Building Brands

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Building Brands

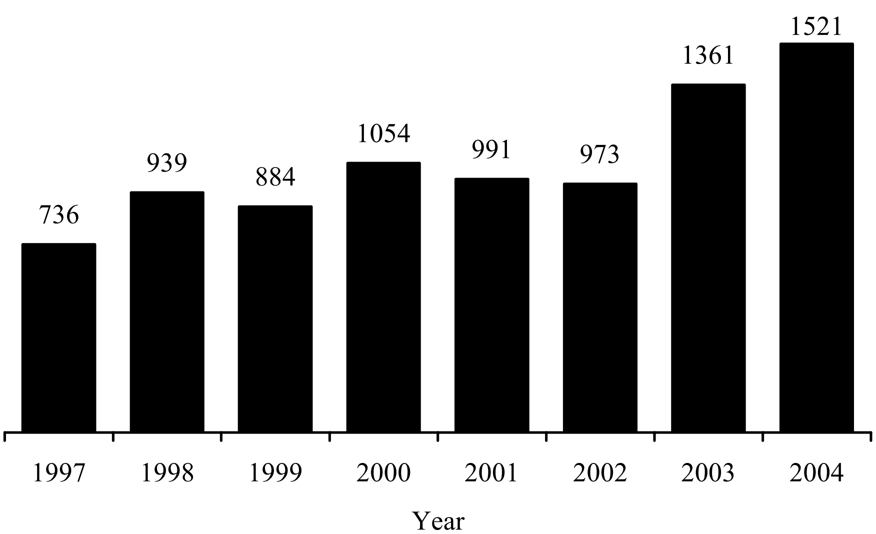
Which marketing strategies are most effective for introducing new brands? This paper sheds light on this issue by ascribing growth performance to firms' post-launch marketing choices. We decompose the success of a new brand into its ultimate market potential and the rate with which it achieves this potential. 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 brands' long-term advertising, promotion, distribution, and product strategy. We perform the analysis on 225 new brand introductions across 22 product categories over five years to develop generalized findings regarding 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 revenue for new brands than either discounting, or 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.

Keywords: Diffusion, New Products, Marketing Mix, Dynamic Linear Model, Empirical Generalization

1 Introduction

Markets are often characterized by extensive new product activity and the pace of innovation is accelerating. For example, 1521 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, as 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). Though essential to firms' overall performance, few new brands reach the status of an established brand; a majority eventually fails. 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.

Figure 1: Number of New CPG Brand Introductions, 1997-2004



Note: The figures include entirely new brands or new brand extensions but exclude 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*"

Perhaps as a result, the growth of new brands has received substantial amount of interest in the marketing literature. Recent research on new product diffusion has advanced our understanding on how external factors such as economic conditions (van den Bulte 2000), consumer differences and competitive setting (Steenkamp and Gielens 2003), and product and country characteristics (Tellis, Stremersch, and Yin 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 regarding how marketing affects the growth and/or market potential of durable goods (see Bass, Jain, and Krishnan 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. Accordingly, little information exists on the drivers of diffusion for *non-durable* goods. In this paper, we shed light on diffusion in repeat purchase contexts by offering an integrated view across the entire marketing mix and afford insights into introduction strategies that enhance the potential for successful roll-outs.

By considering launch strategies, we advance the literature on new product diffusion in two ways; by conducting an empirical generalization pertaining to the efficacy of marketing strategies in the context of new product launch, and by developing a methodology to achieve these aims. Specifically,

- 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. Though 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. Surprisingly much less emphasis has been placed on distribution and product line. By considering launch strategies in their entirety, we control for potential correlations across various marketing instruments and we can gauge their relative effect in order 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, Gupta, and Lehmann 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 Dynamic Linear Model (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).

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) This paper	Kalish (1983, 1985), Kalish and Lilien (1986), Kamakura and Balasubramanian (1988), Horsky (1990), Jain and Rao (1990), Bass, Krishnan and Jain (1994), Mesak and Berg (1995), Mesak (1996) This paper
Promotion	Lilien, Rao and Kalish (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) This paper	Dodson and Muller (1978), Mesak (1996) This paper
Place	Mesak (1996) This paper	Jones and Ritz (1991), Mesak (1996) This paper
Product	This paper	This paper

Note: 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 unless otherwise mentioned.

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 in the preceding literature on these factors. Overall, we find that access to distribution plays the greatest role in the success of a new brand. Our 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 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 pay-off; if the marginal cost of additional distribution is less than 24% 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 .7% of marginal retail revenue. Increasing product line length is profitable when the marginal cost of doing so are less than 6% 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 briefly overview the estimation process. After discussing the data, we provide variable operationalizations and develop expectations regarding the role of marketing strategy on new brand performance. The results are given next followed by managerial implications drawn from several simulations. The last section concludes.

