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Although managers often hope to obtain long-term benefits with temporary marketing actions, academic studies imply that their chances are slim. Extant research has implicitly assumed that the brand itself carries no influence over whether marketing promotions have the power to lift sales permanently. Using panel data for seven years from 100 brands across seven product categories, the authors employ a two-stage approach in which long-term promotional effectiveness is first estimated with persistence modeling and then these effectiveness estimates are related to brand equity and new product introductions. By examining a broad range of brands in each category, the authors find that positive sales evolution from promotional efforts is fairly common, especially for small brands. Moreover, the authors find that both permanent and cumulative sales effects from marketing promotions are greater for brands with higher equity and more product introductions, whereas brands with low equity gain greater benefits from product introductions. These results offer new research and managerial insights into the presence and conditions for persistent benefits from marketing promotions.

Keywords: brand equity, new product introductions, persistence modeling, long-term marketing effectiveness, promotions

The Impact of Brand Equity and Innovation on the Long-Term Effectiveness of Promotions

Marketing scholars and practitioners have increasingly become interested in understanding the extent to which various marketing actions affect performance. A rising concern for both academics and practitioners is that a failure to demonstrate the impact of marketing could not only weaken the influence of the marketing function (Webster, Malter, and Ganesan 2005) but also challenge its credibility (Rust et al. 2004). As managers strive for improved performance, a common criticism is an emphasis on short-term results rather than long-term returns. Accordingly, scholars are

exploring the long-term effects from various marketing efforts to offer insight into marketing strategies that deliver a sustainable competitive advantage (e.g., Dekimpe and Hanssens 1999; Pauwels, Hanssens, and Siddarth 2002; Pauwels et al. 2004).

An empirical generalization from this literature is that permanent sales effects from temporary marketing actions, such as price promotions, feature advertising, and displays, are rare (Franses, Srinivasan, and Boswijk 2001; Nijs et al. 2001; Pauwels, Hanssens, and Siddarth 2002). Much of this research has focused exclusively on the top-three- or top-four-selling brands in the category (rare exceptions include Bronnenberg, Mahajan, and Vanhonacker 2000; Van Heerde, Gupta, and Wittink 2003), thus implicitly assuming that the brand itself carries no influence on the effects from its temporary marketing actions. However, brands vary in their positional advantage and thus may realize differential permanent and cumulative effects from marketing actions.

Recent research in marketing has also substantiated the importance of the brand in generating differential effects from marketing actions. For example, higher-equity brands are able to generate higher immediate returns from their marketing-mix efforts (Slotegraaf, Moorman, and Inman

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2003), and higher-loyalty brands generate greater stockpiling from promotions (Bell, Chiang, and Padmanabhan 1999). Therefore, rather than succumb to the conclusion that there is little potential for long-term marketing effectiveness, we argue that the underlying value of a brand affects the permanent and cumulative effects of different marketing actions.

To examine this assertion, we focus on explaining the across-brand variation in the permanent and cumulative sales elasticity from display, feature advertising, and price promotions. Specifically, delineating the underlying value of a brand by its equity, or revenue premium (Ailawadi, Lehmann, and Neslin 2003), we expect that brands with higher equity have an established strength in the market that generates long-term effectiveness of promotional efforts. Moreover, because innovation is a cornerstone of value creation (Mizik and Jacobson 2003), we also focus on a brand's new product introductions. In particular, we investigate the direct and complementary effects regarding the extent to which a brand's new product introductions influence promotional response and whether these benefits differ for brands of varying equity. Using panel data for seven years from 100 brands across seven product categories, we employ a two-stage approach in which we first estimate the long-term marketing effectiveness with persistence modeling and then relate those effectiveness estimates to the brand. In contrast to extant research, which has typically focused on a few top brands, we examine nearly all brands in the category (varying from 9 to 25 per category) to capture greater variability across brands. Briefly, our results illustrate two critical findings that offer new understanding of long-term effects of marketing. First, our examination shows that permanent effects from promotional efforts are *not* rare, as is currently believed, but rather are common across categories, especially for smaller brands. Second, our results show that a brand's equity and new product introductions influence the long-term sales elasticity and unit effects generated from its promotional efforts.

THEORETICAL FRAMEWORK

Long-Term Effects from Marketing Promotions

Promotional efforts are recognized as a potent tool for managing brands, with in-store displays, feature advertising, and temporary price reductions key components of a traditional promotional mix (Blattberg and Neslin 1990). In examining the effects from promotional efforts, scholars are increasingly pointing to the value of understanding their long-term impact (e.g., Dekimpe and Hanssens 1999; Rust et al. 2004; Srivastava, Shervani, and Fahey 1998). A long-term sales impact may appear in two forms: (1) permanent effects, which represent a true change in baseline sales, and (2) cumulative effects, which summarize the over-time changes (which may be negative or positive) before sales return to baseline (Pauwels, Hanssens, and Siddarth 2002). Indeed, even if no single marketing action has the power to change baseline sales permanently, managers may repeat this action to increase sales, which is beneficial as long as the cumulative effect is positive.

Although research has shown that promotions generate high cumulative effects on brand choice and purchase quantity (Ailawadi and Neslin 1998; Jedidi, Mela, and Gupta 1999; Mela, Jedidi, and Bowman 1998) and on category incidence (Pauwels, Hanssens, and Siddarth 2002, Van

Heerde, Gupta, and Wittink 2003), permanent effects of promotions are rarely observed. In particular, among the top-selling brands analyzed in numerous product categories, fewer than 5% have been shown to experience a permanent impact from promotional efforts (Dekimpe, Hanssens, and Silva-Risso 1999; Nijs et al. 2001; Pauwels, Hanssens, and Siddarth 2002). Given this virtual absence of permanent effects from extant research, no study has analyzed the cross-brand variation in permanent promotional effects. Furthermore, although moderating factors such as national versus private brands (Dekimpe, Hanssens, and Silva-Risso 1999; Pauwels, Hanssens, and Siddarth 2002) and brand market share (Fok et al. 2006; Kopalle, Mela, and Marsh 1999; Macé and Neslin 2004) have been shown to affect the cumulative promotional impact, little is understood about how long-term promotional effects depend on the brand's equity and innovation activity. We discuss these drivers in turn.

The Role of Brand Equity

Brand equity refers to the value of a product with a brand name in comparison with that if the same product did not have a brand name (e.g., Aaker 1991; Ailawadi, Lehmann, and Neslin 2003; Farquhar 1989; Keller 2003). It reflects certain consumer attitudes and associations with a branded product (e.g., Aaker 1991, 1996; Keller 2003) that, in the aggregate, yield specific consequences, such as incremental volume, price premiums, and profit (Ailawadi, Lehmann, and Neslin 2003). These product-market outcomes (Keller and Lehmann 2003, 2006) quantify the incremental benefit due to the brand name and "reflect a culmination of the various mechanisms by which the brand name adds value" (Ailawadi, Lehmann, and Neslin 2003, p. 2). These outcomes are also an important means of quantifying the value of a brand because they are inextricably linked to market forces (e.g., Collis and Montgomery 1995). Whereas different market-based measures have been proposed, a revenue-based measure is likely to be more useful to researchers and marketing managers in demonstrating a brand's value to the firm.¹ Therefore, we base our brand equity measure on the difference in revenue a branded product generates in comparison with the private label (Ailawadi, Lehmann, and Neslin 2003). Because revenue premium and market share are correlated but conceptually different measures (e.g., marketing investments can influence brand equity and market share differentially), it is important to control for market share effects when analyzing the explanatory power of brand equity (Keller and Lehmann 2006). Therefore, we empirically isolate the effects that are specific to brand equity from those that involve market share and marketing activity levels, as detailed in the "Methodology and Data" section.

