GROWING SMALL BRANDS: DOES A BRAND'S EQUITY AND GROWTH POTENTIAL AFFECT ITS LONG-TERM MARKETING PRODUCTIVITY?

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Managers often hope to obtain long-term benefits with temporary marketing actions, especially for brands that are currently small. However, academic research implies their chances are slim: fewer than 5% of marketing actions generate permanent sales effects. Yet extant research has examined brands with similar characteristics, thus implicitly assuming that the brand itself carries no influence over whether its marketing actions attain long-term sales effects. In contrast, recent studies in marketing strategy show that the resources available to a brand influence the returns to its marketing mix actions. Therefore, we argue that brand-specific resources and characteristics will influence the permanent and cumulative effects of their marketing actions.

Using panel data for 7 years from 43 brands in three 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 brand-specific resources. Overall, results indicate that long-term marketing productivity is higher for brands with higher equity and for brands with greater potential for growth (i.e., lower market share, narrower product line, or more new product introductions). These results offer new insight into the potential for long-run marketing effectiveness.

**Keywords:** brand resources, persistence modeling, long-term marketing productivity.
INTRODUCTION

Marketing scholars and practitioners have increasingly become interested in understanding the financial accountability of various marketing actions and expenditures. An alarming concern in both academic and practitioner circles is that a failure to demonstrate the financial contribution 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). While managers strive for improved financial performance, a common criticism is an emphasis on short-term results rather than long-term returns. Accordingly, scholars have begun to explore 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 et al. 2002, 2004).

An empirical generalization from this literature is that temporary marketing actions such as price promotions, feature and display have no permanent sales effects for over 95% of all analyzed brands (Franses et al. 2001; Nijs et al. 2001; Pauwels et al. 2002). Yet much of this research has focused exclusively on the top three or four selling brands in the category (rare exceptions include Bronnenberg et al. 2000 and van Heerde et al. 2004). It is important to note, however, that brands vary in their positional advantage, growth potential and resources available for deployment, and may thus be likely to face different permanent and cumulative effects from their marketing actions. Therefore, rather than succumb to the conclusion that there is little potential for long-run marketing effectiveness, we argue that brand resources and characteristics will influence the permanent and cumulative effects of different marketing actions.

Recent research further substantiates the importance of the brand in generating differential returns to marketing actions. For example, Macé and Neslin (2004) and Bell, Chiang, and Padmanabhan (1999) show that product- or brand-specific characteristics can explain significant variation in promotion elasticities. In addition, Slotegraaf, Moorman, and Inman (2003) show that
brands with higher equity are able to generate higher immediate returns from their marketing mix efforts. Finally, examining the top four selling brands across 25 product categories, Fok et al. (2006) show that brands with higher market share tend to have smaller immediate and cumulative price effectiveness. Overall, this research reinforces our expectation that there is much to be gained from a systematic analysis of the extent to which the brand itself influences the long-term effects from different marketing actions.

In this paper, we examine the extent to which brand-specific resources explain variation in the long-term sales elasticity from display, feature advertising, and price promotions. We focus on a brand’s equity, which can directly enable its competitive advantage (Aaker 1991; Keller 1993), and its growth potential. To foster a broader understanding of the effects due to brand-specific growth potential, we investigate the brand’s market share, product line breadth, and new product introductions as three different avenues of growth. We expect specific limits associated with growth potential, where long-term effects will be less likely to accrue to brands with high market share, a broad product line, or the absence of product innovations. In contrast, we expect brands with higher equity to have established specific strength in the market that generates long-term returns to marketing efforts. Using panel data for 7 years from 43 brands in three 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-specific resources. We explicitly include low-market-share brands in our analysis to capture greater variability in brand-specific resources.

The remainder of this paper is organized as follows. We next provide an overview of the persistence modeling literature and then present our predictions regarding the moderating effects due to brand-specific equity and growth potential. We then describe our dataset and methodology and present our results. We conclude with specific theoretical and managerial implications.
THEORETICAL FRAMEWORK

Previous Studies on Long-term Effects from Marketing Actions

Promotional efforts are recognized as a potent tool for managing brands, with in-store displays, feature advertising, and price promotions key components of a traditional promotional mix (e.g., 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. 2005; Srivastava, Shervani, and Fahey 1998). A long-run 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 et al. 2002). Indeed, even if no single marketing action has the power to permanently change baseline sales, managers may repeat the action to increase sales, which is beneficial as long as the cumulative effect is positive.

Cumulative effects from promotional efforts have been investigated with various methods. Distributed lag response models have shown that promotions increase purchase quantity over time (Ailawadi and Neslin 1998; Jedidi, Mela, and Gupta 1999; Mela, Jedidi, and Bowman 1998). In addition, persistence models and nonparametric models have shown that promotions generate higher cumulative effects on category incidence compared to brand switching (Pauwels et al. 2002, van Heerde et al. 2004). In contrast, permanent effects of promotions are rarely observed. In particular, among the top-selling brands in numerous product categories, fewer than 5% of brands analyzed experience a permanent impact from promotional efforts (Dekimpe et al. 1999; Nijs et al. 2001; Pauwels et al. 2002).

As for cross-brand variation of promotion effects, previous studies have analyzed moderating factors such as national versus private brands (Dekimpe et al. 1999; Pauwels et al. 2002), brand market share (Fok et al. 2006; Kopalle et al. 1999; Macé and Neslin 2004) and promotional depth
and frequency (Srinivasan et al. 2004). However, research has yet to consider brand-specific resources such as brand equity, product line breadth, and new product introductions. Moreover, given the virtual absence of permanent effects for top-selling brands, no study has analyzed the cross-brand variation in permanent promotional effects. Therefore, this paper aims to offer a systematic investigation of whether a specific brand’s characteristics influence the extent to which it exhibits permanent and cumulative effects from its marketing actions. As we expect the same directional results for both types of long-term effects, we formulate the hypotheses as such below.

**Brand Equity**

A brand is a key market-based asset of a firm (Srivastava et al. 1998); an asset that is difficult for others to imitate or substitute and offers a fundamental source of competitive advantage (e.g., Barney 1991). From a resource-based view (RBV) perspective, resources that are valuable, rare and imperfectly mobile provide positional advantages that enable a sustainable competitive advantage (Barney 1991; Wernerfelt 1984). With respect to the underlying value of a brand, higher equity brands generate higher market outcomes, such as revenue premium, than similar products without a strong brand name (Ailawadi, Neslin, and Lehmann 2003). As argued below, we also expect high equity brands to attain greater long-term impact from their display, feature and price promotion efforts.

Brand equity theory purports that consumers react differently to marketing mix efforts for a branded product in comparison to 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, in comparison to that for private labels, lead to greater purchase intentions (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 2006), sometimes even permanently (Dekimpe et al. 1999). Of course, such broad comparisons between national brands and private labels can mask specific effects due to different levels of brand equity of the national brands.

When a brand has stronger equity, consumers hold more favorable, powerful, and unique associations and more highly established familiarity with the brand (Keller 1993). This enables greater recognition and fosters brand choice, such that consumers react more to point-of-purchase activity for familiar brands (Alba et al. 1991). Higher-price, high quality brands also tend to draw more consumers when they promote (Blattberg and Wisniewski 1989). Moreover, exposure to high equity brands through visual means, such as displays or feature advertisements, can also enhance the brand’s competitive advantage (Alba et al. 1991), and offer the potential for long-term returns from promotional efforts for high equity brands. We therefore expect that:

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

**Growth Potential for the Brand**

The above arguments suggest a challenge for brands with low equity. However, long-term sales effects of marketing actions are also likely to depend on the brand’s potential for growth. In particular, brands with higher growth potential are likely to have more fertile conditions for long-term marketing effects, especially from promotional efforts that bring the brand to the consumer’s attention. We therefore formulate hypotheses regarding the influence of brand market share, product line breadth, and new product introductions to examine the extent to which a brand’s growth potential impacts the long-term returns from its marketing actions.

