KATHOLIEKE
UNIVERSITEIT
LEUVEN

DEPARTEMENT TOEGEPASTE ECONOMISCHE WETENSCHAPPEN

RESEARCH REPORT 0127

DO PROMOTIONS BENEFIT MANUFACTURERS, RETAILERS OR BOTH?

by

S. SRINIVASAN
K. PAUWELS
D.M. HANSSENS
M. DEKIMPE

D/2001/2376/0127

Do promotions benefit manufacturers, retailers or both?

Shuba Srinivasan[1]
Koen Pauwels[2]
Dominique M. Hanssens[3]
Marnik G. Dekimpe[4]

August 2, 2001

[1]Assistant Professor of Marketing, A. Gary Anderson Graduate School of Management, University of California, Riverside, CA 92521-0203 (Email: shuba.srinivasan@ucr.edu; Tel: (909) 787-6447; Fax: (909) 787-3970).

[2]Assistant Professor of Marketing, Amos Tuck School of Business Administration, Dartmouth College, Hanover, New Hampshire 03755 (Email: koen.pauwels@dartmouth.edu).

[3]Bud Knapp Professor of Marketing, The Anderson Graduate School of Management, University of California, Los Angeles, CA 90095-1481 (Email: dominique.hanssens@anderson.ucla.edu; Tel: (310) 825-4497; Fax: (310) 206-7422).

[4]Professor of Marketing and Marketing Area Coordinator, Catholic University of Leuven, Naamsestraat 69, 3000 Leuven, Belgium (Email: marnik.dekimpe@econ.kuleuven.ac.be; Tel: +32 (16) 326-957; Fax: + 32 (16) 326-732).

The authors are indebted to the Marketing Science Institute for financial support and to the Dominick's project at the Graduate School of Business, University of Chicago, for making the data available.

Do promotions benefit manufacturers, retailers or both?

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 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 and promotion policies, as well as market-structure and category characteristics, influence promotional impact.

A first major finding of our paper is that price promotions do *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.* Retailer (category) margins, in contrast, 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 and for frequently promoted brands. Moreover, they are higher for storable products and lower in categories with a high degree of brand proliferation. Retailer revenue elasticities, in turn, are higher for brands with frequent and shallow promotions, for storable products and in categories with a low extent 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, and 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), 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, purchase quantity and brand choice (Pauwels et al. 2001).

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. 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. Some argue that, while manufacturer profits from promotions have increased at a steady rate, retailers have been earning lower profits (Farris and Ailawadi 1992; Ailawadi et al. 1999). Likewise, competition among stores may prevent retailers from translating trade allowances into profits (Kim and Staelin 1999). By the same token, Srinivasan and Bass (2001) find that the intensity of price competition at the retail level exceeds what is optimal for the market, but this is not so for manufacturers. In contrast, some believe that power in the channel has shifted toward retailers, so their share of promotion profits should be on the rise (Kadiyali et al. 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 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 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 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). 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 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 seven years of weekly 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.

Having quantified the cumulative promotion effects on performance, we introduce the second-stage analysis to examine how brand and category characteristics influence this promotional impact (section 5). Section 6 elaborates on the results for 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. VAR MODELING OF CUMULATIVE PROMOTIONAL IMPACT

Recent research has used vector-autoregressive (VAR) modeling to distinguish between the short-term and long-term effects of price promotions on different levels of consumer demand (Bronnenberg et al. 2000; Dekimpe et al. 1999; Nijs et al. 2001; Pauwels et al. 2001; Srinivasan et al. 2000). 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, persistent 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 also to capture the performance implications of complex feed-forward and feed-back 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 mitigate 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 is expected to exceed the initial *nominal* promotional period of one to two weeks. Our main interest lies in the net (total) results 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. Performance may, however, also be affected by a variety of other factors. To that extent, in addition to the intercept (a_0), we add four sets of exogenous control variables: (i) two indicators of feature activity: a "price-special" (SP) and a "bonus-buy" (BB) promotional variable 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; 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 in error-correction format, depending on the outcome of preliminary unit-root and cointegration tests. 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:

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

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

where $PERF_t$ refers to the performance variable of interest and $[\varepsilon_{PERF,t}, \varepsilon_{P1,t}, \varepsilon_{P2,t}, \varepsilon_{P3,t}]' \sim N(0,\Sigma)$.[2] k refers to the order of the VAR model, which is determined by 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; Nijs et al. 2001 or Srinivasan et al. 2000 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 the two 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.[3]

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, which is readily observable to managers, and may therefore receive considerable managerial scrutiny,

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

(iii) the combined or total impact over the dust-settling period. In the absence of a permanent impact, this statistic becomes the relevant metric to evaluate a promotion's performance.

Figure 1 shows an example of the incremental effect over time of a price promotion of one cent per ounce in the *stationary* canned-tuna 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 noticeable post-promotional dip around period 2. However, in this specific instance, neither player experiences a persistent or continuing revenue gain (i.e. the incremental revenue impact converges to zero). Furthermore, both the immediate effect ($5,570 versus $1,830) and the cumulative impact ($5,010 versus $440) 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 ($10,010), while both the immediate and cumulative effects (-$11,870 and –$20,380, 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 Figure 1 about here ---

The summary statistics depict the incremental 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 tuna, as an example, the immediate (cumulative) increase in manufacturer revenue of $5,570 ($5,010) is transformed into an elasticity of 3.45 (3.10) by normalizing the incremental performance by the ratio of $24,080 (sample mean of weekly manufacturer revenue) to 14.9 cents (sample mean of weekly price per ounce of the brand). Similarly, the immediate (cumulative) increase in retailer revenue of $1,830 ($440) is transformed into an elasticity of 0.20 (0.05) by normalizing the incremental performance by the ratio of the $134,240 (sample mean of weekly retailer revenue in the tuna category) to 14.9 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 0.99 (-0.18) while the immediate (cumulative) retailer revenue elasticity is –0.39 (-0.66).

