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Few studies have considered the relative role of the integrated marketing mix (advertising, price promotion, product, and place) on the long-term performance of mature brands, instead emphasizing advertising and price promotion. Thus, little guidance is available to firms regarding the relative efficacy of their various marketing expenditures over the long run. To investigate this issue, the authors apply a multivariate dynamic linear transfer function model to five years of advertising and scanner data for 25 product categories and 70 brands in France. The findings indicate that the total (short-term plus long-term) sales elasticity is 1.37 for product and .74 for distribution. Conversely, the total elasticities for advertising and discounting are only .13 and .04, respectively. This result stands in marked contrast to the previous emphasis in the literature on price promotions and advertising. The authors further find that the long-term effects of discounting are one-third the magnitude of the short-term effects. The ratio is reversed from other aspects of the mix (in which long-term effects exceed four times the short-term effects), underscoring the strategic role of these tools in brand sales.

Keywords: marketing mix, long-term effects, brand performance, dynamic linear models, empirical generalizations

The Long-Term Effect of Marketing Strategy on Brand Sales

Firms annually spend hundreds of billions of dollars to implement their marketing strategy, and much headway has been made in explaining how these expenditures enhance brand performance over the short run (Bucklin and Gupta 1999).[1] More recently, attention has been focused on the longer-term effect of marketing strategy on brand performance, particularly with respect to price and promotion (e.g., Boulding, Lee, and Staelin 1994; Jedidi, Mela, and Gupta 1999; Nijs et al. 2001; Pauwels, Hanssens, and Siddarth 2002; Srinivasan et al. 2004; Steenkamp et al. 2005). Yet there has been little emphasis on the effects of product (e.g., line length) and place (e.g., distribution breadth) on brand performance. Accordingly, a critical question remains unanswered (Aaker 1991; Ailawadi, Lehman, and Neslin 2003; Yoo, Donthu, and Lee 2000): Which elements of the marketing mix are most critical in making brands successful?

To illustrate these points, we show in Figure 1 and Figure 2 the historical performance of two brands over a five-year period—one that contracted dramatically (Brand C, C = contracted) and one that grew considerably (Brand G, G = grew). Figure 1 and Figure 2 show sales volume, promotion activity, advertising spending, distribution breadth, and product line length for Brand C and Brand G, respectively, over time. The brands and variables are from a data set that we discuss in more detail in subsequent sections. Comparison of sales volume between the first and the second half of the data reveals a considerable 60% sales contraction for Brand C, which contrasts with an 87% growth for Brand G. This difference in performance leads to the following ques-

[1]By short run, we mean the immediate effect of marketing on current week's sales. In contrast, long run refers to the effect of repeated exposures to marketing over quarters or years.

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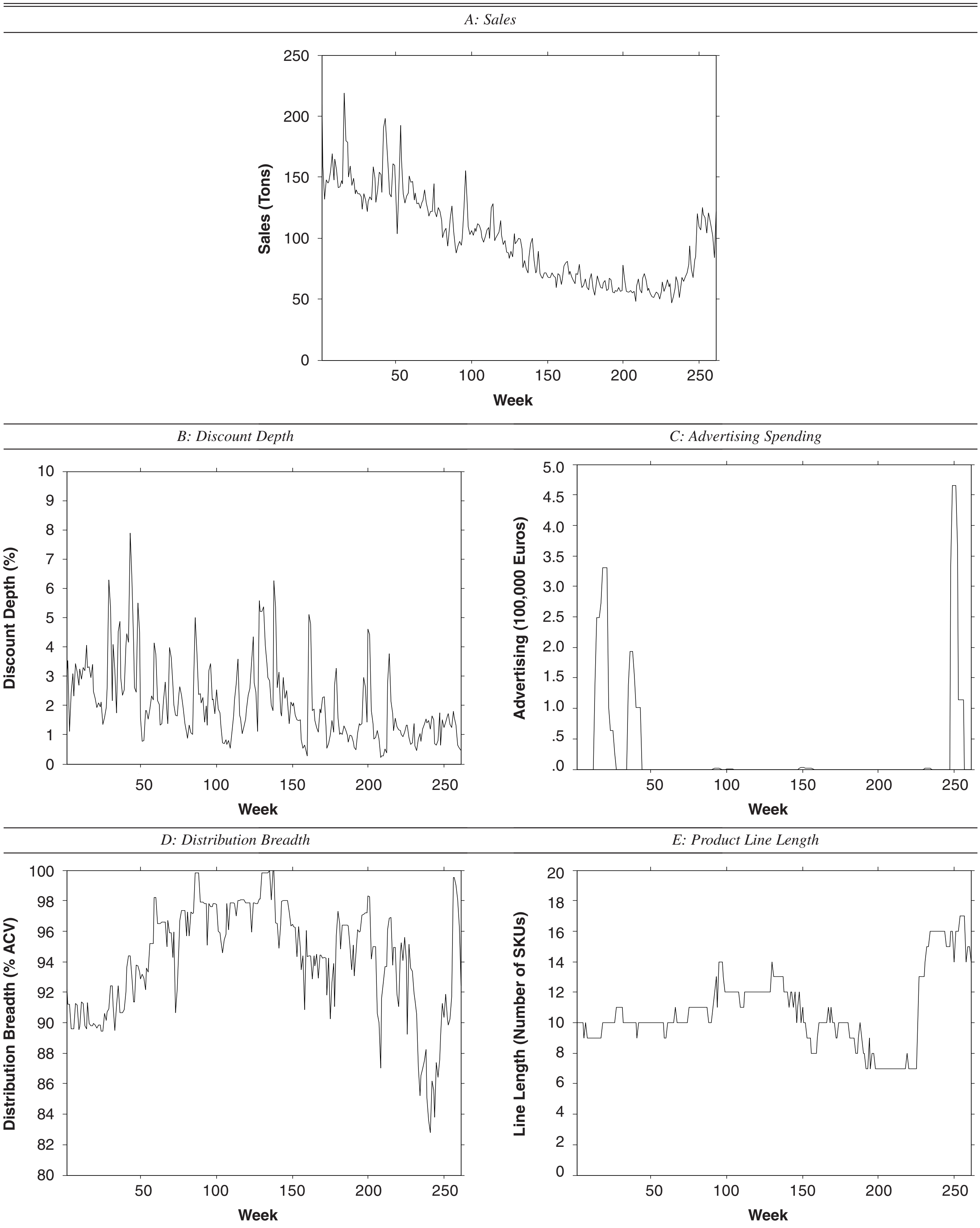
ISSN: 0022-2437 (print), 1547-7193 (electronic)

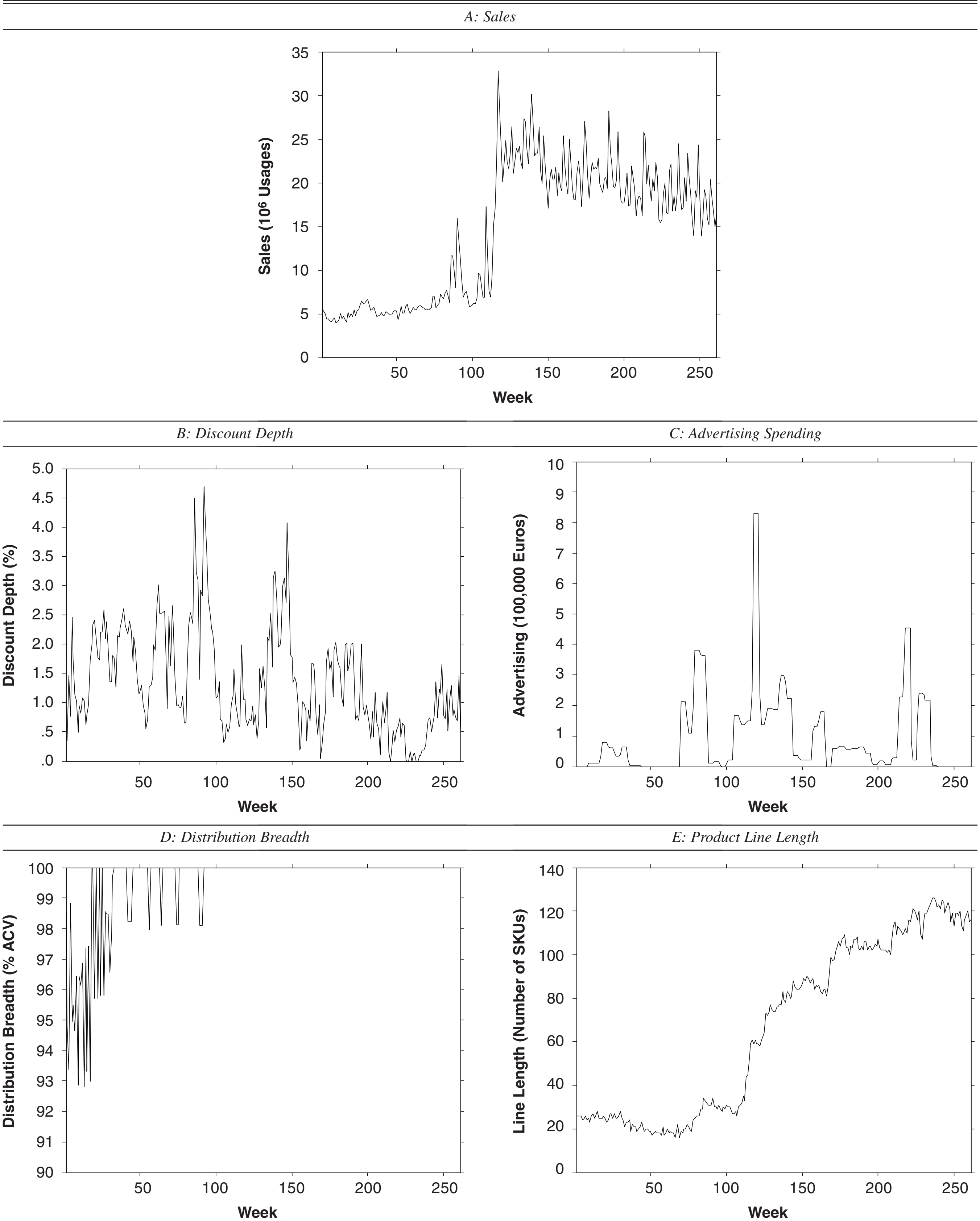
Figure 1
CONTRACTION CASE: BRAND C



Notes: ACV = all commodity volume, and SKU = stockkeeping unit.

