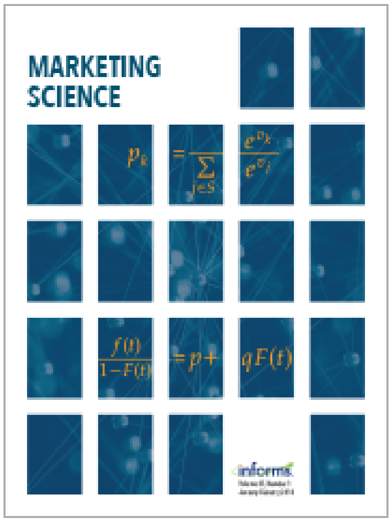

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Building Brands

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Which marketing strategies are most effective for introducing new brands? This paper sheds light on this question by ascribing growth performance to firms' postlaunch marketing choices. We decompose the success of a new brand into its ultimate market potential and the rate at which it achieves this potential. To achieve this aim we formulate a Bayesian dynamic linear model (DLM) of repeat purchase diffusion wherein growth and market potential are directly linked to the new brand's long-term advertising, promotion, distribution, and product strategy. We perform the analysis on 225 new-brand introductions across 22 repeat-purchase product categories over five years to develop generalized findings about the correlates of new-brand success. We find that access to distribution breadth plays the greatest role in the success of a new brand, and that investments in distribution and product innovation lead to greater marginal increases in sales for new brands than either discounting, feature/display, or advertising. Moreover, distribution interacts with other strategies to enhance their effectiveness. These findings underscore the utility of extending marketing mix models of new-brand performance to include product and distribution decisions.

Key words: diffusion; new products; marketing mix; dynamic linear model; empirical generalization
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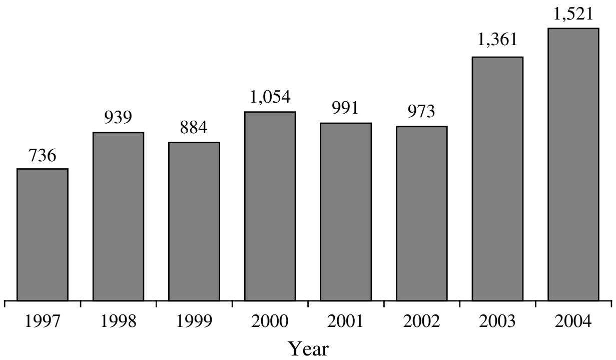
1. Introduction

Markets are often characterized by extensive new-brand activity, and the pace of innovation is accelerating. For example, 1,521 new consumer packaged goods (CPG) brands were introduced to the United States in 2004, double the number of brands introduced in 1997 (Figure 1). Manufacturers use new brands to drive growth in otherwise stable environments because innovation is often envisioned as pivotal to the success of firms. However, the performance of new brands varies markedly across their roll-outs. In CPG markets, only 20% of new brands earn more than \$7.5 million in first year sales, and less than 1% enjoy revenues in excess of \$100 million (Information Resources, Incorporated (IRI) 2005). Although essential to firms' overall performance, few new brands reach the status of an established brand; the majority eventually fail. The IRI survey shows that failure rates have reached 55%. The tension arising between the need to innovate and the low success rate coupled with innovation begs the question of how to facilitate the success of new brands.

Perhaps as a result, the growth of new brands has received substantial interest in the marketing literature (Hauser et al. 2006). Recent research on new-brand diffusion has advanced our understanding of how external factors such as economic conditions (Van den Bulte 2000), consumer differences (Van den Bulte and Joshi 2007), competitive setting (Steenkamp and Gielens 2003), and product and country characteristics (Tellis et al. 2003) affect diffusion of new products across space and time. Moreover, a number of new-product diffusion studies have incorporated internal, manageable factors in the diffusion process. Specifically, these studies have led to important insights into how marketing affects the growth and/or market potential of durable goods (see Bass et al. 2000 for a review).

In spite of these advances, prior research has focused on aspects of the marketing mix in isolation (promotion, product, price, and place), often used *durable goods* brands, and typically considered only one or a few products per study. When various aspects of marketing strategy (e.g., advertising and distribution) are coincidental, considering strategies in isolation can give a misleading picture of which tools are most conducive to a successful launch because the effect of one coincidental strategy can

Figure 1 Number of New CPG Brand Introductions, 1997–2004



Notes. The figures include entirely new brands or new-brand extensions but exclude stock-keeping unit (SKU)-level variety introductions. All food, drug and mass merchandising categories in the U.S. market are included.
Source. Information Resources, Inc. (2005). *2004 New Product Pacesetters*.

be mistakenly attributed to another. Accordingly, little information exists on the drivers of diffusion for *nondurable* goods. In this paper, we shed light on diffusion in repeat-purchase contexts by offering an integrated view across the entire marketing mix, and we afford insights into introduction strategies that enhance the potential for successful roll-outs.

We advance the literature on new-brand diffusion in two ways: by conducting an empirical generalization pertaining to the efficacy of marketing strategies in the context of new-brand launch, and by developing a methodology to achieve these aims.

• First, we explore the effect of various marketing strategies (advertising spending, feature and display activity, regular price, discount depth, product line length, distribution breadth and distribution depth in unison) on new-brand growth across 225 CPG brands. Although some diffusion studies link certain elements of the marketing mix to growth and/or market potential of a new brand (see Table 1), most previous work focuses almost exclusively on the role of price and advertising. Much less emphasis has been placed on distribution and product line, due in part to a paucity of data. As noted by Muller et al. (2007, p. 72). "Of the four P's of the marketing mix, diffusion research so far has created a sound body of knowledge concerning the effects of price and promotion, yet little has been done concerning the other two elements: product and place." By considering launch strategies in their entirety, we control for potential correlations across various marketing instruments, and we can gauge their relative effect to assess which are most efficacious.

• Second, we develop a diffusion model for frequently purchased CPG brands that simultaneously (a) considers the effect of repeat purchases, (b) accommodates a variety of potential diffusion trajectories, (c) separates short-term fluctuations in sales from long-term changes in brand performance arising from various marketing strategies (e.g., Mela et al. 1997), and (d) controls for endogeneity in the marketing mix and models the role of past performance on marketing spend. We do this by formulating a Bayesian DLM of repeat purchase diffusion. In this approach, we model long-term effects by considering the growth process underpinning a brand's baseline sales. We posit that growth in baseline sales follows a diffusion process that is affected by changes in long-term marketing strategies. These strategies (e.g., distribution penetration or advertising stock) are linked to both the rate of growth and the market potential. We further accommodate short-term perturbations about this growth process that arise from short-term marketing activity (e.g., weekly discounts).

We find that distribution and product play a greater role than discounting, feature/display, and advertising in the sales performance of new brands in spite of a focus on these factors in the preceding literature. Overall, we find that access to distribution plays the greatest role in the success of a new brand. Our

Table 1 Selected Studies from Diffusion Literature Incorporating Marketing Mix Instruments

	Growth	Market potential
Price	Eliashberg and Jeuland (1986), Parker (1992), Parker and Gatignon (1994)[a], Mesak and Berg (1995), Mesak (1996)	Kalish (1983, 1985), Kalish and Lilien (1986), Kamakura and Balasubramanian (1988), Horsky (1990), Jain and Rao (1990), Bass et al. (1994), Mesak and Berg (1995), Mesak (1996)
	This paper	This paper
Promotion	Lilien et al. (1981)[a], Horsky and Simon (1983), Kalish (1985), Simon and Sebastian (1987), Rao and Yamada (1988)[a], Hahn et al. (1994)[a], Parker and Gatignon (1994)[a], Mesak (1996)	Dodson and Muller (1978), Mesak (1996)
	This paper	This paper
Place	Mesak (1996)	Jones and Ritz (1991), Mesak (1996)
	This paper	This paper
Product	This paper	This paper

Notes. The studies listed in the table consider diffusion of durable goods unless marked by an "a" for frequently purchased consumer product categories. Promotion includes advertising expenditure.

results also show that advertising plays a greater role in accelerating brand growth than increasing market potential, and that discounting has a positive effect on the time to maturity but a negative effect on long-term market potential. We consider the marginal profits associated with various marketing launch strategies and find that distribution has the highest payoff; if the marginal cost of additional distribution is less than 23% of marginal retail revenue, then it is profitable to expand distribution. In contrast, on average, advertising is profitable only when its marginal costs are less than 0.8% of marginal retail revenue. Increasing product line length is profitable when the marginal cost of doing so are less than 5% of the marginal retail revenue.

The rest of the paper is organized as follows. First, we review the extant literature on repeat-purchase diffusion models. Next, we outline our modeling approach and provide a brief overview of the estimation process. After discussing the data, we provide variable operationalizations and develop expectations about the role of marketing strategy on new-brand performance. The results are given next followed by managerial implications drawn from several simulations. We conclude with some overall thoughts on this paper, its limitations, and possibilities for future research.

2. Modeling New-Brand Diffusion in CPG Categories

Though ubiquitous in marketing, the preponderance of diffusion models has been developed for *durable goods* categories. Modeling new-brand diffusion in frequently purchased *nondurable goods* categories requires a somewhat different approach given the existence of repeat purchases, flexibility of diffusion patterns, and separating short-term fluctuations from long-term performance. We address these issues subsequently.

First, sales arising from *repeat purchases* are especially relevant when considering the diffusion of frequently purchased new CPG brands. In contrast, traditional models of diffusion consider only the first purchases of the consumers and use aggregate category- or brand-level adoption sales data. Parameter estimates of traditional diffusion models are biased when replacement purchases are not separated from first-time purchases (Kamakura and Balasubramanian 1987). To prevent such biases and provide improved sales forecasts, several diffusion model alternatives with replacement purchases have been developed for durable goods (see Ratchford et al. 2000 for a review) as well as non-durable goods (Lilien et al. 1981, Rao and Yamada 1988, Hahn et al. 1994). Given our research context, we follow this stream of repeat-purchase modeling and extend the earlier work by addressing the second challenge (flexible diffusion patterns) and the third challenge (short- versus long-term fluctuations), as we discuss next.