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. 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), price specials, bonus-buy promotions and information on new-product introductions. Moreover, several categories are characterized by major new-product introductions, many of them private labels.[4] Data are available from September 1989 to May 1997, a total of 399 weeks. Beyond the richness in performance and control variables, this data set is also very broad as it covers non-food products (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) and the relationship between prices and peak demand (Chevalier et al. 2000).

Summary information on the data set is provided in Table 1. Some of the categories have fewer than 399 weeks of data due to missing observations -- the average data length is approximately 340 weeks.

--- Insert Table 1 about here ---

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. Since manufacturer inferences cannot be made for the 19 private-label brands, we restrict our analysis to the 56 national brands in assessing the impact of price promotions on manufacturer performance.

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 retailer 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 $WP_{i,t}$, which was also used in Besanko et al. (2001) and Kadiyali et al. (2000), 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 detailed description see http://gsbwww.uchicago.edu/research/mkt/Databases/DFF/W.html). Dominick's may well stock up on inventory during trade deals, in which case the $AAC_{i,t}$ will remain depressed for some time after the nominal deal period (Chevalier et al. 2000). This implies that retailer forward-buying practices are already incorporated in our margin and wholesale price measures (see also Besanko et al. 2001 for a similar argument).

Finally, two store-level performance variables are relevant for 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.

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. Price promotion frequency is defined as the proportion of weeks in which the price of the brand was at least two standard deviations below its average price level. A brand's price-promotion depth is defined as the (percentage) difference between a brand's promotional price (as defined for promotional frequency) and the brand's average price, averaged across all promotion weeks. This measure was also used by Rao, Arjunji and Murthi (1995) and Nijs et al. (2001), among others. The "price-special" and "bonus-buy" promotional variables for each of the three major brands are operationalized as the percentage of SKUs of the brand that are promoted in a given week.

Market and category characteristics

We measure the competitive structure in a given category using two variables. First, heterogeneity in brand shares is captured by the variance in shares across brands (Dhar and

Hoch 1997). Second, the number of SKUs in the category (Narasimhan et al. 1996) captures the extent of brand proliferation. Finally, we use the Narasimhan et al. (1996) storability scales to construct a dummy variable indicating whether the product category is considered perishable (=0) or storable (=1).

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.[5]

4.1 Stationarity of the time series

Table 2 shows the results of the ADF unit-root test. First, for manufacturer sales, we find that three of the 56 series are evolving while four of the 56 manufacturer revenue series are evolving.

--- Insert Table 2 about here ---

However, when a correction is made for structural breaks due to new-product introductions, those seven series are also re-classified as stationary as well. Second, for retailer category sales and category revenues, we find that four of the 25 series are I(1). Once again, these evolving series are re-classified as stationary after controlling for the new-product introductions in the category. Similarly, with respect to retailer margins, we find that three of the 25 series are evolving, but they are re-classified as stationary after controlling for the new-product introductions in the category as well. Fourth, the store revenue and store traffic series are stationary. Finally, 14 out of the 75 retail price series and 16 out of the 75 wholesale price series are classified as evolving according to the ADF-tests. Again, all these price series are re-classified as stationary after we account for new-product introductions using the Zivot and Andrews (1992) structural break test where the break date is determined endogenously.[6]

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). 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. *However, we offer a new generalization that there are no long-term promotion effects on financial performance (manufacturer and retailer revenues, and retailer margins) and on store performance (store revenues and store traffic) either.* By contrast, new-product introductions can affect long-term financial performance. Specifically, the apparent evolution in revenues and margins found in 18 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

Our first-stage analysis reveals a predominantly positive impact of promotions on both brand sales and manufacturer revenues (Table 3).

--- Insert Table 3 about here ---

For brand sales, 52 out of the 56 brands (93%) 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 4 is 3.77 (3.52) while the average (median) cumulative price promotion elasticity is 4.42 (3.76).

--- Insert Table 4 about here ---

With regard to manufacturer revenue, 49 out of 56 brands (88%) obtain significant total effects, which are positive in 44 cases (79%) and negative in 5 cases (9%). 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 4 is 2.65 (2.51) while the average (median) cumulative price-promotion elasticity is 1.95 (2.01).

In contrast to Nijs et al. (2001), who find that the immediate promotion effect on volume is amplified over time, our results show that the cumulative positive impact on manufacturer revenue is smaller than its immediate effect. We attribute this result to the fact that wholesale prices take a longer time than sales volumes to return to their pre-promotion level. As shown in Table 5, the average length of the dust-settling period is about 6 weeks for brand sales, but about 8 weeks for wholesale prices.[7] In other words, sales effects of a promotion die out sooner than wholesale price effects do; the inertia in wholesale prices creates a financial penalty to promoters. We discuss the implications of this result in the following section.