Figure 2

GROWTH CASE: BRAND G



Notes: ACV = all commodity volume, and SKU = stockkeeping unit.

tion: What strategies discriminate between the performances of these brands?

For example, Brand C's downward-sloping sales (Figure 1, Panel A) during its first four years coincide with frequent and deep discounting (Panel B), negligible advertising (Panel C), lower distribution (Panel D), and shorter product line (Panel E). Notably, its sales turn around in the last year of the data. This period is characterized by increased product variety, distribution, and advertising, while discounting was curtailed, suggesting a long-term link between the brand's performance and marketing strategy rather than cyclical changes in performance (e.g., Pauwels and Hanssens 2007).

Brand G's sales (Figure 2, Panel A) show a marked increase shortly after week 100. This might illustrate the (autonomous) takeoff of a small brand (Golder and Tellis 1997). However, a more direct link between brand performance and its marketing strategy can be established. The increase in sales coincides with heavy product activity (Panel E), high advertising spending (Panel C), increased distribution (Panel D), and diminished price promotions (Panel B). These examples suggest a link between the brand's performance and marketing strategy.

Together, these examples suggest that product, distribution, and advertising enhance brand performance, while discounts do little in the way of brand building. Yet these cases are anecdotal (and involve only two categories), and the various mix effects are confounded. Indeed, the correlation between these strategies suggests that it is especially important to consider them in unison; otherwise, an assessment of effects in isolation might lead to the attribution of a brand's success to the wrong strategy. By analyzing the weekly performance of 70 brands in 25 categories over five years, we identify the marketing-mix strategies that correlate most highly with growth in brand sales and with the potential to command higher prices.

The results substantiate the belief that distribution and product decisions play a major role in the (short- plus long-term) performance of brands. By computing the relative long-term sales elasticities of the various marketing strategies, we find that product effects are 60% and distribution effects are 32%. In contrast, the effects of advertising and discounting are only 6% and 2%, respectively. Moreover, while the long-term negative effect of discounting is only one-third of the magnitude of its positive short-term effect, the long-term effects of the other marketing variables tend to be 4–16 times their short-term effects, testifying to their long-term role in brand performance. In addition, the total (long-term plus short-term) elasticities of line length and distribution breadth are more substantial (1.37 and .74, respectively) than the advertising and discount elasticities (.13 and .04, respectively). These results illustrate that discounts do little to build a brand over the long run.

These findings arise from the application of a multivariate dynamic linear model (DLM) that links brand sales to marketing strategy. The approach offers a flexible means for assessing how marketing affects intercepts and sales response parameters (e.g., elasticities) over time. Moreover, the approach (1) controls for endogeneity in pricing and marketing variables, (2) partials the role of past performance from marketing spending, and (3) considers competitive interactions in marketing. To our knowledge, the DLM has not been applied to a problem of this scale.

We organize the article as follows: First, we discuss the literature on long-term effects of the marketing mix on brand performance. Second, we discuss theories pertaining to how the marketing mix affects brand performance in the long run. Third, we develop the model and provide an overview of the estimation. Fourth, we describe the data and variables. Fifth, we present the results. Last, we conclude with a summary of findings and future research opportunities.

LITERATURE ON LONG-TERM EFFECTS OF THE MARKETING MIX

Table 1 samples the current state of the literature on long-term effects and indicates (1) a prevalent focus on certain marketing instruments, (2) the existence of various brand performance measures, and (3) a clear divide between modeling approaches. We address these issues subsequently and highlight our points of difference and parity.

First, Table 1 indicates that most studies focus on promotion and advertising rather than distribution and product. Thus, these studies cannot provide insights into the relative effects of marketing variables and risk suffering from an omitted variable bias because these strategies can be correlated.

On a related note, personal interviews with senior research managers at different consumer packaged goods firms yielded a similar focus regarding the prevalence of advertising and discounting in industry research. Yet these managers express uncertainty about whether this attention is misplaced in the sense that product and distribution actually play a greater role in brand performance. Accordingly, the question "How does the marketing mix influence brand equity in the long run?" has been a top research priority of the Marketing Science Institute since 1988 (e.g., Marketing Science Institute 2008). A reason this question has been around for so long is that answering it requires the combination of extensive data sets and a methodology that can measure long-term effects while coping with the common challenges of empirical modeling, such as (1) endogeneity in marketing, (2) performance feedback (e.g., the effect of past sales on current marketing expenditures), and (3) competitive interactions. This research meets these challenges, as we discuss in the following sections.

A second observation from Table 1 is that these studies differ in their use of brand performance measures. Brand performance or brand equity has been conceptualized and operationalized using stock market returns (Simon and Sullivan 1993), brand attitudes (Aaker 1991), and brand sales or choice data (Ailawadi, Lehmann, and Neslin 2003). Although each has its respective benefits, most studies in Table 1 fit in the third stream, as does the current study.

Research embedded in this stream commonly proposes different measures for brand equity. The first measure suggests assessment of brand equity through base sales, which is operationalized as the brand intercept in a sales model (Kamakura and Russell 1993; Kopalle, Mela, and Marsh 1999).[2] The second measure pertains to the notion that well-differentiated brands can command higher regular prices

[2]Base sales are a brand's sales when all marketing variables are at their means. This is different from baseline sales, which is sales in the absence of a promotion.

Table 1

CURRENT LITERATURE ON LONG-TERM EFFECTS OF MARKETING VARIABLES

	Effect of						
	Promotion	*Advertising*	*Distribution*	*Product*	*Effect on*	*Modeling Approach*	*Number of Categories*
Clarke (1976)		✓			Brand sales	VPM	1
Baghestani (1991)		✓			Brand sales	VAR	1
Dekimpe and Hanssens (1995)		✓			Chain sales	VAR	1
Papatla and Krishnamurthi (1996)	✓				Choice	VPM	1
Mela, Gupta, and Lehmann (1997)	✓	✓			Choice	VPM	1
Mela, Jedidi, and Bowman (1998)	✓				Incidence and quantity	VPM	1
Mela, Gupta, and Jedidi (1998)	✓	✓			Market structure	Mixed	1
Kopalle, Mela, and Marsh (1999)	✓				Brand sales	VPM	1
Jedidi, Mela, and Gupta (1999)	✓	✓			Choice and quantity	VPM	1
Foekens, Leeflang, and Wittink (1999)	✓				Brand sales	VPM	1
Dekimpe and Hanssens (1999)	✓	✓			Brand sales	VAR	1
Dekimpe, Hanssens, and Silva-Risso (1999)	✓				Brand and category sales	VAR	4
Srinivasan, Popkowski Leszczyc, and Bass (2000)	✓		✓		Market share	VAR	2
Bronnenberg, Mahajan, and Vanhonacker (2000)	✓	✓	✓		Market share	VAR	1
Nijs et al. (2001)	✓				Category sales	VAR	560
Pauwels, Hanssens, and Siddarth (2002)	✓				Incidence, choice, and quantity	VAR	2
Srinivasan et al. (2004)	✓				Margin and revenue	VAR	21
Pauwels (2004)	✓	✓		✓	Brand sales	VAR	1
Van Heerde, Mela, and Manchanda (2004)				✓	Market structure	VPM (DLM)	1
Pauwels et al. (2004)	✓			✓	Financial measures	VAR	1
Steenkamp et al. (2005)	✓	✓			Brand sales	VAR	442
Sriram, Balachander, and Kalwani (2007)	✓	✓		✓	Brand sales	VPM	2
Ataman, Mela, and Van Heerde (2008)	✓	✓	✓	✓	Brand sales (new brands only)	VPM-SE (DLM)	22
Slotegraaf and Pauwels (2008)	✓			✓	Brand sales	VAR	7
Srinivasan, Vanhuele, and Pauwels (2008)	✓	✓	✓		Brand sales	VAR	4
This article	✓	✓	✓	✓	Brand sales and elasticity	VPM-SE (DLM)	25

Notes: VPM = varying parameter model, VAR = vector autoregressive model, DLM = dynamic linear model, and SE = system of equations.

and margins than otherwise similar goods (Swait et al. 1993). Because price premiums are inversely related to the brand's regular price elasticity (Boulding, Lee, and Staelin 1994; Nicholson 1972), regular price elasticity is a second measure of brand performance.[3] Consistent with this literature, we consider both perspectives in assessing the long-term effect of marketing strategy on brand performance. In contrast, Ataman, Mela, and Van Heerde (2008) emphasize the effect of the marketing mix on sales and not the implications for elasticities. Another point on which the current study differs from Ataman, Mela, and Van Heerde is that they consider only new brands. These brands are qualitatively different from the mature brands we study; mature brands have an installed base of customers and an existing distribution network, which are lacking for new brands.