Regarding the effect of brand equity, we expect that higher-equity brands attain greater long-term sales elastic-

¹Measures that attempt to value the future potential of a brand are often subjective, such as the multiplier used by Interbrand and purchase intent used by Equitrend. Other market-based measures, such as market share, are not likely to capture the underlying value of the brand, because they ignore price premium and value-priced strategies. Finally, customer mindset measures are valuable from a diagnostic perspective (including the segment-level utilities in Rangaswamy, Burke, and Oliva [1993] and Kamakura and Russell [1993]), but they are not available for a wide range of (especially small) brands to researchers and are difficult to connect to the value a brand offers to the firm (Keller and Lehmann 2006).

ity from their display, feature, and price promotion efforts. In general, consumers are purported to react differently to marketing-mix efforts for a branded product in comparison with efforts for an unbranded product (Keller 1993). Research comparing differences between national brands and private labels offers some support for this argument. For example, advertising for national brands leads to greater purchase intentions than it does for private labels (Bearden, Lichtenstein, and Teel 1984). In addition, price promotions offered for private labels typically yield a lower immediate category incidence elasticity than those for national brands (Srinivasan et al. 2004) but benefit the competing brands in the category more in the long run (Pauwels 2007). Yet such broad comparisons between national brands and private labels can mask specific effects due to different levels of brand equity of the national brands, which the current research investigates.

When a brand has stronger equity, consumers hold more favorable, powerful, and unique associations with the brand and have a more established familiarity with the brand (Keller 1993). Because of the highly firm-specific, legally protected, and socially complex processes by which a brand is created and managed over time, a positional barrier is generated (Wernerfelt 1984) that likely influences the effectiveness of its marketing promotions. Moreover, research indicates that these effects may be long-term, with promotions garnering greater effects for familiar brands (Alba, Hutchinson, and Lynch 1991) and higher-price, high-quality brands (Blattberg and Wisniewski 1989). In addition, exposure to high-equity brands through visual means, such as displays or feature advertisements, may enhance a brand's competitive advantage (Alba, Hutchinson, and Lynch 1991). Thus:

H₁: Brands with higher equity generate higher long-term sales elasticity from (a) display, (b) feature advertising, and (c) price promotion efforts than brands with lower equity.

The Complementary Role of Product Introductions

The foregoing arguments suggest a challenge for brands with low equity. However, although low-equity brands may have little value to exploit, they can create value by delivering products to the marketplace, which is a cornerstone of value creation (Mizik and Jacobson 2003) and a valuable resource in itself (e.g., Cooper 1998; Pauwels et al. 2004).

When a product is introduced to the market, it tends to signal something new. As a result, consumers are more likely to pay attention to the communication efforts for these products, as has been demonstrated for television advertising (Lodish et al. 1995). We expect similar effects for a product's display, feature advertising, and price promotions. In particular, a substantial segment of consumers appears to use display and feature advertising as heuristics when forming consideration sets (Zhang 2006). Thus, when a brand introduces products, we expect that the visibility generated for the brand offers a positive reinforcement to the visibility generated by the promotional efforts, similar to the complementarity effects demonstrated between value creation and value appropriation (Moorman and Slotegraaf 1999). This complementary effect should further facilitate the long-term sales effects from promotional efforts.

Furthermore, the long-term returns from promotional efforts are likely to be higher for product introductions to the extent that buying a new product can be risky and pro-

motions offer a risk premium for trial (Blattberg and Neslin 1990). Consequently, if the new product better satisfies the desires of specific consumers, they will repurchase it (Kalyanaram and Urban 1992), thereby generating long-term sales for the brand. Thus:

H₂: Brands with more product introductions generate higher long-term sales elasticity from (a) display, (b) feature advertising, and (c) price promotion efforts.

Finally, we expect that product introductions generate greater long-term effectiveness of promotional efforts for low-equity brands than for high-equity brands. Although a brand with higher equity may command a halo effect that could enhance the effects produced from introducing products, high-equity brands likely experience ceiling effects. The introduction of products is also an avenue by which lower-equity brands may realize greater long-term sales effects from marketing promotions. Three specific arguments support this assertion.

First, product introductions pose trade-offs in that they offer several advantages and potential pitfalls, including cannibalization and product failures. Such pitfalls are more likely for high-equity brands that have already established strong positive consumer attitudes and familiarity. In contrast, building up the product portfolio of a low-equity brand can signal a brand-building strategy that is rewarded by the market (Lane and Jacobson 1995). Second, although new product introductions may offer certain benefits, brand dilution becomes a concern if a brand is extended too often (Keller and Aaker 1992). Because brands with higher equity tend to encapsulate stronger associations and attitudes among consumers (Keller 1993), brand dilution may be more likely to occur when many new products are introduced for brands with higher equity. Third, the awareness generated from the introduction of new products is likely to be more beneficial to a brand with lower equity. In particular, consumer awareness or familiarity is an underlying element of brand equity (Aaker 1991; Keller 1993), and brand awareness plays a dominant role in consumer choice (e.g., Hoyer and Brown 1990). Consequently, low-equity brands that introduce more new products can generate greater awareness for the brand, whereas high-equity brands have already established awareness so the introduction of new products remains beneficial but to a lesser extent. In other words, the awareness generated by promotional efforts combined with that from new product introductions attenuates at a greater rate for brands with high equity than for brands with low equity. Thus:

H₃: Regarding long-term sales elasticity from promotions, a negative interaction exists between brand equity and new product introductions; lower-equity brands with new product introductions generate a higher long-term sales elasticity from (a) display, (b) feature advertising, and (c) price promotion efforts than higher-equity brands with new product introductions.

Additional Drivers of Long-Term Returns to Marketing Promotions

In addition to brand equity and new product introductions, several other factors may affect long-term sales elasticity of marketing promotions. We discuss potential brand-level, firm-level, and category-level factors and account for such factors in our analysis.

In terms of brand-level factors, a brand's product line breadth and its market share may either increase or decrease the long-term effectiveness of promotions. In particular, broader product lines can not only reach the needs of heterogeneous customers (Kekre and Srinivasan 1990; Quelch and Kenny 1994) but also create more competition for consumers' attention, generate clutter (Keller 2003), and weaken product choice (Broniarczyk, Hoyer, and McAlister 1998; Malhotra 1982; Zhang and Krishna 2007). Likewise, promotions on high-share brands may generate substantial category expansion (Bell, Chiang, and Padmanabhan 1999; Bronnenberg and Mahajan 2001) or draw business away from competing retailers (Moorthy 2005). However, high-share brands experience greater postpromotion dips (Macé and Neslin 2004) and smaller cumulative effects from their price promotions (Fok et al. 2006).

Firm-specific factors may also affect the long-term effectiveness of promotions. Although large firms may suffer from complacency and inertia in how they conceive and execute marketing campaigns (Hambrick and D'Aveni 1988), they may also benefit from their clout over retailers and consumers (Scherer 1980). Likewise, firms with more employees may engender specific processes regarding internal knowledge transfer that may affect the extent to which a firm's marketing efforts reap long-term effects. In particular, internal knowledge transfer is often a complex process that drives competitive advantage (Luo, Slotegraaf, and Pan 2006; Maltz and Kohli 1996), and when the sheer number of employees in a firm is higher, there are more opportunities for knowledge sharing.