--- Insert Table 5 about here ---

4.2.2 Retailer performance: category sales and category revenues

For the retailer's category sales, we observe significant total effects for 53 out of the 75 brands, as seen in Table 3. Compared to 46 brands (62%) with a positive impact, only 7 brands (9%) have a negative impact. The average (median) elasticity is 0.54 (0.45) for the immediate impact, and 0.87 (0.51) 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. Therefore, category-demand effects due to store switching are captured to differing degrees in the two studies. 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, promotional policies 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 49 out of 75 brands (65%), only 29 (39%) of those are positive, and 20 (26%) 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, and becomes –0.05 (0.02). While the immediate price-promotion elasticity is still positive, the cumulative price promotion elasticity over the dust-settling period is around zero, 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, *promotional policies are less financially attractive to retailers than they are to manufacturers.*

A common finding from Table 4 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. As mentioned earlier in the context of wholesale prices, this result indicates that the price series have more inertia than the volume series, i.e. retail prices take more time to revert to their original base level after a promotion shock. In fact, Table 5 shows that the length of the dust-settling period is even slightly higher for retail prices (about 9 weeks) than for wholesale prices (about 8 weeks). In contrast, category sales series revert to their mean level in about 5 weeks. In other words, retailers still suffer revenue and margin losses even after the sales effects of a promotion have died out. This finding is intriguing, and may result for two reasons: (i) intensified competitive reactions that delay a return to their pre-promotional level for some of the price series involved (as elaborated in section 2), and/or (ii) a deliberate managerial choice to increase post-promotion prices only in small increments. Indeed, retailers may return to regular prices only gradually in order to avoid a sticker-shock effect (Greenleaf 1995). VAR models and their associated IRFs are ideally suited to capture both phenomena, neither of which would have been picked up in traditional, volume-based promotion-response models.

These findings suggest that, from a financial point of view, managers' well-documented focus on immediate results ignores an unexpected side effect of promotions (Dekimpe and Hanssens 1999). 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 several weeks before returning to their pre-promotion levels. Note that our results control for the possibility of forward buying which depresses the retailer's wholesale prices due to the AAC procedure described in section 3. Absent such forward-buying behavior, the negative financial effects of promotions for the retailer would be even higher.

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 41 brands (55%) experience a negative total impact. The average (median) immediate price-promotion elasticity is – 0.33 (0.25) while the corresponding average (median) total price promotion elasticity is – 1.29 (-0.72). *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 significant total effects for only 32 out of 75 brands. Twelve brands (16%) experience a positive total impact on store revenue while 20 brands (27%) experience a negative total impact. The average (median) immediate price-promotion elasticity for store revenue is 0.50 (-0.69) while the corresponding average (median) price promotion elasticity is -1.34 (-1.81). The results for *store traffic* are similar: only 25 out of the 75 brands have significant total effects. Nine brands (12%) experience a positive total impact, while 16 brands (21%) experience a negative total impact of price promotions on store traffic. All nine brands with a positive impact on store traffic are national brands. This validates 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). The occurrence of negative store-traffic effects, however rare, may indicate that promotions can reduce the need for future store visits, as consumers stockpile the promoted products. In other words, promotions may train consumers to buy more on fewer occasions (Mela et al. 1998). 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 others reporting only weak store-substitution effects of promotions (see, for example, Kumar and Leone 1988; Walters and Mackenzie 1988). Finally, only four of the nine (44%) 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 is likely due to the fact that the additional traffic generated by loss-leader promotions consists mainly of cherry-picking consumers.

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 the evidence 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 effect on retailer margins. 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 3, of the 14 (20) brands that had negative immediate (cumulative) retailer revenue impact, 11 (18) are national brands while the rest are private label brands. Focusing on these national brands, if only immediate effects are measured, the compensation potential is weak, i.e. for only one of the 11 brands (9%) 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 only two out of the 18 national brands (11%) 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.

4.3. Validation

To assess the time-robustness of our results, we determine to what extent they are sensitive to the sample time window. Such a test is possible in our context because we have over seven years of consecutive weekly observations. Using the same VAR specification as in section 2, we perform a longitudinal split-half validation around the mid-date 11/25/1993, which generates two sample periods of approximately 200 weeks each, still sufficiently large samples for VAR estimation. This resulted in an estimation of over 250 additional VAR systems.

--- Insert Table 6 about here ---

For each of the considered performance measures, we use the impulse response functions to derive the mean (median) immediate and total (cumulative) promotional elasticity estimates. These estimates, shown in Table 6, are of the same sign and very close in magnitude for all performance metrics, indicating that our substantive findings on promotional effectiveness are robust over time.

Overall, our results indicate that the interests of manufacturers and retailers are not necessarily aligned. It is therefore important to understand the drivers of promotional revenue generation, so that well-informed decisions can be made on promotional strategy and revenue sharing. This is the subject of section 5.

5. DRIVERS OF PROMOTIONAL PERFORMANCE

5.1 Second-stage analysis: moderators and methodology

Our first-stage results revealed that, on average, price promotions are not advantageous for 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. Specifically, we consider two categories of variables: *brand* characteristics (market share, private label versus national brand, promotional depth and promotional frequency) and *category* characteristics (market concentration, SKU proliferation and product storability). Previous literature on these characteristics (e.g. Blattberg et al. 1995; Narasimhan et al. 1996; Bell et al. 1999; Nijs et al. 2001) allows us to formulate expectations for their moderating effect on total promotional elasticity. However, most of these references consider the volume (q) impact of promotions, whereas we focus on the revenue (p*q) 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 the 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. Table 7 highlights the previous literature that serves as a basis for including these factors.