A third observation from Table 1 is that there are two dominant approaches in modeling the long-term effects of the mix: varying parameter models and vector autoregressive (VAR) models. Although inertia in marketing spending (Pauwels 2004) and performance feedback (Horvath et al. 2005) are integral parts of VAR models, they often ignore varying parameter effects. Varying parameters are relevant because marketing strategy affects both base sales (intercepts) and price elasticities. In contrast, varying parameter models (including the Bayesian variant "DLM") often ignore inertia and feedback effects; yet these are important to calculate the returns accruing from marketing investments over the long run. Therefore, in our application, we combine the two approaches and develop a varying parameter model (DLM variant) for a system of equations that considers the role of inertia in marketing spending and performance feedback. Our analysis indicates that both inertia and feedback are substantial.

In summary, this study extends the current literature on the long-term effects of marketing strategy on brand performance by (1) considering the full marketing mix, (2) adopting base sales and price elasticity as performance measures, and (3) specifying a system of equations with time-varying parameters.

THE EFFECT OF THE MIX ON BRAND PERFORMANCE

In the following sections, we provide an overview of the current literature on the long-term effects of price promotions, advertising, distribution, and product on brands and their relationships to base sales and regular price elasticity (see Table 2). Our discussion of distribution and product is more tentative given the dearth of work in the area. We then conclude by discussing the relative efficacy of the various marketing strategies.

[3]Assume that brand i faces a multiplicative demand curve, $q_i = \alpha_i p_i^{\beta_{ii}} \Pi p_j^{\beta_{ij}}$ for all $j \neq i$, where q_i is demand, p_i is the regular price of brand i, α_i is the intercept, and β_{ij} the price elasticity of brand i to brand j. If the marginal cost of production is c_i, the profit function is given by $\pi_i = q_i(p_i - c_i)$. Then, solving max $\pi_i = 0$ for p_i gives profit maximizing price, $p_i^* = c_i/[(1/\beta_{ii}) + 1]$. Thus, price, as well as the percent profit margin $= (p_i - c_i)/p_i \equiv -1/\beta_{ii}$, increases as regular price elasticity decreases. Note further that when the demand function is multiplicative, competitor price drops from the first-order condition.

Table 2

EXPECTED MARKETING-MIX EFFECTS ON BASE SALES AND REGULAR PRICE ELASTICITY

		Predicted Effect on	
Variable	*Operationalization*	*Base Sales (Intercept)*	*Regular Price Elasticity*[a]
Discounting	Discount depth	Positive/negative	Negative
Advertising	Expenditure	Positive	Positive
Distribution	% ACV-weighted distribution	Positive	Positive/negative
Line length	Number of SKUs	Positive	Positive

[a]A positive effect on regular price elasticity means that the elasticity become less negative; a negative effect means that it become more negative.
Notes: ACV = all commodity volume, and SKU = stockkeeping unit.

Price Promotion

Some studies in the literature suggest a negative long-term impact of price promotions on base sales (Foekens, Leeflang, and Wittink 1999; Jedidi, Mela, and Gupta 1999), while other studies suggest the opposite effect because of the positive effects of state dependence (Keane 1997) and purchase reinforcement (Ailawadi et al. 2007). Still others have found only a fleeting negative effect (Pauwels, Hanssens, and Siddarth 2002). Overall, it is not clear whether the positive effect dominates the negative effect on base sales, and thus a large-scale generalization seems necessary. In contrast, discounting policies are typically found to decrease price elasticities (make them more negative) by focusing consumers' attention on price-oriented cues (Boulding, Lee, and Staelin 1994; Mela, Gupta, and Lehmann 1997; Papatla and Krishnamurthi 1996; Pauwels, Hanssens, and Siddarth 2002).

Advertising

Brand-oriented advertising (e.g., nonprice advertising) strengthens brand image, causes greater awareness, differentiates products, and builds brand equity (Aaker 1991; Keller 1993). Advertising may also signal product quality, leading to an increase in brand equity (Kirmani and Wright 1989). Accordingly, several authors have found that advertising has a positive and enduring effect on base sales (e.g., Dekimpe and Hanssens 1999).

With respect to the effect of advertising on price elasticity, two schools of thought in economic theory offer alternative explanations. First, information theory argues that advertising may increase competition by providing information to consumers about the available alternatives, thus making price elasticities more negative. Second, market power theory argues that advertising may increase product differentiation, thus making price elasticity less negative (Mitra and Lynch 1995). On a related note, Kaul and Wittink (1995) indicate that brand-oriented advertising increases price elasticity while price-oriented advertising decreases it. Mela, Gupta, and Lehmann (1997) note that national brand television advertising is predominantly brand oriented. Accordingly, we expect that national television advertising, as observed in the data, increases price elasticities (making them less negative).

Product

Similar to advertising, product activity (e.g., innovations, changes in form) enhances a brand's perceived quality, increases purchase likelihood, and builds equity (Berger, Draganska, and Simonson 2007). We posit that the long-term effect of increased product line length on base sales is incumbent on the degree to which cannibalization offsets incremental sales garnered by serving more segments. In general, we argue that offering more products has a small but positive effect on base sales because we do not expect cannibalization to entirely offset the increased demand. Accordingly, several studies in the literature suggest that product line length is positively related to brand performance in the long run (Ataman, Mela, and Van Heerde 2008; Pauwels 2004; Sriram, Balachander, and Kalwani 2007; Van Heerde, Srinivasan, and Dekimpe 2010). We expect that more differentiated or customized alternatives increase price elasticity (making it less negative) because strongly differentiated items can serve loyal niches.

Distribution

Distribution breadth (the percentage of distribution that carries a brand) can affect brand performance, but as with product, theoretical and empirical evidence for these effects is limited. We expect that increases in the breadth of distribution lead to higher base sales because the wider availability facilitates consumers' ability to find the brand (Bronnenberg, Mahajan, and Vanhonacker 2000).

We can formulate two competing expectations for the effect of distribution breadth on price elasticity. First, broader distribution may increase the chance of within-brand price comparison across stores, commonly called "cherry picking" (Fox and Hoch 2005). This leads to an increased emphasis on price and an attendant decrease in price elasticity. Second, in contrast, broader distribution signals manufacturer commitment to the brand and, potentially, its success in the marketplace. A similar signaling effect is also observed for advertising (Kirmani and Wright 1989). Given the competing arguments, we treat the effect of distribution breadth on elasticity as an empirical question. Table 2 summarizes the expected effects of marketing on brand performance.

Relative Effects

Of interest is the relative magnitude of these effects. To our knowledge, no research has incorporated all these effects into a single framework over a large number of categories, so any discussion of the relative magnitude of these effects is necessarily speculative. Complicating this task, marketing strategy is affected by performance feedback, competitor response, and inertia. For example, a positive effect on base sales can be amplified in the presence of inertia because the positive effect manifests not only in the current period but in subsequent periods as well. There is ample reason to believe that some aspects of the mix might be more enduring than others; for example, it takes more time to make changes to the product line than to implement a price discount.

Personal communications with firms and colleagues suggest that most people expect distribution and product to have the greatest overall long-term effects on brand sales. Distribution and product line length are necessary conditions for sales: No distribution or products imply no sales. Some evidence for this already exists in the literature. Two recent studies (Ataman, Mela, and Van Heerde 2008; Srinivasan, Vanhuele, and Pauwels 2008) have shown that distribution plays a central role in building brands. Product innovation is also likely to have considerable effects because it is a core source of differential advantage. In contrast, advertising and pricing are more limited in their ability to differentiate goods, especially because discounting is often viewed as a short-term tactic to generate immediate sales. In summary, we expect that product and distribution matter the most for brand performance in the long run.

MODELING APPROACH

Overview

We allow the base sales and regular price elasticity to vary over time as a function of marketing strategy. Dynamic linear models (Ataman, Mela, and Van Heerde 2008; West and Harrison 1997) are well suited to this problem. The general multivariate form of our model is as follows:

$$\text{(1a)} \qquad Y_t = F_t\theta_t + X_t\eta + Z_t\zeta + \upsilon_t, \text{ and}$$

$$\text{(1b)} \qquad \theta_t = G\theta_{t-1} + Z'_{t-1}\gamma + \omega_t,$$

where Y_t is a vector in which the log sales of brand j in chain s at time t is stacked across brands and chains; F_t is a regressor matrix consisting of an intercept and log regular price; X_t is a regressor matrix including several control variables, such as feature/display and seasonality, which affect sales; and Z_t includes brands' marketing strategies—specifically, advertising expenditures, price discounting, distribution breadth, and product line length. We assume that $\upsilon_t \sim N(0, V)$, where V is the covariance matrix of error terms in Equation 1a.

The observation equation (Equation 1a) models the short-term effect of marketing activities on sales. Note that this equation yields period-specific estimates (stacked in θ_t) for intercepts (base sales) and regular price elasticities. We allow these to vary over time as described in the system equation (Equation 1b) to measure the long-term effect of marketing strategies on base sales and regular price elasticity. The system evolution matrix G measures the duration of these strategies—comparable to the decay rate of advertising stock. We assume the stochastic term ω_t to be distributed N(0, W).

Importantly, the DLM methodology accounts for evolution/nonstationarity in the data. According to West and Harrison (1997, pp. 299–300), DLM approaches model the original time series directly, without data transformations, such as differencing. High levels of nonstationarity cannot usually be removed by differencing or other data transformations but instead are directly modeled through a DLM representation. For a detailed discussion on the benefits of DLM methodology and its relationship to other time-series models (e.g., VAR), see Van Heerde, Mela, and Manchanda (2004) and West and Harrison (1997). Next, we elaborate on this basic specification (i.e., Equations 1a and 1b) and detail how we extend it to control for endogeneity in prices and marketing mix and performance feedback.

