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Long-run effects of price promotions in scanner markets

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Abstract

Good marketing decisions require managers' understanding of the response function relating performance measures to variations in the marketing mix. We use unit-root techniques to address market response in evolving markets, with a focus on their response to price promotions. We distinguish between evolution at the primary-demand vs. selective-demand level, and examine four consumer product categories for which high-quality scanner records are available. We find category and brand sales to be predominantly stationary, with differences in promotional impact between national and private-label brands. Even in the rare occurrence of performance evolution, the long-term effects of price promotions are not necessarily positive. © 1999 Elsevier Science S.A. All rights reserved.

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1. Introduction

Marketing managers are principally concerned with the allocation of scarce marketing resources such as sales force, advertising and promotion, for the

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purpose of improving the market and profit performance of their products or brands. The quality of their decisions greatly depends on their understanding of the way in which customers and competitors will respond to these efforts, in the short run as well as the long run. Econometric methods have been used to enhance this understanding, resulting in a vast body of empirically tested knowledge on the relationship between market performance and marketing investments (see, e.g. Hanssens et al., 1990).

The main focus of this response modeling, however, has been on 'short-run forecasting and optimization procedures, while assuming an essentially stable environment' (Wind and Robertson, 1983, p.13). Still, the environments in which marketing decisions are made may well be *evolving*, due to changes in technology, consumer preferences and/or competition (Dekimpe and Hanssens, 1995b). Consequently, many of the resource-allocation problems faced by marketers contain an important long-run dimension. For example, advertising expenditures may affect sales levels immediately, but they can also contribute to the establishment of a long-run brand image. Customers often react negatively to a sudden price change, but may adapt to higher prices over time. These and other long-term marketing behaviors should be conceptually understood and empirically quantified if we are to improve the practice of effective marketing resource allocation.

This paper addresses both the concepts and the empirics of market response in evolving markets. We argue that long-term time-series techniques are ideally suited to measure market evolution and relate it to marketing decisions. In doing so, we distinguish between market response at the primary-demand (product-category) and selective-demand (brand-sales) level, and identify four potential scenarios depending on their stable/evolving character. We illustrate these principles on four consumer product categories (catsup, liquid detergent, soup and yogurt) for which high-quality scanner records on sales and the marketing mix are available, and focus on the over-time impact of the brands' *price promotions*.

Over the last decade, a growing body of literature has documented that temporary retail price reductions substantially increase sales, that customers adjust their reference price because of frequent price promotions, and that cross-promotional effects tend to be asymmetric, with higher-quality brands impacting the weaker brands disproportionately (see Blattberg et al. (1995) or Bronnenberg and Wathieu (1996)). The debate is still open, however, on whether (1) price promotions have any long-run effects, (2) whether they only induce brand switching, or also result in market-expansion effects, and (3) whether asymmetric effects are reflected in differing impact *durations* or only in a distinct instantaneous effect. The first issue is critical to the effective use of price promotions, especially in light of the concern that they may actually be detrimental to the long-term health of the brand. The second issue, whether or not part of the observed sales increase during (and shortly after) a price promotion is gained at the expense of the other players in the market, affects the strength of competitive reaction, and ultimately, the profitability of a brand's promotional activity. Finally, insights in the total cumulative cross-effect of price promotions initiated by, respectively, national and private-label brands will contribute to the ongoing debate on the asymmetric drawing power of national brands.

The remainder of the paper is organized as follows. In Section 2, we make a case for distinguishing between stable and evolving performance patterns, both at the primary- and selective-demand level, and introduce four potential scenarios that emerge when jointly considering both dimensions. In Section 3, we indicate how long-run time-series techniques can be used to empirically distinguish between these scenarios, and to model short- and long-run responsiveness in each. We briefly review previous marketing applications of these techniques, and show how they can contribute new knowledge in the promotion-effectiveness literature. Empirical findings are presented in Section 4, and we conclude in Section 5 with some empirical and analytical generalizations, and some areas for future research.

2. Marketing in stable and evolving environments

The statistical distinction between stationary (stable) and non-stationary (evolving) sales or demand behavior has important ramifications for marketers.[1] If sales are mean reverting without level shifts, marketing actions produce at most temporary deviations from the brand's average performance level. If sales are evolving, on the other hand, there is no such reversion tendency, and there is a potential for long-term marketing effectiveness. Subsequent multivariate analyses (cointegration and/or persistence models, see Sections 3 and 4) should then establish whether or not the brand's marketing actions actually affect its observed sales evolution (Dekimpe and Hanssens, 1995a,b). Obviously, if discrete marketing actions (e.g. a single promotion) cause a structural break in the data-generating process, such as a level-shift in the mean of otherwise stable sales, that too is strong evidence of long-run marketing effectiveness, as illustrated in Leone (1987) and Hanssens et al. (1990, p. 148). As discussed in Section 4, no evidence of such promotion-induced breaks was found in our data, so we will quantify the over-time impact of price promotions – operationalized as unexpected price shocks – on the assumption that the parameters of the process do not change as a result of these shocks (see Pesaran and Samiei (1991) for a similar assumption).

[1] In what follows, the mean-stationary model is used as alternative hypothesis, since in most marketing settings, this corresponds to a more realistic scenario than a trend-stationary model (Dekimpe, 1992).

Evolution in sales can exist at the *primary-demand* (industry sales) and/or the *selective-demand* (brand sales) level. While most marketing practitioners and researchers focus on selective demand, the primary-demand component is important, even critical, for several reasons:

- Evolution in primary demand allows for persistent market-expansive effects of marketing investments. For example, Compaq's introduction of a new line of aggressively-priced personal computers in the early nineties opened up a large new market segment (home computing). Likewise, advertising campaigns that attract new buyers to a product category can have a continuing effect when some of them become regular users.
- In the presence of market expansion, marketing actions are less likely to cause permanent damage to competition, and retaliatory behavior is expected to be less severe. Conversely, with stable primary demand, the rules of zero-sum competitive equilibria are more likely to apply. Absent market expansive effects of marketing actions, the only way a company can build a long-run advantage over the competition is by inducing consumers to switch loyalty.