--- Insert Table 7 about here ---

Econometrically, this stage uses weighted least-squares estimation of 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.

5.2 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 ---

5.2.1 Manufacturer revenue

Table 8 shows that the total promotional impact on manufacturer revenue is moderated by the market share and the promotional frequency of the promoting brand, as well as by the product storability and SKU proliferation of the category. We elaborate on these results below.

The higher the market share of the promoting brand, the lower the total promotional impact on manufacturer revenue. 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. 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 increases with promotional frequency for selective demand (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 impact 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 implies less brand switching by consumers, and thus a lower promotional impact on selective demand (Narasimhan et al. 1996). Our alternative explanation refers to a category crowding effect. The smaller the number of SKUs in the category, the more a promotion will 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 other SKUs.

Finally, we find that the promotional impact on manufacturer revenue is higher for storable products than for perishable products. This result extends the volume findings by Bell et al. (1999) for the immediate effects, and the volume findings by Pauwels et al. (2001) for the total effects. Storable products are by definition easier to stockpile, which increases consumer willingness to buy them in large quantities (Wansink et al. 1998; Bell et al. 1999). Moreover, product inventory at home typically increases consumption rates (Ailawadi and Neslin 1998), which may cause additional purchases over the dust-settling period.

5.2.2 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 product storability 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), this advantage is offset by the margin loss on subsidized baseline sales. This 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, 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 conflicts of interest. 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. Just as deeper discounts yield lower discount sales elasticities (Jedidi et al. 1999), they worsen the negative margin impact of promotions.

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). In contrast, retailer margin effects do not depend on the SKU proliferation in the category.

Finally, storable products obtain higher promotional effects on category revenues. This result extends the volume findings by Raju (1992) and Narasimhan et al. (1996) for the immediate effects, and the volume findings by Pauwels et al. (2001) for the total effects. Similar to our findings for market share, manufacturer and retailer interests are aligned. As a result, promoting small brands in storable 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 twenty-five categories over 399 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 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 a promotional-dust settling period spanning several weeks, but they are not permanent. Manufacturer revenue, retailer revenue and retailer margins are predominantly 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. Moreover, the inertia (time-to-mean-reversion) of wholesale and retail prices is generally higher than that of sales volumes, which cause the cumulative financial impact of a promotion to be lower than its immediate impact.

(ii) Over the dust-settling period, price promotions have positive revenue effects for manufacturers (in almost all cases) and retailers (in some instances), but with regard to margins, they are typically *not* beneficial for the retailer. Consequently, manufacturer side payments are needed in order to offset retailer losses. However, only in a small fraction of the cases is there sufficient manufacturer surplus to allow for such side payments. 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 low-share brands, for brands with high promotional frequency, for storable products and in categories with few SKUs. Similarly, retailer revenue elasticities are higher for brands with frequent and shallow promotions, for storable 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 brand 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 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 may be 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 analysis aggregates sales data across the different stores of the supermarket chain, which may have caused some aggregation bias. However, over the period of study, Dominick's conducted a chain-wide promotional strategy in which prices were lowered uniformly across all stores in the chain for a given item (Hoch et al. 1995, Montgomery 1997). Therefore, potential biases due to aggregation across stores with different promotional policies are not a major issue in our study (Allenby and Rossi 1991). Aside from this aggregation across stores, we also aggregated across SKUs, and more research is needed to assess the sensitivity of our substantive findings to this practice. Fourth, 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.

References

Achenbaum, Alvin A. and Kent F. Mitchel (1987), "Pulling away from push marketing," *Harvard Business Review*, (May-June), 38-40.

Ailawadi, Kusum (2001), "The retail power-performance conundrum: What have we learned?" *Journal of Retailing,* forthcoming.

Ailawadi, Kusum L., Paul Farris, and Ed Shames (1999), "Trade promotion: Essential to selling through resellers," *Sloan Management Review*, 41 (1), 83-92.

Ailawadi, Kusum L. and Scott A. Neslin (1998), "The effect of promotion on consumption: Buying more and consuming it faster," *Journal of Marketing Research*, 35 (3), 390-398.

Allenby, Greg and Peter Rossi (1991), "There is no aggregation bias: Why macro logit models work," *Journal of Business and Economic Statistics*, 9 (1), 1-14.

Assunçao, Joao L. and Robert J. Meyer (1993), "The rational effect of price promotions on sales and consumption," *Management Science*, 39 (5), 517-535.

Bawa, Kapil, Jane T. Landweshr, and Aradhna Krishna (1989), "Consumer response to retailers' marketing environments: An analysis of coffee purchase data," *Journal of Retailing*, 65 (Winter), 471-495.

Bell, David R., Jeongwen Chiang, and V. Padmanabhan (1999), "The decomposition of promotional response: An empirical generalization," *Marketing Science,* 18 (4), 504-526.

Besanko, David, Jean-Pierre Dubé, and Sachin Gupta (2001), "Retail pass-through for competing brands," Working paper, Kellogg Graduate School of Management, Northwestern University.

Blattberg, Robert, Richard Briesch, and Ed Fox (1995), "How promotions work," *Marketing Science*, 14 (3), G122-132.

Blattberg, Robert and Kenneth Wisniewski (1989), "Price-induced patterns of competition," *Marketing Science*, 8 (4), 291-309.

Bloom, Paul, Gregory Gundlach, and Joseph Cannon (2000), "Slotting allowances and fees: Schools of thought and the views of practicing managers," *Journal of Marketing*, 64 (2), 92-108.