Model Specification

Observation equation: short-term effects. To capture the short-term effect of marketing activity on a brand's sales in a given chain, we operationalize Equation 1a as a log-log model, similar to Van Heerde, Mela, and Manchanda (2004) and others:

$$\begin{aligned}
\text{(2)} \quad \overline{\ln \text{SALES}}_{jst} = {} & \alpha_{jt} + \beta_{jt}\overline{\ln \text{RPR}}_{jst} + \mu_j\overline{\ln \text{PI}}_{jst} + \varphi_j\overline{\text{FND}}_{jst} \\
& + \sum_{\substack{j'=1 \\ j' \neq j}}^{J} \rho_{1j'j}\overline{\ln \text{CRPR}}_{j'st} + \sum_{\substack{j'=1 \\ j' \neq j}}^{J} \rho_{2j'j}\overline{\ln \text{CPI}}_{j'st} \\
& + \tau_{0j}\text{TEMP}_t + \sum_{i=1}^{I} \tau'_{ij}\text{HDUM}_{it} + \zeta_{1jt}\overline{\text{ADV}}_{jt} \\
& + \zeta_{2j}\overline{\text{DSC}}_{jt} + \zeta_{3j}\overline{\text{DBR}}_{jt} + \zeta_{4j}\overline{\text{LLN}}_{jt} + \xi_{jst} + \upsilon^S_{jst},
\end{aligned}$$

where ln SALES_{jst} represents the log-sales of brand j in chain s in week t; ln RPR_{jst} is the log-inflation-adjusted regular price; ln PI_{jst} is the log of price index, which is defined as the ratio of actual price to regular price; FND_{jst} indicates whether there was a feature and/or display without a price discount; ln $\text{CRPR}_{j'st}$ and ln $\text{CPI}_{j'st}$ are log-cross-regular prices and log-cross-price indexes, respectively; TEMP_t is the average temperature in week t; and HDUM_{it} is a vector of holiday dummies for events such as Christmas and Easter. The four marketing variables are advertising expenditure (ADV_{jt}), national discount depth (DSC_{jt}), distribution breadth (DBR_{jt}), and product line length (LLN_{jt}).

We standardize all variables (after taking logs, if applicable) within brand chain to control for unobserved fixed effects and indicate this by the overbar. This standardization also facilitates comparison of effect sizes across the mix and categories (in which price is typically expressed in different equivalency units such as liters or grams) and implies that the model uses within-brand variation over time for inferences.

In Equation 2, α_{jt} is the brand-specific time-varying intercept, which can be construed as base sales because all independent variables have been mean centered. The time-varying brand-specific regular price elasticity coefficient β_{jt} is the second central parameter.

We also incorporate several control variables in the model: μ_j is the promotional price elasticity, φ_j is the feature and/or display log multiplier, $\rho_{1j'j}$ and $\rho_{2j'j}$ are cross-regular and -promotional price elasticities, and τ_{ij} (i = 0, …, I) captures seasonal variation. In addition, ζ_{kj} (k = 1, …, 4) capture the short-term (contemporaneous) effects of marketing activities on sales. Given the rich literature on advertising dynamics (e.g., Bass et al. 2007; Naik, Mantrala, and Sawyer 1998), we allow the advertising effect to vary over time (ζ_{1jt}) with a random-walk evolution $\zeta_{1jt} = \zeta_{1jt-1} + \omega^{\zeta}_{jt}$. We include ξ_{jst}, a brand-chain specific intercept, to account for potential first-order autoregressive errors ($\xi_{jst} = \lambda^{\xi}_{js}\xi_{jst-1} + \omega^{\xi}_{jst}$). Finally, υ^S_{jst} is an error term, which is assumed to be distributed normal and independent across time.

System equation: long-term effects. A core contention of this research is that brands' base sales and regular price elasticities vary over time as a function of marketing variables. To test these conjectures, we specify the long-term effect of marketing strategies on these two performance measures by operationalizing Equation 1b as follows:

$$\alpha_{jt} = \delta_j^{\alpha} + \lambda_j^{\alpha}\alpha_{jt-1} + \gamma_1^{\alpha}\overline{ADV}_{jt-1} + \gamma_2^{\alpha}\overline{DSC}_{jt-1} + \gamma_3^{\alpha}\overline{DBR}_{jt-1} + \gamma_4^{\alpha}\overline{LLN}_{jt-1} + \omega_{jt}^{\alpha}, \text{ and} \quad (3a)$$

$$\beta_{jt} = \delta_j^{\beta} + \lambda_j^{\beta}\beta_{jt-1} + \gamma_1^{\beta}\overline{ADV}_{jt-1} + \gamma_2^{\beta}\overline{DSC}_{jt-1} + \gamma_3^{\beta}\overline{DBR}_{jt-1} + \gamma_4^{\beta}\overline{LLN}_{jt-1} + \omega_{jt}^{\beta}. \quad (3b)$$

Here, the γs measure the effect of marketing variables on the base sales and regular price elasticities. These are the central parameters of interest in our analysis because they measure the effect of marketing strategy on brand performance. Standardization of the four marketing variables implies that their parameter estimates are driven by time-varying marketing strategies for a given brand rather than a cross-sectional comparison of marketing strategies across brands. The λs represent the decay rate of these effects, where λ is positive. A value near 0 implies that the effect of marketing strategy is brief, whereas a value of 1 implies that the effect of the strategy is more enduring (the recursion in 3 implies a geometric decay of marketing effects). We assume that all ωs are independently distributed but brand specific, with zero mean and a diagonal covariance matrix W.

The intuition behind our observation and system equations is that they decompose the short-term from the long-term marketing effects, as well as the brand effects from the chain effects if necessary. The short-term effects, given by the response parameters in Equation 2, capture the contemporaneous effects of marketing variables on a given week's sales of a brand within a given chain. For example, μ_j captures the current-period effect of a chain-specific discount on brand sales in a given week. We capture the long-term effects of marketing through the influence of marketing variables on α_{jt} (base sales) and β_{jt} (regular price elasticity), as we show in Equations 3a and 3b. Thus, γ_2^{α} captures the effect of a brand's cumulative historical discounting on base sales. Likewise, whereas μ_j captures the short-term effect of a local or chain-specific discount on sales, ζ_{2j} captures the short-term effect of national discounting policy on local or chain-level brand sales. Researchers might expect the contemporaneous effect of national discounting to be small when local chain effects are controlled for because not all stores within a chain adopt the promotion; indeed, this is what we find. Note that this treatment of promotion at the national brand level is consistent with the other aspects of the marketing mix.

Price and marketing-mix endogeneity, performance feedback, and competitor response. Bijmolt, Van Heerde, and Pieters's (2005) meta-analysis indicates that price endogeneity plays a major role in price response estimates. To mitigate this bias, we adopt an approach that is analogous to a limited-information simultaneous equations approach to the endogeneity problem. That is, we replace the supply-side model with a linear specification that includes instrumental variables as the independent variables, and we allow for correlation between the demand-side error term and the supply-side error term. Specifically, we construct the following equation:

$$\overline{\ln RPR}_{jst} = \mu_{0j}^{RPR} + \mu_{1j}^{RPR}\overline{\ln RPR}_{jst-1} + \mu_{2j}^{RPR}TEMP_t + \mu_{3j}^{RPR}\overline{\ln SALES}_{jt-3}^{Own} + \mu_{4j}^{RPR}\overline{\ln SALES}_{jt-3}^{Cross} + \upsilon_{jst}^{RPR}. \quad (4)$$

The specification assumes that a brand's regular price in a particular chain ($\overline{\ln RPR}_{jst}$) is a manifestation of its (latent) national pricing strategy μ_{0j}^{RPR}. Deviations from this strategy arise from seasonal and random effects. We use lagged regular price ($\overline{\ln RPR}_{jst-1}$) to capture inertia in pricing (Yang, Chen, and Allenby 2003). By including lagged national sales of the focal brand and lagged sum of competing brands' national sales ($\overline{\ln SALES}_{jt-3}^{Own}$ and $\overline{\ln SALES}_{jt-3}^{Cross}$, respectively), we can control for own- and cross-performance feedback.[4] We estimate Equations 2 and 4 simultaneously and let error terms υ_{jst}^{S} and υ_{jst}^{RPR} be correlated to account for price endogeneity in the observation equation. We also specify a similar equation for promotional price ($\overline{\ln PI}_{jst}$).

Finally, we specify an additional equation for each marketing variable to control for performance feedback in marketing spending. Otherwise, the imputed link between marketing spending and brand performance may be an artifact of the effect of past performance on marketing spending. Another key advantage of this approach is that it affords a parsimonious control for changes in long-term marketing strategies of competing brands because the sales of these brands are a function of their marketing strategies. Therefore, we include the following regression equation in the system for all four marketing variables:

$$\overline{Z}_{ijt} = \mu_{0j}^{Zi} + \mu_{1j}^{Zi}\overline{Z}_{ijt-1} + \mu_{2j}^{Zi}TEMP_t + \mu_{3j}^{Zi}\overline{\ln SALES}_{jt-3}^{Own} + \mu_{4j}^{Zi}\overline{\ln SALES}_{jt-3}^{Cross} + \upsilon_{ijt}^{Zi}, \quad (5)$$

where $\overline{Z}_{ijt}$ is the ith marketing variable of brand j during week t; μ_{1j} captures inertia in marketing; μ_{2j} accounts for seasonality; and the parameters μ_{3j} and μ_{4j} capture, respectively, the own- and cross-performance feedback effects for marketing variable i. This specification builds on the work of Horvath and colleagues (2005), who show that own- and cross-performance feedback are more informative than direct competitive action in the prediction of marketing-mix activity. In support of this, recent research has shown that cross-instrument competitive reactions are predominantly zero (e.g., Ataman, Mela, and Van Heerde 2008; Pauwels 2007; Steenkamp et al. 2005). Equation 5 implies that marketing spending is affected by a geometrically weighted sum of own- and competing-brand sales from the preceding periods. Therefore, the model captures phenomena such as retailers' disadoption of brands whose sales have been declining for several months (e.g., Franses, Kloek, and Lucas 1998). Finally, the model accommodates dynamic dependencies among all the marketing variables through the mediating impact of sales (e.g., Bronnenberg, Mahajan, and Vanhonacker 2000).