**Brand Market Share**

Brand market share represents a logical limit for long-term marketing effects. As a brand captures a higher percentage of the market, its opportunity for growth through in-store promotions
becomes more limited, according to the ‘market development index’ (Best 2005) and ‘hierarchy of effects’ model (Lavidge and Steiner 1961). Each step up the ladder moves the consumer closer to purchase, so if many consumers are already buying the brand, then there is little room for in-store promotions to create long-term effects. As such, large established brands utilize in-store promotions for an immediate sales boost (Blattberg and Neslin 1990) without expectations of fundamentally changing customer purchase habits (Ehrenberg 1988). Correspondingly, higher share brands have been shown to incur greater post-promotions dips (Macé and Neslin 2004) and lower cumulative price effects on sales (Fok et al. 2006).

In contrast, in-store promotions for small brands may bring them to the attention of shoppers, generate trial (or otherwise help them move a step further up the hierarchy ladder) and thus may improve sales in the long run. Such benefits are permanent if the promotion induces purchase by previous non-buyers, and at least some of them continue to buy the brand even off-promotion (Pauwels et al. 2002). Alternatively, the promotion has to be repeated to again induce purchase by such shoppers, and thus manifests itself as a cumulative effect. In any case, smaller brands have more room to grow than larger brands, so that marketing efforts for smaller brands are more likely to generate permanent and cumulative effects.

**H2**: Brands with lower market share have a higher long-term sales elasticity from their (a) display, (b) feature advertising, and (c) price promotion efforts than brands with higher market share.

**Product Line Breadth**

Broader product lines are often argued as necessary to better satisfy the needs of heterogeneous customers (e.g., Kotler 1986; Quelch and Kenny 1994) and can result in higher overall market share for a firm (Kekre and Srinivasan 1990). However, as a brand offers more line extensions, its opportunity for growth becomes limited, as it must balance maximizing market
coverage with minimizing product overlap (Keller 2003). Indeed, Morgan and Rego (2006) report that Other conceptual arguments and empirical findings also suggest a negative effect of product line breadth on the long-term effects of marketing actions.

In particular, a broad product line creates more competition for consumers’ attention, can generate clutter, and becomes more taxing or frustrating to consumers. Broader product lines may also confuse consumers and weaken product choice (Malhotra 1982). Broniarczyk, Hoyer, and McAlister (1998) show that consumers find it more difficult to shop in stores where there are broad product lines. In addition, Zhang and Krishna (2005) show that a reduction in the number of a brand’s stock-keeping units (SKUs) can actually increase consumer choice for the brand. Although promotional efforts may attempt to cut through the competitive clutter, these efforts may further increase the demand on consumers’ cognitive resources and produce negative long-term effects. Indeed, Narasimhan, Neslin, and Sen (1996) as well as Srinivasan et al. (2004) show that promotions are less effective in categories with a large number of brands. When faced with numerous choices, consumers are likely to become overwhelmed, so that the long-term effectiveness of promotions is lower for brands with broader product lines.

**H3:** Brands with a broader product line generate a lower long-term sales elasticity from (a) display, (b) feature advertising, and (c) price promotion efforts than brands with a narrower product line.

**New Product Introductions**

The introduction of new products is an avenue by which brands are able to recognize growth. In contrast to product line breadth, a product introduction tends to signal something new to the market. When brands have something new to say, consumers are more likely to pay attention to their communication efforts, as has been demonstrated for TV advertising (e.g. Lodish et al. 1995). We expect similar effects for display, feature advertising and price promotions. In
particular, when a brand introduces new products, the visibility generated for the brand complements the visibility generated by the promotional efforts, similar to the complementarity effects demonstrated between value creation and value appropriation (Mizik and Jacobson 2003; Moorman and Slotegraaf 1999). This complementary effect should further facilitate the long-term effects of marketing actions.

Furthermore, the long-term returns from promotional efforts are likely to be higher for new product introductions to the extent that buying a new product is risky and promotions offer a risk premium for trial (Blattberg and Neslin 1990). Again, if the new product better satisfies the desires of specific consumers, they will repurchase it (Kalyanaram and Urban 1992) and thus generate long-term benefits to the brand. We therefore predict the following:

\[ H_4: \] Brands with more new product introductions generate a higher long-term sales elasticity from (a) display, (b) feature advertising, and (c) price promotion efforts.

Given that new product introductions offer a means for growth, should we assume that this growth potential yields the same benefits to brands with different equity? We expect that there will be a difference, such that managers of low-equity brands could utilize new product introductions as a way to improve long-term promotional effectiveness. More directly, we expect new product introductions for brands with lower equity to generate greater long-term effects from promotional efforts than new product introductions for brands with higher equity. The logic behind this expectation stems from the awareness generated from new product introductions. 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 that new product introductions remain beneficial, but to a lesser extent. In other
words, the awareness generated by promotional efforts combined with new product introductions will attenuate at a greater rate for brands with high equity than for brands with low equity.

\textbf{H}_5: \hspace{0.5cm} \text{Regarding long-term promotional elasticity, a negative interaction exists between brand equity and new product introductions: lower equity brands with more 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 more new product introductions.}

\textbf{METHODOLOGY AND DATA DESCRIPTION}

The persistence modeling framework (Dekimpe and Hanssens 1995) consists of several methodological steps, summarized in Table 1. First, we examine the time series properties for all variables to establish whether temporary marketing actions may have permanent effects on sales. Based on these times series properties, we formulate models of the dynamic interactions between sales, brand marketing and competitive marketing actions for each brand and each year. Next, we use the estimated coefficients to simulate the over-time impact of a marketing action on sales, known as the impulse response function, which allows us to quantify the cumulative and permanent sales elasticity of marketing actions. Finally, we assess our hypotheses by relating these estimated effects to brand resources in a fixed effects panel weighted-least squares regression. We explain each step in detail below.

\textbf{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 in Enders (2004) and the Kwiatkowski-Phillips-Schmidt-Shin test (1992). The former maintains evolution as the null hypothesis (and is the most popular in marketing applications), while the latter maintains stationarity as the null
hypothesis. Each test is estimated in two forms: with and without a deterministic time trend. Convergent conclusions of these different tests yield higher confidence in our variable classification (Maddala and Kim 1998). Finally, the cointegration test of Johansen (1991) verifies whether any combination of evolving variables is in long-run equilibrium.

**Modeling Dynamic Interactions: VARX Models**

Second, we specify vector-autoregressive (VARX) models that are well suited to measure 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.