In sum, the presence or absence of evolution in primary demand may influence marketing effectiveness, competitive marketing behavior and, ultimately, the market structure of an industry. Schultz and Wittink (1976) derive a set of analytical conditions for the presence of primary-demand vs. selective-demand effects of the marketing mix. The conditions are stated as a set of first-order derivatives of various performance measures (brand sales, industry sales and market shares) with respect to the marketing mix, which can be estimated econometrically. Several authors have made estimates of these derivatives, and a review of their results may be found in Hanssens et al. (1990). However, *none* of these studies have examined whether these estimates have a temporary or a permanent character to them. Therefore, there is little, if any, empirical evidence for the existence of permanent primary demand effects of, for example, advertising or pricing strategies.

From a marketing-strategic perspective, evaluating stable vs. evolving conditions at the level of industry vs. brand sales gives rise to four possible scenarios:

- *Stable brand sales in a stable category*: all sales gains and losses are of a temporary nature, and brand marketing is tactical in nature. In such environments, the brand's relative position or market share is also stable, and all marketing effects are either intrinsically short-lived, or self-canceling in the long run (cf. infra). While management decisions may still have strong short-run share or profit implications, they reflect tactical moves that are unrelated to the strategic or long-run direction of the brand.

- *Stable brand sales in an evolving category*: implies a lack of long-run marketing effectiveness, as the brand is unable to establish permanent gains in spite of operating in an evolving category. While marketing activities can have long-run primary demand effects in such markets, the additional sales do not accrue to the brand, but rather benefit its competitors.
- *Evolving brand sales in a stable category*: this scenario implies that the brand is locked into a strategic battle for long-run position. Moreover, as the category is not moving away from its historical mean, firms are involved in a zero-sum game in which the long-run sales gain for one player always occurs at the expense of a long-run loss for at least one of the other players. This scenario may result in an unprofitable escalation of the competitors' marketing expenditures.
- *Evolving brand sales in an evolving category*: depending on the relative importance of the long-run components in brand and category sales, firms may be able to improve not only their absolute long-run performance, but also their relative position. Moreover, if different brands' performance levels are cointegrated, brands can be seen as riding long-run market waves that could be driven by their marketing spending.

We will not only diagnose which scenario applies to thirteen different brands in four product categories, but will also assess the influence of one important marketing-mix variable, *price promotions*, on the evolution of brand and category sales. Indeed, in their recent review, Blattberg et al. (1995) call the question whether there are any long-run effects of promotions 'the most debated issue in the promotional literature' and 'one for which the jury is still out' (Blattberg et al. 1995, p. G127).

Previous literature has tried to disentangle the various sources of promotional volume. Gupta (1988) found that the majority of the promotional volume was due to brand switching, and Bemmaor and Mouchoux (1991) expect the product-class sales impact of price promotions to be low, if at all existent.[2] Chintagunta (1993), on the other hand, provided evidence of a substantial market-expansion effect. As such, there is still ambiguity about the short-run market-expansion potential of price promotions, and to the best of our knowledge, no study has yet considered their potential long-run primary-demand implications. Indeed, previous studies have implicitly assumed or imposed a *stable* market environment, and have therefore precluded the detection and quantification of any permanent price promotion effects. Unit-root econometrics do not impose this restriction, and will allow us to better quantify the extent of price promotions' long-run effectiveness.

[2] See Blattberg et al. (1995) for a more extensive review.

3. Modeling long-term marketing effects through unit-root econometrics

Unit-root econometrics is well suited to study long-run marketing effectiveness. First, *unit-root tests* identify the presence/absence of a long-run (stochastic-trend) component in the series' data-generating process, and hence distinguish stable from evolving variables. When applied to primary and selective demand, unit-root test results will enable us to classify the different brands into one of the aforementioned strategic scenarios. To avoid the spurious identification of a series characterized by one or more level shifts as evolving, structural-break unit root tests are recommended whenever there is evidence of discrete events such as new product introductions or changes in advertising theme. Next, *impulse-response functions* can be derived from *VAR* (vector-autoregressive) or *VECM* (vector error-correction) models to study the over-time impact of price promotions on both performance levels, and the corresponding multivariate *persistence* estimates will quantify the long-run impact of various price shocks. As indicated before, these estimates assume that the shocks do not alter the structure and/or parameters of the data-generating process.

Extensive technical reviews of these techniques are given in Harris (1995) and Mills (1994), and will not be repeated here. Instead, we briefly review existing marketing applications, and will indicate in Section 4 the actual implementation adopted in our empirical study. Within a marketing context, unit-root tests have been used as a first step in studies on the long-run effectiveness of advertising expenditures (e.g. Baghestani, 1991; Dekimpe and Hanssens, 1995a), and the *absence* of a unit root in most published market-share series has been interpreted as empirical evidence that many markets are in long-run equilibrium where the relative position of the players is only temporarily affected by their marketing activities (Dekimpe and Hanssens, 1995b). In a different context, Dekimpe et al. (1997) found mean reversion in the brand loyalty of multiple brands, which lead them to reject the contention that brand loyalty has been systematically eroded. Structural-break unit root tests (e.g. Perron, 1990) were used in the latter study to control for the potentially confounding effect of new-product introductions.

Once a long-run component has been identified in the series of interest, *cointegration* analysis can be used to determine whether a long-run equilibrium relationship exists among the variables. In the marketing literature, cointegration tests have been used to study whether a brand's sales and advertising are moving together over time (e.g. Baghestani, 1991; Zanias, 1994), whether a product category's long-run evolution is linked to the evolution in some macro-economic variables (Franses, 1994), and whether aggregate advertising spending is related to macro-economic fluctuations (Chowdhury, 1994). In all instances, *error-correction models* were estimated to capture the short-run dynamics towards the identified long-run equilibrium.