Second, the sales trajectory of repeat-purchase goods can follow a litany of *diffusion patterns*. Earlier applications of repeat-purchase diffusion models link growth to marketing activity, allowing for some degree of flexibility, but assume a constant market potential. The assumption of constant market potential implies a relatively quick increase in sales followed by flatness once the brand's market potential is reached. However, when actual sales follow a diffusion pattern with slow take-off, perhaps due to limited initial availability, repeat-purchase diffusion models with constant market potential are ill-suited to capture this phenomenon. Moreover, constant market potential precludes sales declines following the initial success of a new brand. Such declines can arise from cuts in marketing support. A flexible market potential definition, such as the one proposed in this research, overcomes these concerns.

Third, *short-term fluctuations* in sales might mask the true *long-term performance* of the new brand (Mela et al. 1997). Previous applications of repeat-purchase diffusion models for nondurable goods calibrate the diffusion model using monthly or quarterly data for products with relatively smooth sales patterns, such as therapeutic drugs (e.g., Rao and Yamada 1988, Hahn et al. 1994). Such sales data do not often exhibit short-term fluctuations given that these may be aggregated out over the data interval, particularly as short-term marketing activity is uncommon and seasonal patterns are not strong. However, for frequently purchased CPG brands, data sampling rate is typically high, short-term oriented marketing activity is common, and seasonality assumes greater importance. Therefore, the series are far from being smooth. Earlier work in the area recommends that the data be smoothed prior to estimation to eliminate short-term fluctuations (Lilien et al. 1981). Such smoothing procedures will bias the parameters, especially when the variables that build market potential are correlated with the variables that create the short-term fluctuations in sales. We propose a model that separates short-term fluctuations from long-term performance during estimation.

3. Modeling Approach

3.1. General Approach

Consistent with the foregoing discussion, we seek to determine (1) the rate of new-brand growth (and the attendant implications for the time to reach peak sales) and (2) the new brand's ultimate market potential. Accordingly, we predicate our model formulation on the marketing literature on diffusion (Mahajan et al. 1990). Given our emphasis on repeat-purchase goods, our modeling approach closely parallels that of Lilien et al. (1981), Hahn et al. (1994), and Rao and Yamada (1988) but with several key extensions: (1) our model is cast in a dynamic Bayesian setting to accommodate greater modeling flexibility and statistical efficiency; (2) we link both growth and market potential to marketing strategy, given the central aims of our paper; (3) we incorporate performance feedback to control for the role of past sales on future marketing spending; (4) we consider potential competitive effects; and (5) we control for endogeneity of price and the other marketing instruments. Like Lilien, Rao, and Kalish (henceforth LRK), we assume two market segments drive the base demand for a new brand—those generated from new purchases and those from retention.

To formalize this notion, we begin by positing a linear model of brand sales, given by

$$Sales_t = \alpha_t + X_t'\beta + \upsilon_t, \tag{1}$$

where X_t is a matrix of regressors containing *short-term*-oriented marketing activity that capture short-term changes in sales around the brand's growth trajectory and a control for seasonality. α_t is a parameter that captures the long-term growth in brand sales, which is governed by the diffusion process noted above. Because the X_t include weekly discounts, feature and display, and seasonality, α_t can be interpreted as baseline sales (which we again presume to evolve following a diffusion process). The distinction between long-term and short-term marketing effects follows Jedidi et al. (1999), as short-term effects are captured by the effect of a given week's marketing activity, X_t, such as a promotion, and long-term effects are captured by the effect of repeated exposures to marketing, Z_t, on the time-varying parameter α_t (to be discussed later). We assume $\upsilon_t \sim N(0, V)$.

We seek to capture nonlinearity in the baseline sales over time using a diffusion-modeling approach. Following LRK we assume[1]

$$\alpha_t = \delta\alpha_{t-1} + \gamma(\mu - \alpha_{t-1}) + \omega_t, \tag{2}$$

where α_t indicates the base sales for the brand at time t and μ is the base market potential. The first term captures retention effects, as a certain fraction, δ, of the past period's base α_{t-1} will continue to buy on the subsequent purchase occasions. The second term captures the attraction of the remaining potential customers, as a certain fraction, γ, of the remaining market (given by the deviation between the total market potential μ and past base sales α_{t-1}) will buy on the subsequent purchase occasion. The second term therefore represents the diffusion process governing the long-term evolution of baseline sales potential. The parameters γ and μ have an additional interpretation, as γ is reflective of the time of adjustment to the market potential while μ reflects that potential. We assume $\omega_t \sim N(0, W)$.

Figure 2 depicts growth trajectories in baseline sales for various parameterizations of Equation (2). As suggested by this figure, baseline sales can grow quickly early in a brands' life cycle and then asymptote as the brand diffuses through the population. This asymptote is given by $\gamma \cdot \mu/(1-\delta+\gamma)$ if $0 < (1-\delta+\gamma) < 1$. As γ increases, sales reach their asymptote faster. As μ increases, the sales potential grows. All else being equal, faster growth and greater potential lead to higher total sales.

Following LRK we allow the growth parameter to vary over time ($\gamma \to \gamma_t$) and specify this parameter as a function of the long-term marketing strategy used by the firm that introduces the brand, $\gamma_t \equiv Z_t'\gamma$. For example, advertising stock might lead to increased awareness, thus accelerating trial rates. Like Xie et al. (1997), who consider the durables context, we allow the market potential to change over time ($\mu \to \mu_t$). In our application, though, we posit market potential to be a function of the long-term marketing strategy of a brand, $\mu_t \equiv Z_t'\mu$. For example, advertising stock might attract new buyers to the brand by changing their preferences. After substituting the new growth and market potential definitions in Equation (2) we obtain

$$\alpha_t = \delta\alpha_{t-1} + Z_t'\gamma(Z_t'\mu - \alpha_{t-1}) + \omega_t, \tag{3}$$

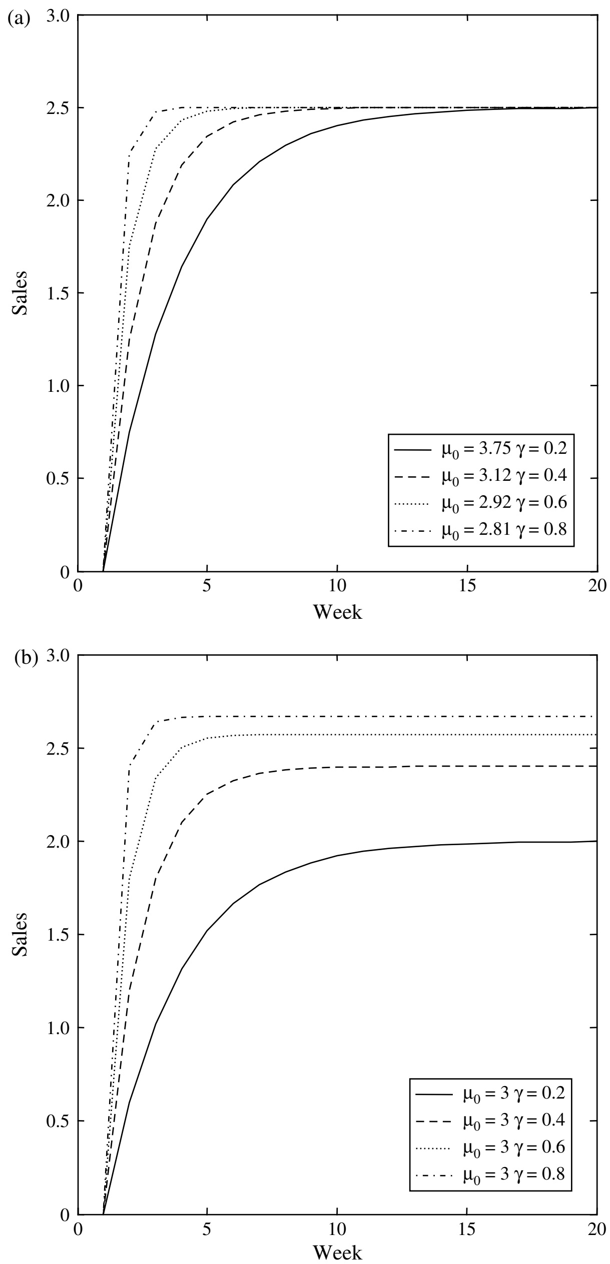
[1] The diffusion model as developed by LRK applies to pharmaceutical detailing and can be expressed as follows:

$$\alpha_t = \alpha_{t-1} + \gamma(\mu - \alpha_{t-1}) + \kappa(\alpha_{t-1} - \alpha_{t-2})(\mu - \alpha_{t-1}) - \rho\alpha_{t-1} + \omega_t,$$

where γ is the innovation parameter, κ is the imitation parameter, and ρ is the effect of competition. We modify this model in two key respects to make it suitable to the packaged goods context we consider. First, we specify word-of-mouth effects to be negligible ($\kappa \approx 0$). This specification is consistent with the findings of Hardie et al. (1998), who find *no word-of-mouth effects across 19 different CPG data sets*. Given (1) high variability in weekly sales arising from weekly promotions, (2) the fact that most products are not consumed the same week of purchase (e.g., detergent has an eight-week purchase cycle), and (3) limited occasion for social interactions within a week, word-of-mouth effects are likely minimal. In contrast, we note that the LRK model applied directly to CPG implies that incremental weekly sales drive word of mouth and that these effects last one week—which are strong assumptions in our context. We tested the assumption of no word-of-mouth effects using a classical approach and find that the fit of the model with word-of-mouth effects is not significantly better than that of the model without word-of-mouth effects (likelihood ratio test statistic $= 7.89$, $p = 0.444$). Taken together, these arguments indicate the lack of word-of-mouth effects in frequently purchased CPG markets. Second, we capture the effect of competition ρ via the baseline repeat parameter, $\delta = 1 - \rho$; that is,

$$\alpha_t = \alpha_{t-1} + \gamma(\mu - \alpha_{t-1}) - \rho\alpha_{t-1} + \omega_t \equiv \delta\alpha_{t-1} + \gamma(\mu - \alpha_{t-1}) + \omega_t.$$

Figure 2 **Growth Trajectory Illustrations**



Notes. Figures assume $\delta = 0.9$. Note that it is also possible to accommodate sigmoidal sales trajectories when market potential (μ) varies over time (μ_t).

where δ is the repeat-purchase rate, which we estimate without imposing any restrictions. γ is the vector of growth parameters, and μ is the vector of market potential parameters associated with each marketing variable.