Using Markov chain Monte Carlo techniques, we estimate Equation 5 together with Equations 2 and 4, and we let error terms υ_{jst}^{S}, υ_{jst}^{RPR}, υ_{jst}^{PI}, and υ_{jst}^{Zi} be correlated. Allowing

[4]In the pricing and marketing-mix equations, which we discuss subsequently, we entertained two sets of exogenous variables: (1) lagged dependent variable and lagged own and competitor sales and (2) lagged dependent variable, lagged own and competitor sales, and lagged composite indexes of competing brands' prices and marketing-mix variables (using a sales weighted average to construct this index). Wu–Hausmann tests performed on a static version of the model indicate endogeneity for both sets of variables. Using Sargan's overidentifying restriction test (similar to Basman's J), we find that the null hypothesis that all instruments are exogenous is rejected with both sets of the instruments. We find that omitting the competitive indexes and substituting the third lag for sales leads to a set of instruments in which exogeneity cannot be rejected.

for contemporaneous correlation among sales, pricing, and marketing-mix equations helps us (1) account for common unobserved shocks that may jointly influence sales and marketing, (2) control for simultaneity without inducing a causal ordering among the contemporaneous effects, and (3) capture covariation in marketing expenditures that may arise from retailer category management practices. The details of the estimation procedure appear in the Web Appendix (http://www.marketingpower.com/jmroct10).

Note that some of the parameters in Equations 2–5 are specified as non–time varying. The state space enlarges exponentially with additional time-varying parameters, and the model yielded poor reliability and convergence when we allowed all parameters, including those for control variables in Equations 2 and 4 and all parameters in Equation 5, to vary. Although the resulting degrees of freedom in Bayesian DLM models are difficult to assess and are data dependent because of the precision of the likelihood and priors, it is evident that strong and perhaps unpalatable assumptions would be necessary to identify time-varying parameters for all the regressors.

EMPIRICAL ANALYSIS

We use a novel data set provided by Information Resources Inc. (IRI [France]) to calibrate our model. These data include five years (first week of 1999 up to and including first week of 2004) of weekly stockkeeping unit (SKU)–store-level scanner data for 25 product categories sold in a national sample of 560 outlets representing 21 chains. The 25 categories vary across dimensions such as food/nonfood, storable/nonstorable, new/mature, and so forth. In addition, TNS Media Intelligence (France) provided the matching monthly brand-level advertising data. Accordingly, the data include temporal and cross-sectional changes in (1) advertising strategies, (2) product offerings, (3) distribution coverage, and (4) pricing strategies. We selected France over the United States because it does not suffer from measurement problems induced by Wal-Mart. Given that Wal-Mart sales are growing and because IRI and ACNielsen do not cover this chain, parameter paths could reflect these changes.

The long duration, coverage of the entire mix, and manifold categories make the data well suited to address the core research questions. Conversely, the data's massive size renders estimation of an SKU-store-level model specification infeasible. As such, we aggregate the data to the brand–chain level. We aggregate to the brand level because our central focus in on the effect of marketing strategy on brand sales, and we aggregate to the chain level because pricing and other marketing policies tend to be fairly consistent within chains in the data.

To avoid any biases due to linear aggregation, we aggregate the data from the SKU–store level to the brand–chain level following the nonlinear procedures that Christen and colleagues (1997) outline. We limit our analyses to the top four chains (184 stores), which account for approximately 75% of the total turnover across all categories, and to three top-selling national brands per category.[5] However, there are three categories, dominated by private labels, in which we observe fewer than three national brands being sold in the top four chains over the entire sample period. This leaves us with 70 national brands. The total number of observations is 73,080 (4 chains × 70 brands × 261 weeks).

The total market share of the top three national brands ranges between 26.1% (oil) and 79.1% (carbonated soft drinks). We present the variables and their operationalizations in the Appendix. In Table 3, we show the descriptive statistics of the data. There is more week-to-week variation in the advertising and discounting variables than in the distribution and product variables. However, because the data span a long period (five years of weekly data), there is sufficient variation in the product and distribution variables to measure their effects.

RESULTS

In this section, we first discuss the results of the short-term sales model. Then, we detail long-term effects, including (1) the effect of the marketing mix on base sales and regular price elasticities and (2) inertia and performance feedback arising from the marketing expenditures model. We conclude by integrating the long- and short-term models to derive insights into the overall effect of marketing strategy on sales over the long and short run and across the mix.

The Short-Term Effects

We consider three sets of parameters in the sales model (Equation 2) for each of the 70 brands: (1) the control variable parameters, such as promotional price elasticity, feature/display multiplier, cross-price elasticities, and seasonality parameters; (2) parameters pertaining to short-term marketing effects; and (3) the time-varying parameters (the intercepts and elasticities). The promotional price elasticity is –3.35 (see Table 4), which is consistent with Bijmolt, Van Heerde, and Pieters (2005). The mean of the feature and display multipliers, which we obtained by taking the anti-log-transformation, is 1.12, which is comparable to other results in the literature (Van Heerde, Mela, and Manchanda 2004). The regular and promotional cross-price elasticity estimates average .07 and .18, respectively, across all brands, which is also similar to other results in the literature (Sethuraman, Srinivasan, and Kim 1999). The coefficient of average weekly temperature is significant (95% posterior density interval excludes zero) in product categories in which sales are expected to exhibit a seasonal pattern (i.e., reaching a peak during summer months in categories such as ice cream and carbonated soft drinks and during winter months in categories such as soup and coffee) and insignificant in others.

Table 4 also indicates that, on average, all marketing-mix variables have a positive short-term effect on sales. The strongest effects pertain to distribution breadth (.016) and product line length (.015), followed by advertising (.008) and discounting (.0001). The average regular price elasticity over time and across brands is –1.45, consistent with the results of Bijmolt, Van Heerde, and Pieters's (2005) meta-analysis.

The Long-Term Effects

Base sales and price elasticity. To exemplify how long-term changes in brand performance evolve over time, Figure 3 plots the base sales and price sensitivity of Brand C.

[5]We omit store brands because they do not advertise and their distribution is limited, so we cannot use these to contrast elements of the marketing mix.