Finally, a large body of previous research has linked promotional returns to category-level variables (e.g., Bolton 1989; Narasimhan, Neslin, and Sen 1996; Nijs et al. 2001; Srinivasan et al. 2004). Thus, it is important to control for them when assessing our hypotheses.

METHODOLOGY AND DATA

Our analysis consists of several methodological steps, which we summarize in Table 1. We begin by examining

the time-series properties to establish whether temporary marketing promotions have permanent effects on sales (Dekimpe and Hanssens 1995). From these times-series properties, we formulate models of the dynamic interactions among sales, brand promotions, and competitive promotions for each brand and each year. Next, we use the estimated coefficients to simulate the over-time impact of a marketing promotion on sales, known as the "impulse response function," which enables us to quantify the cumulative and permanent sales elasticity of marketing promotions. Finally, we assess our hypotheses by relating these estimated effects to brand resources in a sequential hierarchical regression model (Slotegraaf, Moorman, and Inman 2003), which enables us to account for the simultaneity between revenue premium and long-term marketing returns by first regressing revenue premium on brand-level variables and then using the residual in a weighted least squares regression of long-term marketing promotion effects on the specified explanatory variables. We explain each step in detail next.²

Permanent Versus Temporary Change: Unit Root and Cointegration Tests

First, unit root tests verify the univariate time-series properties (stationarity versus evolution) for each variable. The substantive question they address is whether sales are mean-reverting (stationarity) or have changed permanently in the data sample (evolution). We use both the augmented Dickey–Fuller test procedure recommended by Enders (2004) and the KPSS test (see Kwiatkowski et al. 1992). The former maintains evolution as the null hypothesis (and is the most popular in marketing applications), and the latter maintains stationarity as the null hypothesis. Each test is estimated in two forms: with and without a deterministic

²Although this sequential series of different analyses is not the most efficient methodology, it allows estimates to vary at each of the different stages without imposing specific constraints on the model.

Table 1
OVERVIEW OF METHODOLOGICAL STEPS

<i>Methodological Step</i>	<i>Relevant Literature</i>	<i>Research Question</i>
1. <i>Unit Root and Cointegration Tests</i>		
•Augmented Dickey–Fuller test	•Enders (2004)	•Are variables stationary or evolving?
•KPSS test	•Maddala and Kim (1998)	•Are the results robust to null hypothesis?
•Structural break test	•Zivot and Andrews (1992)	•Are the results robust to structural breaks?
•Cointegration test	•Johansen, Mosconi, and Nielsen (2000)	•Are evolving variables in long-term equilibrium?
2. <i>Model of Dynamic Interactions</i>		
•Vector autoregressive (VAR) model	•Dekimpe and Hanssens (1999)	•How do sales and marketing variables interact in the long run and the short run, accounting for the unit roots, cointegration, and structural breaks?
•Vector error correction model	•Franses, Srinivasan, and Boswijk (2001)	
•VAR with structural breaks	•Bai (2000)	
3. <i>Policy Simulation Analysis</i>		
•Impulse response function	•Dekimpe and Hanssens (1999)	•What is the dynamic (sales) response to a (marketing) impulse?
•Generalized impulse response	•Pesaran and Shin (1998)	•What is the immediate effect of an impulse, without imposing a causal ordering?
4. <i>Sequential Regression</i>		
•Regression of revenue premium	•Slotegraaf, Moorman, and Inman (2003)	•What is the revenue premium residual, after controlling for its potential drivers?
•Weighted least squares regression of long-term marketing elasticities	•Srinivasan et al. (2004)	•Which factors drive long-term elasticities, weighted by their estimation accuracy?

time trend. Convergent conclusions of these different tests yield higher confidence in our variable classification (Madala and Kim 1998). We also test for unknown structural breaks with Zivot and Andrews's (1992) test. Finally, Johansen, Mosconi, and Nielsen's (2000) cointegration test verifies whether any combination of evolving variables is in long-term equilibrium and accounts for structural breaks.

Modeling Dynamic Interactions: Vector Autoregressive Models

Second, we specify vector autoregressive (VAR) models that are well suited to measuring the dynamic sales response and interactions between sales and marketing variables (Dekimpe and Hanssens 1999). Both sales variables and marketing actions are endogenous (i.e., they are explained by their own past and the past of the other endogenous variables).

Vector autoregressive models are specified in levels or changes, depending on the results of the unit root tests (if sales and marketing are cointegrated, a vector error correction model is estimated).³ Model specification requires two remaining considerations: the number of lags K , also known as the order of the model, and the variables included as endogenous. We base the former on the Bayesian information criterion, which is a consistent estimator of lag length (Lütkepohl 1993), and test whether we should add lags to pass diagnostic tests on residual autocorrelation (Franses 2005). Regarding the latter, we include 12 variables as endogenous: sales, price, display, and feature for the focal brand, the private label, and a composite of all national brand competitors in the category (Dekimpe and Hanssens 1999) that is based on their aggregate sales and weighted average price, display, and feature. Compared with separate inclusion of variables for each national brand competitor, our choice saves many degrees of freedom, which is particularly important because we consider between 9 and 25 national brands in each category (in comparison with 3 or 4 brands in extant VAR research).⁴

Based on weekly data intervals, Equation 1 presents our VAR model for each brand i :

$$(1) \quad Y_{i,t} = C_{i,t} + \sum_{k=1}^K B(k)_i \times Y_{i,t-k} + U_{i,t},$$

where $Y_{i,t}$ is the (12×1) vector of endogenous variables (sales, price, display, and feature for the focal brand, the private label, and a composite of the competing national brands), $C_{i,t}$ is the (12×1) vector of exogenous variables, $B(k)$ is the (12×12) coefficient matrix for lag k , and $U_{i,t} \sim N(0, \Sigma_u)$. Contemporaneous (same-week) effects are of two kinds. First, the vector of exogenous variables C controls for an intercept α ; a deterministic-trend variable t captures the impact of omitted, gradually changing variables; and 12 seasonal dummy variables represent each four-week period

³If a structural break is detected, we follow Bai's (2000) procedure to estimate a VAR with structural break.

⁴With our proposed model, we need only 12 beta coefficients per lag for each equation. Because lag selected is less than or equal to 3, our parameter-to-observation ratio is less than or equal to 12.5% (i.e., 12×3 beta coefficients, 1 intercept, 1 trend coefficient, and 12 seasonal dummy coefficients = 50 parameters, divided by 399 weeks of observations). In contrast, using all 25 national brands (plus the private label) requires $26 \times 4 = 104$ beta coefficients per lag for each equation.

in the year, using the first four weeks as our benchmark (Nijs et al. 2001; Srinivasan et al. 2004). Second, we estimate the immediate effects of the brand's and competitive marketing promotions on sales through the residual covariance matrix using the generalized impulse response approach (Dekimpe and Hanssens 1999).

Note that this VAR model allows for competitive reaction. In other words, if a marketing promotion engenders both strong consumer response and strong competitive reaction, the latter is included in the net long-term effect of that marketing promotion. Recent research focusing on competition reveals that the impact of such competitive response is little, if any, for fast-moving consumer goods (Pauwels 2004, 2007) and is as likely to be positive as negative (Steenkamp, Hanssens, and Dekimpe 2005). By modeling composite competitive response (rather than the response of each competitor separately), we give up only the opportunity to distinguish which competitors are most affected by the focal brand's marketing promotion and which competitors, in turn, most affect the focal brand's performance. These distinctions are not the focus of this article.