VARX 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). 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 (BIC), 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). As to the latter, we include 8 variables as endogenous: sales, price, display and feature for (1) the focal brand and (2) a composite of all competitors in the category (Dekimpe and Hanssens 1999); i.e., their aggregate sales (CSales), and weighted average price (CPrice), display (CDisp) and feature (CFeat), using the previous year sales as weights (see equation 1). Compared to separate inclusion of variables for each competitor, our choice saves many degrees of freedom, which is particularly important as we consider at least 12 brands in each category (in comparison to 3 or 4 brands in extant VARX papers).
Based on weekly data intervals, equation 1 presents our VARX-model for each brand and each year:

\[
\begin{bmatrix}
  Sales_{i,t} \\
  CSales_{i,t} \\
  Price_{i,t} \\
  CPrice_{i,t} \\
  Disp_{i,t} \\
  CDisp_{i,t} \\
  Feat_{i,t} \\
  CFeat_{i,t}
\end{bmatrix} =
\begin{bmatrix}
  \alpha + \delta \cdot t + \sum \lambda \cdot SD_i \\
  \alpha \cdot CS\cdot Sales + \delta \cdot t + \sum \lambda \cdot CS\cdot SD_i \\
  \alpha \cdot Price + \delta \cdot t + \sum \lambda \cdot Price\cdot SD_i \\
  \alpha \cdot CPrice + \delta \cdot t + \sum \lambda \cdot CPrice\cdot SD_i \\
  \alpha \cdot Disp + \delta \cdot t + \sum \lambda \cdot Disp\cdot SD_i \\
  \alpha \cdot CDisp + \delta \cdot t + \sum \lambda \cdot CDisp\cdot SD_i \\
  \alpha \cdot Feat + \delta \cdot t + \sum \lambda \cdot Feat\cdot SD_i \\
  \alpha \cdot CFeat + \delta \cdot t + \sum \lambda \cdot CFeat\cdot SD_i
\end{bmatrix} + \sum_{k=1}^{T-1} \begin{bmatrix}
  \beta^k_{1,1} & \ldots & \beta^k_{1,T} \\
  \beta^k_{2,1} & \ldots & \beta^k_{2,T} \\
  \vdots & \ddots & \vdots \\
  \beta^k_{T-1,1} & \ldots & \beta^k_{T-1,T}
\end{bmatrix} \begin{bmatrix}
  Sales_{i,t-k} \\
  CSales_{i,t-k} \\
  Price_{i,t-k} \\
  CPrice_{i,t-k} \\
  Disp_{i,t-k} \\
  CDisp_{i,t-k} \\
  Feat_{i,t-k} \\
  CFeat_{i,t-k}
\end{bmatrix} + \begin{bmatrix}
  u_{Si,t} \\
  u_{CSi,t} \\
  u_{Pi,t} \\
  u_{CPi,t} \\
  u_{Di,t} \\
  u_{CDi,t} \\
  u_{Fi,t} \\
  u_{CFi,t}
\end{bmatrix}
\]

with \([u_{Si,t},...,u_{CFi,t}]' \sim N(0,\Sigma_u)\). Contemporaneous (same-week) effects are of two kinds. First, the vector of exogenous variables controls for (i) an intercept \(\alpha\), (ii) a deterministic-trend variable \(t\), to capture the impact of omitted, gradually changing variables, and (iii) 12 seasonal dummy variables \((SD)\) for each 4-week period in the year, using the first 4 weeks as our benchmark. Second, we estimate the immediate effects of the brand’s and competitive marketing actions on sales through the residual covariance matrix using the generalized impulse response approach (Dekimpe and Hanssens 1999).

In a departure from previous persistence modeling papers, we estimate the VARX model for each calendar year. Our rationale is four-fold. First, brand resources and long-term marketing elasticities are likely to change over the full data period of 7 years, as has been demonstrated for the latter by split-sample analyses in Srinivasan et al. (2004) and Pauwels (2006). Second, we study several smaller brands that were only available for 2-3 years. Besides data availability issues, we do not want to base the second-stage estimates for different brands on different time periods. For instance, comparisons of long-term effects between brands available for 7 years to those available for 2 years could be biased: the latter may be higher simply because consumers have become more sensitive to promotions over time (e.g., Kopalle et al. 1998, Srinivasan et al.)
Third, long-term estimates per year increase degrees of freedom for the second-stage analysis and allow us to perform a fixed effects panel model which controls for year-specific changes in the environment, such as the expected growing consumer promotional sensitivity. Fourth, our choice of one calendar year reflects (1) the managerial reality that performance evaluation is typically based on calendar year periods, (2) the researcher reality that much of the brand- and firm-specific resource data are available at the annual but not the weekly level, and (3) the statistical reality that one calendar year covers the full seasonal cycle for fast moving consumer goods and has enough weekly data points for unit root test and model estimation.

For each VARX-model, we estimate sales and marketing variables in log form (obtaining long-term elasticities); marketing elasticities\(^1\) are the reported output of virtually all previous models, including disaggregate choice models (e.g. Gupta 1988) and persistence models (e.g. Pauwels et al. 2002).

**Long-Run Impact of Marketing Actions: Impulse-Response Functions**

The VARX model estimates the baseline of each endogenous variable and forecasts its future values based on the dynamic interactions of all jointly endogenous variables. Based on the VARX 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 action on sales, we compute two forecasts, one based on an information set without the marketing action and the other based on an extended information set that accounts for the marketing action. The difference between these forecasts measures the incremental effect of the marketing action. Importantly, these dynamic effects are not a priori restricted in time, sign, or magnitude. Moreover, immediate (same-week) effects are estimated with the generalized, simultaneous-shocking approach (Pesaran and Shin

\(^1\) We also estimate the model in levels to examine whether our results hold up for long-term unit sales effects.
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, as motivated in Pesaran, Pierse, and Lee (1993) and Sims and Zha (1999).

Our interpretation of the estimated effects follows Pauwels et al. (2002): permanent effects occur when the impulse response function stabilizes at a different level than baseline sales, while 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).

**Second-stage Analysis: Fixed effects panel model with weighted least squares regression**

From the estimates of cumulative and permanent marketing elasticities obtained in the first stage, we assess our hypotheses by examining how these estimates are affected by brand-specific characteristics in a second-stage analysis (Nijs et al. 2001; Srinivasan et al. 2004). We weigh the long-term effect estimates by the inverse of their standard errors in a weighted-least squares regression (ibid.). We also account for the fact that errors may be correlated across regressions for the same year by estimating a fixed-effects model that also yields year-specific effect estimates on long-term promotional effectiveness. In particular, we apply the fixed effect panel model proposed by Davis (2002) for estimating multi-error components models with unbalanced data (as not all years are available for all brands). Incorporating brand-fixed effects is infeasible given that some brands are only available for one year and given the high correlation of such fixed effects with brand-specific resources. Instead, we incorporate category dummies to account for cross-category variation in long-term promotional effectiveness. Finally, we want to avoid potential endogeneity/reverse causality issues with respect to our research hypotheses. For instance, increased long-term promotional effectiveness may increase brand market share and brand equity (rather than the reverse, as implied by our hypotheses) within the year of analysis. Therefore, we
lag all brand measures by one year, regressing for brand $i$ in year $t$, the estimated long-term marketing elasticity $j$ on the prior year’s brand characteristics\(^2\), as specified in equation (2):

$$ELAS_{ijt} = \alpha_{ijt} + \beta_1 \text{EQUITY}_{i,t-1} + \beta_2 \text{SHARE}_{i,t-1} + \beta_3 \text{PLB}_{i,t-1} + \beta_4 \text{NPI}_{i,t-1} + \beta_5 \text{EQUITY}_{i,t-1} \times \text{SHARE}_{i,t-1} + \beta_6 \text{BLOY}_{i,t-1} + \beta_7 \text{FEMPL}_{i,t-1} + \beta_8 \text{FSLS}_{i,t-1} + \beta_9 \text{Juice} + \beta_{10} \text{Detergent} + \beta_{11} \text{Year} + \epsilon_{ijt}$$  \hspace{1cm} (2)

with focal variables brand equity (EQUITY), brand market share (SHARE), product line breadth (PLB) and new product introductions (NPI); control variables brand loyalty (BLOY), number of individuals employed by the firm (FEMPL), parent company sales (FSLS) and category dummy variables as detailed in the next section.