Bolton, Ruth N. (1989), "The relationship between market characteristics and promotional price elasticities," *Marketing Science,* 8 (Spring), 153-169.

Bronnenberg, Bart J. and Vijay Mahajan (2001), "Unobserved retailer behavior in multimarket data: Joint spatial dependence in market shares and promotion variables," *Marketing Science*, forthcoming.

Bronnenberg, Bart J., Vijay Mahajan, and Wilfred Vanhonacker (2000), "The emergence of market structure in new repeat-purchase categories: A dynamic approach and an empirical application," *Journal of Marketing Research*, 37 (1), 16-31.

Bucklin, Randolph and Sunil Gupta (1999), "Commercial use of UPC scanner data," *Marketing Science*, 17 (3), 247-273.

Chevalier, Judith A., Anil K. Kashyap, and Peter E. Rossi (2000), "Why don't prices rise during periods of peak demand? Evidence from Scanner Data," Working paper, University of Chicago GSB.

Dekimpe, Marnik and Dominique Hanssens (1995), "The persistence of marketing effects on sales," *Marketing Science*, 14 (1), 1-21.

Dekimpe, Marnik and Dominique Hanssens (1999), "Sustained spending and persistent response: A new look at long-term marketing profitability," *Journal of Marketing Research*, 36 (November), 397-412.

Dekimpe, Marnik, Dominique Hanssens, and Jorge Silva-Risso (1999), "Long-run effects of price promotions in scanner markets," *Journal of Econometrics*, 89 (1/2), 269-291.

Dhar, Sanjay and Stephen J. Hoch (1997), "Why store brand penetration varies by retailer," *Marketing Science*, 16 (3), 208-277.

Dickey, D.A. and W.A. Fuller (1979), "Distribution of the estimators for autoregressive time series with a unit root," *Journal of the American Statistical Association*, 74, 427-431.

Dickson, Peter R. and Alan G. Sawyer (1990), "The price knowledge and search of supermarket shoppers," *Journal of Marketing*, 54 (3), 42-53.

Drèze, Xavier (1995), "Loss leader and cherry picking: A theoretical and empirical analysis," Unpublished dissertation, University of Chicago, Graduate School of Business, Chicago, IL.

Evans, Lewis and Graeme Wells (1983), "An Alternative Approach to Simulating VAR models," *Economic Letters*, 12 (1), 23-29.

Fader, Peter S. and David C. Schmittlein (1993), "Excess behavioral loyalty for high-share brands: Deviations from the Dirichlet model for repeat purchasing," *Journal of Marketing Research*, 30 (4), 478-493.

Farris, Paul and Kusum L. Ailawadi (1992), "Retail power: Monster or mouse?" *Journal of Retailing*, 68 (Winter), 351-369.

Greenleaf, Eric A. (1995), "The impact of reference price effects on the profitability of price promotions," *Marketing Science*, 14 (1), 82-104.

Helsen, Kristan and David Schmittlein (1992), "Some characterizations of stockpiling behavior under uncertainty," *Marketing Letters,* 3, 5-16.

Hoch, Stephen J., Xavier Drèze, Mary E. Purk (1994), "EDLP, Hi-Lo and margin arithmetic," *Journal of Marketing*, (October), 16-27.

Hoch, Stephen J., Byung-do Kim, Alan L. Montgomery, and Peter E. Rossi (1995), "Determinants of store-level price elasticity," *Journal of Marketing Research*, 32 (1), 17-29.

Jedidi, Kamel, Carl F. Mela, and Sunil Gupta (1999), "Managing advertising and promotion for long-run profitability," *Marketing Science,* 10 (1), 1-23.

Kadiyali, Vrinda, Pradeep Chintagunta, and Naufel Vilcassim (2000), "Manufacturer-retailer channel interactions and implications for channel power: An empirical investigation of pricing in a local market," *Marketing Science*, 19 (2), 127-148.

Kalyanaram, Gurumurthy and John D.C. Little (1994), "An Empirical Analysis of Latitude of Price Acceptance in Consumer Package Goods," *Journal of Consumer Research*, 21, 408-418.

Krishnamurthi, Lakshman and S.P. Raj (1991), "An Empirical Analysis of the Relationship Between Brand Loyalty and Consumer Price Elasticity," *Marketing Science*, 10 (Spring), 172-183.

Kim, S. Y. and Richard Staelin (1999), "Manufacturer allowances and retailer pass-through rates in a competitive environment," *Marketing Science,*18 (1), 59-76.

Kopalle, Praveen, Carl Mela, and Lawrence Marsh (1999), "The dynamic effect of discounting on sales: Empirical evidence and normative pricing implications," *Marketing Science*, 18 (3), 317-332.

Kornelis, Marcel, Peter Leeflang, and Marnik Dekimpe (2001), "Modeling market shake-ups caused by new entrants," paper presented at the Marketing Science Institute conference at Cambridge, MA.

Kumar, V. and Robert P. Leone (1988), "Measuring the effect of retail store promotions on brand and store substitution," *Journal of Marketing Research,* 25, 178-185.

Lal, Rajiv and Chakravarthi Narasimhan (1996), "The inverse relationship between manufacturer and retailer margins: A theory," *Marketing Science*, 15 (2), 132-151.

Marketing Science Institute, 2000. *Research Priorities 2000-2002.* Cambridge, MA.