2 Modeling New Brand Diffusion in CPG Categories

Though ubiquitous in marketing, the preponderance of diffusion models have been developed for *durable goods* categories. Modeling new brand diffusion in frequently purchased *non-durable 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 only consider 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). In order to prevent such biases and provide improved sales forecasts several diffusion model alternatives with replacement purchases have been developed for durable goods (see Ratchford, Balasubramanian, and Kamakura (2000) for a review) as well as non-durable goods (Lilien, Rao, and Kalish 1981; Rao and Yamada 1988; Hahn, Park, Krishnamurthi, and Zoltners 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- vs. 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 imply 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 model with constant market potential are ill-suited to capture this phenomenon. Moreover, the 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 considerations.

Third, *short-term fluctuations* in sales may mask the true *long-term performance* of the new brand (Mela, Gupta, and Lehmann 1997). Previous applications of repeat purchase diffusion models for non-durable 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, Park, Krishnamurthi, and Zoltners 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, Rao, and Kalish 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 both the time for a new product to reach its market potential and the level of that potential. Accordingly, we predicate our model formulation on the marketing literature on diffusion (Mahajan, Muller, and Bass 1990). Given our emphasis on repeat purchase goods, our modeling approach closely parallels that of Lilien, Rao, and Kalish (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 growth and market potential to marketing strategy given the central aims of our paper, 3) we incorporate performance feedback to control the role of past sales on future marketing spend, 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. New purchases drive sales in conjunction with retained customers; however, the long-term potential for brand sales is more closely linked to repeat rates.

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

(1) $$Sales_t = \alpha_t + X_t'\beta + \upsilon_t ,$$

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. If the X_t include only weekly discounts and feature and display, 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, Mela, and Gupta (1999) inasmuch as short-term effects are captured by the effect of a given week's marketing activity, X_t, such as a promotion, and the 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 $\upsilon_t \sim N(0,V)$.

Following LRK we assume[1]

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

[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, Fader and Wisniewski (1998) who find *no word of mouth effects across 19 different consumer packaged goods data sets*. Given (i) high variability in weekly sales arising from weekly promotions and (ii) the fact that most products are not consumed the same week of purchase (e.g., detergent has an 8 week purchase cycle) and (iii) 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 consumer packaged goods 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 $\alpha_t = \alpha_{t-1} + \gamma(\mu - \alpha_{t-1}) - \rho\alpha_{t-1} + \omega_t \equiv \delta\alpha_{t-1} + \gamma(\mu - \alpha_{t-1}) + \omega_t$.

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 inasmuch as a certain fraction, δ, of the base (roughly given by the repeat rate times the incidence rate) will continue to buy on the subsequent purchase occasions. The second term captures the attraction of the remaining potential customers inasmuch 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 represents the diffusion process governing the long-term evolution of baseline sales potential. The parameters γ and μ have an additional interpretation inasmuch as γ is reflective of the time of adjustment to the market potential while μ reflects that potential. All else equal, faster growth and greater potential lead to higher total sales. We assume $\omega_t \sim N(0,W)$.

Following LRK we allow the growth parameter to vary over time $(\gamma \rightarrow \gamma_t)$. We 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. Likewise, we allow for flexibility in diffusion patterns by assuming that the long-term potential for a brand's sales can also be affected by a brand's marketing strategy $(\mu \rightarrow \mu_t)$. Based on our earlier discussion on a new brand's market potential, we posit the market potential to be a function of the long-term marketing strategy of a brand, $\mu_t \equiv Z_t'\mu$. After substituting the new growth and market potential definitions in Equation (2) we obtain,

