, total retailer margins, store revenue, and store traffic.

In a VAR framework, price promotions are operationalized as temporary price shocks whose impact over time is quantified through the corresponding IRFs (see, e.g., Dekimpe et al. 1999 for technical details). To derive the 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 IRF, tracing the incremental impact of the price-promotion shock, is our basic measure of promotion effectiveness.

A critical issue in the derivation of IRFs 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 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 assume 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. Further, we quantify the impact over time of price promotions

³ 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 toward a long-run equilibrium (see Enders 1995 or Dekimpe and Hanssens 1999 for a detailed technical exposition).

on the assumption that the parameters of the data-generating process do not change as a result of these shocks (for similar assumptions in the econometrics and marketing literature, see, e.g., Pesaran and Samiei 1991, p. 479, and Dekimpe et al. 1999, p. 271).

As for the standard errors of the IRF estimates, these are derived by using the following bootstrap procedure: We sample with replacement the original residuals, and then generate new (artificial) performance and price series using the estimated coefficient matrix, estimated from the original data, and the resampled residuals. With these artificial data as input, we re-estimate the VAR model and derive 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 IRF. As is common practice in economics (Lütkepohl 1993, p. 497) and marketing (see, e.g., Dekimpe and Hanssens 1999, Nijs et al. 2001, Pauwels and Srinivasan 2004), 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.⁴

For a detailed overview of all VAR modeling steps, see Enders (1995) and Dekimpe and Hanssens (1999). While IRFs 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 IRF converges); and

(iii) the total or cumulative impact, which combines the immediate effect with all effects across 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,

⁴ Because asymptotic theory suggests the use of symmetric confidence intervals for variables with a normal distribution, we conduct rigorous tests of normality of the residuals using the multivariate extension of the Jarque-Bera residual normality test. The results indicate that the vast majority of the cases (96%) have residuals that do not deviate from multivariate normality. Further, we condition on the exogenous feature and display sequences in conducting the bootstrap simulations, as done in previous research (see, e.g., Lütkepohl 1993, Nijs et al. 2001).

this effect is computed as the sum of all significant impulse response coefficients, for a maximum of 26 periods.

A graphical illustration of these incremental revenue effects may be found in Figure 1 of the online appendix. 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 the retailer and the manufacturer, respectively, 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.⁵

3. Data Description and Variable Operationalization

The database consists of scanner records for more than 20 product categories from a large midwestern 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 prices (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 DFF's wholesale price data

⁵ As an example on a tuna brand, 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).

⁶ Feature and display indicators are called price specials and bonus buys in the DFF's data description. Following Chintagunta (2002) and Pauwels and Srinivasan (2004), 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 Three categories (beer, shampoo, and soap) had less than 265 weeks of data because of missing observations.

Table 1 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, etc.)	61 (97%)	1 (2%)	1 (2%)	53 (84%)	9 (14%)	1 (2%)
Manufacturer revenue (dollars)	55 (87%)	6 (10%)	2 (3%)	46 (73%)	10 (16%)	7 (11%)
Retailer performance						
Category sales (units, pounds, etc.)	39 (62%)	20 (32%)	4 (6%)	34 (54%)	25 (40%)	4 (6%)
Retailer revenue (dollars)	22 (35%)	31 (49%)	10 (16%)	11 (17%)	39 (62%)	13 (21%)
Retailer margins (dollars)	10 (16%)	26 (41%)	27 (43%)	4 (6%)	25 (40%)	34 (54%)
Store revenue (dollars)	19 (30%)	44 (70%)	0 (0%)	8 (13%)	55 (87%)	0 (0%)
Store traffic (customers)	11 (17%)	52 (83%)	0 (0%)	10 (15%)	53 (85%)	0 (0%)

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

(Chintagunta 2002). All data are given at the weekly level. Our IRFs will therefore trace the impact over time of weekly price promotions, which is by far the most frequently occurring promotion length (Cooper et al. 1999). Focusing on the three best-selling brands in 21 categories, we analyze a total of 63 brands.⁸ For a detailed description of the operationalization of the manufacturer and retailer performance measures, as well as that of the holiday dummies in Equation (1), we refer to Pauwels and Srinivasan (2004) or the online appendix.

Brand, Market, and Category 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. Promotion frequency is defined as the number of weeks in which negative price-promotion shocks are at least 5% of the brand's regular price. The regular price, in turn, is defined as the maximum price of the brand, following Raju (1992) and Foekens et al. (1999).⁹ A brand's price-promotion depth, in turn, is defined as the (percentage) difference between a promotional price (as defined for the

frequency count) and the brand's regular price. 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).¹⁰

4. Do Promotions Increase Revenues and Margins?

All performance series for both the retailer and the manufacturer were found to be (level or trend) stationary (we refer to the online appendix for details on the unit-root test results), which supports the empirical generalization that there are no permanent effects of price promotions on volume, i.e., brand sales and category sales (Nijs et al. 2001). 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). Next, we first discuss our main findings concerning the magnitude of the immediate and total price-promotion effects.