Finally, Dekimpe and Hanssens (1995a) have quantified the relative importance of the identified long-run component in market performance through univariate persistence estimates, and have interpreted the short- and long-run interrelationships between performance and advertising spending through impulse-response and multivariate *persistence estimates*.

Overall, the number of published marketing applications of these long-run time-series techniques is limited, in spite of their widespread use in other disciplines such as economics and finance (see, e.g. Harris, 1995; Mills, 1994), and in spite of repeated calls for a longer-run focus in marketing planning and decision making (e.g. Wind and Robertson, 1983). A major barrier to their application in marketing has been a lack of data. Indeed, it is often easier for marketing researchers to obtain cross-sectional rather than longitudinal data sets. In contrast, in both economics and finance, specialized agencies exist that record in a consistent way the over-time behavior of a great variety of variables, including macro-economic indicators, stock prices, and exchange rates. We conjecture that the future of long-run time-series modeling in marketing will be positively and significantly affected by the advent of new data sources that are based on the automatic, real-time recording of purchase or consumption transactions, as opposed to the retrieval of old accounting records.

Scanner data have already provided a major impetus to cross-sectional research in marketing, in particular the study of consumer heterogeneity in market response (see Chintagunta (1993) for a review). This heterogeneity has been investigated at the level of brand choice, purchase quantity and purchase timing. The dominant modeling approach has been the multinomial logit model, not only in published academic research, but also in commercial applications in the packaged-goods sector, according to a recent survey by Bucklin and Gupta (1996). Recently, an interest has emerged in using the same scanner data sources to make inferences about marketing's long-run effectiveness (e.g. Mela et al., 1997; Papatla and Krishnamurthi, 1996). However, these studies still use the conventional battery of statistical techniques to analyze long-run movements in longitudinal data. For example, Mela et al. (1997) use the Koyck specification to measure long-run marketing effects. These methods are appropriate for the study of multi-period sales response in stable markets, where constant means and variances in performance and marketing support have already been established, but as Dekimpe and Hanssens (1995a) argue, they are not well suited to address the more strategically relevant questions about the long-run evolution of a brand in evolving markets. The Koyck model, for example, *implies* that the performance series will return to their pre-expenditure levels, and hence *precludes* the detection of any persistent effects. In Section 4, we illustrate the potential of unit-root econometrics to offer new insights into the long-run dimension of many substantive marketing problems through a large-scale study (13 brands, 4 categories) on the over-time effectiveness of price promotions.

4. Measuring the over-time impact of price promotions

4.1. Data description

A.C. Nielsen household scanner panel data on the purchases of liquid laundry detergent, soup, yogurt and catsup in the Sioux Falls market (South Dakota) were used to construct time series of weekly sales and primary-demand figures. These data sets were made available to the academic research community through the Marketing Science Institute, and have been used extensively in the recent marketing literature (see Chintagunta (1993) for a review).

As some markets have seen a proliferation of brands and sizes (e.g. each brand in the detergent market is typically offered in several sizes ranging from 32 to 128 ounces), we expressed sales in number of ounces sold, and aggregated all different sizes of a particular brand into one figure.[3] For the detergent, soup and yogurt market, we considered the top three brands, while for the catsup market, we considered three national brands and a major private label brand. This resulted in a total of thirteen brand-level series. We further constructed a price-per-ounce variable, and operationalized price promotion as a *temporary* price discount (cf. infra). As features and displays have been shown to strongly affect sales (Blattberg et al., 1995), we control for their presence or absence with dummy variables.

Each time series consists of 113 weekly observations, from the first week of 1986 until the 9th week of 1988. From a statistical point of view, longer time spans may be preferred (e.g. Perron, 1989). However, it is of interest to determine whether long-run inferences can be made from the data that are publicly available to the marketing community. More importantly, longer time series lose their managerial relevance, as ever changing market conditions make managers reluctant to make inferences based on old data (e.g. Glazer and Weiss, 1993).

Our database aggregates consumer choices and marketing conditions to the weekly market level, which causes some loss of information on possible underlying consumer heterogeneity. Thus the dynamic relationships we uncover may be sensitive to aggregation bias (Pesaran and Smith, 1995). However, as Allenby and Rossi (1991) and Leeflang and Wittink (1992) point out, retailers typically use such aggregated data when setting their price and promotion strategies. Allenby and Rossi (1991) further prove that applying aggregate logit models on store-level scanner data is not subject to aggregation bias when three conditions are met: all consumers are exposed to the same marketing-mix variables, the

[3] We therefore focus on long-term promotion effectiveness at the brand level (typically a senior marketing management responsibility), as opposed to the SKU level (typically a junior marketing management responsibility). See Abraham and Lodish (1993) for a more elaborate discussion.

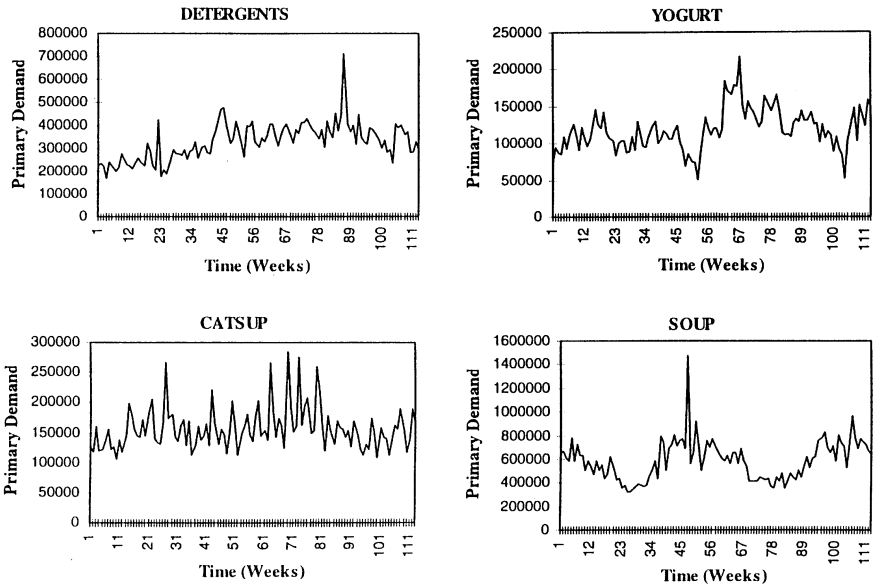


Fig. 1. Primary demand in four scanner product categories.

brands are close substitutes, and the price distribution is not concentrated at an extreme value. We verified that our empirical setting meets these conditions: price distributions are bell shaped with a few outliers (cf. infra), the product categories and competitors are tightly defined, and marketing occurs at the point-of-purchase, which exposes all buyers of the category.