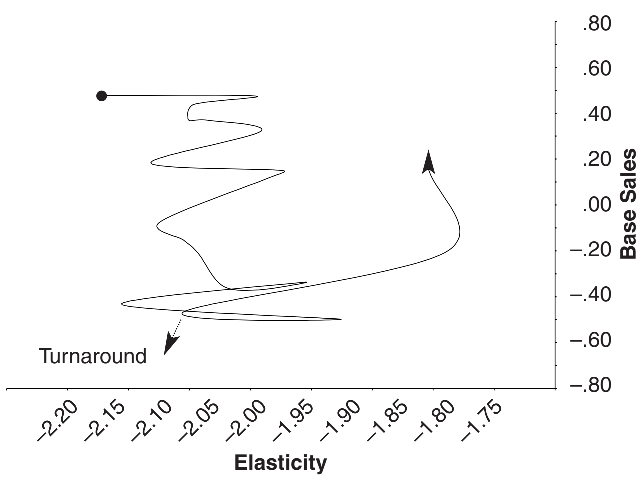
Table 3
DESCRIPTIVE STATISTICS

		Market Share (%)	Discount Depth (%)		Advertising (100,000 Euros)		Distribution (% ACV)		Line Length (Number of SKUs)	
Category	Number of Brands	M[a]	M	Variance[b]	M	Variance	M	Variance	M	Variance
Bath products	3	9.9	2.1	1.8	.584	.9	99.9	.1	50.8	48.9
Beer	3	17.4	2.1	1.8	1.786	6.5	100.0	—	31.0	12.1
Coffee	3	14.4	2.9	2.3	2.877	5.6	100.0	—	36.6	49.9
Chips	1	32.8	3.4	3.2	—	—	99.8	.3	46.6	169.4
Cereals	3	25.4	1.7	1.2	3.784	7.1	96.8	9.5	32.9	13.7
Soft drinks	3	26.4	2.4	1.3	2.825	5.4	99.8	.8	37.2	28.1
Diapers	3	20.8	1.2	1.0	.835	1.0	99.7	.8	51.1	548.4
Detergent	3	15.6	1.4	2.1	2.891	2.6	100.0	—	43.5	170.2
Feminine needs	3	18.9	.9	.6	1.791	1.4	100.0	—	36.2	30.8
Frozen pizza	3	15.8	2.4	2.4	.396	1.0	97.2	7.5	14.8	17.5
Ice cream	3	10.1	3.4	3.9	.664	2.2	98.7	3.5	60.0	739.1
Mayonnaise	3	23.9	1.2	1.3	.818	1.2	99.7	.2	48.8	50.0
Oil	3	8.7	1.6	1.4	.690	.9	99.8	.2	21.2	8.5
Pasta	3	20.7	2.5	1.5	1.126	1.7	100.0	—	105.2	156.5
Paper towel	1	33.9	2.6	1.8	.782	1.4	99.0	1.2	12.4	5.3
Shaving cream	3	17.3	1.0	.7	.123	.2	99.7	.7	27.2	36.1
Shampoo	3	11.3	1.5	1.0	1.776	2.1	99.9	.0	41.3	87.5
Soup	3	24.1	1.0	.9	1.193	3.5	99.7	.2	67.2	107.8
Tea	3	17.2	.4	.2	.282	.4	96.7	15.5	27.8	7.3
Toothpaste	3	17.2	1.3	1.3	1.304	1.3	99.9	.1	34.3	44.1
Toilet tissue	3	14.3	1.9	1.1	.352	.7	97.3	6.5	17.7	5.3
Window cleaner	2	29.4	.6	.4	.027	.1	98.0	6.0	6.0	1.9
Water	3	10.4	1.2	.9	2.492	6.6	100.0	—	25.0	10.6
Yogurt drinks	3	26.3	1.8	3.0	.246	.4	98.7	7.2	11.3	7.8
Yogurt	3	10.8	1.0	.7	1.030	3.9	99.6	1.9	26.4	11.9
All categories	70	18.9	1.8	1.5	1.2268	2.3	99.0	2.5	36.49	94.8

[a]Average across all weeks and brands within a category.
[b]Average across all brands within a category.
Notes: ACV = all commodity volume.

Notably, at the point of the turnaround, both metrics improve. Base sales increase, implying higher levels of demand, and price response lessens, implying that the firm can raise its average price and, thus, margins. Closer inspection of Figure 1 reveals that many aspects of the brand strategy changed at the point of the brand's turnaround (discounts decreased, advertising increased, the product line expanded, and distribution grew), making it difficult to ascertain the determinant factors that drive performance. Pooling across brands, however, enables us to paint a more reliable picture of the tools that are most impactful.

Figure 3
PLOT OF BASE SALES AND PRICE ELASTICITY OVER TIME FOR BRAND C



Specifically, we examine the long-term effect of marketing strategy on base sales and regular price elasticity (Equations 3a and 3b). Across all categories, the marketing effects on base sales and regular price elasticity are given by γ^{α} and γ^{β}, respectively (see Table 5).

Table 5 indicates that advertising spending and product line length increase base sales, as we expected. The negative effect of discounting reflects that excessive discounting lowers base sales, consistent with deal-to-deal buying patterns. The effect of distribution breadth on base sales is negligible because the 90% posterior density interval includes zero. However, as we discuss subsequently, this limited direct long-term effect does not mean that distribution breadth has negligible impact on sales. The indirect long-term effect can remain large if the positive short-term effect of distribution is coupled with a sizable sales feedback effect. We explore the total long-term effects subsequently.

Table 5 further indicates that product line length and advertising increase regular price elasticity (i.e., make it less negative). The result supports the notion that offering more alternatives and high advertising support helps brands better match consumer needs to products and differentiate themselves from the competition. Conversely, discounting decreases price elasticity (i.e., makes it more negative). This result is consistent with previous research, which suggests that discounts make demand more price elastic (Kopalle,

Table 4
PARAMETER ESTIMATES OF SALES AND MARKETING-MIX MODELS

Equation	*Coefficient*	*M*	*Variance*
Sales	Feature/display	.106	.007
	Price index (own)	–3.348	6.136
	Price index (first competitor)	.160	.218
	Price index (second competitor)	.195	.135
	Regular price (first competitor)	.041	.142
	Regular price (second competitor)	.091	.102
	Temperature	.001	.000
	Christmas	–.079	.049
	New Year's	.012	.035
	Easter	.068	.005
	Ascension	–.021	.002
	Bastille Day	–.015	.001
	Assumption	–.052	.003
	Advertising	.008	.004
	Discounting	.000	.001
	Distribution	.016	.003
	Line length	.015	.009
Advertising	Constant	–.001	.000
	Temperature	.001	.000
	Lagged advertising	.851	.002
	Own-performance feedback	–.028	.004
	Cross-performance feedback	.004	.004
Discounting	Constant	.000	.000
	Temperature	.002	.000
	Lagged discounting	.707	.007
	Own-performance feedback	.000	.011
	Cross-performance feedback	.003	.008
Distribution	Constant	.005	.000
	Temperature	–.002	.000
	Lagged distribution	.624	.090
	Own-performance feedback	.037	.015
	Cross-performance feedback	–.012	.010
Line length	Constant	.006	.000
	Temperature	.002	.000
	Lagged line length	.923	.004
	Own-performance feedback	.003	.004
	Cross-performance feedback	–.005	.005
Regular price	Constant	.000	.000
	Temperature	.000	.000
	Lagged regular price	.898	.003
	Own-performance feedback	.000	.000
	Cross-performance feedback	.000	.000
Price index	Constant	.000	.000
	Temperature	.000	.000
	Lagged price index	.703	.007
	Own-performance feedback	.000	.000
	Cross-performance feedback	.000	.000

Notes: Mean and variance across median estimates for 70 brands.

Mela, and Marsh 1999). Finally, Table 5 indicates that the effect of distribution breadth on price elasticity is negative; however, the effect can be considered negligible because the 90% posterior density interval includes zero.[6]

Table 6 displays the median long-term effect across the brands in the category. For each brand j, these are given by $\gamma^\alpha/(1 - \lambda_j^\alpha)$ and $\gamma^\beta/(1 - \lambda_j^\beta)$. Table 6 shows that the magnitudes of the long-term effects on base sales and elasticities vary considerably across categories. Moreover, categories for which the effects on base sales are relatively strong (e.g., diapers, soup) do not necessarily coincide with categories for which the effects on elasticity are relatively strong (e.g., detergent, bath products). This lends support to our two-faceted measures of brand performance. This may be related to the purchase cycle of some of these categories because long-term effects tend to be more enduring as these purchase cycles lengthen; next, we provide an overview of these duration effects.

Duration of base sales and price elasticity dynamics. Also of interest is the duration of these effects, parameterized by λ in our model (Equations 3a and 3b). If a brand has done well, how long do positive effects linger? Conversely, if a brand has done poorly, how long does it take to resuscitate it? Across the 70 brands, the intercept decay parameters range between .48 (25th percentile) and .92 (75th percentile), with a median of .69. This implies that 90% duration intervals of marketing activity (Leone 1995) range from 3.2 to 28.3 weeks with a median of 6.2 weeks. The median decay for regular price elasticity is .44, ranging between .25 (25th percentile) and .73 (75th percentile), and the implied 90% duration intervals range from 1.7 to 7.2 weeks with a median of 2.8 weeks. This implies that the adjustment in elasticity is slightly faster than the adjustment in base sales. In seven categories, the effects of the marketing mix on base sales or elasticities appear to be persistent (nonstationary) because the posterior density intervals for decay parameters include 1 (Dekimpe and Hannsens 1999). Overall, these dynamics imply that, in general, it is possible to recover from a weak position within a couple of months. However, in some instances, it can take 6 months or more to resuscitate a brand.

[6]As long-term drivers of brand performance, we also considered (1) a product variety measure, (2) a distribution depth variable (analogous to shelf facings), and (3) a feature/display variable. However, all variables evidenced minimal explanatory power.

Table 5
MARKETING-MIX EFFECTS ON INTERCEPTS AND ELASTICITIES

			Estimated Effect on			
	Expected Effect on		*Intercept*		*Elasticity*	
Effect of	*Intercept*	*Elasticity*	*Mdn*	*[5th and 95th percentile]*	*Mdn*	*[5th and 95th percentile]*
Discounting	Positive/negative	Negative	–.0044	[–.0061, –.0029]	–.0119	[–.0067, –.0177]
Advertising	Positive	Positive	.0069	[.0052, .0086]	.0083	[.0014, .0139]
Distribution	Positive	Positive/negative	–.0008	[–.0026, .0012]	–.0047[b]	[–.0128, .0027]
Line length	Positive	Positive	.0012[a]	[–.0001, .0025]	.0123	[.0074, .0182]

[a]The effect of line length on base sales crosses zero at 93rd percentile.
[b]The effect of distribution breadth on elasticity crosses zero at 86th percentile.