Mela, Carl F., Sunil Gupta, and Kamel Jedidi (1998), "Assessing Long Term Promotional Influences on Market Structure," *International Journal of Research in Marketing*, 15 (2), 89-107.

Mela, Carl F., Sunil Gupta, and Donald R. Lehmann (1997), "The long-term impact of promotion and advertising on consumer brand choice," *Journal of Marketing Research,* 34 (2), 248-261.

Montgomery, Alan L. (1997), "Creating micro-marketing pricing strategies using supermarket scanner data," *Marketing Science,* 16 (4), 315-337.

Narasimhan, Chakravarthi (1988), "Competitive promotional strategies," *Journal of Business*, 61 (4), 427-449.

Narasimhan, Chakravarthi, Scott A. Neslin, and Subrata K. Sen (1996), "Promotional elasticities and category characteristics," *Journal of Marketing*, 60 (2), 17-31.

Nijs, Vincent, Marnik Dekimpe, Jan-Benedict. E.M. Steenkamp, and Dominique Hanssens (2001), "The category demand effects of price promotions," *Marketing Science*, 20 (1), 1-22.

Olver, James M. and Paul W. Farris (1989), "Push and pull: a one-two punch for packaged products," *Sloan Management Review*, (Fall), 53-61.

Pauwels, Koen (1999), "Pricing policies, brand franchise and competitive environment: What drives total promotional effectiveness?" Research paper, Anderson Graduate School of Management, UCLA.

Pauwels, Koen, Dominique Hanssens, and S. Siddarth (2001), "The long-term effects of price promotions on category incidence, brand choice and purchase quantity," Working paper, Anderson Graduate School of Management, UCLA.

Perron, Pierre (1989), "The great crash, the oil price shock and the unit root hypothesis," *Econometrica,* 57 (6), 1361-1401.

Powers, Keiko, Dominique Hanssens, Hser Yih-ing, and Anglin M. Douglas (1991), "Measuring the long-term effects of public policy: The case of narcotics use and property crime," *Management Science*, 37 (6), 627-644.

Putsis, William and Ravi Dhar (1999), "Category expenditure, promotion and competitive market interactions: Can promotions *really* expand the pie?" Working paper, London Business School.

Raju, Jagmohan (1992), "The effect of price promotions on variability in product category sales," *Marketing Science,* 11 (Summer), 207-20.

Rao, Ram C., Ramesh V. Arjunji, and B. P. S. Murthi (1995), "Game theory and empirical generalizations concerning competitive promotions," *Marketing Science*, 14 (3), G89-G100.

Sethuraman, Raj, V. Srinivasan, and Doyle Kim (1999), "Asymmetric and neighborhood cross-price effects: Some empirical generalizations," *Marketing Science*, 18 (1), 23-41.

Siddarth, S., Randolph E. Bucklin, and Donald G. Morrison (1995), "Making the cut: Modeling and analyzing choice set restriction in scanner panel data," *Journal of Marketing Research*, 32 (3), 255-266.

Sivakumar, K. and S. P. Raj (1997), "Quality tier competition: How price change influences brand choice and category choice," *Journal of Marketing*, 61 (3), 71-84.

Srinivasan, Shuba and Frank M. Bass (2000), "Cointegration analysis of brand sales and category sales: Stationarity and long-run equilibrium in market shares," *Applied Stochastic Models in Business and Industry*, 16, 159-177.

Srinivasan, Shuba and Frank M. Bass (2001), "Diagnosing competitive responsiveness: Disentangling retailer-induced and manufacturer-induced reactions," paper presented at the MSI conference at Cambridge, MA.

Srinivasan, Shuba, Peter Popkowski Leszczyc, and Frank M. Bass (2000), "Market share response and competitive interaction: The impact of temporary, evolving and structural changes in prices," *International Journal of Research in Marketing*, 17 (4), 281-305.

Urbany, Joel E., Peter Dickson, and Alan Sawyer (2000), "Insights into cross- and within-store price search: Retailer estimates vs. consumer self-reports," *Journal of Retailing*, 76 (2), 243-258.

Walters, Rockney G. and Hekki Rinne (1986), "An empirical investigation into the impact of price promotions on retail store performance," *Journal of Retailing,* 62 (3), 237-266.

Walters, Rockney G. and S. B. MacKenzie (1988), "A structural equation analysis of the impact of price promotions on store performance," *Journal of Marketing Research*, 25, 51-63.

Wansink, Brian, Robert J. Kent, and Stephen J. Hoch (1998), "An anchoring and adjustment model of purchase quantity decisions," *Journal of Marketing Research*, 35 (1), 71-81.

Zivot, Eric and Donald W. K. Andrews (1992), "Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis," *Journal of Business and Economic Statistics*, 10 (3), 251-270.