4.2. Diagnosing category evolution

Total category sales in the four product categories are depicted in Fig. 1. To formally assess the stable or evolving character of these series, we applied several versions of the Augmented Dickey Fuller (ADF) test. Table 1 first lists the standard test statistics, in which we varied the number of lagged difference terms (p) between 0 and 4, and subsequently used the Schwarz Bayesian Criterion (SBC) to select the order of the test equation within that range. We found evidence of $I(1)$ or evolution in only one category, soup, suggesting its potential for long-run market-expansion effects. The detergent, catsup and yogurt markets, on the other hand, were all found to be stationary.

The graphs in Fig. 1 also suggest the presence of occasional outliers, some of which are due to price promotions. As shown in Franses and Haldrup (1994), not accounting for these outliers might produce spurious stationarity. We

Table 1
Unit-root tests

A. Primary demand									
	ADF	*p*	*ADFO*	*p*	*ADF w/entries*	*p*			
Detergent	−2.97	2	−3.26	1	−8.31	0			
Yogurt	−4.29	0	−4.52	0	−5.21	0			
Catsup	−3.46	4	−11.95	0	–				
Soup	−2.14	2	−2.15	2	–				
B. Detergent sales					*B. Detergent prices*				
Tide	−3.58	2	−6.13	0	Tide	−2.21	2	−4.36	0
Wisk	−7.35	0	−5.59	1	Wisk	−2.79	1	−3.28	1
Era	−6.76	0	−8.56	0	Era	−4.1	0	−4.51	0
C. Yogurt sales					*C. Yogurt prices*				
	ADF	*p*	*ADFO*	*p*		*ADF*	*p*	*ADFO*	*p*
Dannon	−3.04	2	−4.28	1	Dannon	−8.12	2	−6.33	0
Yoplait	−4.44	0	−3.94	0	Yoplait	−2.82	2	−3.01	2
Private label	−2.84	3	−5.84	0	Private label	−3.22	2	−2.93	2
D. Catsup sales					*D. Catsup prices*				
	ADF	*p*	*ADFO*	*p*		*ADF*	*p*	*ADFO*	*p*
Hunts	−6.55	2	−6.65	1	Hunts	−5.3	0	−5.68	0
Delmonte	−5.44	1	−7.27	1	Del Monte	−3.42	3	−6.72	0
Heinz	−8.88	0	−9.4	0	Heinz	−3.5	2	−3.17	2
Private label	−7.91	0	−8.69	0	Private label	−3.66	0	−4.07	0
E. Soup sales					*E. Soup prices*				
	ADF	*p*	*ADFO*	*p*		*ADF*	*p*	*ADFO*	*p*
Swanson	−5.3	0	−3.67	0	Swanson	−5.3	0	−3.32	1
Campbell	−2.27	2	−2.26	2	Campbell	−3.61	1	−5.32	0
Private label	−7.65	0	N.A.	0	Private label	−2.93	2	N.A.	0

Critical values (5%): −2.89 (ADF and ADFO), −3.33 (ADF w/ entries).

assessed in a stepwise fashion whether or not these outliers affected our unit-root test results.[4] First, we controlled for price promotions – characterized by simultaneously high sales and low prices – with a single dummy variable. Next, we added separate dummy variables for additional outliers that were identified as isolated extreme points in a variable's histogram. As shown in Table 1, ADFO column, our substantive conclusions were not affected.[5]

Two of our categories (detergent and yogurt) experienced two new-product entries in the considered time span, which could have caused a structural break

[4] See Abraham and Lodish (1993) for a conceptually similar two-step procedure.

in the mean level of primary demand. Even though not accounting for such events has been shown to bias the test results *toward* the unit-root conclusion (Perron, 1990), there was still no evidence of evolution in those series. When applying the testing procedure in Perron and Vogelsang (1992b) to explicitly account for these a priori determined potential break points, the evidence in favor of stability became even stronger (Table 1, ADF w/ entries-column). Finally, we applied the testing procedure in Perron and Vogelsang (1992a) where the potential break-point is not set a priori but rather determined empirically, to the evolving soup series. Again, our results were found to be robust, in that the unit-root null hypothesis was not rejected with this testing procedure either (min $t_\alpha = -2.64$, with $t_{\text{crit}} = -4.25$).

The combined findings of the different unit-root tests indicate that the potential for long-run market expansion effects of price promotions is restricted to the soup market. In the three other instances, we found that, *in spite of numerous marketing interventions by the incumbents over the considered time span, category demand for detergents, catsup and yogurt behaved as a series of fluctuations around a constant mean.*[6]

4.3. Diagnosing the incumbents' selective demand and pricing behavior

The unit-root test results for the brands' sales series are also presented in Table 1. While the ADF test occasionally indicates a unit root, the outlier-controlled ADF tests reject the unit-root hypothesis in all but one case. Again, we conclude that in spite of numerous marketing interventions, the demand fluctuations of all incumbent catsup, detergent, yogurt and soup brands are stable. The sole exception is the mild evolutionary behavior in the sales of Campbell which, given Campbell's dominant share in the soup category, is also

[5] We also applied formal outlier-detection methods, in particular Chen and Liu (1993), but were limited by the many potential outlier observations due to repeated promotional activity, relative to the time sample. Extensive sensitivity analyses were therefore performed to ensure that the results were insensitive to the choice of outliers. For example, when adding or subtracting one data point identified as an outlier relative to the number used in the ADFO column of Table 1, the substantive findings were unaffected.