For each VAR model, we estimate sales and marketing promotions in log form (obtaining long-term elasticities). Sales elasticities are the reported output of most previous models, including disaggregate choice models (e.g., Gupta 1988) and persistence models (e.g., Pauwels, Hanssens, and Siddarth 2002). As a validation (see our subsequent discussion), we also estimate the model in levels to obtain unit sales effects.

Long-Term Impact of Marketing Actions: Impulse Response Functions

The VAR model estimates the baseline of each endogenous variable and forecasts its future values on the basis of the dynamic interactions of all jointly endogenous variables. Based on the VAR coefficients, impulse response functions track the over-time impact of unexpected changes (shocks) to the marketing variables on forecast deviations from the baseline.

To derive the impulse response functions of a marketing promotion on sales, we compute two forecasts, one based on an information set without the marketing promotion and one based on an extended information set that accounts for the marketing promotion. The difference between these forecasts measures the incremental effect of the marketing promotion. Importantly, these dynamic effects are not restricted a priori in time, sign, or magnitude. Moreover, immediate (same-week) effects are estimated with the generalized, simultaneous-shocking approach (Pesaran and Shin 1998), which does not require the researcher to impose a causal ordering among the endogenous variables (Dekimpe and Hanssens 1999). Finally, we follow established practice in marketing research and assess the statistical significance of each impulse response value by applying a one-standard-error band (see Pesaran, Pierse, and Lee 1993; Sims and Zha 1999). Our interpretation of the estimated effects follows the work of Pauwels, Hanssens, and Siddarth (2002): Permanent effects occur when the impulse response function stabilizes at a different level than baseline sales, whereas cumulative effects are obtained by summing all significant impulse response coefficients until the function stabilizes—either at the permanent effect or at baseline sales (permanent effect = 0).

Sequential Hierarchical Regression

In our final step, we regress the estimated permanent and cumulative sales elasticities on brand equity, new product introductions, and other potential drivers to test our hypotheses. We use sequential hierarchical regression because (1) our analysis involves nested data (weekly scanner data for the calculation of long-term promotional effects are regressed on aggregate brand measures) and (2) brand equity, or revenue premium, is itself a function of variables such as market share. We decided against the alternative of instrumental variables regression given the lack of strong instruments (i.e., variables that a priori should affect either brand revenue premium or long-term promotional effects, but not both). Substituting the proposed elasticity drivers directly into Equation 1 (simultaneous estimation) is not only infeasible, because the elasticity estimates are derived from impulse response functions, which are a complex function of the VAR coefficients (Nijs et al. 2001; Srinivasan et al. 2004), but also inconsistent with our aim to estimate permanent elasticities and assess their drivers without imposing an elasticity structure (Assmus, Farley, and Lehmann 1984; Bolton 1989).

We first regress each brand i 's revenue premium (RP_i) on several potential drivers to obtain a residual that is exogenous of product line breadth, market share, price, and promotional activity:

$$(2) \quad RP_i = c_i + \gamma_1(PLB_i) + \gamma_2(Share_i) + \gamma_3(P_i) + \gamma_4(PF_i) \\ + \gamma_5(PD_i) + \gamma_6(Disp_i) + \gamma_7(Feat_i) + \gamma_k Z_k + \varepsilon_i,$$

where PLB refers to product line breadth of brand i , Share refers to its market share, P refers to its regular price (highest price in the data period), PF refers to its price promotional frequency, PD refers to its average price promotional depth, $Disp$ and $Feat$ refer to its display and feature activity, and Z refers to category dummies. Equation 2 yields a residual that, by construction, is orthogonal to RP that includes marketing activity variables, and thus it isolates current brand value not explained by such activity. In the absence of publicly available consumer mind-set metrics for the wide range of brands we analyze, we believe that this residual offers a single-number measure of brand equity that implicitly captures the aggregate consumer mind-set associated with the brand related to general associations, familiarity, liking, and perceived quality and is based on readily available data across brands and categories.

Having obtained ε_i from Equation 2 as the measure of brand equity ($EQUITY_i$), we assess our hypotheses using the weighted least squares regression in Equation 3, in which the long-term effect estimates are weighted by the inverse of their standard errors (Nijs et al. 2001; Srinivasan et al. 2004):

$$(3) \quad LTE_{ij} = \alpha_{ij} + \beta_{1j}(EQUITY_i) + \beta_{2j}(NPI_i) \\ + \beta_{3j}(EQUITY_i \times NPI_i) + \beta_{gj}X_{gi} + \beta_{kj}Z_k + v_{ij},$$

where LTE are the long-term elasticity estimates for each of the j marketing promotions (display, feature, price promotion), NPI refers to new product introductions, and X_g is the matrix of brand- and firm-level control variables.

Validation

We assess the validity of our results in two ways. First, we investigate the out-of-sample forecasting accuracy of the proposed VAR model in Equation 1. To this end, we estimate the models only on the first years of data, using the last year as a holdout sample to calculate their forecasting accuracy in one-step-ahead (static) forecasts.⁵

Second, our substantive results on the impact of brand equity and new product introductions (Equation 3) are based on long-term sales elasticities. Although these have the advantage of comparability across settings, managers may care more about unit effects (Sethuraman and Srinivasan 2002; Sethuraman, Srinivasan, and Kim 1999; Van Heerde, Gupta, and Wittink 2003). This is likely the case for retailers that need to decide which brand to promote, display, and feature (Pauwels 2007). Likewise, manufacturers of several brands may look for the biggest bang for their buck in unit sales effects and thus will prefer to push a (larger) brand with higher unit effects of promotions rather than a (smaller) brand with higher promotional elasticity. To calculate unit effects, we estimate the VAR models in levels instead of logs. The resultant impulse response functions now yield the unit effects of promotions, which become the dependent variables in Equation 3.

Data Description

Our data set is constructed from several sources. We use scanner panel data from the Dominick's Finer Foods project at University of Chicago's Kilts Center, which we supplement with data from the COMPUSTAT database and company Web sites. The scanner panel data are for Dominick's Finer Foods, one of the two largest supermarket chains in the Chicago area. The relevant variables include unit sales, retail prices, and feature ("price special") and display ("bonus buy") activity at the stockkeeping unit (SKU) level. Sales are aggregated and marketing variables are averaged from the SKU to the brand level using the standard practice (e.g., Pauwels, Hanssens, and Siddarth 2002) of adopting constant weights rather than varying (current-period) weights to compute the weighted prices. All price data are appropriately deflated using the Consumer Price Index. The data period runs from September 1989 through May 1997.⁶

We investigate the effects of display, feature advertising, and price promotions for 100 brands across seven product categories. Following previous VAR literature, we operationalize a price promotion as a negative price shock (Dekimpe, Hanssens, and Silva-Risso 1999; Nijs et al. 2001; Pauwels, Hanssens, and Siddarth 2002; Srinivasan et al. 2004). We operationalize the feature and display variables as the sales-weighted percentage of SKUs of a brand that are featured/displayed in a given week. We then

⁵We estimate the models for all brands with the last three years of data available, because it is standard practice in econometrics to use one-third of the data as a holdout sample (e.g., Banerjee, Lumsdaine, and Stock 1992; Swanson and White 1997).

⁶Any selection effect is minimal because our sample includes all brands that appeared in the category for at least one year (not necessarily the full seven years). Thus, we exclude only brands that were in the category for less than a year because it would yield insufficient observations for unit root tests and model estimation.

transform these [0, 1] variables into continuous positive variables by the Cox transformation = $x/1 - x$.