The Z_t in Equation (3) play a long-term role in the trajectory of brand growth as a result of the carryover implied by the lagged α_t in Equation (3). Conditioned on Z_t constant at $Z_t = Z$, Equation (3) becomes a Koyck model whose carryover is given by $\delta - Z'\gamma$ (to see this, note (3) is equivalent to $\alpha_t = \lambda\alpha_{t-1} + Z'\gamma \cdot Z'\mu + \omega_t$ where $\lambda = \delta - Z'\gamma$). The model in Equation (3) therefore implies the rate of innovation growth is affected by δ and $Z'\gamma$, with lower values of $\delta - Z'\gamma$ implying faster adjustment to the long-term sales level, given by $Z'\gamma \cdot Z'\mu/(1-\delta+Z'\gamma)$ if $0 < (1-\delta+Z'\gamma) < 1$. The steady-state sales equation further implies that an increase in Z yields an increase in the long-term sales level of a brand when μ is positive.

The interaction of the growth and market potential parameters admit innumerable paths for brand sales. For example, as $\delta - Z'\gamma$ approaches 0 and $Z'\gamma \cdot Z'\mu$ becomes sufficiently large, sales will adjust immediately to a high mean but also fall again quickly when marketing support is withdrawn. Conversely, a low value for γ and a low value for μ imply that the brand will neither generate large sales nor increase sales quickly (see Figure 2). The model further allows diffusion speed and market potential to move in opposite directions, as parameters μ and γ are estimated freely: Marketing activities that increase the market potential might slow the speed to reach that higher market potential. In sum, Equation (3) provides a flexible model of baseline sales growth, which can change in response to the marketing mix.

The model defined in Equations (1) and (3) belongs to a family of Bayesian time-series models known as the DLMs (West and Harrison 1997). In the next section, we discuss model specification and provide a brief overview of the estimation procedure.

3.2. Model Specification

Our goal is to explain how marketing mix activity generates growth and builds market potential for a new brand. We achieve this by estimating the transfer function DLM developed in the previous section (see Bass et al. 2007; Van Heerde et al. 2007, 2004 for other DLM applications in marketing). The observation equation, which separates short-term fluctuations from long-term sales, is specified as a linear sales model,

$$\overline{Sales}_{jt} = \alpha_{jt} + \overline{X}'_{jt}\beta_j + v^S_{jt}, \tag{4}$$

where $\overline{Sales}_{jt}$ is the vector of sales of brand j at time t, and $\overline{X}_{jt}$ includes variables that might generate short-term fluctuations in sales. We standardize all variables within brands and indicate this with a superscripted bar. α_{jt} is the baseline sales for brand j and evolves over time, following the repeat-purchase diffusion process as specified in the following evolution equation:

$$\alpha_{jt} = \delta_j\alpha_{jt-1} + \overline{Z}'_{jt}\gamma(\overline{Z}'_{jt}\mu - \alpha_{jt-1}) + \omega_{0jt}. \tag{5}$$

$\overline{Z}'_{jt}$ is a vector of standardized marketing strategy variables posited to affect diffusion. The standardization ensures we can pool different units across categories and control for unobserved time-invariant brand effects.[2] The parameter δ_j captures the brand-specific repeat-purchase rate, whereas γ and μ capture growth and market potential due to marketing effort, respectively.

The observation equation and the evolution equation specified in (4) and (5) can be compactly written as

$$Y_{jt} = F_{jt}\theta_{jt} + X_{jt}\beta_j + v_{jt}, \tag{6}$$

$$\theta_{jt} = G_{jt}\theta_{jt-1} + h_{jt} + \omega_{jt}, \tag{7}$$

where Y_{jt} is the standardized sales of brand j in week t, and $F_{jt} = 1$. X_{jt} is the matrix of standardized regressors that create short-term fluctuations in sales. We assume $v_{jt} \sim N(0, V)$, where V is the observation equation error variance. The time-varying parameter vector $\theta_{jt} = \alpha_{jt}$ evolves as described in Equation (7). Rearranging the terms in Equation (5) gives $G_{jt} = \delta_j - \overline{Z}'_{jt}\gamma$. Then the second term on the right-hand side of Equation (7) is $h_{jt} = (\overline{Z}'_{jt}\gamma)(\overline{Z}'_{jt}\mu)$. The stochastic term ω_{jt} are distributed $N(0, W)$, where W is the evolution equation error variance.

3.3. Marketing Mix Endogeneity, Performance Feedback, and Competition

We specify an additional equation for each marketing mix instrument to control for endogeneity in the marketing mix, partial out the role of past performance, and control for competitive effects. To address *endogeneity*, we follow an approach analogous to instrumental variables wherein lagged endogenous variables serve as instruments. Moreover, we allow for correlation between the demand-side error term and the supply-side error term to account for common unobserved shocks in the system.

We control for *performance feedback* (i.e., sales gains lead to increased marketing) by including lagged national sales in each marketing equation. Past success in distribution—and hence sales, for example—might lead to increased distribution in subsequent periods. Given that firms might also react to changes in the competitive landscape, we also consider competitive marketing activity in the category.

For each marketing mix instrument the foregoing discussion results in a time-varying mean DLM,

$$\overline{Z}_{ijt} = \zeta_{ijt} + v^{Z}_{ijt}, \tag{8}$$

$$\zeta_{ijt} = \pi_{0ij} + \pi_{1ij}\zeta_{ijt-1} + \pi_{2ij}\overline{Sales}_{jt-1} + \sum_{k=1}^{K}\pi_{k+2,\,ij}\overline{CZ}_{kct-1} + \omega_{ijt}, \tag{9}$$

where Z_{ijt} is the ith marketing mix instrument of brand j in week t, and CZ_{kct-1} is the sales-weighted average of the kth marketing mix instrument for competitors in category c ($j \in c$) in week $t-1$.[3] Equation (8) posits that observed marketing spending is a manifestation of an underlying latent national strategy (ζ_{ijt}), and deviations from this strategy arise from random shocks. Equation (9) defines the evolution of this latent strategy as a function of its past value, the past performance of the focal brand, and past marketing activities of competition. The parameter π_{1ij} is associated with the lagged national strategy and captures inertia in the marketing spending. $\overline{Sales}_{jt-1}$ is the focal brand's lagged standardized national sales. Thus the parameter π_{2ij} captures own-performance feedback effect for the marketing mix instrument i. Finally, the parameters $\pi_{k+2,\,ij}$ capture correlations between the focal brand's marketing and that of its competitors. The superscripted bar indicates that the variable is standardized.

3.4. Estimation

We estimate Equations (8) and (9) together with Equations (4) and (5) and let error terms v^{S}_{jt} and v^{Z}_{ijt} be correlated to account for common unobserved shocks in the observation equations.[4] We place normal priors on all parameters of the observation equation, the evolution equation, and the marketing mix equations. The evolution equation error covariance matrix is assumed to be diagonal, and we place an inverse Gamma prior on its diagonal elements. As we allow for correlation between the observation equation error terms and the marketing mix equation error terms, the associated error covariance matrix is full. Therefore, we place an inverse Wishart prior. Given these priors, the estimation is carried out using DLM updating within a Gibbs sampler. Conditional on β, π, V, W, h_t, and G_t, the time-varying intercepts are obtained via the forward-filtering, backward-sampling procedure (Carter and Kohn 1994, Frühwirth-Schnatter 1994). The parameters of the baseline sales evolution are estimated using a random walk Metropolis-Hastings algorithm, because the evolution equation is nonlinear in parameters. The details of the sampling chain are provided in the appendix.

[2] Standardization does not affect the ease of managerial interpretation because we can always convert standardized values back to their original scale.

[3] The kth marketing mix instrument of the composite competitor in a given category is computed as the weighted average of marketing mix instruments of top five brands in that product category. We use average market share in the most recent 13 weeks ($t-1, t-2, \ldots, t-13$) as rolling weights in the aggregation.

[4] We estimated an alternative diagonal error correlation. The log Bayes factor (BF) (West and Harrison 1997) favored the full matrix specification over the diagonal matrix specification ($\log \mathrm{BF} = 18{,}642$).

4. Data and Variables

4.1. Data

We calibrate our model on a novel data set provided by IRI (France). The data cover more than five years (1/1/1999 to 2/1/2004) of weekly SKU store-level scanner data for 25 product categories sold in a national sample of 560 stores operated by 21 different chains. We also use matching monthly brand-level advertising data provided by TNS Media Intelligence (France).

Data are aggregated from the SKU store level to national brand level following the procedures outlined in Christen et al. (1997) to avoid any biases due to aggregation. Because the sales model in Equation (7) is linear, we first aggregated the data from SKU-store to brand-store level in a linear fashion (discussed in §4.2). Using lagged *all commodity volume* (ACV), we then calculated an ACV-weighted average of brand-store level independent variables to obtain national-brand level data.

Between January 1, 1999 and February 1, 2004, we observe 365 new national brand introductions in 25 product categories. Of these new brands, 55 fail within the mentioned time window. For a single category, the number of new-brand introductions varies between 5 and 38, with an average of 17 brands. On average, we observe the first 152 weeks of the new brand's life cycle, with a minimum of 15 weeks and a maximum of 264 weeks. We select brands with at least two years of data, regardless of whether they succeed or fail, which leaves us with 225 new-brand introductions in 22 categories (as opposed to line extensions within existing brands).[5] See Table 2 for descriptive statistics.

4.2. Variables

The selection of variables is linked to our goal of contrasting the relative efficacy of the marketing mix in generating new-brand growth. The variables considered represent the conjunction of those suggested by theory and those available in the data. In this section we detail each variable and its anticipated effect on the diffusion of new brands. We first discuss the variables in the observation, or sales, equation and then consider the variables in the growth equation.