Table 6
LONG-TERM EFFECTS OF MARKETING-MIX EFFECTS ON INTERCEPTS AND ELASTICITIES

	Intercept				*Elasticity*			
Category	*Discounting*	*Advertising*	*Distribution*	*Line Length*	*Discounting*	*Advertising*	*Distribution*	*Line Length*
Bath products	–.010	.016	–.002	.003	–.415	.268	–.161	.431
Beer	–.021	.032	–.004	.005	–.017	.012	–.007	.016
Coffee	–.034	.052	–.006	.009	–.022	.014	–.009	.022
Chips	–.014	.022	–.003	.004	–.021	.014	–.009	.022
Cereals	–.014	.023	–.002	.004	–.022	.015	–.009	.023
Soft drinks	–.020	.032	–.004	.005	–.016	.011	–.007	.018
Diapers	–.181	.278	–.031	.048	–.022	.015	–.008	.022
Detergent	–.008	.013	–.001	.002	–.035	.023	–.014	.038
Feminine needs	–.009	.014	–.002	.002	–.023	.016	–.009	.024
Frozen pizza	–.041	.063	–.007	.011	–.026	.018	–.010	.027
Ice cream	–.068	.105	–.012	.018	–.076	.049	–.029	.078
Mayonnaise	–.033	.052	–.006	.009	–.017	.011	–.006	.016
Oil	–.014	.021	–.002	.004	–.019	.011	–.007	.018
Pasta	–.010	.015	–.002	.003	–.025	.016	–.011	.025
Paper towel	–.121	.184	–.020	.031	–.021	.014	–.008	.020
Shaving cream	–.007	.011	–.001	.002	–.018	.012	–.008	.019
Shampoo	–.011	.017	–.002	.003	–.017	.011	–.006	.017
Soup	–.069	.106	–.012	.018	–.042	.024	–.015	.043
Tea	–.009	.014	–.002	.002	–.015	.011	–.006	.017
Toothpaste	–.008	.013	–.001	.002	–.025	.018	–.010	.026
Toilet tissue	–.010	.014	–.002	.002	–.029	.020	–.011	.030
Window cleaner	–.013	.020	–.002	.003	–.031	.020	–.012	.032
Water	–.008	.012	–.001	.002	–.016	.011	–.006	.017
Yogurt drinks	–.099	.149	–.017	.025	–.066	.042	–.027	.075
Yogurt	–.015	.023	–.002	.004	–.020	.013	–.008	.020
All categories	–.014	.022	–.002	.004	–.022	.015	–.009	.022

Notes: We computed the long-term effects of marketing variables over a five-year horizon. Table entries are medians across brands in a product category.

Price and marketing-mix expenditure dynamics. We summarize the findings that pertain to the regular and promotional price equations (Equation 4) and the four marketing-mix models (Equation 5). First, we compared the fit of a model with no endogeneity and performance feedback with that of a model with these controls. A log–Bayes factor of 12,992 suggests that it is critical to control for endogeneity and performance feedback.[7] Second, Table 4 shows that inertia in prices and marketing mix ranges between .62 (distribution) and .92 (line length). Third, better historical performance leads to greater marketing spending (i.e., increased distribution coverage and longer product lines), highlighting the importance of controlling for performance feedback when evaluating the long-term effect of marketing strategy. Finally, we find that cross-sales performance feedback is usually zero.

The Short- and Long-Term Effects of Marketing Variables on Sales

So far, our discussion about the long-term effect of marketing variables on base sales and elasticities has focused on the γ in Equation 3. However, to quantify the full impact of marketing variables on sales, we also need to consider the direct (contemporaneous) effects of marketing variables on sales through Equation 2, the indirect effects through the inertia and feedback effects present in Equation 5, and their implications on chain-level regular prices and price indexes through Equation 4.

To calculate the full effects of the marketing variables ($\overline{ADV}_{jt}$, $\overline{DSC}_{jt}$, $\overline{DBR}_{jt}$, $\overline{LLN}_{jt}$) on sales over the short and long run, we set each variable at its mean and then increase each marketing variable, in turn, by 1% in week t. The effect on ln(sales) in week t (through Equation 2) is the short-term elasticity, $\hat{\eta}_k^s$, where k denotes the element of the mix (e.g., advertising) and s indicates the short run. This shock in marketing also carries forward to future periods in several ways, including inertia (μ_{1j}^{zi} in Equation 5), performance feedback (μ_{3j}^{zi} in Equation 5), and the long-term effect on base sales and price elasticity in Equation 3. We compute the cumulative implication of this shock for ln(sales) over a time window of 52 weeks (weeks t + 1, …, t + 52), representing the long-term elasticity, $\hat{\eta}_k^l$. The total effect ($\hat{\eta}_k^t$) is given by the long-term effect plus the short-term effect. To compute the relative effect, we calculate $|\hat{\eta}_k^p|/\Sigma_k|\hat{\eta}_k^p|$, where p = {s, l, t}. Table 7 shows the contemporaneous, long-term, and total

Table 7
SALES IMPACT OF 1% TEMPORARY INCREASE IN MARKETING SUPPORT (%)

	Contemporaneous	*Long Term*	*Total*
Discounting	.06	–.02	.04
Advertising	.01	.12	.13
Distribution	.13	.61	.74
Line length	.08	1.29	1.37

Notes: Table entries are medians across brands.

[7]We computed the log–Bayes factor as the difference between the harmonic mean of the log–marginal likelihood of one-step-ahead forecasts of the benchmark model and that of the null model (West and Harrison 1997, p. 394).

brand sales elasticity of the marketing mix, and Figure 4 presents a pie chart of the relative effects.

Several striking results emerge. First, the short-term elasticities ($\hat{\eta}_k^s$) of distribution and product are predominant. The distribution elasticity is .13, the product elasticity is .08, the discount elasticity is .06, and the advertising elasticity is .01.[8] The short-term depth elasticity is slightly larger than the mean of .02 that Jedidi, Mela, and Gupta (1999) report, and the short-term advertising elasticities appear to be somewhat smaller than the average of .05 for mature brands that Lodish and colleagues (1995) report.

Second, the long-term elasticities ($\hat{\eta}_k^l$) of product (1.29) and distribution (.61) dwarf the elasticities for advertising (.12) and discounting (–.02). The long-term advertising elasticity (.12) is lower than the empirical generalization (.20) that Hanssens, Parson, and Schultz (2001, p. 329) report. This difference, as well as the differences we discussed in the previous paragraph, might be attributable to (1) the inclusion of the full marketing mix as regressors (most studies to date include only a subset [see Table 1], possibly suffering omitted variable biases) or (2) changes in the effectiveness of advertising and promotion over time.

Third, we find that the magnitude of the negative long-term effect of promotion is approximately one-third the magnitude of the positive short-term effect, consistent with the result for a single category that Jedidi, Mela, and Gupta (1999) report. In contrast, the ratio is reversed for other marketing-mix instruments, making the greater long-term impact on brand building evident. For these other instruments, the long-term effects are 4 to 16 times the short-term effects. The larger long-term effect results from an interaction between a large short-term effect and substantial carryover. In particular, product has the highest inertia, and distribution has the highest sales performance feedback. As a result, the total effect of these instruments is much larger than for promotion.

Finally, the total (short-term plus long-term) elasticity $\hat{\eta}_k^t$ (and its share of the sum of total elasticities) of product is 1.37 (60%), and the long-term elasticity for distribution breadth is .74 (32%). In sharp contrast, the effect of advertising is only .13 (6%), and for discounts, it is .04 (2%). Thus, we find evidence that distribution and product play the major roles in discriminating between the performance of mature brands, despite the emphasis of prior research on discounts and advertising (e.g., Jedidi, Mela, and Gupta 1999). This result is consistent with the common wisdom that distribution and product are among the most important components of marketing strategy.

SUMMARY

Marketing managers spend billions of dollars annually on their marketing programs, but few studies systematically assess the long-term effect of these programs over many brands and categories. Moreover, extant research focuses largely on advertising and promotions (see Table 1) but not on product or distribution.

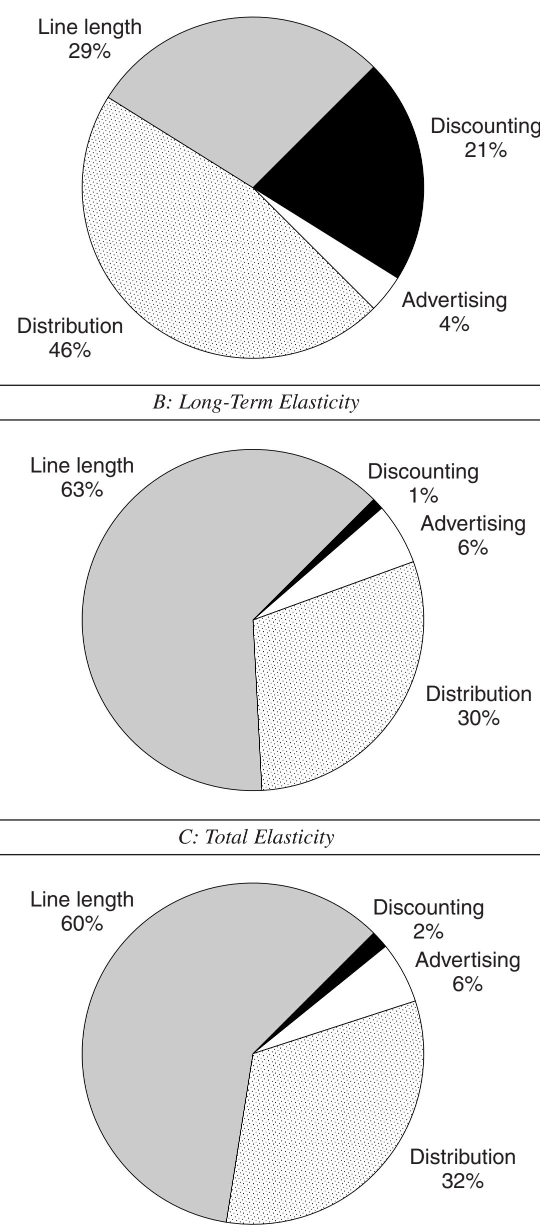
This study attempts to address both the data and the modeling requirements. We use five years of weekly data across 25 categories and 70 brands sold in the four largest chains in France. By relating the performance of these brands to their integrated marketing-mix strategy, we offer insights into which strategies are most likely to lead to long-term advantages for brands. We apply a DLM to the data, which enables us to model both sales and the marketing mix as dependent variables and helps us accommodate endogeneity, performance feedback, and competitive interactions (through cross-performance feedback effects).