[6] For the stable series (i.e. where the unit-root null hypothesis was rejected), the question remains whether there is any evidence of a structural change in the parameter values, and if so, whether this change could be attributed to a marketing (in casu, promotional) activity. Successive-window tests, as implemented in the E-views 2.0 software, were performed on the parameter estimate for the lagged dependent variable in the unit-root test equations. A visual inspection revealed very stable estimates, and hence, no evidence of such a break (detailed results are available from the authors upon request). Subsequent analyses on the impact of price promotions over time will therefore assume that these shocks will not cause such a structural change either.

found at the primary-demand level.[7] In terms of our strategic scenarios, the following classification results:

	Stable brand sales	Evolving brand sales
Stable category sales	Catsup brands (4) Detergent brands (3) Yogurt brands (3)	
Evolving category sales	Swanson soup Private Label Soup	Campbell soup

Most brands (10) fall in the stable-brands/stable-industry category, which implies that their relative positions (market shares) will only be temporarily affected by marketing activities as well.[8] Marketing activities for these brands may still have market-expansive and/or selective demand effects, and these may differ in magnitude and duration across brands (cf. Section 4.4). However, the effects are all bound to be temporary in nature.

The finding of predominantly stable sales is corroborated by the unit-root test results on prices, since all thirteen ADF0 tests reject the null hypothesis of a unit root in prices (Table 1). The test statistics, however, were generally lower in absolute value for prices than for brand sales, indicating that prices will, on average, take a longer time to return to their pre-shock mean than consumer sales. This observation will be validated in Section 4.4 through multivariate impulse-response calculations.

In sum, while the statistical power of each individual unit-root test could be improved (Perron, 1989), the combined evidence of finding stationarity in 28 out of 30 different series is very strong.

4.4. Diagnosing the effectiveness of price promotions

Unit-root tests are only indicative of the potential for long-run marketing effectiveness. To capture the potential long-term impact of price promotions, multivariate analyses are needed linking price promotions to the longitudinal behavior in performance. We therefore derived impulse-response functions from VAR models specified in the levels of the stable variables, and in the first

[7] Also in this case, an application of the Perron and Vogelsang (1992a) procedure confirmed the presence of a unit root (min $t_\alpha = -2.71$ for Campbell sales).

[8] Similar findings were reported by Lal and Padmanabhan (1995) who conducted deterministic-trend regressions on the market shares of multiple frequently purchased consumer goods, and found few significant slope coefficients.

difference for the evolving variables (i.e. soup primary demand and Campbell selective demand). To avoid potential degrees-of-freedom problems when estimating extended VAR models (e.g. when several competitors' performance and marketing-mix variables are included simultaneously as endogenous variables), we estimated separate models for category and brand sales. Furthermore, we estimated a separate VAR model for each brand's selective demand. Apart from the performance measure, we included the prices of all major competitors in each VAR model, and controlled for the presence of features and display through exogenous dummy variables. In the detergent and yogurt analyses, two additional step dummy variables were added to control for the new-brand entries. As an example for the detergent market, the following VAR model was used to derive the over-time impact on the primary demand for liquid detergents (S_{det}) of price shocks to the major brands Tide (TI), Wisk (WI) and Era (E):

$$\begin{bmatrix} S_{\mathrm{det},t} \\ P_{TI,t} \\ P_{WI,t} \\ P_{E,t} \end{bmatrix} = \begin{bmatrix} C_{\mathrm{det}} \\ C_{TI} \\ C_{WI} \\ C_{E} \end{bmatrix} + \sum_{i=1}^{I} \begin{bmatrix} \phi^i_{11} & \phi^i_{12} & \phi^i_{13} & \phi^i_{14} \\ \phi^i_{21} & \phi^i_{22} & \phi^i_{23} & \phi^i_{24} \\ \phi^i_{31} & \phi^i_{32} & \phi^i_{33} & \phi^i_{34} \\ \phi^i_{41} & \phi^i_{42} & \phi^i_{43} & \phi^i_{44} \end{bmatrix} \times \begin{bmatrix} S_{\mathrm{det},t-1} \\ P_{TI,t-1} \\ P_{WI,t-i} \\ P_{E,t-i} \end{bmatrix}$$

$$+ \begin{bmatrix} \eta^F_{11} & \eta^F_{12} & \eta^F_{13} \\ \eta^F_{21} & \eta^F_{22} & \eta^F_{23} \\ \eta^F_{31} & \eta^F_{32} & \eta^F_{33} \\ \eta^F_{41} & \eta^F_{42} & \eta^F_{43} \end{bmatrix} \times \begin{bmatrix} F_{TI,t} \\ F_{WI,t} \\ F_{E,t} \end{bmatrix}$$

$$+ \begin{bmatrix} \eta^D_{11} & \eta^D_{12} & \eta^D_{13} \\ \eta^D_{21} & \eta^D_{22} & \eta^D_{23} \\ \eta^D_{31} & \eta^D_{32} & \eta^D_{33} \\ \eta^D_{41} & \eta^D_{42} & \eta^D_{43} \end{bmatrix} \times \begin{bmatrix} D_{TI,t} \\ D_{WI,t} \\ D_{E,t} \end{bmatrix}$$

$$+ \begin{bmatrix} \delta_{11} & \delta_{12} \\ \delta_{21} & \delta_{22} \\ \delta_{31} & \delta_{32} \\ \delta_{41} & \delta_{42} \end{bmatrix} \times \begin{bmatrix} entry_1 \\ entry_2 \end{bmatrix} + \begin{bmatrix} e_{\mathrm{det}.t} \\ e_{TI,t} \\ e_{WI,t} \\ e_{E,t} \end{bmatrix}$$