4.2.1. Sales Equation Variables. The dependent variable in Equation (1), $Sales_{jt}$, is the sales volume of a new brand, which is calculated as the sum of sales across all stores in a given week. We posit the sales to be affected by a number of short-term variables, including brand-level discount depth ($Disc_{jt}$), feature or display support (FoD_{jt}), and average weekly temperature ($Temp_t$). Thus, $X_{jt} = \{Disc_{jt}, FoD_{jt}, Temp_t\}$. We measure the SKU store-level depth of promotion by one minus the ratio of the actual price to the regular price. The brand store-level promotion depth variable is chosen as the maximum discount depth across SKUs (e.g., Mela et al. 1997), and the national brand level variable is calculated as the store ACV-weighted average of the brand store-level data. The brand store-level feature and display variable take the value of one if at least one SKU from the brand's product line is on promotion in a given week. The national brand-level averages for these variables are calculated across stores in a linear fashion using lagged store ACV as weights. We expect discounts and feature/display intensity to have a positive short-term effect on sales, while temperature affords a parsimonious control for seasonality.

4.2.2. Evolution Equation Variables. We now discuss the operationalization of the marketing mix variables in Z_{jt} in the evolution Equation (5), along with our expectations about the role they play in growth and market potential. Table 3 summarizes our expectations.

Price. We define the price of a brand as the regular price in a given store week. Consistent with previous studies (e.g., Mela et al. 1997), we select the minimum regular price per 1,000 volume units across SKUs of a brand. The national brand-level average price is calculated across stores in a linear fashion, using lagged store ACV as weights.

Previous research provides unequivocal evidence that regular price reductions influence the growth of new-brand sales (Parker and Gatignon 1994, Parker 1992). However, there is a lack of consensus on whether price also affects the market potential. Bass et al. (1994) and Kamakura and Balasubramanian (1987, 1988) find no impact from price, whereas Mesak and Berg (1995) and Kalish and Lilien (1986) report negative impact. However, like Eliashberg and Jeuland (1986), we expect that lower prices stimulate additional demand as the brand matures. Moreover, the brand can achieve high market-penetration rate rather quickly because lower initial prices motivate the potential buyers to make the purchase earlier (Bass and Bultez 1982). In sum, we expect lower prices to facilitate growth and increase market potential for a new brand.

Discounts. Discounts encourage trial purchases for the first-time buyers. They reduce search costs for the consumer, generate awareness, and increase the likelihood of adoption (Kalish 1985). Anderson and Simester (2004) find that deep discounts also increase repeat rates of first time buyers; thus, discounts accelerate growth. However, the effect of discounting on market potential is not clear. Discounting can build

[5] Of these 225 new brands, 8 are brand extensions and 217 are entirely new brands. The substantive results are robust to the exclusion of these eight brands.

Table 2 Descriptive Statistics

Category	No. of new brands	No. of brands in category	Sales volume new brand (×1,000)	Sales volume (×1,000) category mean	Sales value (×1,000)	Advertising (×1,000)	Price (per 1,000)	Distribution breadth (%)	Product line length	Distribution depth (%)	Discount depth (%)	Feature/display (/100)
Bath products												
M	25	326	50.0	639.3	62.9	75.0	13.3	2.3	2.7	0.8	3.1	18.4
SD			(119.2)	(2,563.9)	(108.2)	(112.8)	(7.7)	(4.8)	(1.9)	(0.4)	(2.4)	(12.9)
Beer												
M	36	961	1,030.4	2,263.9	249.3	27.5	3.9	4.5	2.3	1.0	2.2	18.3
SD			(2,330.2)	(26,826.5)	(440.2)	(47.8)	(2.2)	(9.8)	(1.1)	(0.5)	(1.4)	(12.0)
Butter												
M	12	382	2,183.6	2,029.9	1,979.7	40.9	5.0	9.7	3.0	2.0	2.7	21.1
SD			(2,182.5)	(6,609.9)	(2,094.6)	(69.8)	(2.0)	(19.9)	(2.0)	(1.0)	(2.4)	(19.6)
Cereals												
M	7	118	647.1	2,454.0	401.8	2.7	6.1	4.6	3.9	2.3	2.5	6.2
SD			(1,194.0)	(12,290.8)	(585.6)	—	(3.0)	(5.2)	(4.3)	(1.4)	(4.4)	(5.4)
Chips												
M	5	86	4,143.0	6,144.1	1,456.2	—	2.3	9.9	5.2	4.2	2.8	13.5
SD			(8,011.8)	(16,199.5)	(3,041.2)	—	(0.9)	(19.1)	(8.4)	(2.4)	(1.1)	(8.6)
Coffee												
M	16	306	93.2	1,444.5	121.2	—	9.0	1.9	4.0	1.5	7.0	34.0
SD			(143.2)	(7,309.0)	(175.6)	—	(2.9)	(2.8)	(5.6)	(0.8)	(10.8)	(31.5)
Feminine needs												
M	3	65	49.0	180.8	721.5	—	71.7	18.7	2.6	1.7	0.9	4.7
SD			(30.1)	(426.6)	(661.3)	—	(27.7)	(14.2)	(0.9)	(0.2)	(0.6)	(4.9)
Frozen pizza												
M	3	72	2,002.9	1,861.1	1,514.3	32.4	5.7	11.8	6.8	6.0	2.0	13.6
SD			(1,013.1)	(4,492.1)	(998.8)	—	(3.5)	(2.9)	(7.8)	(2.5)	(0.9)	(3.0)
Ice cream												
M	19	211	1,046.3	2,465.1	805.2	2.3	5.0	8.2	6.0	1.3	2.3	11.5
SD			(1,521.1)	(7,615.9)	(1,146.9)	—	(2.6)	(11.1)	(7.6)	(0.7)	(1.9)	(9.5)
Mayonnaise												
M	9	234	248.6	879.9	250.3	63.9	10.7	8.3	2.2	1.9	1.6	16.2
SD			(572.8)	(4,773.1)	(499.3)	(88.4)	(4.5)	(17.9)	(1.9)	(1.4)	(0.9)	(12.1)
Mineral water												
M	3	143	7.4	19.9	651.9	82.3	5.3	10.3	2.8	3.4	1.1	22.8
SD			(11.1)	(65.6)	(553.9)	—	(6.9)	(12.5)	(1.1)	(0.8)	(1.1)	(33.3)
Paper towel												
M	2	66	25.2	31.1	991.7	—	269.0	2.6	1.0	14.2	1.5	18.5
SD			(6.6)	(71.8)	(309.3)	—	(13.8)	(0.2)	(0.0)	(2.5)	(1.0)	(13.0)
Pasta												
M	16	334	656.6	2,562.8	93.1	1.7	4.3	2.4	6.2	1.7	3.2	17.2
SD			(1,675.1)	(17,300.3)	(124.8)	(1.3)	(3.4)	(3.0)	(5.2)	(0.8)	(2.6)	(10.6)
Shampoo												
M	9	172	1,211.9	1,143.0	2,013.7	89.0	9.8	22.8	6.1	1.5	1.0	7.0
SD			(1,950.2)	(2,895.2)	(3,136.9)	(95.8)	(4.7)	(26.6)	(6.6)	(1.3)	(0.6)	(4.9)
Shaving cream												
M	4	51	138.4	529.4	213.8	—	10.4	7.7	1.9	3.9	0.9	8.2
SD			(130.7)	(1,265.2)	(306.1)	—	(8.6)	(6.2)	(1.1)	(1.5)	(0.6)	(6.3)
Soup												
M	21	333	1,643.5	2,244.3	584.8	31.2	3.3	8.9	6.6	1.9	1.8	12.4
SD			(3,714.1)	(18,135.0)	(1,235.8)	(50.7)	(2.0)	(16.2)	(7.3)	(1.0)	(1.4)	(9.6)
Tea												
M	8	178	13.8	109.2	179.1	4.3	64.0	5.4	4.4	2.4	1.9	14.0
SD			(11.0)	(481.3)	(159.9)	(6.7)	(26.9)	(6.3)	(1.9)	(1.1)	(2.0)	(13.4)
Toothpaste												
M	1	84	0.3	522.0	53.8	—	877.2	6.7	1.0	1.8	0.5	10.0
SD			—	(1,720.9)	—	—	—	—	—	—	—	—
Water												
M	14	189	58.7	88.4	2,938.6	93.6	3.4	22.0	3.5	2.6	0.7	9.9
SD			(54.2)	(342.1)	(3,101.4)	(55.6)	(4.6)	(20.4)	(1.7)	(0.6)	(0.3)	(12.6)
Window cleaner												
M	1	54	98.8	752.0	13.9	—	0.9	3.0	1.0	12.2	1.1	10.9
SD			—	(1,990.3)	—	—	—	—	—	—	—	—

Table 2 **(cont'd.)**

Category	No. of new brands	No. of brands in category	Sales volume new brand (×1,000)	Sales volume (×1,000) category mean	Sales value (×1,000)	Advertising (×1,000)	Price (per 1,000)	Distribution breadth (%)	Product line length	Distribution depth (%)	Discount depth (%)	Feature/display (/100)
Yogurt												
M	8	226	534.1	10,762.0	279.7	132.0	4.7	4.8	2.4	0.9	1.3	7.0
SD			(846.7)	(37,229.1)	(363.7)	—	(1.7)	(6.2)	(0.8)	(0.3)	(0.9)	(6.3)
Yogurt drink												
M	3	37	1,777.1	5,043.5	751.4	—	3.6	10.7	2.1	5.8	0.7	3.3
SD			(1,248.1)	(14,107.6)	(495.4)	—	(2.2)	(4.6)	(1.0)	(1.9)	(0.1)	(1.3)

Notes. M, mean; SD, standard deviation of average marketing support across all brands. The mean and standard deviation of advertising, discount depth, and feature/display are calculated using nonzero observations.

customer loyalty through rewards and thus might help the brand build baseline sales through increased familiarity and experience, or simply through purchase reinforcement or habit persistence (Ailawadi et al. 2007, Keane 1997, Pauwels et al. 2002, Slotegraaf and Pauwels 2006). On the other hand, discounting can also have a negative long-term impact because it could erode brand equity (Ataman et al. 2006, Jedidi et al. 1999).

Feature/Display. We also consider the role of nonprice promotions in the diffusion of a new brand. Feature promotions, retail displays, and other in-store communication tools are manufacturer-retailer joint advertising efforts. Such nonprice promotions make the new brand salient and promote it to the shopper traffic (Gatignon and Anderson 2002). In a sense, they work in the same way that advertising does. Therefore, we expect features and displays to facilitate growth and increase market potential at the same time.