Table 1: Dominick's Database*

Category	Starting date	Ending Date	Weeks
Analgesics	09/14/1989	05/01/1997	399
Beer	06/06/1991	10/05/1995	227
Bottled juice	09/14/1989	05/01/1997	399
Cereals	09/14/1989	02/09/1995	283
Cheese	09/14/1989	05/01/1997	399
Cookies	09/14/1989	10/06/1994	265
Crackers	09/14/1989	09/08/1994	261
Canned soup	09/14/1989	04/17/1997	397
Dish detergent	09/14/1989	05/01/1997	399
Front-end candies	09/14/1989	05/01/1997	399
Frozen dinners	05/28/1992	05/01/1997	258
Frozen juice	09/14/1989	05/01/1997	399
Fabric softener	09/14/1989	05/01/1997	399
Laundry detergents	09/14/1989	05/01/1997	399
Oatmeal	06/06/1991	05/01/1997	309
Paper towels	09/14/1989	05/01/1997	399
Refrigerated juice	09/14/1989	05/01/1997	399
Soft drinks	09/14/1989	07/14/1995	253
Shampoos	02/20/1992	02/09/1995	156
Snack crackers	09/14/1989	10/06/1994	265
Soaps	01/09/1992	05/01/1997	278
Toothbrushes	09/14/1989	05/01/997	399
Canned tuna	09/14/1989	01/11/1996	331
Toothpaste	09/14/1989	05/01/1997	399
Bathroom tissue	09/14/1989	05/01/1997	399

Table 2: 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	53	3	0	-
Manufacturer revenue	52	4	0	-
Retailer Performance				
Category sales	21	4	0	-
Retailer revenue	21	4	0	-
Retailer margins	22	3	0	-
Store revenue	1	0	-	-
Store traffic	1	0	-	-
Price Series				
Retail price	61	14	1	0
Wholesale price	59	16	3	0

a- All series in the table are stationary at the 5% levels with the exception of one retail price series and four wholesale price series that are stationary at the 10% level using the ADF unit-root test.

b- Perron break test (1989)

c- Zivot and Andrews break test (1992)

Table 3: 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...)	56 (100%)	0 (0%)	0 (0%)	52 (93%)	3 (5%)	1 (2%)
Manufacturer revenue (dollars)	56 (100%)	0 (0%)	0 (0%)	44 (79%)	7 (12%)	5 (9%)
Retailer Performance						
Category sales (units, pounds...)	53 (71%)	14 (19%)	8 (10%)	46 (62%)	22 (29%)	7 (9%)
Retailer revenue (dollars)	35 (47%)	26 (35%)	14 (18%)	29 (39%)	26 (35%)	20 (26%)
Retailer margins (dollars)	9 (12%)	31 (41%)	35 (47%)	6 (8%)	28 (37%)	41 (55%)
Store revenue (dollars)	16 (21%)	45 (61%)	14 (18%)	12 (16%)	43 (57%)	20 (27%)
Store traffic (customers)	8 (11%)	54 (72%)	13 (17%)	9 (12%)	50 (67%)	16 (21%)

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

Table 4: 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	3.77 (3.52)	4.42 (3.76)
Manufacturer revenue	2.65 (2.51)	1.95 (2.01)
Retailer performance		
Category sales	0.54 (0.45)	0.87 (0.51)
Retailer revenue	0.19 (0.09)	-0.05 (0.02)
Retailer margins	-0.33 (-0.25)	-1.29 (-0.72)
Store revenue	0.50 (-0.69)	-1.34 (-1.81)
Store traffic	0.13 (-0.85)	-0.06 (0.01)

Table 5: Time to mean reversion for sales and price

Variable	Time to mean reversion*
<u>**Manufacturer**</u>	
Brand sales	6.0 weeks (3.4)
Wholesale price	8.3 weeks (5.9)
<u>**Retailer**</u>	
Category sales	5.0 weeks (2.6)
Retail price	9.4 weeks (6.9)

* The cut-off point is determined when the impulse response parameter is no longer significantly different from zero, using the criterion |t-value| > 1.00 and > 1.65 (between brackets).

Table 6: Split-sample validation – mean price-promotion elasticities for the different performance series*

	Immediate promotional effects	Immediate promotional effects	Immediate promotional effects	Total (cumulative) promotional effects	Total (cumulative) promotional effects	Total (cumulative) promotional effects
	Full sample	**Sample 1****	**Sample 2****	**Full sample**	**Sample 1****	**Sample 2****
Manufacturer Performance						
Brand sales	3.77	3.52	3.84	4.42	3.92	4.21
Manufacturer revenue	2.65	2.36	2.73	1.95	1.77	2.05
Retailer Performance						
Category sales	0.54	0.49	0.60	0.87	0.60	0.89
Retailer revenue	0.19	0.15	0.20	-0.05	-0.12	-0.04
Retailer margins	-0.33	-0.27	-0.34	-1.29	-1.32	-1.12
Store revenue	0.50	0.65	0.46	-1.34	-0.99	-1.34
Store traffic	0.13	0.23	0.10	-0.06	-0.02	-0.17

*To avoid information overload, we only report the mean results for each sample. The results on the median are equally robust.
**Sample 1 is from starting date (shown in Table 1 for each category) to 11/25/1993, while Sample 2 is from 11/25/1993 to ending date (shown in Table 1).