Our selection of product categories is based on several criteria. First, the category needs to have a private-label offering because its revenue is subtracted from a national brand's revenue to obtain brand revenue premium (Ailawadi, Lehmann, and Neslin 2003). Second, the category needs to include several small brands to offer sufficient variation in our brand-specific measures. This also enables us to address a gap in previous literature, in which, empirically, all previous VAR models focus on large brands (i.e., the top three or four brands in a category). Third, because promotional elasticities may differ across categories (e.g., Narasimhan, Neslin, and Sen 1996), we select both food and nonfood categories and categories that differ in product size (because larger or bulky products are more difficult to store) and perishability. Finally, we searched for categories that included numerous brands that were owned by publicly traded firms for access to firm- and brand-specific data.⁷ Our seven product categories include bottled juice, toothpaste, laundry detergent, cheese, soft drinks, paper towel, and toilet tissue. Table 2 displays the names and range in market share for the 100 brands in these categories. Note that by examining nearly all brands in each category, the variance in brand size is dramatic and thus enables us to capture the long-term sales returns of promotions for much smaller brands.

Brand-specific measures derived from scanner panel data include brand equity, new product introductions, brand

market share, and product line breadth. As we described previously, our measure of brand equity is based on the brand's revenue premium. We measure revenue premium (RP) for each brand i as the revenue premium that accrues to brand i compared with private label pl in the product category, using the method that Ailawadi, Lehmann, and Neslin (2003) prescribe:

$$(4) \quad RP_i = (\text{Volume}_i \times \text{Price}_i) - (\text{Volume}_{pl} \times \text{Price}_{pl}).$$

This measure captures the brand's performance in the marketplace through both the price premium and the sales volume it commands, encompassing product-market outcomes that define a brand's equity. Importantly, although price premium is one measure of brand performance, brands can enact a value-conscious strategy and therefore boast high equity without commanding a price premium. At the same time, a brand with high sales volume may not enjoy high equity if it follows a strategy of directly competing with private-label offerings. As a result, revenue premium offers an objective and diagnostic measure of brand equity that reflects a more complete perspective of a brand's performance in the marketplace and the culmination of the various mechanisms by which a brand name adds value (Ailawadi, Lehmann, and Neslin 2003). Our measure of brand equity (EQUITY) then reflects the residual obtained from Equation 2 to isolate brand value not accounted for by current marketing activity. Although this sequential approach may not fully solve endogeneity concerns with respect to the effect of market share on revenue premium, it alleviates the potential concern that our results may be driven by a market share effect rather than by a brand equity effect.

New product introductions (NPI) refer to the total number of new SKUs the brand introduced. Following Pauwels's (2004) procedure, we identified a new product introduction as the data set inclusion of a new SKU that

Table 2
OVERVIEW OF ANALYZED BRANDS AND RANGE OF MARKET SHARE

<i>Category</i>	<i>Analyzed Brands</i>	<i>Number of Brands</i>	<i>Market Share Range</i>
Bottled juice	All Sport, Del Monte, Gatorade, Hawaiian Punch, Hi-C, Juicy Juice, Minute Maid, Mott's, Northland, Ocean Spray, POWERade, Seneca, Speas Farm, Tree Top, Tropicana, V8, Veryfine, Welch's	18	.1%–27%
Toothpaste	Aim, Aquafresh, Arm & Hammer, Close-Up, Colgate, Crest, Mentadent, Pepsodent, Rembrandt, Topol, Ultra Brite, Viadent	12	.2%–31%
Laundry detergent	Ajax, All, Cheer, Dreft, Dynamo, Era, Fab, Fresh Start, Oxydol, Purex, Surf, Tide, Wisk	13	1%–40%
Cheese	Borden, County Line, Frigo, Healthy Choice, Kraft, Land O'Lakes, Laughing Cow, Sargento, Stella, Velveeta, Weight Watchers	11	.2%–45%
Soft drinks	7 UP, A&W, Barq's, Canada Dry, Clearly Canadian, Coca-Cola, Crush, Crystal Geyser, Dr Pepper, Fresca, IBC, LaCroix, Mountain Dew, New York Seltzer, Pepsi, Perrier, Royal Crown, Rite, Slice, Snapple, Sprite, Squirt, Sunkist, Tab, Vernors	25	.1%–28%
Paper towel	Bounty, Brawny, Coronet, Gala, Green Forest, Hi-Dri, Job Squad, Kleenex, Mardi Gras, Scott, Sparkle, Viva	12	2%–31%
Toilet tissue	Angel Soft, Charmin, Coronet, Cottonelle, Green Forest, Kleenex, Northern, Scott, White Cloud	9	.3%–25%

⁷The same firm may own several brands within the same category and across categories, yielding the same values for the firm-level variables of these brands. Therefore, the errors in Equation 3 may not be independently distributed. We acknowledge this limitation and call for further research on this matter.

Table 3
VARIABLE OPERATIONALIZATION

Variable	Operationalization	Data Source
Display activity	“Bonus buy” activity at the SKU level, averaged from the SKU to the brand level. Varies continuously between 0 and 1 because it represents sales-weighted percentage of SKUs displayed in a given week (transformed into continuous positive variables by the Cox transformation).	Dominick’s Finer Foods scanner panel database
Feature activity	“Price special” activity at the SKU level, averaged from the SKU to the brand level. Varies continuously between 0 and 1 because it represents sales-weighted percentage of SKUs featured in a given week (transformed into continuous positive variables by the Cox transformation).	Dominick’s Finer Foods scanner panel database
Price promotion	A negative price shock (Dekimpe, Hanssens, and Silva-Risso 1999; Nijs et al. 2001; Pauwels, Hanssens, and Siddarth 2002; Srinivasan et al. 2004).	Dominick’s Finer Foods scanner panel database
Brand equity (EQUITY)	The residual of Equation 2; that is, the regression of brand revenue premium (Ailawadi, Lehmann, and Neslin 2003) on current marketing activity.	Dominick’s Finer Foods scanner panel database
New product introductions (NPI)	The total number of new SKUs that the brand introduced. Stock-out, reentry, and seasonal offerings are not included.	Dominick’s Finer Foods scanner panel database
Product line breadth (PLB)	The total number of SKUs that a brand offers.	Dominick’s Finer Foods scanner panel database
Market share (SHARE)	The proportion of category revenue accounted for by a brand’s revenue.	Dominick’s Finer Foods scanner panel database
Firm size (FEMPL, FSLs)	The number of people employed by the parent firm and the annual sales of the parent firm.	COMPUSTAT

stayed in the market for several months to avoid counting stock-out/reentry situations and seasonal offerings.

With respect to the control variables, we calculate market share (SHARE) as brand revenue divided by category revenue, and we calculate product line breadth (PLB) as the total number of SKUs a brand offers. For the firm-specific factors, we obtain the number of people the firm (FEMPL) employs and parent firm sales (FSLs), and we use the log-transformation of both variables in our analysis. Table 3 provides an overview of the operationalization of our variables.

RESULTS

Brand Sales Evolution

Table 4 shows the results of our unit root tests for all brands, summarized by quartile according to market share. First, note that positive sales evolution is common, occurring in 14% of all brands, compared with less than 5% of cases in which only the top brands are considered (Nijs et al. 2001; Pauwels, Hanssens, and Siddarth 2002). Second, positive sales evolution is more likely for smaller brands; indeed, no brand over 3.1% market share showed positive sales evolution over the full period. Category-specific results (which are available on request) are consistent; the occurrence of positive sales evolution varies from 11% (toilet tissue) to 18% (cheese). These findings are robust to the choice of the unit root test’s null hypothesis and to structural breaks in the data period.