Figure 4
RELATIVE ELASTICITIES ACROSS THE MIX

A: Short-Term Elasticity

B: Long-Term Elasticity

C: Total Elasticity



[8]The discount depth elasticity (.06) should not be confused with the price promotion elasticity (–3.35). Note that a 1% increase in discount depth at the chain level (DSC_{jst}), arising from a 1% increase in national discount depth (DSC_{jt}), corresponds to a much smaller decrease in the price index variable ($PI_{jst} = 1 – DSC_{jst}$). This relationship, coupled with the low average discount depth observed in the data (1.8%), explains the modest magnitude of discount depth elasticity. Thus, although our emphasis is on the national level, we consider the chain-level reflection (PI_{jst}) of the new national discounting strategy (DSC_{jt}) in the elasticity calculation.

Using the DLM, we link marketing strategy to two components of brand performance: base sales and regular price elasticity. First, after controlling for short-term sales spikes induced by discounting, we find that all aspects of the marketing mix exhibit a positive short-term direct effect on sales, most notably distribution and line length.

Second, the mix also evidences indirect effects through base sales and price response. Base sales are positively affected by advertising but negatively affected by discounting over the long run. Thus, discounting plays a largely tactical role by generating strong bumps in the short run, but it has adverse effects as a strategic long-term marketing instrument. Regular price elasticities are decreased by discounting and distribution, but they are increased by advertising and line length. We suspect that the negative effect of distribution on price elasticity is due to increased potential for consumers to shop across stores. Third, the median 90% average decay of the mix effect on base sales is approximately 6.2 weeks. The corresponding figure for elasticities is 2.8 weeks. Fourth, dynamics are also present through performance feedback and inertia in spending. Performance feedback is strongest for distribution, while inertia is strongest for product. Fifth, when combined, all these effects indicate that product (60%) and distribution (32%) have a substantially larger relative effect on brand sales over the long run than discounting (2%) or advertising (6%). Finally, we find that the magnitude of the dynamic effect of a promotion is one-third the magnitude of its contemporaneous effect. This ratio is reversed for other aspects of the marketing mix, suggesting their greater potential to make an enduring impact on brand sales.

LIMITATIONS

The findings are subject to several notable limitations, some of which point out several future research opportunities. First, the DLM is well suited to linking marketing activity to intercepts and elasticities but cannot easily be scaled to a large number of variables, periods, and observations because (1) the state space explodes and, along with it, the computer memory needed for estimation and (2) convergence of each model run takes weeks. Therefore, our use of the DLM amplifies the trade-off between model parsimony and completeness. Accordingly, we made several assumptions to render the analysis feasible.

Second, our model does not allow for different decay factors for different marketing variables. A canonical transfer function DLM can be written to overcome this limitation, and different decay parameters can be estimated for each marketing variable using a data augmentation step in the Gibbs sampler.

Third, several potential interactions exist in the marketing mix. For example, advertising itself may facilitate new distribution. We control for these effects indirectly through lagged performance feedback, which embeds the marketing actions that firms pursue in preceding periods.

Fourth, we assume that the effects of feature and display are fixed over time. Undoubtedly, these effects can change over time with marketing strategy. Expansion of the model to accommodate these effects would render such insights unreliable as a result of increased model complexity. In an analysis not reported herein, we estimated a simpler version of the DLM in which all parameters were time varying, but the time paths were not specified to vary with the marketing mix. The estimated parameter paths for price and the intercept were largely the same as observed in our model, suggesting that the omission of time-varying effects for feature and display does not bias the results.

Fifth, we aggregate data to the chain level. It would be desirable to extend this research to the store level because that would enable us to study interretail price competition. Chain-level measures are more noisy, and the reduction in observations reduces power. As a result, this research is a conservative test of the hypotheses. Chain-level analysis is not uncommon in marketing (e.g., Slotegraaf and Pauwels 2008; Srinivasan et al. 2004), perhaps because marketing activity tends to be correlated across stores within a chain.

Sixth, we consider the top four chains and three largest brands in each category. As such, the results should be interpreted from the perspective of managers with large brands selling through predominantly large chains. It would be worthwhile to consider whether the results generalize to smaller brands and outlets.

Seventh, our focus is on mature brands, and it is interesting to conjecture how the stage in product life cycle moderates our analysis. For example, in the context of new consumer packaged goods brands, Ataman, Mela, and Van Heerde (2008, Table 6) find that gaining access to distribution has a greater impact on sales than extending the product line, contrary to the findings in this article. However, in line with our findings, they find that advertising and discounting elasticity magnitudes are much smaller than those of distribution and line length.

Eighth, our analysis pertains to consumer packaged goods products. In the context of other products or services, evidence suggests that distribution matters more than advertising (e.g., in the motion picture industry, see Elberse and Eliashberg 2003; on the diffusion of cable television, see Mesak 1996). Analyzing sales and marketing data on established non–consumer packaged goods brands, Pauwels and colleagues (2004) find that the positive short-term impact of product line length on firm performance dominates that of discounting—similar to our findings; however, this relationship is reversed in the long run.

Ninth, because of the lack of data, we cannot include the perceived quality of the brands (e.g., Aaker and Jacobson 1994) as a driver of brand performance. However, perceived quality is a fixed effect, so our standardization should control for its omission.

Tenth, we find that better historical performance leads to increased distribution coverage and more SKUs on the shelves, results for which retailers may be responsible since they act as gatekeepers. It may also be that manufacturers spend more money on push marketing for brands that performed well. Disentangling the two explanations would be worthwhile. Related to this, we consider retail price elasticities when evaluating the effect of observed marketing strategies on brand performance. However, retail prices embed behaviors of both the retailers and the firms that supply them. Accordingly, a formal accounting for the role of retailers would help firms disentangle those aspects of marketing strategy that are more salient to the firm and those that are more relevant to the retailer.

Finally, our data are from France, and it remains unclear whether some distribution elements are unique in France relative to other regions. France is similar to other Western European countries and comparable to the United States on several marketing statistics (see Steenkamp et al. 2005, Table 2). However, compared with the United States, in France, retail concentration is higher, while advertising and discounting intensity is lower. In the face of these differences, we may speculate that the effect of distribution will be attenuated in the United States, while the effects of advertising and discounting will be stronger. The results in IRI's (2008) long-term Drivers Consortium Study partially support the notion that distribution and advertising are critical for long-term growth in the U.S. market, with advertising being the largest driver.

Despite these limitations, we believe that this article makes an important first step in documenting the overall long-term effects of the entire marketing mix on brand sales. We hope that this study stimulates additional research that analyzes these effects in more detail, enabling even more finely tuned recommendations for marketing executives.

APPENDIX: VARIABLE OPERATIONALIZATIONS

Observation (Sales) Equation Variables

The dependent variable of the observation equation is sales volume, which we calculate as the all commodity volume–(ACV-) weighted geometric average of total sales of a brand in a given store–week, across stores in a given chain.[9] The core independent variable is regular price, for which we use the regular price series provided in the IRI data sets. It represents the normal price in the absence of a price discount. We aggregate it similar to Mela, Gupta, and Lehmann (1997), using the minimum regular price per 1000 volume units across SKUs of a brand in a given store and week as the regular price for that brand. This measure has the added benefit of not being sensitive to the particular sales weighting scheme selected. Moreover, it exploits price variation in the data that might be understated in the event that one major SKU lowers its regular price. We calculate average chain-level brand regular price in the nonlinear way, as Christen and colleagues (1997) outline. In addition, we include competing brands' regular prices. We also include the own- and cross-brand price index variable (actual price over regular price) to control for promotional price discounts. We assume that a brand is on feature or display if any SKU of that brand is on feature or display in a given store and week. We calculate chain-level feature and display variables by taking the ACV-weighted arithmetic average across stores in a given week (see Christen et al. 1997). The feature and display variable is set to zero when there is a price discount of 5% or more. The benefit of this transformation is a considerable reduction in correlation between price and the variable for feature and display (Van Heerde, Leeflang, and Wittink 2000).[10] As such, the feature and display variable measures the effects of these activities in the absence of a price cut, while the price variable measures the impact of price changes that are possibly communicated through feature and display. Finally, we use average weekly temperature to account for any seasonal patterns inherent in sales and include dummy variables to control for Christmas, New Year's, Easter, Ascension, Bastille Day, and Assumption.

State Equation Variables

We operationalize long-term marketing strategies from the weekly measures, described subsequently: The model then creates a geometric decay–weighted average of the weekly variables to capture their long-term effect (see Equations 3a and 3b). We measure the price discount fraction as one less the ratio of the actual to the regular price. We calculate national-level averages across stores and chains in a linear way. We construct a weekly advertising expenditure variable from our monthly data by dividing the monthly figures by the number of days in a month and then summing across days for the corresponding weeks (Jedidi, Mela, and Gupta 1999).[11] Following Bronnenberg, Mahajan, and Vanhonacker (2000), we use ACV-weighted distribution as a measure of breadth of distribution. The ACV approach weights a product's distribution by the total dollar volume sold through a particular store. Thus, ACV gives more distribution credit for an item that is carried in a large-dollar-volume store than for that in a small-dollar-volume store. Finally, we use line length as the product variable: the number of products available for a given brand in a given chain in a given period (week).

[9]We use current-period store-level ACVs for categories because these are parsimonious to the construct and vary negligibly from historical ACVs. Therefore, the choice of time frame is immaterial.

[10]We also estimated a model with feature and display not set to zero when there was a price discount. We found the collinearity to be sufficiently large that the price and promotion parameters were not well identified.

[11]Tellis and Franses (2006) indicate that a data interval bias exists when estimating at the higher levels of time aggregation. In contrast, we use the lowest level of time aggregation.

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