Table 7: Literature support for the drivers of promotional impact

Drivers	Brand sales	Category sales	Price
Brand characteristics			
National brands	Allenby and Rossi (1991)	Putsis and Dhar (1999) Pauwels (1999) Sivakumar and Raj (1997) Blattberg and Wisniewski (1989)	Narasimhan (1988)
Market share	Blattberg et al. (1995) Bolton (1989) Fader and Schmittlein (1993) Pauwels (1999)	Blattberg et al. (1995) Bell et al. (1999) Krishnamurthi and Raj (1991) Bronnenberg and Mahajan (2001)	Blattberg et al. (1995) Narasimhan (1988)
Promotion frequency	Dickson and Sawyer (1990) Siddharth et al. (1995) Jedidi et al. (1999)	Bell et al. (1999) Nijs et al. (2001)	Mela et al. (1997; 1998) Assuncao and Meyer (1993)
Promotion depth	Kalyanaram and Little (1994)	Helsen and Schmittlein (1992) Raju (1992)	Jedidi et al. (1999) Narasimhan (1988)
Market and category characteristics			
Variance in shares	Bawa et al. (1989)	Raju (1992) Bell et al. (1999) Bawa et al. (1989) Nijs et al. (2001)	
Number of SKUs		Narasimhan et al. (1996)	
Storability	Bell et al. (1999) Pauwels et al. (2001)	Narasimhan et al. (1996) Bell et al. (1999) Raju (1992) Pauwels et al. 2001 Wansink et al. (1998) Ailawadi and Neslin (1998) Nijs et al. (2001)	

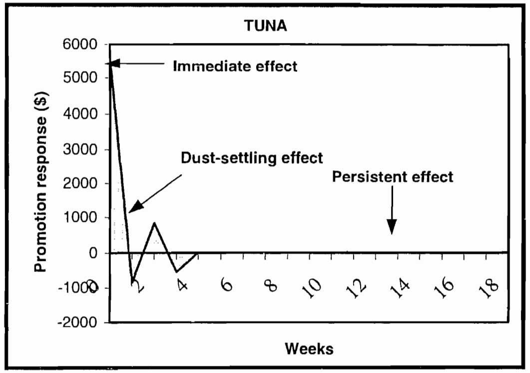
Table 8: Moderating role of brand, market structure and category characteristics on total price-promotion elasticities*
(standardized coefficients with standard errors in parentheses)

Promotional Impact Drivers	Manufacturer revenue	Retailer revenue	Retailer margin
Brand characteristics			
National brands	---	-0.027 (0.063)	0.020 (0.070)
Market share	-0.212 (0.090)***	0.005 (0.053)	-0.200 (0.064)***
Promotional frequency	0.144 (0.071)**	0.063 (0.036)*	-0.100 (0.05)**
Promotional depth	-0.029 (0.127)	-0.176 (0.069)***	-0.245 (0.076)***
Market and category characteristics			
Variance of shares	0.049 (0.090)	0.055 (0.048)	-0.023 (0.092)
Number of SKUs	-0.237 (0.076)***	-0.084 (0.039)**	0.074 (0.079)
Storability	0.141 (0.070)**	0.104 (0.044)***	0.068 (0.066)

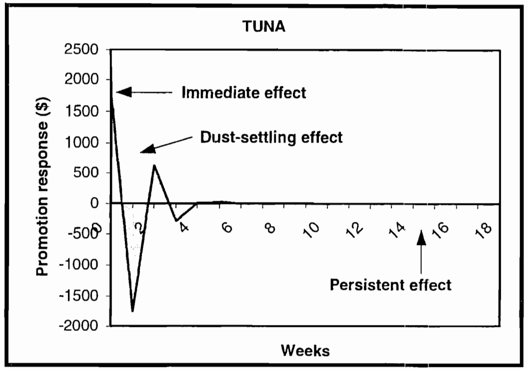
*** = $p < 0.01$
** = $p < 0.05$
* = $p < 0.10$

Fig. 1: Impulse-Response functions

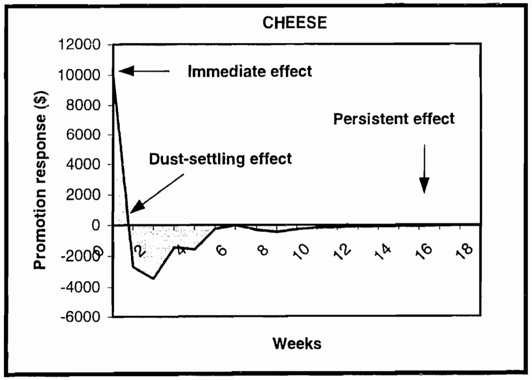
A: Impulse response function of a price promotion of one cent per ounce on manufacturer revenue



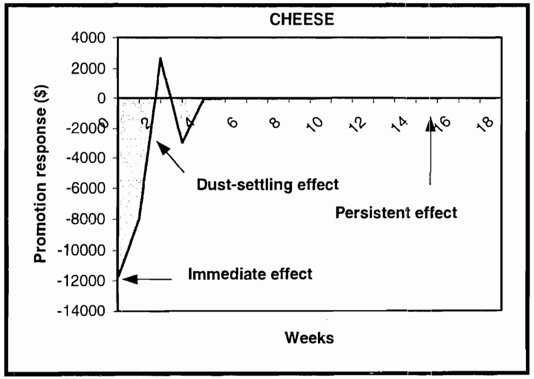
B: Impulse response function of a price promotion of one cent per ounce on retailer revenue



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] In case of level stationary series, the δ parameters becomes 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 the case where the break date is endogenously determined (cf. infra), we added additional dummy variables in the VAR model corresponding to this break date.

[3] VAR models as given in equation (1) are very flexible to capture all kinds of lagged effects. To capture instantaneous effects as well, the simultaneous-shocking approach introduced by Evans and Wells (1983) and used in a marketing setting by Dekimpe and Hanssens (1999) and Nijs et al. (2001) is adopted.

[4] Product categories in which the most successful new-product introduction was 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."

[5] All results are generated using Eviews4 software.

[6] 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.

[7] The magnitude of these periods is shorter when we impose a higher standard of statistical significance, but the conclusions about stronger price inertia remain.