Cumulative and Permanent Marketing Elasticities

After estimation of the VAR models, we calculate the impulse response functions to obtain the cumulative and permanent elasticity of sales to price promotions, feature, and display. Figure 1 illustrates these functions for price

promotions by the V8 and Gatorade bottled-juice brands (food product) and the Close-Up and Rembrandt toothpaste brands (storable, nonbulky product).

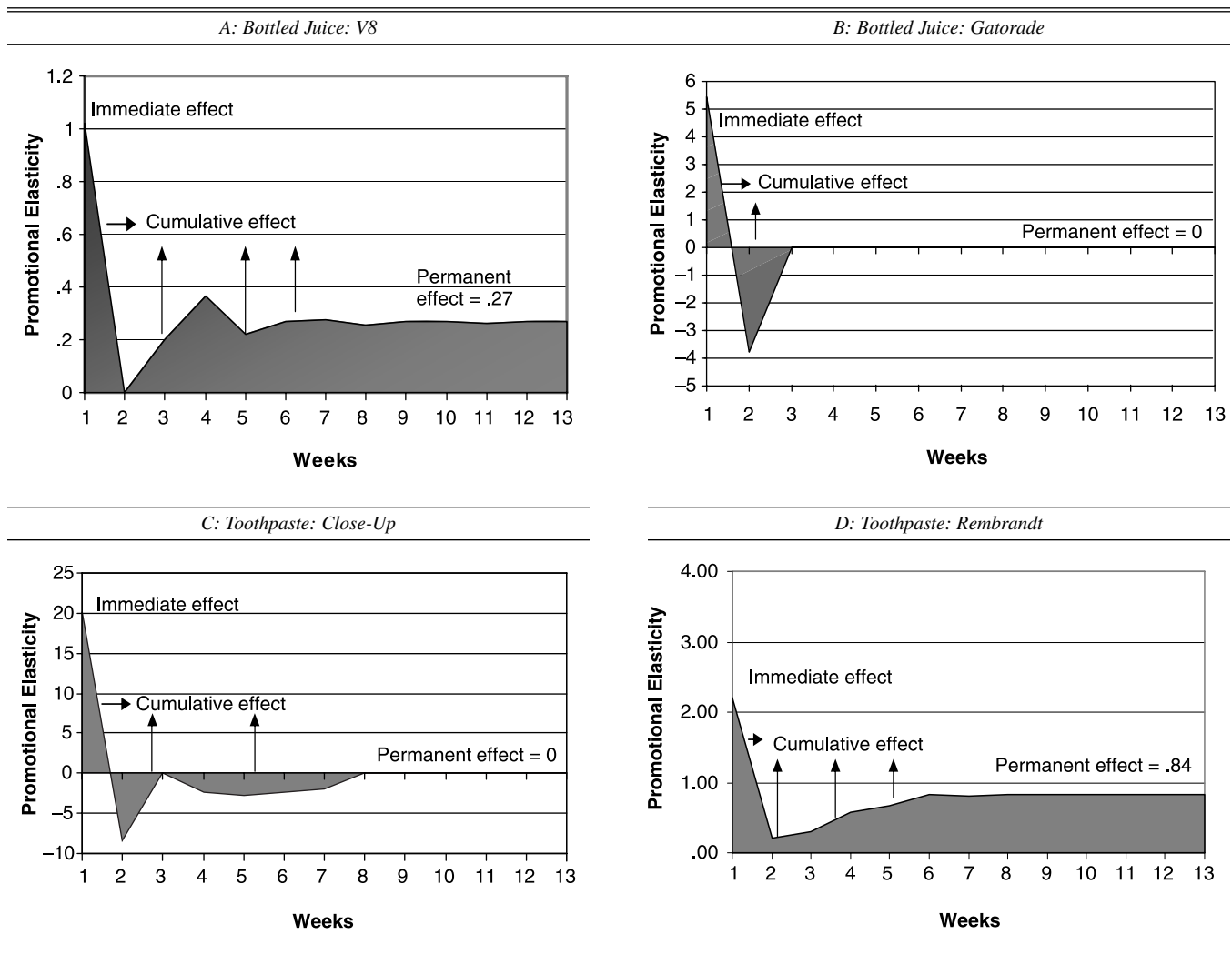
Gatorade and Close-Up, for which the unit root tests show mean-reverting sales, experience strong immediate (same-week) effects of their price promotions. However, the negative postpromotion dip partially cancels this benefit, so the cumulative effect (the shaded area under the curve) is lower than the immediate effect. Both the stronger immediate effect and the longer postpromotion dip for Close-Up likely reflect the product’s stockpiling ease: Consumers find it easy to “forward buy” on a promotion for many weeks to come. However, for both Close-Up and Gatorade, sales revert back to baseline, and there is no permanent impact of the price promotion.

In contrast, V8 and Rembrandt benefit from the virtual absence of postpromotion dips. Instead, positive purchase

Table 4
UNIT ROOT TEST RESULTS, BY MARKET SHARE (MS)
QUARTILE

	Number of Brands	Average Market Share	Positive Sales Evolution?
Large brands (MS ≥ 8%)	25	20%	0 (0%)
Medium-size brands (3% ≤ MS < 8%)	25	5%	1 (4%)
Small brands (1.25% ≤ MS < 3%)	25	2%	7 (28%)
Very small brands (MS < 1.25%)	25	.5%	6 (24%)
All brands	100	7%	14 (14%)

Figure 1
IMPULSE RESPONSE OF PRICE PROMOTION ON SALES



reinforcement adds to positive immediate effects and results in a larger cumulative effect. These two brands also enjoy permanent sales increases; that is, the impulse response function stabilizes at a value greater than 0. Across all brands, the average cumulative and permanent marketing elasticities appear in Table 5.

This study is the first to examine permanent sales elasticities across a wide range of brands, and of interest, they are an order of magnitude lower than the average cumulative elasticities. Still, the relative effectiveness among the marketing promotions remains the same. Price promotions (.06) yield a higher permanent elasticity than feature (.003) and display (.002). Furthermore, the standard deviation around the averages is substantial, providing the variation

for our subsequent analysis on how brand equity and innovation affect these elasticities.

Brand Equity and Innovation as Drivers of Long-Term Promotional Effectiveness

We obtain our estimate of brand equity from regressing brand revenue premium on the explanatory variables, as we specify in Equation 2. The results show that revenue premium is positively related to market share and regular price (which is consistent with its operationalization), but it is negatively related to membership in the paper towel category.⁸ Furthermore, revenue premium is not significantly affected by product line breadth (because of its high correlation with market share) or by promotional activity (display, feature, price promotional depth, and frequency). The latter is consistent with the low correlation of revenue pre-

Table 5

CUMULATIVE AND PERMANENT MARKETING ELASTICITIES

	Display	Feature	Price Promotion
Cumulative (SD)	.06 (.18)	.07 (.15)	.87 (1.88)
Permanent (SD)	.002 (.01)	.003 (.01)	.06 (.19)

⁸We speculate that this may be due to the utilitarian and low-involvement nature of this category, but we leave the examination of this issue to further research.

mium with these promotional variables (also reported in Ailawadi, Lehmann, and Neslin 2003) but with the high correlation of revenue premium with market share and price. As a result, Equation 2 yields nearly identical residuals as a regression of revenue premium on market share, regular price, and category dummies.