**Data Description**

Our dataset is constructed from several sources. First, we utilize scanner panel data from the Dominick’s Finer Foods project at University of Chicago’s Kilts Center, which we supplement with data from Information Resources, Inc. (IRI), the Compustat database, and company websites. 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 SKU level. Sales are aggregated and marketing variables averaged from the SKU to the brand level using the standard practice (e.g. Pauwels et al. 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, so we estimate VARX models for the calendar years 1990-1996.

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\(^2\) We regress 1990 long-term elasticities on SHARE, PLB and NPI derived from the last quarter of 1989 since data to construct these measures was unavailable before September 1989 (all other measures rely on the full-year 1989 data).
To generate empirical generalizations, we investigate the effects of display, feature advertising, and price promotions\(^3\) for 43 brands across three product categories. Our selection of product categories is based on several criteria. First, 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, where empirically all previous VARX-models focus on large brands (i.e., the top three or four brands in a category). Second, because promotional elasticities may differ across categories (e.g., Narasimhan et al. 1996), we select both food and non-food categories as well as categories that differ in product size (since larger or bulky products are more difficult to store). Third, we searched for categories that included numerous brands that were owned by publicly traded firms for access to firm and brand-specific data. Our three product categories are bottled juice, toothpaste, and laundry detergent.

Table 2 displays the names and range in market shares for the 43 brands in these categories. It is important to note that by examining at least 12 brands in each category, the variance in brand size is quite dramatic, allowing us to capture the long-term marketing effects for much smaller brands. Since some brands are not available for all seven years, our second-stage fixed effects model is not based on 301 brand-years (43 brands times 7 years), but on 217 brand-years for display and price elasticities. For feature advertising elasticities, we lose another 17 brand-year combinations because several of the smaller brands are not featured at all in certain years. This plausibly reflects the retailer’s belief that only featuring large brands has the power to draw traffic into the store (Bronnenberg and Mahajan 2001; Pauwels 2006). As a result, we can not include own feature activity for that year in the brand’s VARX model.

\(^3\) Following previous VARX-literature, a price promotion is operationalized as a negative price shock (Dekimpe et al. 1999, Nijs et al. 2001, Pauwels et al. 2002, Srinivasan et al. 2004).
Brand-specific resources derived from scanner panel data include annual measures for brand equity, brand market share, product line breadth, and new product introductions. We measure brand equity (EQUITY) from the IRI-data on price/volume and volume/share as the revenue premium that accrues to a branded product compared to the private label, utilizing the method proscribed by Ailawadi et al. (2003). From the Dominick’s data, brand market share (SHARE) represents the average annual volume share that the brand holds in the category. Product line breadth (PLB) refers to the average number of SKUs associated with the brand during the year. And, new product introductions (NPI) refer to the total number of new SKUs that the brand introduced during the year. Following the procedure in Pauwels (2004), we identified a new product introduction as the dataset inclusion of a new SKU that stayed in the market for several months to avoid counting stock-out/re-entry situations and seasonal offerings.

In addition to these focal measures, we also include other brand-specific measures that may have an extraneous effect. We control for brand loyalty (BLOY) since it can play a role in consumers’ price sensitivity, which we calculated as the share of category requirements (Bhattacharya et al. 1996) and collected from the IRI dataset. We also include two firm-specific measures for the parent firm that owns the brand. Consistent with prior research that controls for firm-specific effects, we include the number individuals employed by the firm (FEMPL); we collected this data from the Compustat database and used a log transformation in the analysis. We also include parent company sales (FSLS) to account for overall firm size, which was also collected from the Compustat database. Finally, we include category dummy variables to control for any extraneous effects related to the three different categories, using toothpaste (the non-food, easily storable category) as the benchmark.

Table 3 presents the correlations across our brand-specific measures. Some measures are logically related to each other. For example, brands with broader product lines and more new
product introductions tend to have higher market share ($\sigma = 0.76$ and $\sigma = 0.52$, respectively). As a robustness check, we therefore also run equation (2) without market share (because a broader product line is more likely to cause high market share than vice versa) and compare the results.

Brand equity and market share have a low correlation of 0.04, which indicates that the revenue premium measure in our sample is mostly driven by price premium. Next to brands with high scores (e.g., Crest, Tide) and low scores (e.g., Pepsodent, Ajax) on both share and equity, our dataset thus also contains brands with low market share and high equity (e.g., V8, Rembrandt) and brands with high market share and low equity (e.g., Very Fine, Aqua Fresh). Further inspection reveals that small brands attain higher equity when they offer a few highly valuable and thus highly priced varieties. In contrast, many large brands offer a broad array which includes basic varieties that compete more closely with private labels, thus diluting their price premium. This explanation is consistent with Morgan and Rego’s (2006) finding that a greater number of brands with lower consumer quality perceptions yields higher market share of the brand portfolio. We note too that many pairwise correlations are low or even negative and that, as a whole, our set of brand resource measures does not appear to suffer from severe multicollinearity.

RESULTS

Brand sales evolution

Tables 4, 5, and 6 show the results of our unit root tests for both the full period and for the yearly periods of brands in the bottled juice, toothpaste and laundry detergent categories, respectively\(^4\). Observe that across the three categories, there is remarkable consistency in the occurrence of sales evolution: between 15-18% of all cases. This holds whether we consider the full period of brand sales data (which is the standard approach in previous persistence modeling

\[^4\] Detailed results available upon request from the second author.
papers), or whether we consider sales evolution in specific years. As to the former, note that only those brands with less than 3% market share experience sales evolution over the full period in which their data are available. In this respect, our results complement previous persistence modeling papers that consider only large brands and found little or no sales evolution for fast moving consumer goods. As to the latter, note that even very large brands may experience sales evolution in certain years, including the market leaders in two categories. In this respect, our results reinforce the arguments by Pauwels (2001) that full-period analysis may mask periods of evolution. Moreover, sales evolution by both small and large brands implies the potential to find permanent marketing effects for both types, allowing us to relate this rich variation in brand market share and other brand-specific resources to permanent marketing elasticities.

**Cumulative and permanent marketing elasticities**

After estimation of the VARX models and calculation of the impulse response functions, we obtain the cumulative and permanent marketing elasticities for each brand-year combination, as summarized in Table 7. Across the three categories, we observe that feature advertising has higher cumulative and permanent elasticity than displays. This is consistent with the notion that feature advertising may bring the brand to the attention of shoppers who have not tried it before and thus generate long-term benefits when these consumers buy the brand again later. Moreover, note that price promotional elasticities are higher for the two non-food categories compared to bottled juices, both for cumulative and for permanent effects.