Advertising. We construct the weekly advertising support variable from the available monthly advertising expenditure data by dividing the monthly figures by the number of days in a month, and then totaling across days for the corresponding weeks (Jedidi et al. 1999). This enables us to model marketing response at the highest frequency available in the data, avoiding the potential for data aggregation bias (Tellis and Franses 2006).

A number of studies have investigated the role of advertising in new-product diffusion (e.g., Dodson and Muller 1978, Horsky and Simon 1983, Kalish 1985, Simon and Sebastian 1987). National brand-oriented advertising, which serves information and persuasion functions simultaneously in the context of new brands, produces high awareness levels, differentiates brands, and builds brand equity (Aaker 1996). Thus, it helps build market potential. Elberse and Eliashberg (2003) find that advertising is crucial for new-brand performance, especially in the early stages of introduction. Moreover Lodish et al. (1995) find that advertising works better when brands are new, implying a positive growth effect.

Table 3 **Summary of Expectations**

	Growth	Market potential
Advertising	+	+
Regular price	−	−
Discounting	+	0
Feature and display	+	+
Distribution breadth	++	++
Distribution depth	++	++
Line length	++	++

Distribution breadth. We use ACV-weighted distribution as a measure of distribution breadth (Bronnenberg et al. 2000). ACV weights a brand's distribution by the total dollar volume sold through a particular store, giving more distribution credit to a large dollar volume store than it does to a small dollar volume store.

Early work on new-product diffusion tended to overlook the role distribution plays in building new brands. These studies typically explain the success of a new brand by factors such as advertising or price, and they assume that the brand is always available to the consumers. A notable exception is the study by Jones and Ritz (1991), where the authors note that a new brand cannot build sales if the consumers cannot find a store in which they can purchase it. Recent research on new products devotes more attention to distribution decisions and explains realized demand conditional on product availability. Such an approach is appropriate especially in competitive environments where customers visit the retail stores and decide what to buy based on which brands are available (Krider et al. 2005). Taking this view Bronnenberg et al. (2000) show that in new repeat-purchase product categories market shares are strongly influenced by retailer distribution decisions. Other studies confirm that distribution is a critical factor influencing new-product performance (Elberse and Eliashberg 2003, Gatignon and Anderson 2002, Neelamegham and Chintagunta 1999). In light of these findings, we expect distribution to be an important element in explaining the new brand's growth and market potential.

Distribution depth. We measure distribution depth as the number of SKUs a brand offers in the category in a given store relative to the total number of SKUs in that category in that store. This measure reflects how many different SKUs of a particular brand are carried, on average, at each point of ACV distribution. We calculate the distribution variables at the store level and then calculate national averages.

Any marketing activity that spreads information in proportion to the number of products in the market, such as self-advertising by just being on a supermarket shelf, could generate awareness for a new brand (Eliashberg and Jeuland 1986). Therefore, we expect distribution depth to facilitate growth and build market potential.[6]

Line length. We measure the brand line length by the number of SKUs a brand offers in a given week. Our discussion about the role that brand line length plays in the diffusion process of a new brand is rather tentative because theoretical and empirical evidence on this issue is virtually nonexistent. We argue that, holding all else constant, more SKUs provide assortment and increase the probability of trying an item from the new brand's line. Also, having more alternatives might serve more segments. Therefore, we expect line length to increase market potential and facilitate growth. Because the marginal change in baseline arising from the addition of new SKUs might decrease, we specify log-transformed line length in the model.[7]

Relative effects. As indicated in Table 1, thus far no research has incorporated all marketing mix instruments into a single diffusion framework, let alone into a repeat-purchase diffusion framework for CPG categories. Therefore, the relative importance of marketing instruments in building new CPG brands is undocumented. However, relative effects sizes are of central interest to managers because they point out areas in which it might be more desirable to allocate marketing funds. We argue that line length and distribution (breadth and depth) should assume the greatest importance (denoted by ++ in Table 3) because (1) a consumer, given her reluctance to shop across stores or markets, will not adopt a brand if it is not available in the stores she visits (Bronnenberg and Mela 2004, Jones and Ritz 1991), and (2) said consumer will also be unlikely to purchase goods if there are not variants or items that match her needs. Yet availability and alternative options require awareness, hence advertising and feature/display should be in the second tier of critical elements of the diffusion process.

[6] Distribution depth and line length capture different aspects of brand strategy, as reflected in a relatively modest correlation of 0.35. The correlation is modest because line length is the number of products a brand offers *at the national level*, while distribution depth is the fraction of a store's category assortment that belong to the brand, which is thus measured *at the store level* (and next averaged across stores). As a consequence, line length is a decision variable that is under direct control for a manufacturer, whereas distribution depth depends to a large extent on the willingness of the retailer to carry the brand's products. Hence, a high line length does not necessarily coincide with a deep distribution.

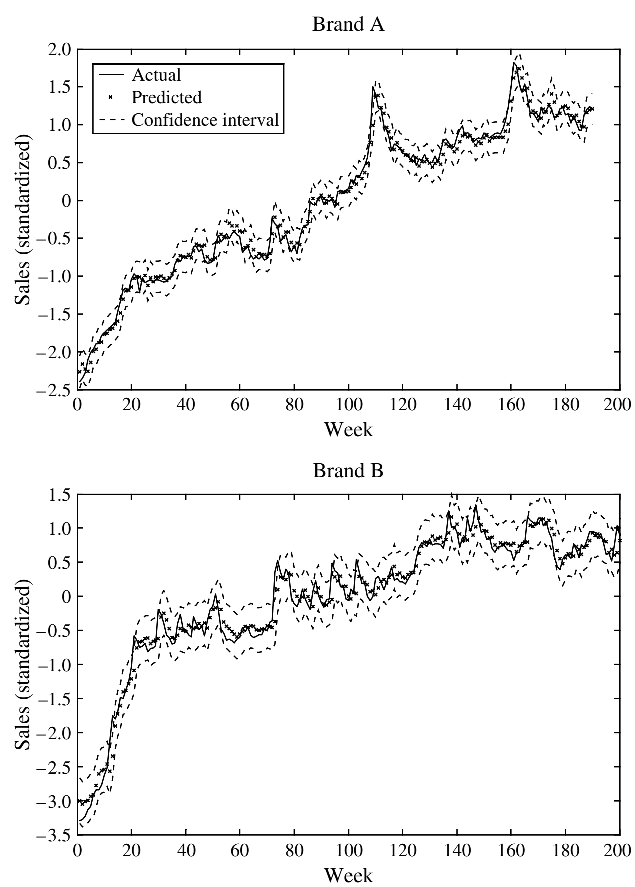
[7] The log BF (927.5) favored the model with decreasing returns over the model with constant return.

5. Results

We estimate the DLM specified above using a Gibbs sampler and run the sampling chain for 30,000 iterations (15,000 for burn-in and 15,000 for sampling with a thinning of 10). The repeat-purchase diffusion model with flexible growth and market potential specification, coupled with the ability of the DLM methodology to accommodate potential nonstationarity in brand launch, provides excellent fit to the data (see Figure 3). Across 225 brands we analyze in the paper, the median correlation between actual and predicted sales is 0.88.

For all 225 brands we consider three sets of parameters: (1) the short-term marketing effects (β) on sales model specified in Equation (4); (2) the long-term marketing strategy effects on growth (γ) and market potential (μ), as well as the repeat-purchase rate

Figure 3 **Actual vs. Predicted Sales of Two Selected Brands**



parameter (δ) in the baseline sales evolution model as shown in Equation (5); and (3) the marketing mix inertia, performance feedback, and cross-marketing mix parameters (π) in the marketing mix endogeneity model specified in Equation (9). We discuss each set of parameters in sequence.

5.1. The Sales Model

Table 4 shows the inverse-variance weighted average (to afford more weight to more reliable estimates) of discounting, feature/display, and average weekly temperature estimates at the category level. Both discounting and feature/display parameter estimates exhibit face validity because each stimulates same-week sales (average estimates across all brands are 0.03 and 0.05, respectively). The 90% posterior confidence interval of the average weekly temperature coefficient typically excludes zero for brands from product categories that are expected to exhibit seasonal patterns (e.g., soup and ice cream), whereas the coefficient is negligible for others.

5.2. The Baseline Sales Evolution Model

Of central interest to this research are the estimates on the evolution of baseline sales (α_t), including (1) repeat-purchase effects (δ), how marketing mix instruments correlate to sales growth (γ) for new brands; and (2) the role these instruments play in the market potential (μ) for a new brand. Table 4 indicates that increases in advertising support, distribution breadth, line length, and discount correlate with faster growth for new brands, whereas increases in regular prices inhibit the diffusion process. These findings are in line with the expectations. The effect of distribution depth on growth is negligible. Surprisingly, we find that feature and display intensity

Table 4 **Parameter Estimates (Sales Model)**

Category	Discounting	Feature/display	Temperature	Repeat rate
		Observation equation parameters[a]		
All categories	0.03	0.05	−0.00	0.94
Bath products	0.04	0.14	−0.00	0.89
Beer	0.02	0.09	0.00	0.86
Butter	0.00	0.02	−0.01	0.94
Cereals	0.09	−0.01	−0.01	0.98
Chips	0.06	0.00	−0.02	0.92
Coffee	0.04	0.04	−0.00	0.85
Feminine needs	0.05	0.02	0.00	0.98
Frozen pizza	0.22	−0.08	−0.01	0.92
Ice cream	0.05	0.10	0.00	0.95
Mayonnaise	−0.00	0.11	−0.00	0.91
Mineral water	0.03	0.01	0.00	0.99
Paper towel	0.24	0.05	−0.00	0.91
Pasta	0.00	0.04	−0.00	0.91
Shampoo	0.04	0.11	0.00	0.94
Shaving cream	0.03	0.04	−0.01	0.97
Soup	0.03	0.06	−0.01	0.94
Tea	0.00	0.08	−0.01	0.95
Toothpaste	0.03	0.01	−0.01	1.02
Water	0.00	0.00	−0.00	1.00
Window cleaner	0.03	0.10	−0.00	1.01
Yogurt	0.03	0.05	−0.01	0.98
Yogurt drink	0.01	0.03	−0.01	0.97

	Growth			Market potential		
Marketing activity	Median	5th and 95th percentile		Median	5th and 95th percentile	
			Growth and market potential parameters[b]			
Constant	**0.0948**	**0.0868**	**0.1035**	**0.1008**	**0.0760**	**0.1288**
Advertising	**0.0077**	**0.0003**	**0.0153**	0.0275[c]	−0.0036	0.0609
Regular price	**−0.0110**	**−0.0147**	**−0.0074**	**−0.0793**	**−0.1098**	**−0.0488**
Discounting	**0.0148**	**0.0116**	**0.0183**	**−0.0323**	**−0.0515**	**−0.0102**
Feature and display	**−0.0088**	**−0.0106**	**−0.0071**	**0.2971**	**0.2517**	**0.3517**
Distribution breadth	**0.0231**	**0.0194**	**0.0268**	**0.7951**	**0.7418**	**0.8507**
Distribution depth	−0.0003	−0.0041	0.0037	**0.1344**	**0.1056**	**0.1698**
Line length (log)	**0.0089**	**0.0049**	**0.0132**	**0.0998**	**0.0668**	**0.1312**

Notes. (a) Variance-weighted average of median estimates across brands. (b) Bold indicates that 90% posterior confidence interval excludes zero. (c) The market potential effect of advertising crosses zero at 92nd percentile.

slows diffusion of new brands, although the effect is quite small. When combined with positive short-term effects and the large effect of feature/display on market potential, the net effect is positive (as we show in the subsequent section).