With respect to our predictions, Table 6 presents the results of the weighted least squares regression of each long-term elasticity estimate on its potential drivers. All six regressions have adequate fit. The F-statistics are significant, and each model explains between 19% and 27% of the variance in the dependent variable.

First, brand equity appears to be a powerful predictor of the long-term effectiveness of marketing promotions. In particular, in support of H₁, brands with higher equity enjoy higher cumulative and permanent elasticity from their display, feature advertising, and price promotions. For example in the bottled-juice category, Ocean Spray and V8 command strong brand equity, and indeed we find that their promotional efforts yield greater long-term effects than those of the lower-equity brands All Sport and Hawaiian Punch.

Second, new product introductions are another powerful predictor; they positively affect the long-term effectiveness of marketing promotions, in support of H₂. For example, in the toothpaste category, Pepsodent introduced three times fewer new products than Rembrandt and obtained lower long-term elasticities across all three promotional actions. Thus, having something new to say appears to increase the effectiveness of promotional actions. This implication is especially important for low-equity brands because they enjoy higher benefits from new product introductions. Indeed, in support of H₃, the interaction between new product introductions and brand equity is negative and significant for all analyzed promotions.

As for the control variables, we observe that brands with higher product line breadth obtain significantly lower cumulative display and feature elasticities and lower permanent display and price promotion elasticities. This result is in line with recent arguments and findings that SKU pro-

liferation can generate clutter and consumer frustration, thus reducing consumer reaction to marketing (Broniarczyk, Hoyer, and McAlister 1998; Malhotra 1982; Zhang and Krishna 2007). In contrast, market share does not significantly affect long-term elasticities when we control for the other drivers. Likewise, both firm-level variables (employees and sales) fail to significantly explain long-term sales elasticities to marketing promotions. Finally, only a few category dummies are significant. Compared with the bottled-juice benchmark, soft drinks obtain higher cumulative and permanent display elasticities, detergents obtain higher cumulative and permanent feature elasticities, and both cheese and laundry detergent obtain a higher permanent price promotion elasticity. In summary, we find broad support for our hypotheses, and the results are fully consistent for cumulative and permanent elasticities.

Validation: Predictive Validity and Drivers of Long-Term Sales Unit Effects

We assess the predictive validity of the VAR models by computing Theil's inequality coefficient, a scale-invariant measure bounded between 0 and 1 (with 0 indicating perfect fit). This measure ranges from .10 to .19 for the analyzed brands, indicating satisfactory forecasting accuracy. To illustrate, Figure 2 compares the actual and forecasted sales for Pepsodent toothpaste, which shows the median forecasting accuracy (root mean square error = 13.01, Theil's inequality coefficient = .144).

Note that though the VAR model accurately predicts the (promotion-induced) bumps in sales, it tends to underestimate the magnitude of the bump and to overestimate sales around the bump. These characteristics are common in predictive models.

To examine the extent to which our results for elasticities hold up for sales unit effects, Table 7 presents the results of our analysis explaining the unit (absolute) effects of promotions on sales. Overall, the unit effect models have adequate fit. The F-statistics are significant, and each model explains 19%–51% of the variance in the dependent variable. As for our hypotheses, all coefficients are in the predicted direc-

Table 6
BRAND RESOURCES AS DRIVERS OF CUMULATIVE AND PERMANENT MARKETING ELASTICITIES

		<i>Cumulative Display</i>	<i>Cumulative Feature</i>	<i>Cumulative Price</i>	<i>Permanent Display</i>	<i>Permanent Feature</i>	<i>Permanent Price</i>
H ₁ : +	Brand equity (EQUITY)	.0765**	.0810**	.3130**	.0057**	.0076***	.0426*
H ₂ : +	New product introduction (NPI)	.0077***	.0061***	.0023***	.0006***	.0005***	.0009***
H ₃ : -	EQUITY × NPI	-.0138**	-.0157***	-.0468***	-.0009**	-.0010**	-.0267***
	Product line breadth	-.0032**	-.0025**	-.0238	-.0003**	-.0001	-.0031**
	Market share	-.1740	.1317	-.3154	-.0073	.0017	-.2107
	Parent company employees	.0001	-.0000	.0000	.0000	.0000	.0002
	Parent company sales	-.0016	-.0010	-.0139	-.0001	-.0002	-.0042
	Toothpaste	-.0732	.0832	.1861	-.0069	.0047	.0367
	Paper towel	.0856	-.0097	-.9284	.0066	.0001	-.0436
	Cheese	-.0064	-.0123	-.7924	.0029	.0019	.1993**
	Laundry detergent	.0281	.1147**	.9154	.0016	.0101**	.1412*
	Bathroom tissue	-.0216	.0004	-.6514	-.0022	-.0010	-.0259
	Soft drinks	.1686**	-.0202	-.2649	.0136**	.0001	.0322
	Adjusted R ²	.25 (.13)	.27 (.15)	.20 (.12)	.26 (.13)	.24 (.12)	.19 (.06)

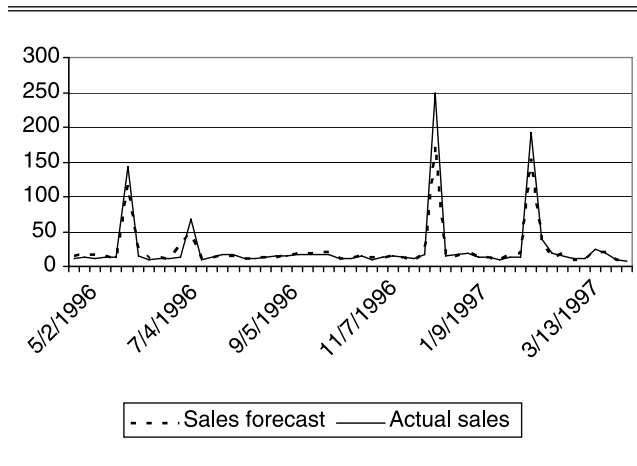
**p* < .10.

***p* < .05.

****p* < .01.

Figure 2

COMPARING THE FORECASTED SALES AND ACTUAL SALES FOR PEPSODENT IN THE LAST YEAR OF DATA



tion and significant at the 5% level. In terms of brand-specific controls, the most notable difference is related to the impact of product line breadth. Although this variable negatively affects long-term elasticities, it does not significantly affect long-term unit effects. We speculate that the lower elasticity for brands with a broad product line is negated by their higher overall ability to satisfy the needs of heterogeneous customers (Quelch and Kenny 1994), leading to higher unit sales (Kekre and Srinivasan 1990). Moreover, high-share brands obtain higher cumulative unit effects of price promotions, consistent with previous arguments on their sales/traffic-drawing power (Bronnenberg and Mahajan 2001; Moorthy 2005). Finally, although soft drinks obtain higher cumulative price effects than the benchmark (bottled juice), both paper towel and toilet tissue stand out as yielding higher unit benefits from promotions.

In summary, the investigation of unit effects to marketing promotions shows convergent support for our hypotheses. Brands with higher equity and more new product introductions obtain higher unit benefits from display, feature, and price promotions, and creating brand value through new product introductions appears to be especially beneficial for low-equity brands.