4.1.1. Effects Over Time of Price Promotions on Manufacturer Performance: Brand Sales and Brand Revenues. Our first-stage analysis reveals a predominantly positive impact of promotions on both brand sales and manufacturer revenues (Table 1).¹¹

For brand sales, 61 (97%) of the brands experience a positive immediate effect, while 53 (84%) obtain a significant and positive total effect. To assess

⁸ Initially, we considered 25 categories. However, four of them experienced a major new product introduction that caused a structural break in the data-generating process of some of the performance series, as identified through preliminary structural break unit root tests. Following the suggestion of an anonymous reviewer, we excluded these categories from further consideration. The 21 remaining categories in our sample are analgesics, beer, bottled juice, cereal, cheese, cookies, crackers, canned soup, dish detergent, front-end candies, frozen juice, fabric softener, laundry detergent, refrigerated juice, soft drinks, shampoo, snack crackers, soap, canned tuna, toothpaste, and bathroom tissue.

⁹ We verified that the results are robust to the choice of maximum price versus average price as the benchmark price. The measures of promotional frequency and promotional depth across categories are similar for both benchmarks.

¹⁰ We are grateful to S. Neslin for making the storability and impulse-buying scales available to us.

¹¹ All results are generated using EViews 4.1 software.

Table 2 Descriptive Statistics for Immediate and Total Price-Promotion Elasticities for the Different Performance Series

	Immediate promotional effects (1)	Total (cumulative) promotional effects (2)	Net dynamic promotional effects (2)–(1)
	Mean (Median)	Mean (Median)	Mean
Manufacturer performance			
Brand sales	3.59 (3.20)	4.17 (3.72)	0.58
Manufacturer revenue	2.55 (2.35)	2.01 (2.30)	–0.54
Retailer performance			
Category sales	0.52 (0.36)	0.62 (0.50)	0.10
Retailer revenue	0.19 (0.09)	–0.05 (–0.05)	–0.24
Retailer margins	–0.35 (–0.23)	–0.90 (–0.70)	–0.55
Store revenue	0.00 (0.00)	0.00 (0.01)	0.00
Store traffic	0.00 (0.01)	0.00 (0.00)	0.00

the size of this effect, we subsequently calculated price-promotion elasticities at the mean following the method outlined in §2. The average (median) immediate price-promotion elasticity in Table 2 is 3.59 (3.20), while the average (median) cumulative price-promotion elasticity is 4.17 (3.72). This average total elasticity is similar to the average value of 3.94 reported in Steenkamp et al. (2004) in their large-scale analysis on promotion effectiveness in The Netherlands.

With regard to manufacturer revenue, 53 out of 63 brands (84%) obtain significant total effects, which are positive in 46 cases (73%) and negative in 7 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 2 is 2.55 (2.35), while the average (median) cumulative price-promotion elasticity is 2.01 (2.30).

4.1.2. Effects Over Time of Price Promotions on Retailer Performance: Category Sales and Category Revenues

For the retailer’s category sales, we observe significant total effects for 38 out of the 63 brands as seen in Table 1. Compared to 34 brands (54%) with a positive impact, only 4 brands (6%) have a negative impact. The average (median) elasticity is 0.52 (0.36) for the immediate impact and 0.62 (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 because of country-specific differences between the United States and The Netherlands, or could be because of 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 (on average) 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, on average, 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 24 out of 63 brands (38%), only 11 (17%) of those are positive, while 13 (21%) have a negative total impact. In contrast to manufacturer revenue, the average (median) immediate price-promotion elasticity is only 0.19 (0.09), and the total price-promotion elasticity is even smaller: –0.05 (–0.05). While the immediate price-promotion elasticity is still positive, the cumulative price-promotion elasticity during 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 nonpromoted 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 2 is that, for both market players, the total promotional elasticity exceeds the immediate elasticity for sales, but not for revenues, i.e., the net dynamic effect reported in the final column of Table 2 is positive for sales, but negative for revenues. In other words, the additional effects in the postpromotion 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 prepromotion levels.

4.1.3. Effects Over Time of Price Promotions on 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 4 brands (6%) experience a positive total impact on category margins, while 34 brands (54%) experience a negative total impact. The average (median) immediate price-promotion elasticity is -0.35 (-0.23) while the corresponding average (median) total price-promotion elasticity is -0.90 (-0.70). Here, too, there are strong negative postpromotion 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 8 out of 63 brands (13%) experience a positive total impact, while 55 brands (87%) experience no significant total impact. The results for *store traffic* are similar: Only 10 out of the 63 brands (15%) experience a positive total impact, while 53 brands (85%) experience no significant total impact of price promotions on store traffic. All 10 brands with a positive impact on store traffic are national brands. This is in 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 DFF's chain, and other authors reporting only weak store-substitution effects of promotions (see, for example, Walters and Rinne 1986). Finally, only 4 of the 10 (40%) 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 because the additional traffic generated by loss-leader promotions consists mainly of cherry-picking consumers (Walters and Rinne 1986).