To illustrate the long-term effects of price promotions across brands and categories, Figures 1-4 display the significant coefficients of the response of sales to a negative impulse of price (a price promotion) for the Gatorade and V8 bottled juice brands (food product) and the Close-up and Rembrandt toothpaste brands (storable, non-bulky product), respectively.
Gatorade and Close-up, for which the unit root tests show mean-reverting sales, do experience strong immediate (same-week) effects of their price promotions. However, the negative post-promotion dip partially cancels this benefit, so that the cumulative effect (the shaded area under the curve) is lower than the immediate effect. Both the higher immediate effect and the longer post promotion 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. Yet 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 post promotion dips: instead positive purchase reinforcement adds to positive immediate effects, which are lower compared to those of their competitors, and results in a larger cumulative effect. These two brands also enjoy permanent sales increases: the impulse response function stabilizes at a value above 0. What explains these stark differences in long-term promotional effects between brands from the same category? For one, we know that V8 has a much smaller market share than Gatorade and that Rembrandt enjoys higher brand equity than Close-up. We turn next to our systematic assessment of how brand resources impact these cumulative and permanent elasticities.

**Brand Resources as Drivers of Cumulative and Permanent Marketing Elasticities**

Table 8 presents the results of our second-stage fixed effects panel model using weighted-least squares regression. All six fixed effects panel models have adequate fit: the F-statistic is significant and each model explains 15% to 38% of the variance in the dependent variable.

First, brand equity appears to be a powerful predictor of long-term marketing productivity. 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 (mean revenue premium = 0.61 and 0.56, respectively) and we indeed find that their promotional efforts yield higher long-term
returns than those of lower equity brands All Sport and Hawaiian Punch (with mean revenue
premium = 0.04 and -0.04, respectively). The value of high brand equity has also been
documented for the V8 brand, whose creative advertising increased its competitive stance in the
category (Eastlack and Rao 1986). Our results thus reinforce the importance of understanding the
underlying value of brand equity and its role in generating long-term marketing returns.

Furthermore, the results show that brands with growth potential are able to generate higher
cumulative and permanent effects from their marketing efforts. First, the cumulative and
permanent sales elasticities are higher for display and price promotions on lower share brands, in
support of H1a and H1c. However, long-term feature elasticities are not significantly higher for
lower share brands, which is unexpected but consistent with retailer arguments that only features
on large brands are noticed by consumers and induce store visit and brand purchase. It is plausible
that consumers need a minimum level of brand familiarity before paying attention to its features in
retailer communications. Second, product line breadth is associated with lower long-term
elasticities, as predicted in H3, though this impact is only significant for cumulative and
permanent elasticities of feature advertising in our basic model. When we omit market share from
the analysis for our results robustness check (given its high correlation with product line breadth),
this negative effect of product line breadth is significant for all analyzed elasticities5.

Finally, results indicate that new product introductions are another powerful predictor of
long-term marketing productivity. In particular, results indicate that brands with more new
product introductions enjoy larger cumulative and permanent sales elasticity from display, feature
and price promotions, offering strong support for H4. For instance, Pepsodent introduced three
times fewer new products than Rembrandt and obtained lower long-term elasticities across all

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5 As the significance of product line breadth is the only substantive difference between equation (2) and the models
without ‘market share’, we conclude our findings on direction and significance of the moderator variables are robust
to the potential collinearity issue noted in our data section.
three promotional actions. Thus, having something new to say does appear to increase the
effectiveness of promotional actions. Such synergy is also in line with the promise of integrated
marketing communications. In addition, the interaction between new product introductions and
brand equity is significantly negative for feature and price promotions, in support of H5b and H5c.
Therefore, there is hope for low-equity brands: they can obtain higher long-term benefits from
new product introductions.

As for the control variables, we observe that firms with more employees enjoy higher long-run
price promotion elasticities, both in a cumulative and a permanent sense. In contrast, firms with
higher sales have lower cumulative price promotion elasticities. Finally, compared to toothpaste,
bottled juice brands experience lower long-run (cumulative and permanent) price promotion
elasticities, while liquid detergent brands experience lower permanent price promotion elasticities.

In sum, we find support for most of our hypotheses, and our results are fully consistent for
cumulative versus permanent elasticities. Table 9 summarizes our hypotheses and findings
regarding the impact of brand-specific resources on long-term promotional elasticities.

**Convergence Check: Brand Resources as Drivers of Long-term Unit (Absolute) Effects**

To examine the extent to which our results for elasticities hold up for absolute unit effects,
we estimate each VARX model in absolute numbers to obtain long-turn effects in units, and
complete the subsequent steps as outlined in Table 1. A few recent papers have uncovered that
empirical generalizations based on elasticities may not reflect absolute sales effects; for instance in
the context of the decomposition of sales promotion effects (van Heerde et al. 2004) and of
asymmetric and neighborhood cross-price effects (Sethuraman et al. 1999, Sethuraman and
Srinivasan 2002). The distinction between elasticities and absolute effects is relevant when either
1) the elasticity calculation is not based on the same (independent and dependent) variables (e.g.,
sales promotion effects on incidence, choice and quantity), or 2) the denominator; in the case of
unit sales, is vastly different across brands. The former rationale does not apply to our research, but the latter does. For instance, we may find that the display elasticity of a lower share brand is higher than that of a higher share brand, but that the higher share brand has higher absolute display effects on sales. Table 10 presents the results of our second-stage fixed effects panel models explaining the unit (absolute) effects of promotions on sales.

Overall, all models have adequate fit: the F-statistic is significant and each model explains 25% to 33% of the variance in the dependent variable. With respect to brand equity, its impact is not as strong when examining absolute unit effects. Though higher equity brands obtain higher long-term unit sales effects, this relationship is only significant for price promotions. It is plausible that the awareness that a higher equity brand has established limits its long-term unit effects of display and feature. For market share, its negative effect on long-term unit sales is not significant, and its effect is even positive for cumulative price promotion effects. Logically, the lower elasticity for market leaders is offset by their higher customer base, and they obtain similar unit effects. To the extent that retailers care not about elasticities but about unit effects, they thus appear justified to deny ‘affirmative action’ to lower share brands (e.g. Pauwels 2006).

Convergent results are quite strong regarding new product introductions. That is, our elasticity findings on new product introductions fully hold for unit effects: brands with more new product introductions enjoy significantly higher long-term unit sales effects of display, feature and price promotions. Likewise, the negative interaction between new product introductions and brand equity is significant for all cases: low equity brands obtain a particular benefit from new product introductions in terms of their long-term promotional effects on unit sales.

The major difference with our findings for long-term elasticities appears for product line breadth; brands with a broader product line obtain higher cumulative effects of display and feature advertising. In other words, the lower elasticity for brands with a broad product line is more than
compensated 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). This ‘brand line breath’ finding also mirrors the recent ‘brand portfolio’ results in Morgan and Rego (2006). They find that companies who “mass-market their brands to appeal to the lowest-common denominator” obtain lower customer loyalty but higher market share for their brand portfolio.

Finally, firms with more employees enjoy higher cumulative unit sales effects for both display and price promotions. In contrast, firms with higher sales experience lower cumulative price promotion effects, as do bottled juice brands compared to toothpaste brands.

**DISCUSSION**

In the quest to understand the long-term performance implications of various marketing actions, several recent papers have applied the persistence modeling approach to promotional activities for fast moving consumer goods. However, these studies have predominantly examined whether cumulative or permanent effects exist by examining the top three or four brands in a category. In this context, this paper is the first to 1) offer a systematic investigation of the extent to which the brand itself influences how its promotional efforts generate long-term returns, and 2) generate new insights into the long-term sales potential of promotion efforts by including small brands in our analysis. Our results across the different brand-specific resources further reinforce the importance of understanding the underlying role of the brand in its performance returns. As a result, 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 actions can have long-term effects on a brand’s sales and that the brand’s resources play an important role in these effects. Though prior studies have shown that cumulative effects are positive but
permanent effects are quite rare, our examination of 12 to 18 brands per category demonstrated that permanent effects are fairly common. In addition, our results show that cumulative and permanent promotional effects are influenced by several brand-specific resources, such as brand equity and new product introductions in addition to those studied in previous literature.