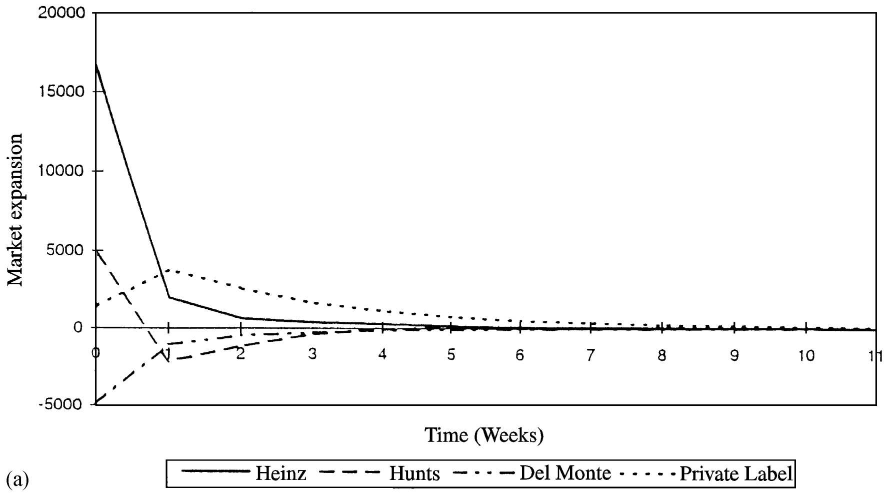
where D_{TI} indicates whether or not Tide was on display in any given week (similar definitions apply for the other feature and display variables), $entry_i$ ($i = 1,2$) is a step dummy variable, and I is the order of the VAR model determined on the basis of the SBC criterion.

As with any econometric model, restrictions on the information set may affect one's conclusions. We therefore tested our findings for consistency across primary and selective demand specifications (cf. infra) and, in unreported analyses, we verified the robustness of the results across alternative specifications of the final VAR model. Impulse-response functions derived from VAR models have been criticized because of the ambiguity that arises when the equation error terms are correlated. Following Dekimpe and Hanssens (1995a), we imposed a temporal ordering on the endogenous variables, in that we always assigned causal priority to the price variable that was shocked, and always ordered the performance variable last, so that it could be influenced instantaneously by all prices. Putting sales last in the temporal sequence makes intuitive sense when working with weekly data, as firms cannot immediately adjust retail prices to incoming market information. For the ordering among the price variables, numerous robustness checks were conducted, and our results were not sensitive to the imposed causal ordering. This robustness is due to the fact that all instantaneous cross-price effects, as reflected in the residual correlation matrix, were very small. This corroborates Leeflang and Wittink's (1992) finding that it takes firms and retailers some time to react to competitive price promotions.

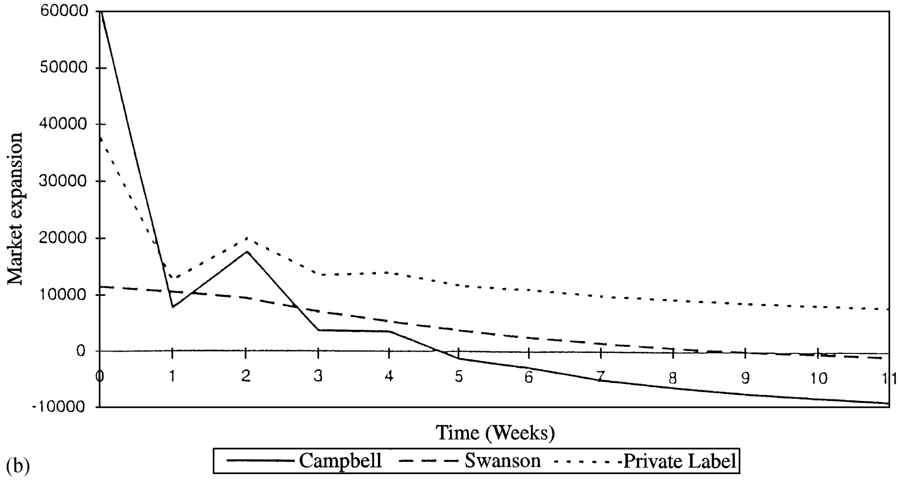
Price promotions are temporary (Blattberg et al., 1995) price reductions offered to the consumer, which can be operationalized as one-time shocks to the VAR system. To enhance the comparability of the findings across brands and product categories, we trace the over-time impact of a *one-standard-error* shock. This approach captures price promotions in relative rather than in absolute dollar terms (Blattberg et al., 1995), and reflects that the perceived depth of a monetary discount depends on the unpredictability of the action (Leeflang and Wittink, 1996).

4.4.1. *Price dynamics in the stable catsup market*

The market-expansive effects of the various brands in the catsup market are depicted in Fig. 2A, which shows that both the *magnitude* and *duration* of their temporary impact on category sales differ considerably. We observe a larger instantaneous effect for the bigger brands (especially Heinz and Hunts), while the private-label brand has a more prolonged impact. Table 2 compares the different brands in terms of their total cumulative primary-demand effect. In computing this total, we summed all impulse-response weights with a t-statistic greater than one in absolute value (see Dekimpe and Hanssens (1995a), Pesaran et al. (1993), or Van de Gucht et al. (1996) for a conceptually similar procedure). This cutoff point is generous and translates into fairly wide confidence intervals, causing our results to be indicative, rather than precise estimates of the resulting cumulative effectiveness. When interpreting our findings, we therefore focus on (1) the *overall* form of the response functions, and (2) *consistent* patterns across product categories.



(a)



(b)

Fig. 2. (a) Market expansion effects in the stable catsup market. (b) Market expansion effects in the evolving soup market.

Primary-demand effects are due to a variety of factors, such as the attraction of new customers to the product category, increased consumption by current buyers, purchase acceleration and stockpiling. The latter two factors have an inherent temporary character. However, the absence of persistent effects suggests that the first two factors have, at most, a short-lived effect as well. As for

Table 2
Short- and long-run market-expansion effects of price promotions[a]

Product category	Brand	Cumulative effect	Persistence
Catsup	Heinz	16,198	0
	Hunts	4717	0
	Del Monte	− 4901	0
	Private label	10,332	0
Liquid detergent	Tide	0	0
	Wisk	15,675	0
	Era	16,634	0
Yogurt	Yoplait	11,134	0
	Dannon	1638	0
	Private label	10,999	0
Soup	Campbell	∞	− 8703
	Swanson	∞	− 6754
	Private label	∞	8749

[a] Effects resulting from a one standard error price promotion.