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 promotion allowances (Bloom et al. 2000). To answer this question, we compare the magnitude of the positive manufacturer revenue impact with that of the negative retailer revenue impact resulting from promotions. In Table 1, out of the 10 (13) brands that had negative immediate (cumulative) retailer revenue impact, 7 (10) 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 1 of the 7 brands (14%) 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 10 national brands with negative total 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.

We assessed the robustness of our substantive insights to various issues: (i) our treatment of display and feature activity as exogenous variables, (ii) the fact that we aggregated our data across stores with (potentially) heterogeneous marketing-mix activities, (iii) our inclusion of only a single performance measure at a time, (iv) the potentially incomplete description of the price-setting mechanism in our model, (v) the omission of possible demand interdependencies between complementary and substitute categories, (vi) the fact that the adopted wholesale price operationalization might be affected by forward-buying practices, and (vii) the potential overparameterization of our VAR specification. In all instances, the substantive findings were found to be very robust, and the out-of-sample forecasting performance of our focal model was comparable (and, in most instances, even better) than that of competing (simpler) specifications. We refer to the online appendix for full details on all validation exercises.

Table 3 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	0.120 (0.067)*	0.054 (0.132)	−0.091 (0.107)
Market share	−0.128 (0.062)**	0.037 (0.066)	−0.229 (0.086)***
Promotional frequency	0.141 (0.061)***	0.141 (0.052)***	−0.076 (0.021)***
Promotional depth	0.021 (0.067)	−0.143 (0.071)**	−0.128 (0.042)***
Market and category characteristics			
Variance of shares	0.069 (0.092)	0.047 (0.091)	−0.033 (0.045)
Number of SKUs	−0.178 (0.069)***	−0.105 (0.060)*	−0.672 (0.910)
Private-label share	−0.248 (0.130)*	−0.062 (0.071)	0.109 (0.091)
Storability	0.044 (0.051)	−0.075 (0.084)	−0.072 (0.051)
Impulse	0.082 (0.046)*	0.047 (0.025)*	0.043 (0.082)

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

5. Drivers of Promotional Performance

5.1. 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 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 little a priori structure, prior marketing theory will drive our selection of second-stage covariates. Specifically, we consider two categories of variables: (1) *brand* characteristics (market share, private-label versus national brand, promotional frequency and promotional depth) and (2) *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), 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 total (cumulative) 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.

5.2. Results of Second-Stage Analysis

The findings of our second-stage analysis are presented in Table 3.

5.2.1. Manufacturer Revenue. Table 3 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 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 et al. 2002) of promotions on selective demand. High-share brands are likely to operate on the flat portion of their sales response functions.¹² 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

¹² Evidently, the lower *elasticity* (i.e., relative to mean performance) impact of high-share brands does not necessarily imply that they have lower *absolute* impact on performance.

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 et al. 2002). Frequent promotions may make promotions more 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. 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 many consumers in categories with a large private-label share (Ailawadi et al. 2001b). 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 categories with high private-label share. Additionally, impulse goods obtain higher promotion effects on manufacturer revenue because promotions are likely to stimulate the impulse to buy the brand (Narasimhan et al. 1996).

5.2.2. Retailer Category Revenue and Category Margin. Table 3 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 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), 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), 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 (Assunção 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 nonpromoted 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.

6. Conclusions

In this paper, we have investigated the manufacturer revenue, the retailer revenue, and the retailer margin effects of price promotions for 21 categories over 265 weeks. The breadth of the sample allows us to derive empirical generalizations on price-promotion effectiveness and its drivers. To 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 during 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 during the dust-settling period.

(ii) During 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. This 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 to offset retailer losses. However, only in a 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, DFF's, in one geographic region (the Chicago area). Depending on specific characteristics (e.g., their relative power) of other retailers, 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 that the manufacturer may incur about which no information was available, such as slotting allowances, buy-back charges, failure fees, and so on. Our result that 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. Third, our substantive insights were derived from VAR models. Starting with Sims (1980), many econometricians have argued that, in the absence of structural breaks, VAR models are suitable in policy simulations, especially through the impulse-response functions derived from these models. While VAR models are reduced-form models, we operate under the assumption that the parameters of this reduced-form specification are not altered because of a *single* promotional shock (see our discussion in §2). We feel this assumption is reasonable, especially in the promotion-intensive environments characteristic of most fast-moving consumer goods. When studying a change in promotional strategy (e.g., a retailer dropping all promotions), in contrast, this assumption would be harder to defend and policy simulations based on (reduced-form) VAR models would be less appropriate (see also Darnell and Evans 1990 for a more elaborate discussion on this issue). Future research should focus on the development of structural models that address the profitability

impact of major retailer policy changes, similar to the manufacturer policy change studied in Ailawadi et al. (2001a).

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 nonlinear relations between promotional impact and the second-stage characteristics as well as the potential endogeneity of these characteristics. Fifth, our findings are based on data from well-established, mature product categories. Because promotions often work better for new products, more research is needed on whether these findings can be generalized to new product categories. 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.

An electronic companion to this paper is available at <http://mansci.pubs.informs.org/ecompanion.html>.

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