Second, we extend current research that has examined the effects from brand size. For example, Fok et al. (2006) show that brands with higher market share have lower cumulative price effectiveness. Our results converge regarding lower cumulative price effectiveness; yet we also show lower permanent display and price promotion elasticities for higher share brands. This supports our argument that brands with higher market share are likely to have less room for growth, and consequently less likely to attain permanent returns to their promotional efforts. In this regard, our findings add a silver lining to the cloud of challenges that recent research revealed for growing small brands: not only do they face a demand-side ‘triple jeopardy’ as they are purchased by fewer consumers, less often, and with less behavioral loyalty (Fader and Schmittlein 1993) but also a supply chain disadvantage as retailers are less likely to pass through and support their manufacturer promotions (Pauwels 2006). Our results suggest that, if passed through and supported by displays, these promotional efforts may facilitate the growth and revitalization of small brands. For example, Topol toothpaste contained meaningful associations with consumers, was purchased for $200,000 in 1973, and turned into a vital, high-margin brand with $23 million in sales 10 years later (Wansink 1997).

Third, our detailed analysis of brands with different equity sheds new light on the role of the brand in long-term returns to different promotional efforts. Extending beyond the usual distinction between national brands versus 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 returns to promotional efforts. This supplements extant research that shows brands with higher
equity capture higher immediate returns to marketing efforts (Slotegraaf et al. 2003). Moreover, it reveals lower consumer sensitivity to price increases that high equity brands enjoy. For instance, while Eastlack and Rao (1986) demonstrated 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 this asymmetry in long-term sales effects for price increases versus decreases is an important, but as yet under-researched benefit for high equity brands.

There do, however, 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 do higher equity brands. Though higher equity brands draw more consumers when they promote, they have also attained 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 say something new to consumers, such as new product introductions, the strong associations typical for higher equity brands 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 future research. As a caveat, the scope of our study did not permit analysis of the implications of promotions on brand equity itself. If brand equity is a ‘reservoir’ of good-will (Ambler 2001), it remains to be seen whether and which marketing efforts deplete this reservoir versus feed it, and this is an ongoing and crucial debate in the marketing literature (e.g. Aaker 1991, Ataman et al. 2006).

Fourth, our results indicate that the introduction of new products can generate fertile ground for long-term returns to marketing actions, especially when these brands have something new to say 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 necessarily the way to achieve long-term marketing returns: feature advertising elasticities are lower in the long run compared to brands with narrower product lines. Why then do brands tend to expand their assortment? One answer may lie in our finding that a broad product line generates higher long-term effects in absolute unit sales – plausibly due to their ability to meet heterogeneous needs of a broader customer base. 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 recently decided to reduce low-volume, low-margin SKUs to reduce complexity and increase focus on the SKUs that have higher profit potential (2005 ConAgra 10K report).

Finally, our results also highlight a possible firm-level effect regarding the long-term returns to promotional efforts. In particular, brands owned by firms with more employees enjoy higher cumulative and permanent elasticities from their price promotions, and higher cumulative sales unit effects from display and price promotions. It is plausible that specific processes involved in internal knowledge transfer offer a positional advantage that affects the extent to which a firm’s marketing efforts reap long-term effects. In particular, the transfer of knowledge is a complex process that is intricately woven across firm functions and drives competitive advantage (Luo, Slotegraaf, and Pan 2006; Maltz and Kohli 1996). When the sheer number of employees in a firm is higher, there are more opportunities for knowledge sharing and this underlying web of interconnected knowledge may become even more complex and difficult to imitate. For instance, brand managers may benefit from learning creative new ideas and ‘best practices’ regarding in-store promotions from other brand managers in a large organization that are unavailable to outsiders. In contrast, having higher sales is associated with lower price promotional elasticities in
the long run, which may reflect less creative execution or focus (Dickson 1992; Hambrick and D’Aveni 1988).

**Current Limitations and Further Research**

The current study has limitations that yield avenues for further research. First, we examined the long-term returns to marketing efforts by focusing on display, feature advertising, and price promotions, but 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. Examination of couponing, brand-specific advertising, and other forms of marketing efforts could assess whether differences exist across these marketing efforts. Second, our data sample is limited to one large retailer in a major U.S. city and to three product categories due to the large effort required to obtain brand resource measures on the many brands within each category. Future research may therefore examine more categories to uncover category-specific effects as well as retailer and manufacturer-specific effects. Third, though our research controls for firm-specific effects, we do not distinguish between 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.

**CONCLUSIONS**

This research has established that a brand’s equity and its growth potential play a significant role in its long-term marketing productivity. Importantly, and in contrast to extant research, we expanded the scope of investigation and demonstrate that permanent effects of promotions on sales are quite common and that both permanent and cumulative elasticity are driven by brand-specific resources. While our results illustrate that brands with higher equity can generate long-
term returns to marketing efforts, 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 returns to promotional efforts. These results have important implications regarding the impact of the brand itself and the potential for long-run marketing effectiveness.
## Table 1
Overview of Methodological Steps

<table>
<thead>
<tr>
<th>Methodological step</th>
<th>Relevant literature</th>
<th>Research question</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Unit root and cointegration tests</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Augmented Dickey-Fuller Test</td>
<td>Enders (2004)</td>
<td>Are variables stationary or evolving?</td>
</tr>
<tr>
<td>KPSS test</td>
<td>Maddala and Kim (1998)</td>
<td>Are the unit root results robust to null hypothesis?</td>
</tr>
<tr>
<td>Cointegration test</td>
<td>Johansen (1991)</td>
<td>Are evolving variables in long-run equilibrium?</td>
</tr>
<tr>
<td>2. Model of dynamic interactions</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Vector Autoregressive model</td>
<td>Dekimpe and Hanssens (1999)</td>
<td>How do sales and marketing variables interact in the long run and the short run, accounting for the unit root and cointegration results?</td>
</tr>
<tr>
<td>VAR-model in differences</td>
<td>Srinivasan et al. (2004)</td>
<td></td>
</tr>
<tr>
<td>Vector Error Correction model</td>
<td>Franses et al. (2001)</td>
<td></td>
</tr>
<tr>
<td>3. Policy simulation analysis</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Impulse response function</td>
<td>Dekimpe and Hanssens (1999)</td>
<td>What is the dynamic (sales) response to a (marketing) impulse?</td>
</tr>
<tr>
<td>Generalized impulse response</td>
<td>Pesaran and Shin (1998)</td>
<td>What is the immediate effect of an impulse, without imposing a causal ordering?</td>
</tr>
<tr>
<td>4. Second-stage analysis</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Weighted least-squares regression</td>
<td></td>
<td>What is the impact of brand resources on a long-term elasticity, weighted by its estimation accuracy and controlling for error correlation among equations?</td>
</tr>
<tr>
<td>Fixed-effects panel model</td>
<td>Davis (2002)</td>
<td></td>
</tr>
</tbody>
</table>