Table 3
Selective-demand effects of price promotions by the market leader

Market leader	Cumulative effect on own performance	Persistent effect on own performance
Heniz	21,879	0
Tide	25,776	0
Yoplait	6418	0
Campbell	$-\infty$	− 9159

the selective-demand effects, we report in Tables 3 and 4 the cumulative own-demand effects of price shocks to the market leader (Heinz) and the private-label brand. When comparing these figures with their market-expansion effects, we see that the competitive implications differ vastly. For Heinz, its own sales gains (21,900) exceed its market-expansion effect (16,200), implying that *a substantial fraction of its gains come at the expense of the competition.* Price promotions for the private-label brand, on the other hand, benefit some competitors, as its market-expansion effect (10,300) is greater than its own gains (1400). This supports the scenario that price promotions by the cheaper private label brand temporarily attract new buyers to the product category, who also try out some

Table 4
Selective-demand effects of price promotions by private-label brands

Product category	Cumulative effect on own performance	Persistent effect on own performance
Catsup	1402	0
Yogurt	5592	0
Soup	6845	0

of the national brands in their repeat purchases. Part of this expansion effect of the private label brand, however, is also due to price-matching behavior of the two leading national brands, Heinz and Hunts.

Finally, we observe that, consistent with the univariate results in Section 4.3, prices exhibit a substantial degree of 'stickiness': they revert to the mean at a slower rate (i.e. after approx. 8 weeks) than their corresponding sales level. This price stickiness has a negative effect on the *profitability* of promotional plans because customers can take advantage of a still lower than average price even though their purchase quantities have already returned to mean levels.

4.4.2. Price dynamics in the stable yogurt and detergent markets

The results in yogurt and detergents follow similar patterns: (1) all primary- and selective- demand effects of price promotions are temporary, (2) price promotions by the private-label brand cause a market-expansion effect that partially accrues to the national brands, and (3) the price fluctuations of a majority of the brands are stickier than their customers' responsiveness. In the detergent market, price promotions by the market leader (Tide) are competitive only, in the terminology of Schultz and Wittink (1976). They cause a substantial own-demand effect that is *completely* at the expense of the other brands. Overall, the dynamics of price promotions and market response are comparable across these three different product categories.

4.4.3. Price dynamics in the evolving soup market

The primary-demand effects in the soup market are depicted in Fig. 2B. The incremental impact of price promotions by the three major brands does *not* converge to zero as in the stable catsup market (Fig. 2A), but stabilizes at a non-zero level. For the leading brand, Campbell, we see a large immediate impact of 59,700. This differential impact then oscillates over time, and eventually reaches an asymptotic persistence level of − 8,703, which is *negative but small* relative to the initial positive impact. Similar results are obtained for Campbell's selective demand (see Table 3). Thus, even though Campbell's price promotions are highly effective in the short run, they set into motion a set of opposite forces that cause the eventual long-run impact to be self-canceling or even damaging to the brand.

Once again, a different picture is obtained for the private-label brand. Its price promotions have a *persistent* market-expansion effect, even though they only *temporarily* benefit its own performance. Private-label price promotions appear to be powerful enough to either increase consumption or to attract previous non-buyers to the category who subsequently become national-brand buyers. This scenario is validated when analyzing the private-label's promotional cross-effect on the sales of Campbell, with a persistent positive impact of 3800.

In conclusion, the observed evolution in the soup category and market leader sales is somewhat, but *not strongly* affected by price promotions. Their predominant effects occur in the short run, and are different for the market leader vs. private label.

5. Discussion

Our unit-root based econometric analyses of thirteen brands in four product categories have quantified the short- and long-run effects of price promotions, both at the primary- and selective-demand level. Even though there is variability across brands and product categories, some empirical generalizations emerge:

- Category sales, brand sales and brand prices in scanner markets generally follow a mean-stationary process. In a majority of cases, there is faster mean reversion for sales than for prices.
- Price promotions have a temporary impact on the brand's and the market's future sales levels. Only in the highly concentrated soup market is there evidence of a long-run promotion effect, with relatively low persistence.
- Even though price promotions by the market leader tend to have the largest immediate effect, their cumulative impact is more limited, and mostly *competitive* in nature.
- Private-label brand promotions, on the other hand, can expand the market and actually *enhance* the performance of national brands.

The latter findings establish the existence of another asymmetry between price promotions initiated by national vs. private-label brands. Previous research had provided evidence that price promotions by national brands have a higher instantaneous drawing power (e.g. Blattberg et al., 1995; Bronnenberg and Wathieu, 1996). This phenomenon was also observed in our impulse-response functions. However, when considering the total over-time impact on both selective and primary demand, this conclusion should be qualified. Moreover, our findings invite national brands to rethink their perception of private-label brands as detrimental to their long-run viability. Instead, the behaviors we observe are more akin to *co-opetition* than to competition (Brandenburger and Nalebuff, 1996). While private-label and national brands visibly compete for market share, they may mutually benefit in other dimensions, for example the stimulation of primary demand.

Our findings also invite some scrutiny of the question as to *why* there is so much observed stationarity in performance and marketing effort. After all, brand managers are compensated and motivated to *improve* their market position and profitability over time, so one would expect to see evolutionary behavior in sales and marketing spending. Instead, we find that most position improvements are temporary in our four major consumer product categories. There are two possible explanations:

(a) the marketing-mix variables of these brands, as well as the cross-effects from their competitors, intrinsically have only temporary effects. Whether or not competitive reaction is desirable depends on the trade-off between lower sales with same marketing costs vs. same sales with higher marketing costs.