DISCUSSION

As part of the overall advancement toward understanding the long-term effectiveness of marketing actions, several recent studies have applied the persistence modeling approach to promotional activities for fast-moving consumer goods. Although the research in this domain has offered important insight, the focus on the top three or four brands in a category may have produced a limited perspective. Our research diverges from extant research in that it is the first (1) to generate new insights into the permanent sales effects of promotion efforts by including a more complete set of brands in the category, so that small brands are also incorporated into the analysis, and (2) to offer a systematic investigation of the extent to which brand equity and innovation influence the long-term effectiveness of promotional efforts. Overall, our robust results reinforce the importance of understanding the underlying role of the brand, and consequently our research offers several implications.

How Brands Affect Long-Term Promotional Elasticities

First, our investigation of brands across a broader range in size reveals that marketing promotions can have long-term effects on a brand's sales and that brand equity plays an important role in these effects. Although prior studies have shown that cumulative effects are positive but permanent effects are rare, our examination of 9–25 brands per category demonstrates permanent effects are fairly common. In addition, our results show that brand equity influences both cumulative and permanent promotional effects.

Table 7
BRAND RESOURCES AS DRIVERS OF CUMULATIVE AND PERMANENT MARKETING SALES UNIT EFFECTS

	Cumulative Display	Cumulative Feature	Cumulative Price	Permanent Display	Permanent Feature	Permanent Price
Brand equity (EQUITY)	1.700**	16.000**	510.000***	.375**	.373**	59.700***
New product introduction (NPI)	.520***	.827**	2.171***	.046***	.037**	.107***
EQUITY × NPI	-.252***	-2.510**	-23.400**	-.063***	-.057***	-10.500***
Product line breadth	-.052	.440	50.704	-.010	-.011	-1.819
Market share	30.387	58.312	19,044.240**	-1.139	-1.481	35.990
Parent company employees	.002	-.033	2.644	.001	.001	.257
Parent company sales	-.015	.353	-18.335	-.007	-.006	.000
Toothpaste	-4.448	19.245	-1177.915	-.656	-.080	-83.566
Paper towel	30.019***	106.957***	652.210	.505	1.245*	2.430
Cheese	1.816	7.101	-1040.604	-.000	.830	53.963
Laundry detergent	-.972	-2.768	-765.597	.012	.089	-52.621
Bathroom tissue	14.382**	77.323***	6712.793***	-.202	.027	-42.879
Soft drinks	6.548	-18.999	2629.911*	.858**	.309	59.236
Adjusted R ²	.51 (.43)	.40 (.29)	.40 (.30)	.27 (.15)	.19 (.06)	.19 (.06)

*p < .10.
**p < .05.
***p < .01.

In particular, our analysis of brands with different equity sheds new light on the role of the brand on long-term effectiveness of different promotional efforts. Extending beyond the usual distinction between national brands and private labels, we empirically measure the degree of brand equity and find that it has a significant, positive effect on the extent to which a brand generates long-term effects from promotional efforts. This supplements extant research that shows that brands with higher equity capture higher immediate returns to marketing efforts (Slotegraaf, Moorman, and Inman 2003). Moreover, our results complement findings on lower consumer sensitivity to price increases for high-equity brands. For example, whereas Eastlack and Rao (1986) demonstrate that the V8 brand did not suffer a long-term drop in sales after a price increase, our results show that its price promotions can permanently increase sales. We believe that this asymmetry in long-term sales effects for price increases versus decreases is an important but underresearched benefit of brand equity.

However, there appear to be ceiling effects associated with strong brand equity. In particular, our results show that lower-equity brands obtain higher long-term benefits from new product introductions than higher-equity brands. Although higher-equity brands draw more consumers when they promote, they also attain stronger associations (Keller 1993). A large number of brand associations can be a limiting factor (Meyers-Levy 1989), and we find that when actions are taken to communicate something new to consumers, such as new product introductions, the strong associations that are typical for higher-equity brands seem to limit the effect of brand equity on long-term sales. Thus, there appears to be a ceiling on the extent to which high-equity brands can benefit from specific marketing actions, which is an important area for further research.

Second, our results indicate that the introduction of new products can generate fertile ground for long-term effectiveness of marketing promotions, especially when these brands communicate something new to consumers. For example, V8 Splash blended fruit juice, Rembrandt's Low-Abrasion Whitening Toothpaste for Kids, and the uniqueness of Fresh Start's detergent packaging all offered something new to consumers when these products were introduced. Thus, revitalizing a brand through new product introductions can generate long-term effects when the brand is promoted. However, ever-expanding product lines are not the key to success. Taken together, our results suggest that brand managers should carefully monitor the breadth of the brand's product line so that new product introductions can communicate something new to consumers and ill-performing line extensions can be pulled from the market. For example, ConAgra (2005) recently decided to reduce low-volume, low-margin SKUs to reduce complexity and to increase focus on the SKUs that have higher profit potential.

Finally, this article extends current research on the negative impact of brand size on promotional returns (e.g., Fok et al. 2006). Indeed, brands with a shallow product line obtain higher promotional elasticities than brands with a broad product line. In this regard, our findings add a silver lining to the cloud of challenges that come with growing small brands. Not only do such brands face a demand-side "triple jeopardy" because they are purchased by fewer con-

sumers, less often, and with less behavioral loyalty (Fader and Schmittlein 1993), but they also face a supply chain disadvantage because retailers are less likely to pass through and support their manufacturer promotions (Pauwels 2007). Our results suggest that if the retailer passes through promotional efforts, the efforts may facilitate the growth and revitalization of small brands. Our demonstration of such permanent benefits is important for brand managers, who are often strapped for resources and thus need to focus on actions that obtain a larger return for the dollar. For example, Topol toothpaste experiences permanent promotional benefits in our sample. Wansink (1997) discusses how this brand was purchased for \$200,000 in 1973 and was turned into a vital, high-margin brand with \$23 million in sales ten years later.

Current Limitations and Further Research

This study has limitations that yield avenues for further research. First, we examined the long-term effectiveness of marketing efforts by focusing on display, feature advertising, and price promotions, but we could not include other forms of marketing efforts. For example, we were unable to investigate the long-term elasticity of couponing, because many brands in the categories we examined did not show any record of this activity. In addition, we measured brand equity using readily available data across brands of various sizes and categories and across the full period of data. Therefore, we encourage additional research on the role of couponing, advertising, and other marketing efforts, as well as the use of direct measures for brand equity that include consumer mind-set metrics, such as perceived quality, and capture a possible dynamic to the brand equity measure. Second, our data sample is limited to one large retailer in a major U.S. city and to seven product categories of fast-moving consumer goods. Further research could examine other types of products to uncover product-specific, retailer-specific, or manufacturer-specific effects, as well as inter-retailer competition. Third, although our research controls for firm-specific effects, we do not distinguish among different strategic objectives a firm may have for different brands. Examining brands at different stages in their life cycle could offer additional insight into how revitalization efforts for a brand may be affected by different marketing efforts. Analyzing the impact of regular price changes to a brand, rather than price promotions, might also offer valuable insight. Finally, examining the extent to which different marketing investments influence a brand's equity is an important area for further research and could potentially offer insight into whether and which marketing efforts will deplete or build a brand's equity.

In conclusion, this research established that a brand's equity and new product introductions play a significant role in the long-term sales elasticity and unit effects from its marketing promotions. In contrast to extant research, we expanded the scope of investigation to demonstrate that positive sales evolution is common for small brands and that both permanent and cumulative elasticity are driven by brand equity and innovation. Although brand equity is beneficial, brands with lower equity may look to product innovation not just as a growth driver by itself but also as a means to achieve higher long-term sales effectiveness from promotional efforts.

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