## Table 2
Overview of Analyzed Brands and the Range of Market Share

<table>
<thead>
<tr>
<th>Category</th>
<th>Analyzed Brands</th>
<th>Market Share Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bottled juice</td>
<td>All Sport, DelMonte, Gatorade, Hawaiian Punch, Hi-C, Juicy Juice, Minute Maid, Motts, Northland, Ocean Spray, Powerade, Seneca, Speas, Tree Top, Tropicana, V8, Very Fine, Welch's</td>
<td>0.1% – 27%</td>
</tr>
<tr>
<td>Toothpaste</td>
<td>Aim, Aqua Fresh, Arm &amp; Hammer, Close-Up, Colgate, Crest, Mentadent, Pepsodent, Rembrandt, Topol, Ultra Brite, Viadent</td>
<td>0.2% – 31%</td>
</tr>
<tr>
<td>Detergent</td>
<td>Ajax, All, Cheer, Dref, Dynamo, Era, Fab, Fresh Start, Oxydol, Purex, Surf, Tide, Wisk</td>
<td>1% – 40%</td>
</tr>
</tbody>
</table>
Table 3  
Correlation Matrix of Brand Resource Measures

<table>
<thead>
<tr>
<th></th>
<th>EQUITY</th>
<th>SHARE</th>
<th>PLB</th>
<th>NPI</th>
<th>BLOY</th>
<th>FEMPL</th>
<th>FSLS</th>
</tr>
</thead>
<tbody>
<tr>
<td>EQUITY</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SHARE</td>
<td>0.04</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>PLB</td>
<td>-0.04</td>
<td>0.76</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NPI</td>
<td>0.00</td>
<td>0.52</td>
<td>0.65</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BLOY</td>
<td>-0.01</td>
<td>0.34</td>
<td>0.50</td>
<td>0.34</td>
<td>1.00</td>
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<td></td>
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<tr>
<td>FEMPL</td>
<td>-0.09</td>
<td>-0.13</td>
<td>-0.12</td>
<td>0.02</td>
<td>0.03</td>
<td>1.00</td>
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<td>FSLS</td>
<td>0.00</td>
<td>-0.04</td>
<td>-0.06</td>
<td>0.03</td>
<td>0.09</td>
<td>0.78</td>
<td>1.00</td>
</tr>
<tr>
<td>Brand</td>
<td>Average Market Share</td>
<td>Years of data availability</td>
<td>Sales evolving for full data period?</td>
<td>Number of years with evolving sales</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>---------------</td>
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<td>-----------------------------</td>
<td>-------------------------------------</td>
<td>-------------------------------------</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ocean Spray</td>
<td>27%</td>
<td>7</td>
<td>0</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gatorade</td>
<td>21%</td>
<td>7</td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Very Fine</td>
<td>12%</td>
<td>7</td>
<td>0</td>
<td>1</td>
<td></td>
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</tr>
<tr>
<td>Motts</td>
<td>11%</td>
<td>7</td>
<td>0</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Welch's</td>
<td>7%</td>
<td>7</td>
<td>0</td>
<td>1</td>
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<tr>
<td>Tropicana</td>
<td>6%</td>
<td>7</td>
<td>0</td>
<td>0</td>
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<td></td>
</tr>
<tr>
<td>Treetop</td>
<td>5%</td>
<td>7</td>
<td>0</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HI-C</td>
<td>3%</td>
<td>5</td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Allsport</td>
<td>2%</td>
<td>2</td>
<td>1</td>
<td>2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Minute Maid</td>
<td>2%</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>V8</td>
<td>1%</td>
<td>5</td>
<td>1</td>
<td>4</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Powerade</td>
<td>1%</td>
<td>3</td>
<td>0</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hawaiian Punch</td>
<td>1%</td>
<td>5</td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Speas</td>
<td>1%</td>
<td>3</td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Juicy Juice</td>
<td>0.1%</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Del Monte</td>
<td>0.1%</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Seneca</td>
<td>0.1%</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Northland</td>
<td>0.1%</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Percentage of brands with evolving sales 17% 16%
### Table 5
**Unit root test Results: Toothpaste Category**

<table>
<thead>
<tr>
<th>Brand</th>
<th>Average Market Share</th>
<th>Years of data availability</th>
<th>Sales evolving for full data period?</th>
<th>Number of years with evolving sales</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crest</td>
<td>31%</td>
<td>7</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>Colgate</td>
<td>22%</td>
<td>7</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Aqua Fresh</td>
<td>10%</td>
<td>7</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>Viadent</td>
<td>10%</td>
<td>2</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Arm &amp; Hammer</td>
<td>8%</td>
<td>6</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Mentadent</td>
<td>8%</td>
<td>3</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Close-up</td>
<td>4%</td>
<td>7</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Aim</td>
<td>2%</td>
<td>7</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Ultra Bright</td>
<td>2%</td>
<td>7</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Pepsodent</td>
<td>2%</td>
<td>7</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Rembrandt</td>
<td>1%</td>
<td>4</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>Topol</td>
<td>0.2%</td>
<td>3</td>
<td>1</td>
<td>2</td>
</tr>
</tbody>
</table>

**Percentage of brands with evolving sales**

|                | 17% | 18% |
## Table 6

**Unit root test Results: Laundry Detergent Category**

<table>
<thead>
<tr>
<th>Brand</th>
<th>Average Market Share</th>
<th>Years of data availability</th>
<th>Sales evolving for full data period?</th>
<th>Number of years with evolving sales</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tide</td>
<td>40%</td>
<td>7</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Wisk</td>
<td>13%</td>
<td>7</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Cheer</td>
<td>11%</td>
<td>7</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>All</td>
<td>9%</td>
<td>7</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Surf</td>
<td>7%</td>
<td>7</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Era</td>
<td>4%</td>
<td>7</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Dreft</td>
<td>3%</td>
<td>7</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Purex</td>
<td>3%</td>
<td>7</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>Dynamo</td>
<td>3%</td>
<td>2</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Fresh Start</td>
<td>2%</td>
<td>4</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>Ajax</td>
<td>2%</td>
<td>7</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Oxydol</td>
<td>1%</td>
<td>7</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>Fab</td>
<td>1%</td>
<td>4</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

**Percentage of brands with evolving sales**  
15%  
16%
### Table 7
Overview of the Cumulative and Permanent Marketing Elasticities across Categories