Table 4 further reveals that feature and display activity, brand line length, distribution breadth, and distribution depth correlate positively with market potential for new brands, whereas the 80% posterior predictive interval for advertising excludes zero (tantamount to a one-sided p-value of 10% in classical statistics). As expected, low prices are associated with higher market potential. Consistent with the literature on the long-term effect of discounts, the effect of discounting on market potential is negative (Mela et al. 1997). Note the dual role of discounts in leading to faster growth but lower market potential.

Across the 225 brands, the repeat-purchase parameters, δ, range between 0.83 (25th percentile) and 0.98 (75th percentile), with a median of 0.94. The variation of repeat purchase parameter estimates across product categories does not reveal major differences. This median repeat-purchase rate across all brands suggests that for most brands, 90% of the long-term sales effect for new brands materializes within the first 52 weeks (Leone 1995). To our knowledge, this is the first study to conduct an empirical generalization of time to peak sales for new packaged goods brands.

5.3. Relative Effect Sizes

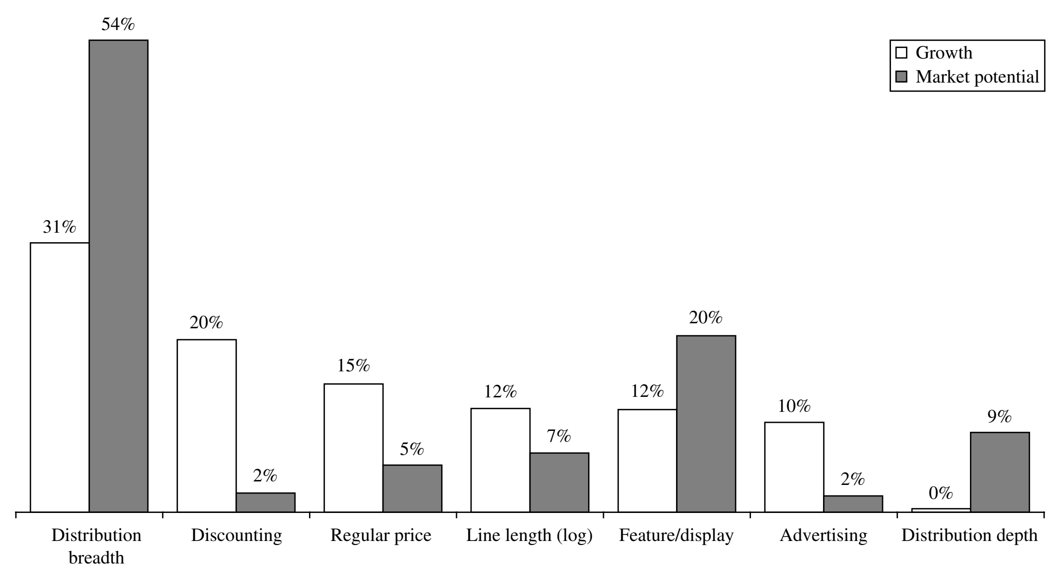
The foregoing discussion reveals that marketing strategy plays a role in the diffusion of new brands but affords little insight into which strategies explain the greatest amount of variation in the sales performance of new brands. Accordingly, we consider the relative effect sizes of the marketing mix variables by computing the ratio of (1) the standardized coefficient for a given marketing mix instrument to (2) the sum of all standardized marketing mix coefficients. In the calculation, we use the absolute values of the standardized coefficients for the growth and market potential parameters, respectively. Figure 4 presents the relative effects of the marketing mix instruments.

Figure 4 makes it apparent that distribution breadth is the single most important marketing mix instrument in generating growth (relative effect of 31%) and building market potential (relative effect of 54%) for a new brand. Although the result is not altogether surprising (a brand cannot have sales without distribution), the precise effect of size relative to other variables is less obvious as (1) *the effect of distribution exceeds all other strategies combined* in generating growth; and (2) it is also the case that a brand cannot have sales without a product line, yet this effect is not as considerable. Distribution breadth and depth assume greater importance in building market potential (jointly 63%) than accelerating growth (jointly 31%). After distribution, discounting has the second-largest impact on growth (20%). Feature and display have the second-largest effect on market potential (20%), which implies that their short-term effect on weekly sales is supplemented by their ability to build long-run demand for new brands.

5.4. Marketing Mix Models

Now we briefly summarize the results of the marketing mix instrument equations presented in Equations (8) and (9). First, we find that past sales typically has little effect on current marketing. A notable exception is the effect of past sales on distribution breadth.

Figure 4 **Relative Effects Across Marketing Mix Instruments**



Note. The bars represent the size of the instrument's absolute parameter estimate divided by the sum of the absolute parameter estimates.

In 57% of all cases, we observe that past sales have a positive effect on future distribution. Second, the coefficients for the inertial effect of past marketing range from 0.39 (for feature/display) to 0.80 (for distribution breadth), indicating the largest effect again arises from distribution breath. Collectively, these two results underscore the importance of controlling for performance feedback and amplify our finding that distribution plays a major role in brand building.

Finally, we find that competitor effects are predominantly zero for the marketing mix instruments. Steenkamp et al. (2005) observe a similar result in the context of advertising and pricing for mature brands, and Pauwels (2007) observes the same in discounting and feature/display. We extend this finding across the marketing mix.

5.5. Model Comparison

Our analysis presumes that (1) baseline sales follow a dynamic growth process, and (2) this process is linked to marketing strategy. To test the first assumption, we contrast our full model (M0) to one wherein no dynamics are exhibited in baseline growth (M1), that is $\alpha_{jt} = \bar{Z}'_{jt}\pi + \omega_{0jt}$. To test the second assumption, we contrast our full model (M0) with one wherein observed growth is independent of long-term marketing strategy (M2), that is $\alpha_{jt} = \delta_j \alpha_{jt-1} + \gamma(\mu - \alpha_{jt-1}) + \omega_{0jt}$. Table 5 indicates the full model outperforms these benchmarks on the log BF for one-step-ahead forecasts.

Table 5 Predictive Fit of Focal Model and Nested Benchmark Models

Model	Time-varying parameters	Log BF
M0	Dynamics and marketing	—
M1	No dynamics	9,870
M2	No marketing	408

Note. Log Bayes factor is relative to M0.

6. Managerial Implications

We next consider the ramifications of our analysis for new-brand launch marketing strategies. As a prelude, we note limits inherent in the archival data analysis that we propose, namely that parameter estimates might not be invariant to our policy simulations. That said, in the context of a dynamic problem with many agents, states, and controls, the imposition of assumptions to identify a more structural solution may induce more problems (dimensionality of the state-space, restrictive assumptions, etc.) than it redresses.

6.1. Long-Term Marketing Mix Elasticities for New Brands

Procedure. Using our model, one can assess how marketing strategies affect brands' steady-state sales and rate of growth. Our analysis proceeds by using our model to forecast a brand's sales with all marketing mix variables set to their historical means. Denote this estimate as S_0. S_0 serves as the basis for a comparison to sales forecasted under an alternative strategy. In this strategy, we increase the considered marketing activity by 10% and calculate a new level of sales, denoted S_1. One can then obtain the percentage of sales change due to 10% permanent marginal increase in marketing spending by comparing the sales level of the new case to the base case $((S_1 - S_0)/S_0) \equiv \Delta$. In these calculations, we considered only the first 52 weeks after launch because, as noted above, 90% of the long-term marketing effects materialize within 52 weeks (see also Leone 1995). Table 6 summarizes the results of our policy simulation.

Findings. The first column in Table 6 reports the average sales change across 225 brands analyzed in this study. The large variation in effect sizes across brands is largely driven by variation in marketing spending across brands. The table indicates three strata of effect sizes. The most effective stratum comprises distribution breadth (a 10% arc elasticity of 7.6%), regular price (5.1%), and distribution depth (3.1%). The implied average regular price elasticity (0.51) is low relative to meta-analytical results for regular prices and new brands (Bijmolt et al. 2005). This result might reflect the lower price sensitivity of consumers who try new brands (Ghosh et al. 1983, Parker 1992). The next stratum includes line length and feature/display (1.5%). The least effective group of strategies for affecting new-brand sales includes discounting (which actually has a negative marginal effect) and advertising. This finding is notable, as Table 1 also suggests these are the most-often considered instruments in past research.