(b) they intrinsically have long-run effects, but because of competitive activities, they cancel each other out in the long run. In this scenario, a brand manager has no choice but to respond to an aggressive action of a competitor, such as a price promotion, lest (s)he wants to risk the permanent loss of sales.

In Appendix A, we address these explanations analytically, and derive whether or not brand actions and counteractions that intrinsically have long-run effects can produce a time series of sales that is mean-stationary, in the absence of structural breaks in the data-generating process. We consider three competitive scenarios: firms set their budgets independently, a leader/follower scenario, and both firms set their budget as a function of the other brand's decision. We show that case (b), where the apparent stationarity of sales would mask competing long-run effects *cannot* occur in the first two competitive-reaction scenarios, and is *unlikely* to occur in the third scenario. *Thus, actual 'do or die' promotional wars are unlikely to exist in stationary markets and many of the promotional battles one observes in the current market place may actually reflect unnecessary escalations.*

This analytical result is tight and our combined empirical evidence of sales stationarity in scanner markets is strong. Still, in some instances it is difficult to empirically designate an individual time series as being stationary or evolving with a low persistence level. More work is therefore needed to enhance the power of unit-root tests. Moreover, for any selected size (α) of the empirical testing procedure, the possibility remains that one erroneously rejects the unit-root hypothesis. As such, one should not be surprised to observe unnecessary promotion escalations, as risk-averse managers with asymmetric loss functions are likely to assume persistent competitive effects and react accordingly even if the evidence for their brand and category is weak.

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Appendix A

We consider whether brand actions and counteractions that intrinsically have long-run effects can still result in performance series which are mean-stationary. For the sake of simplicity, we assume that both prices (P and CP) are mean-reverting, but a similar reasoning applies when the control variables are evolving. Three scenarios are considered, which have been observed repeatedly in empirical research (see, e.g. Hanssens et al., 1990):

A.1. Case 1. Independent price setting

The simplest case of independent price setting is given by

$$S_t = \alpha_s + \beta_1(L)P_t + \beta_2(L)CP_t + e_{S,t}\,, \tag{A.1a}$$

$$P_t = \alpha_P + e_{P,t}\,, \tag{A.1b}$$

$$CP_t = \alpha_{CP} + e_{CP,t}\,, \tag{A.1c}$$

where $e_{S,t}$, $e_{P,t}$ and $e_{CP,t}$ are white-noise residuals, and where $\mathrm{cov}(e_{P,t}, e_{CP,t+i}) = 0$, $\forall i$. After appropriate substitutions, we get

$$S_t = \alpha^* + \beta_1(L)e_{P,t} + \beta_2(L)e_{CP,t} + e_{S,t}. \tag{A.2}$$

A temporary price reduction will have a continuing impact if the partial derivative of S_{t+k} ($k \to \infty$) with respect to $e_{P,t}$ is non-zero (assuming, as before, that they do not cause a structural break). Obviously, this can only occur if $\beta_1(L)$ is an infinite-lag polynomial whose coefficients do not converge to zero. In that case, however, the variance of the right-hand side of Eq. (A.2) will grow without bound, while the left hand-side (S_t) is a finite-variance variable, which would create an inconsistent model specification (Granger, 1981). Hence, $\beta_1(L)$ cannot be an infinite-order polynomial, and neither P nor CP can have a continuing impact.

A.2. Case 2. One firm is the leader, the other the follower

In this second scenario, Eq. (A.1c) is changed to reflect the fact that the competitor sets his/her prices as a function of our current and/or past prices,

$$CP_t = \alpha_{CP} + \kappa(L)P_t + e_{CP,t}, \tag{A.3}$$

with $\text{cov}(e_{P,t}, e_{CP,t+i}) = 0, \forall i$. After appropriate substitutions, we get

$$S_t = \alpha^* + [\beta_1(L) + \beta_2(L)\kappa(L)]e_{P,t} + \beta_2(L)e_{CP,t} + e_{S,t}. \tag{A.4}$$

Using a similar reasoning, P and CP can only have a continuing (and supposedly canceling) impact if $\beta_1(L)$ and $\beta_2(L)$ are infinite-lag polynomials whose coefficients do not converge towards zero. This situation leads to a similar inconsistency. Even in the unlikely event that the $\kappa(\,)$ coefficients cancel 'an infinite number of contributions to the total variance' in the term between square brackets, the β_2-terms would still cause an infinite-variance right-hand side.

A.3. Case 3. Both firms react to each other's (current and past) prices

Eq. (A.1b) is updated to reflect this new scenario:

$$P_t = \alpha_A + \kappa_1(L)CP_t + e_{P,t}\,, \tag{A.5a}$$

$$CP_t = \alpha_{CP} + \kappa_2(L)P_t + e_{CP,t}. \tag{A.5b}$$

After appropriate substitutions, the performance equation becomes

$$S_t = \alpha^* + \frac{[\beta_1(L)\kappa_1(L) + \beta_2(L)]}{1 - \kappa_1(L)\kappa_2(L)}e_{CP,t} + \frac{[\beta_2(L)\kappa_2(L) + \beta_1(L)]}{1 - \kappa_1(L)\kappa_2(L)}e_{P,t} + e_{S,t}. \tag{A.6}$$

In this case, it is possible that, even when $\beta_1(L)$ and $\beta_2(L)$ are infinite-lag polynomials (and thus reflect underlying long-run effects), both the left- and right-hand side have a finite variance. However, this masking of long-run effects would only occur if both competitors react in such a way that they *completely* cancel out the other firm's promotional effect for an *infinite* number of periods to come.[9] It is only if this very stringent (and therefore unlikely) condition is met, that one would see a masking of underlying long-run or continuing effects.

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[9] To give a specific example, if $\beta_1(L)$ is an infinite-lag polynomial, it is not sufficient that the competitive reactions result in a net zero effect in period 1, period 2, …, period 20; they must cancel the firm's promotional effect in so many periods that there are only a finite number of periods which offer a contribution to the variance on the right-hand side.

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