<table>
<thead>
<tr>
<th>Category</th>
<th>Cumulative Display</th>
<th>Cumulative Feature</th>
<th>Cumulative Price Prom</th>
<th>Permanent Display</th>
<th>Permanent Feature</th>
<th>Permanent Price Prom</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bottled Juice Mean (Median)</td>
<td>0.07 (0.01)</td>
<td>0.32 (0.02)</td>
<td>1.11 (0.25)</td>
<td>0.00 (0.00)</td>
<td>0.01 (0.00)</td>
<td>0.05 (0.00)</td>
</tr>
<tr>
<td>Toothpaste Mean (Median)</td>
<td>0.19 (0.02)</td>
<td>0.39 (0.02)</td>
<td>2.73 (0.76)</td>
<td>0.01 (0.00)</td>
<td>0.03 (0.00)</td>
<td>0.15 (0.00)</td>
</tr>
<tr>
<td>Detergent Mean (Median)</td>
<td>0.16 (0.02)</td>
<td>0.63 (0.04)</td>
<td>2.86 (0.55)</td>
<td>0.01 (0.00)</td>
<td>0.04 (0.00)</td>
<td>0.11 (0.00)</td>
</tr>
<tr>
<td></td>
<td>Cumulative Display</td>
<td>Cumulative Feature</td>
<td>Cumulative Price</td>
<td>Permanent Display</td>
<td>Permanent Feature</td>
<td>Permanent Price</td>
</tr>
<tr>
<td>----------------</td>
<td>--------------------</td>
<td>--------------------</td>
<td>------------------</td>
<td>-------------------</td>
<td>-------------------</td>
<td>-----------------</td>
</tr>
<tr>
<td>EQUITY</td>
<td>0.0557 ***</td>
<td>0.9180 ***</td>
<td>1.8061 ***</td>
<td>0.0046 ***</td>
<td>0.0683 ***</td>
<td>0.1430 ***</td>
</tr>
<tr>
<td>SHARE</td>
<td>-0.4871*</td>
<td>-1.6743</td>
<td>-4.0046 **</td>
<td>-0.0367*</td>
<td>-0.0995</td>
<td>-0.1361**</td>
</tr>
<tr>
<td>PLB</td>
<td>-0.0003</td>
<td>-0.0119 **</td>
<td>-0.0328</td>
<td>0.0000</td>
<td>-0.0010*</td>
<td>-0.0029</td>
</tr>
<tr>
<td>NPI</td>
<td>0.0112 *</td>
<td>0.1006 ***</td>
<td>0.3583 ***</td>
<td>0.0011**</td>
<td>0.0076 ***</td>
<td>0.0342 ***</td>
</tr>
<tr>
<td>EQUITY * NPI</td>
<td>-0.0060</td>
<td>0.1086 ***</td>
<td>-0.2051 *</td>
<td>-0.0004</td>
<td>-0.0081 ***</td>
<td>-0.0145**</td>
</tr>
<tr>
<td>FEMPL</td>
<td>0.0178</td>
<td>-0.0426</td>
<td>1.1717 ***</td>
<td>0.0016</td>
<td>-0.0044</td>
<td>0.1034***</td>
</tr>
<tr>
<td>FSLN</td>
<td>-0.0000</td>
<td>-0.0000</td>
<td>-0.0001 ***</td>
<td>0.0000</td>
<td>0.0000</td>
<td>-0.0000</td>
</tr>
<tr>
<td>BLOY</td>
<td>-0.0018</td>
<td>0.0066</td>
<td>-0.0553</td>
<td>-0.0001</td>
<td>0.0004</td>
<td>-0.0037</td>
</tr>
<tr>
<td>Bottled Juice</td>
<td>-0.0333</td>
<td>0.1522</td>
<td>-2.5209**</td>
<td>-0.0024</td>
<td>0.0090</td>
<td>-0.1444**</td>
</tr>
<tr>
<td>Laundry Detergent</td>
<td>0.0489</td>
<td>0.0628</td>
<td>-1.0829</td>
<td>0.0028</td>
<td>-0.0005</td>
<td>-0.1123*</td>
</tr>
<tr>
<td>F-stat</td>
<td>2.32 ***</td>
<td>7.12 ***</td>
<td>4.45 ***</td>
<td>2.17 ***</td>
<td>7.13 ***</td>
<td>6.06 ***</td>
</tr>
<tr>
<td>R² (adjusted)</td>
<td>0.16 (0.09)</td>
<td>0.38 (0.33)</td>
<td>0.26 (0.20)</td>
<td>0.15 (0.08)</td>
<td>0.36 (0.31)</td>
<td>0.33 (0.27)</td>
</tr>
</tbody>
</table>

*  p < .10  **  p < .05  ***  p < .01
Table 9
Summary of Results for Hypotheses

<table>
<thead>
<tr>
<th>Long-term elasticity is higher for:</th>
<th>Supported for Display?</th>
<th>Supported for Feature?</th>
<th>Supported for Price Promotion?</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1 Brands with higher equity</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>H2 Brands with lower market share</td>
<td>✓</td>
<td></td>
<td>✓</td>
</tr>
<tr>
<td>H3 Brands with a narrower product line</td>
<td></td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>H4 Brands with more new product introductions</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>H5 Lower equity brands with more new product introductions (negative interaction)</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
</tbody>
</table>
### Table 10

**Brand Resources as Drivers of Cumulative and Permanent Marketing Unit Effects**

<table>
<thead>
<tr>
<th></th>
<th>Cumulative Display</th>
<th>Cumulative Feature</th>
<th>Cumulative Price</th>
<th>Permanent Display</th>
<th>Permanent Feature</th>
<th>Permanent Price</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>EQUITY</strong></td>
<td>195.37</td>
<td>842.14</td>
<td>12204.56*</td>
<td>20.56</td>
<td>68.96</td>
<td>1506.49***</td>
</tr>
<tr>
<td><strong>SHARE</strong></td>
<td>-1161.19</td>
<td>-6410.30</td>
<td>210432***</td>
<td>-106.45</td>
<td>-564.19</td>
<td>-1175.79</td>
</tr>
<tr>
<td><strong>PLB</strong></td>
<td>22.70*</td>
<td>94.29*</td>
<td>-550.35</td>
<td>1.18</td>
<td>5.09</td>
<td>5.46</td>
</tr>
<tr>
<td><strong>NPI</strong></td>
<td>247.65***</td>
<td>933.17**</td>
<td>10679.65***</td>
<td>20.21***</td>
<td>74.77***</td>
<td>936.16***</td>
</tr>
<tr>
<td><strong>EQUITY * NPI</strong></td>
<td>-114.46***</td>
<td>-451.67**</td>
<td>-5241.52***</td>
<td>-9.16***</td>
<td>-32.61***</td>
<td>-526.13***</td>
</tr>
<tr>
<td><strong>FEMPL</strong></td>
<td>259.10***</td>
<td>1045.33</td>
<td>20911.36***</td>
<td>13.15</td>
<td>59.69</td>
<td>652.56</td>
</tr>
<tr>
<td><strong>FSLS</strong></td>
<td>-0.02</td>
<td>-0.08</td>
<td>-1.69***</td>
<td>0.00</td>
<td>0.00</td>
<td>-0.04</td>
</tr>
<tr>
<td><strong>BLOY</strong></td>
<td>12.42</td>
<td>90.54</td>
<td>562.32</td>
<td>0.74</td>
<td>4.70</td>
<td>37.66</td>
</tr>
<tr>
<td><strong>Bottled Juice</strong></td>
<td>-683.57</td>
<td>-2339.60</td>
<td>-33177.83*</td>
<td>-14.16</td>
<td>-66.24</td>
<td>-359.84</td>
</tr>
<tr>
<td><strong>Laundry Detergent</strong></td>
<td>-570.43</td>
<td>-2286.03</td>
<td>-409.36</td>
<td>-22.58</td>
<td>-124.15</td>
<td>385.49</td>
</tr>
<tr>
<td><strong>F-stat</strong></td>
<td>6.81***</td>
<td>6.38***</td>
<td>4.88***</td>
<td>4.66***</td>
<td>4.25***</td>
<td>5.01***</td>
</tr>
<tr>
<td><strong>R² (adjusted)</strong></td>
<td>0.35</td>
<td>0.33</td>
<td>0.28</td>
<td>0.27</td>
<td>0.25</td>
<td>0.26</td>
</tr>
</tbody>
</table>

* p < .10  
** p < .05  
*** p < .01
Figure 1
Impulse response of price promotion on sales for Bottled Juice: V8

Immediate effect = 1.02
Cumulative effect = 2.62
Permanent effect = .27

Figure 2
Impulse response of price promotion on sales for Bottled Juice: Gatorade

Immediate effect = 5.45
Cumulative effect = 1.68
Permanent effect = 0
Figure 3
Impulse response of price promotion on sales for Toothpaste: Closeup

Figure 4
Impulse response of price promotion on sales for Toothpaste: Rembrandt
REFERENCES