Marginal Profit Analysis. Table 6 illuminates a marginal profit approximation. Let C_0 denote the cost

Table 6 Equilibrium Sales Value Impact of 10% Permanent Increase in Marketing Support (%)

	Mean	Standard deviation	1st Quartile	Median	3rd Quartile
Advertising spending	0.25	0.24	0.08	0.16	0.31
Regular price	−5.13	3.72	−6.87	−4.45	−2.81
Distribution breadth	7.61	4.06	5.27	6.61	8.80
Line length	1.53	1.11	0.76	1.25	1.73
Distribution depth	3.18	1.91	1.98	2.68	3.78
Discount depth	−0.24	1.40	−0.18	−0.12	−0.07
Feature/display	1.53	1.09	0.78	1.21	1.99

Note. As a result of a 10% permanent increase in regular prices, sales reaches a 5.1% lower equilibrium level than it would have reached had the price been kept constant at its mean.

of the base marketing strategy, Δ denote the sales increase in Table 6 arising from a 10% increase in the marketing mix, R_0 indicate the revenue of the base strategy, MM denote the manufacturer gross margins, and RM denote the retailer gross margins. Then the manufacturer profits under the base case are $\Pi_0 = (1 - RM) * (MM) * R_0 - C_0$. With a 10% increase in the marketing expenditure, profits become $\Pi_1 = (1 + \Delta) * (1 - RM) * (MM) * R_0 - (1 + 0.10) * C_0$ (assuming that a percent increase in costs leads to a percent increase in marketing). The condition that $\Pi_1 > \Pi_0$ therefore implies that it is profitable to increase marketing spend *on the margin* when the resulting increase in marginal revenue, $((1 - RM) * (MM) * \Delta * R_0)$ is greater than the resulting increase in marginal cost, $0.1 * C_0$. Assuming a retailer gross margin of RM = 25% of retail sales (Agriculture and Food Canada Report 2005) and a manufacturer gross margin of MM = 40% (Grocery Management Association 2006), this condition reduces to $C_0/R_0 < 3 * \Delta$.

Stated differently, the marginal profits of marketing investment become positive when costs as a percent of retail revenue are less than $3 * \Delta$. For distribution ($\Delta = 0.076$), this implies it is profitable on the margin to invest in distribution when distribution costs are less than 23% of retail revenue. On the other end of the spectrum, it is profitable to advertise ($\Delta = 0.0025$) only when the marginal cost of advertising is less than 0.8% of revenue. Given most firms budget about 5% of manufacturer sales for advertising (or 3.75% of retail sales), this suggests that further increases in advertising are, on average, unwarranted (though variation across categories imply different strategies dominate in different categories). The thresholds for line length and distribution depth are 5% and 10%, respectively, while the threshold for feature display is 5%.

6.2. Strategic Launch Options

Prior research has speculated on the relative merits of various marketing strategies in the context of product diffusion (skimming versus penetration pricing, constant versus decreasing advertising, national versus phased brand roll-out, and simultaneous versus sequential product line entry). Our empirical generalizations not only afford empirical insights into these strategies, but also extend prior work to consider their interactions. In particular, we contend that the efficacy of marketing strategies is amplified by strong distribution.

Simulation Design. To explore these interactions we generate a 2 (skimming/penetration pricing) × 2 (constant/decreasing advertising) × 2 (national distribution/phased roll-out) × 2 (simultaneous/phased brand entry) design and ensure the strategies are well within the observed range of the marketing mix instruments. We use a 52-week duration because most brands reach their maximum sales by this time. Initializing new-brand sales at zero, we forecast demand for all 225 brands over the 52 weeks after launch using the parameters estimated in our model.

Price Skimming vs. Penetration Pricing. Penetration pricing is considered optimal for new durable goods (e.g., Horsky 1990, Kalish 1985, Mesak and Berg 1995). Our skimming/penetration condition contrasts (1) a strategy wherein the launch price is one standard deviation above the historical mean price at launch and one standard deviation below the historical mean price at 52 weeks (price skimming) to (2) a strategy wherein the regular price is held constant one standard deviation below the mean (penetration).

Constant vs. Monotonically Decreasing Advertising Spending. Prior literature argues that decreasing returns to scale in advertising favors a monotonically decreasing advertising strategy (Dockner and Jørgensen 1988, Horsky and Mate 1988, Horsky and Simon 1983, Kalish 1985). Our constant/decreasing advertising manipulation contrasts (1) advertising held at one standard deviation above its historical mean (constant) to (2) a case where advertising decreases from one standard deviation above the mean to one standard deviation below (decreasing).

National Launch vs. Phased Roll-Out. Despite the pivotal role distribution plays in new-brand diffusion, little academic research exists on distribution strategies over time in the context of new-brand diffusion (Bronnenberg and Mela 2004, Jones and Ritz 1991). Our national launch/regional condition manipulation contrasts (1) holding distribution at one standard deviation above its historical mean (national launch) with (2) increasing distribution from one standard deviation below the mean to one standard deviation above the mean (phased roll-out).

Simultaneous vs. Phased Brand Entry. Moorthy and Png (1992) and Wilson and Norton (1989) argue that it is effective to release all variants early in the brand life cycle except when cannibalization is present. In the simultaneous/phased entry manipulation we compare (1) an increase from one standard deviation below the mean to one standard deviation above the mean (phased) to (2) a constant level of brand line length held at one standard deviation above the historical mean observed in the data (simultaneous).

Table 7 reports the sales and growth effects of the strategic launch options. The *sales impact* is expressed as percentage gains relative to a base case wherein marketing activity is held fixed at historical mean levels over the 52-week duration (see Panel A). In this case, sales peak at week 41, with 90% of growth within 14 weeks. We express the *growth impact* as the difference between the time it takes a brand to reach 90% of maximum sales in the base case and the

Table 7 **Sales and Growth Impact of Strategic Trade-Offs**

	Marketing mix instruments			Sales		Growth	
Pricing	Advertising	Distribution	Brand line	M	SD	M	SD
			Panel A: Base case				
At mean	At mean	At mean	At mean	4.01×10^7	1.05×10^8	14	—

	Marketing mix instruments			Sales impact		Growth impact	
Pricing	Advertising	Distribution	Brand line	M	SD	M	SD
			Panel B: Interaction effects (relative to base case)				
Penetration	Decreasing	National	Simultaneous	61.1	33.3	−4.9	0.2
Penetration	Constant	National	Simultaneous	63.6	34.8	−4.0	0.0
Skimming	Decreasing	National	Simultaneous	52.9	29.3	−1.3	0.8
Penetration	Decreasing	National	Phased	52.3	28.8	−1.0	1.0
Skimming	Constant	National	Simultaneous	55.5	30.7	0.3	1.6
Penetration	Constant	National	Phased	54.9	30.3	0.8	2.1
Skimming	Decreasing	National	Phased	44.2	24.9	6.0	3.9
Skimming	Constant	National	Phased	46.8	26.4	8.4	4.9
Penetration	Decreasing	Phased	Simultaneous	8.9	4.7	27.3	4.1
Penetration	Constant	Phased	Simultaneous	11.3	6.1	27.7	3.8
Skimming	Decreasing	Phased	Simultaneous	3.0	2.4	28.5	3.6
Penetration	Decreasing	Phased	Phased	2.2	1.7	28.6	3.6
Skimming	Constant	Phased	Simultaneous	5.4	3.7	28.8	3.4
Penetration	Constant	Phased	Phased	4.6	3.0	29.0	3.4
Skimming	Decreasing	Phased	Phased	−3.1	0.1	29.6	3.2
Skimming	Constant	Phased	Phased	−0.7	1.2	29.9	3.0

Notes. M (mean) and SD (standard deviation) are computed across 225 brands. For example, with penetration pricing, decreasing advertising, national launch, and simultaneous line entry, an average brand enjoys 61.1% more sales in the first year and reaches the 90% mark 4.9 weeks earlier than it does in the base case.

time to reach 90% of maximum sales under an alternative strategic option. Of note, distribution effects are considerably larger than the effect of all other strategies. Moreover, national launch interacts with (1) low price and broader lines to enhance market potential and growth and (2) advertising to facilitate growth.[8] Taken together, these interactions suggest broad access to distribution is a necessary condition for effective marketing.

7. Conclusions

Although new brands are central to the success of organizations, large numbers of these brands fail each year. For example, Hitsch (2006) reports that 75% of new-product introductions fail in the ready-to-eat breakfast cereal category. It is therefore a long-standing and central question in marketing to explain why some brands fail and some succeed. This research seeks to be a step in that direction by linking the sales outcomes for 225 new brands across 22 product categories over a five-year period to ascertain which marketing strategies discriminate successful brands in terms of sales and time to penetrate the market. In contrast to prior research pertaining to the effects of marketing strategy on the sales of new brands, we generalize our analysis across many categories and incorporate an array of marketing strategies that span the entire marketing mix. Moreover, we use statistical controls for marketing mix endogeneity and performance feedback in our analysis. We contend an empirical generalization that assesses the relative efficacy of launch strategies has remained heretofore unaddressed in the marketing literature.

To achieve this aim, we formulate a Bayesian DLM of repeat-purchase diffusion. The methodology extends the literature on repeat-purchase diffusion models (e.g., Lilien et al. 1981) to incorporate dynamics in the growth process over time and the endogeneity of marketing spend. Our state-space formulation of the repeat-purchase model enables us to achieve these goals. This innovation also enables a multitude of additional potential specifications given its inherent flexibility in estimation. Using this approach, we find:

• The relative effect sizes of the various strategies (standardized to sum to one) on market potential are as follows: distribution breadth 54%, feature/display 20%, distribution depth 9%, line length 7%, regular price 5%, advertising 2%, and discounting 2%. Thus, over the range of our data, the effect of distribution

[8] We tested for these interactions using a classical analysis of variance of the sales and growth columns in Table 7 on the design variables in the rows of Table 7.

exceeds the combined effect of all other marketing effects. This underscores the importance of obtaining distribution for new brands.[9] This finding supplements that of Ataman et al. (2007), who find that distribution plays a central role in explaining differences in sales across geographic regions in France. The result further underscores the desirability of ascertaining the antecedents of distribution including, for example, the use of slotting allowances (Sudhir and Rao 2006) and suggests the study of penetration into distribution is an substantially under-researched area in marketing (we suspect this might be due in part to a lack of good data). The relative effect sizes of the various strategies on the growth parameter (standardized to sum to one) are as follows: distribution breadth 31%, discounting 20%, regular price 15%, line length 12%, feature/display 12%, advertising 10%, and distribution depth 0.1%.

- With the exception of discounting, all strategies have a positive total effect on sales. Discounts quicken diffusion but have a negative effect on long-term market potential.
- Not only does distribution have the largest direct impact on sales, but it also interacts with other strategies to enhance their efficacy.
- Using a simulation predicated on our data, we find the breakeven thresholds to be lowest for distribution breadth and depth and highest for advertising and discounting.

Our findings have a number of managerial implications. First, the results of our analysis can be informative to firms seeking to allocate funds across the mix in a means consistent with their growth objectives. Given that discounting accelerates growth at half the rate of distribution breadth, firms can trade off the cost of a two-standard-unit increase in discounting with a one-standard-unit increase in distribution breadth. Second, like all diffusion models, the model developed herein can be used to forecast the sales growth of new brands; however, in this instance the model can be used under various marketing scenarios for repeat-purchase goods. Given the empirical generalization, firms can choose analog products to engage these forecasts even with little data and then update them as new data become available; the Bayesian nature of our model allows the modeler to readily update the parameter estimates.

As with any research, the findings summarized above are subject to several extensions/limitations. Many limitations are not unique to this study but are inherent in empirical models of sales response predicated on secondary data. These extensions/limits include the following. First, we focus exclusively on national brand introductions and exclude private labels; presumably, retailers would be quite interested in private label brands and the strategies that ensure their viability. Second, brand extensions are an important topic in their own right, and comparing marketing strategy efficacy of brand extensions to that of entirely new brands can further enhance our understanding of successful roll-out strategies. Third, traditional models of diffusion in repeat purchase contexts separate growth due to word of mouth effects from innovation effects. We focus on the latter, given that word-of-mouth effects are largely absent in packaged goods (Hardie et al. 1998). Nonetheless, it would be desirable to extend this model for durable goods contexts in which word-of-mouth plays a greater role. Fourth, the data preclude us from taking a more nuanced view of innovation and diffusion. For example, we do not consider how personal and product characteristics or organizational capabilities moderate diffusion rates (Cooper 1998, Gatignon and Robertson 1986, Rogers 1976). Sixth, our model does not provide a formal accounting of retailer decision making. A national roll-out strategy is not only incumbent on a firm's choice to distribute nationally, but also on the willingness of retailers to adopt a new brand (Bronnenberg and Mela 2004).

Our analysis is a step toward a more complete view of the role of postlaunch marketing strategy on the diffusion of frequently purchased CPG brands. In light of our findings and the foregoing limitations, we hope this work will stimulate further research on new-brand launch, especially with regard to the role distribution plays in the success of new brands.

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Appendix. Model Estimation

The observation equation and the evolution equation of the multivariate DLM for brand j ($j = 1, \ldots, 225$) are

$$Y_{jt} = F_{jt}\theta_{jt} + X_{jt}\beta_j + v_{jt}, \tag{10}$$

$$\theta_{jt} = G_{jt}\theta_{jt-1} + h_{jt} + \omega_{jt}, \tag{11}$$

where Y_{jt} is a vector that stacks standardized sales and marketing mix instruments. From now on, we drop the brand subscript j for simplicity. $F_t = I_{M+1}$, where M (=7) is the

[9] The finding that feature/display is the second most important instrument to build market potential coincides with results from Pauwels and Hanssens (2007), who find that promotional variables are especially effective in turning brand performance around. Together, these results imply that "marketing strategy is in the details." We thank an anonymous reviewer for this observation.

number of marketing mix variables. X_t is the matrix of regressors that create short-term fluctuations in sales. For a given brand, we assume $v_t \sim N(0, V)$ and $\omega_t \sim N(0, W)$, where V and W are full and diagonal matrices, of size $(M+1) \times (M+1)$, of error variances, respectively. The time-varying parameter vector, $\theta_t' = (\alpha_t', \zeta_t')$, evolves as described in (11).

Step 1. $\theta_t \mid Y_t, V, W, \beta, G_t, h_t$.

For each brand we sample from the conditional distribution of θ using the forward-filtering, backward-sampling algorithm proposed by Carter and Kohn (1994) and Frühwirth-Schnatter (1994). First, for $t = 1, \ldots, T$ we forward filter to obtain the moments m_t and C_t. Conditional on $\widetilde{Y}_t$, V, W, β, G_t, h_t and $\theta_0 \mid D_0 \sim N(m_0, C_0)$, where $\widetilde{Y}_t = Y_t - X_t'\beta$:

- The prior at time t is $\theta_t \mid D_{t-1} \sim N(a_t, R_t)$, where $a_t = G_t m_{t-1} + h_t$ and $R_t = G_t C_{t-1} G_t' + W$.
- One-step-ahead forecast at time t is $\widetilde{Y}_t \mid D_{t-1} \sim N(f_t, Q_t)$, where $f_t = F_t a_t$ and $Q_t = F_t R_t F_t' + V$.
- The posterior distribution at time t is $\theta_t \mid D_t \sim N(m_t, C_t)$, where $m_t = a_t + R_t F_t' Q_t^{-1}(\widetilde{Y}_t - f_t)$, and $C_t = R_t - R_t F_t' Q_t^{-1} F_t R_t$.

At $t = T$ we sample a matrix of evolution parameters from the distribution $N(m_t, C_t)$. Next we sequence backward for $t = T-1, \ldots, 1$ sampling from $p(\theta_t \mid \theta_{t+1}, rest) \sim N(q_t^*, Q_t^*)$, where $q_t^* = m_t + B_t(\theta_{t+1} - a_{t+1})$, $Q_t^* = C_t - B_t R_{t+1} B_t'$, and $B_t = C_t G_{t+1}' R_{t+1}^{-1}$. We select $m_0 = 0$ and $C_0 = 0.1$ as the initial values.

Step 2. $V \mid \theta_t, Y_t, \beta$.

For a given brand, we assume that the observation equation error variance matrix, of size $(M+1) \times (M+1)$, is full. We place an inverse Wishart prior, with (n_{V0}, S_{V0}). Then the full conditional posterior distribution is also inverse Wishart, with $n_{V1} = n_{V0} + T$ and $S_{V1} = S_{V0} + \sum_{t=1}^{T} (Y_t - X_t'\beta - F_t\theta_t)'(Y_t - X_t'\beta - F_t\theta_t)$. We use a diffuse prior with $n_{V0} = (M+1) + 2$ and $S_{V0} = 0.001 \times I_{M+1}$.

Step 3. $W \mid \theta_t, \lambda, \delta, \phi$.

We assume that the evolution equation error-variance matrix, of size $(M+1) \times (M+1)$, is diagonal for a given brand. We place an inverse Gamma prior on the elements of this matrix, with $n_{W0}/2$ degrees of freedom and a scale parameter of $S_{W0}/2$. The full conditional posterior distribution is also distributed inverse Gamma with $n_{W1} = n_{W0} + T - 1$ and $S_{W1} = S_{W0} + \sum_{t=1}^{T} (\theta_t - G_t\theta_{t-1} - h_t)'(\theta_t - G_t\theta_{t-1} - h_t)$. We use a diffuse prior with $n_{W0} = 3$ and $S_{W0} = 0.001$.

Step 4. $\delta \mid \alpha_t, W, \phi, \mu$, $\gamma \mid \alpha_t, W, \delta, \mu$, and $\mu \mid \alpha_t, W, \delta, \phi$.

Conditional on the sampled baseline sales series across all brands, the evolution equation is nonlinear in parameters and there is no closed-form density for the parameters. Therefore, we use a random walk Metropolis-Hastings step within the Gibbs sampler to obtain the parameter estimates. We discuss only the estimation of the brand-specific repeat rates. The estimation of $\phi \mid \theta_t, W, \mu, \delta$ and $\mu \mid \theta_t, W, \delta, \phi$ follows directly. We generate the candidate repeat purchase rate draw by $\delta_j^{(m)} = \delta_j^{(m-1)} + z$, where (m) denotes mth iteration, and z is a random draw from $N(0, \kappa I)$. We select κ such that the acceptance rate is between 20%–50% (Chib and Greenberg 1995). The candidate draw is accepted with the probability $\alpha^* = \min\{1, \alpha\}$, where

$$\alpha = \frac{\pi(\delta_j^{(m)} \mid \theta_t, W, \phi, \mu)}{\pi(\delta_j^{(m-1)} \mid \theta_t, W, \phi, \mu)}, \tag{12}$$

and $\pi(\cdot)$ is conditional likelihood of Equation (11) evaluated at each draw.

Step 5. $\pi \mid \theta_t, W$.

To obtain the conditional posterior distribution of the brand-specific evolution equation parameters associated with the ith marketing mix instrument (π_i), we define $K_{iT} = [1_{T-1} \zeta_{iT-1} Sales_{jT-1} Sales_{j'T-1}]$ and $W_{iT} = W_i \otimes I_{T-1}$. We place a normal prior on the parameters, $\pi_i \sim N(\underline{\mu}_{\pi}, \underline{\Sigma}_{\pi})$. Then the full conditional posterior is also normal with $\pi_i \sim N(\bar{\mu}_{\pi} \bar{\Sigma}_{\pi})$, where $\bar{\mu}_{\pi} = \bar{\Sigma}_{\pi}\{\underline{\Sigma}_{\pi}^{-1}\underline{\mu}_{\pi} + [K_{iT} W_{iT}^{-1} \zeta_{iT}]\}$, and $\bar{\Sigma}_{\pi} = \{\underline{\Sigma}_{\pi}^{-1} + [K_{iT} W_{iT}^{-1} K_{iT}']\}^{-1}$.

Step 6. $\beta \mid \theta_t, V$.

To obtain the brand-specific conditional posterior distribution of the nontime-varying observation equation parameters β, we define $\bar{Y}_t = Y_t - F_t\theta_t$ and $V_T = V \otimes I_T$. We place a normal prior on the parameters, $\beta \sim N(\underline{\mu}_{\beta}, \underline{\Sigma}_{\beta})$. Then the full conditional posterior is also normal with $\beta \sim N(\bar{\mu}_{\beta} \bar{\Sigma}_{\beta})$, where $\bar{\mu}_{\beta} = \bar{\Sigma}_{\beta}\{\underline{\Sigma}_{\beta}^{-1}\underline{\mu}_{\beta} + [X_t V_T^{-1} \bar{Y}_t]\}$, and $\bar{\Sigma}_{\beta} = \{\underline{\Sigma}_{\beta}^{-1} + [X_t V_T^{-1} X_t']\}^{-1}$.

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