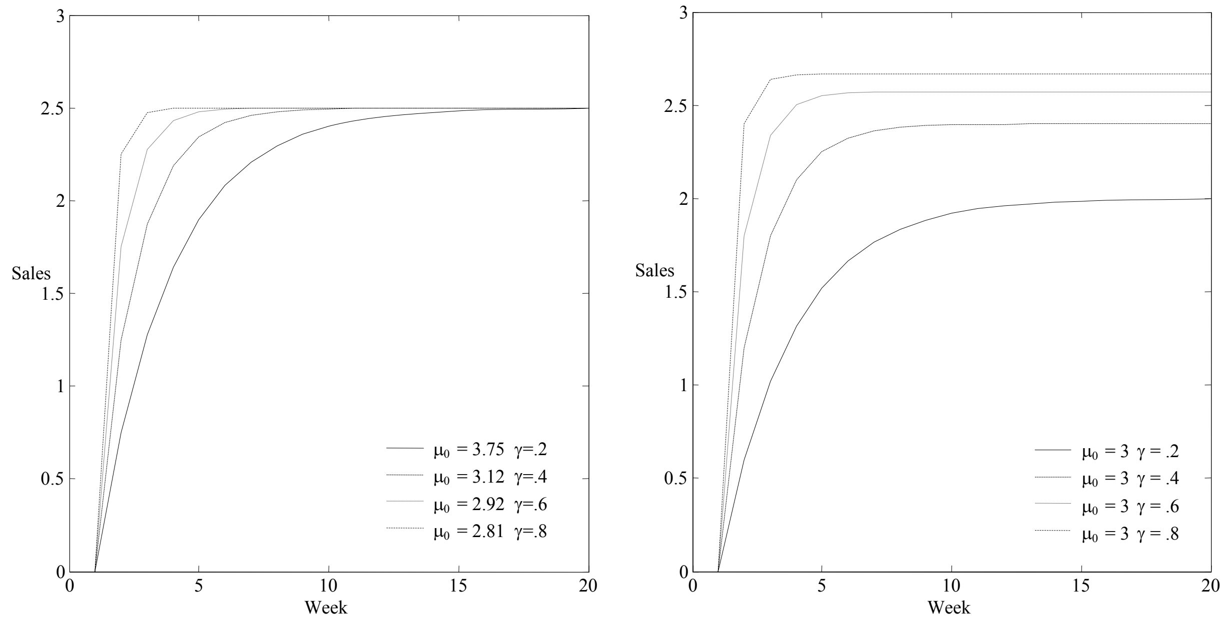
$$\alpha_t = \delta\alpha_{t-1} + Z_t'\gamma(Z_t'\mu - \alpha_{t-1}) + \omega_t \, , \tag{3}$$

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. Together, these parameters govern the rate of sales, as we show next.

Note, that 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 recursion in Equation (3). Conditioned on Z_t constant at $Z_t = Z$, Equation (3) is a geometric decay model whose carryover is given by $\delta - Z'\gamma$. The model in Equation (3) 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 $0 < (1-\delta + Z'\gamma) < 1$. Thus, when $\gamma > 0$ an increase in Z leads to faster growth. When μ and γ are positive, an increase in Z implies an increase in the long-term sales level of a brand. As $\delta - Z'\gamma$ approaches 0 and $Z'\mu$ becomes sufficiently large, sales will adjust immediately to a high mean but also fall again quickly when marketing support is withdrawn. Given the Z have a carryover effect, we denote these long-term marketing effects. However, Z also embeds an intercept; therefore even in the absence of marketing spend, baseline sales may adjust quickly to the maximum defined by the intercept parameter (denoted μ_0) and then not fall. Likewise, a low value for $\delta - Z'\gamma$ can imply fast adjustment in the absence of marketing spend. Thus, a high value for γ and a high value for μ_0 imply that a brand will quickly ascend to a high level of sales, while a low value for γ and a low value for μ_0 imply that the brand will neither generate large sales nor increase sales quickly (see Figure 2). In sum, Equation (3) provides a flexible model of brand 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 Dynamic Linear Models (West and Harrison 1997). In the next section we discuss model specification, and provide a brief overview of the estimation procedure.

Figure 2: Growth Trajectory Illustrations



(a) (b)

Note: Figures assume scalar Z=1 for all t and $\delta = .9$. Note that it is also possible to accommodate sigmoidal sales trajectories when market potential $Z_t'\mu$ varies over time.

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, Helsen and Dekimpe 2007, and Van Heerde, Mela, and Manchanda 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,

$$(4) \qquad \overline{Sales}_{jt} = \alpha_{jt} + \overline{X}'_{jt}\beta_j + \upsilon^S_{jt},$$

where $\overline{Sales}_{jt}$ is the vector of sales of brand j at time t, and $\overline{X}_{jt}$ includes variables that may 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 effect diffusion. The standardization assures we can pool different units across categories and control for unobserved fixed effects. 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,

$$Y_t = F_t\theta_t + X_t\beta + \upsilon_t , \tag{6}$$

$$\theta_t = G_t\theta_{t-1} + h_t + \omega_t , \tag{7}$$

where Y_t is a vector that stacks the standardized sales of brand j in week t, and $F_t = 1$. X_t is the matrix of standardized regressors that create short-term fluctuations in sales. We assume $\upsilon_t \sim N(0,V)$, where V is the matrix of observation equation error variances. The time varying parameter vector $\theta_t = \alpha_t$, evolves as described in Equation (7). Rearranging the terms in Equation (5) gives the diagonal system evolution matrix G_t with $\delta_j - \overline{Z}'_{jt}\gamma$ on its diagonal. Then the second term on the right hand side of Equation (7) is $h_t = (\overline{Z'}_{jt}\gamma)\overline{Z'}_{jt}\mu$. The stochastic term ω_t are distributed, $\omega_t \sim N(0,W)$, where W is a diagonal matrix of evolution equation error variances.

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. In order 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. In addition, we include the lagged performance of the *competing brands* to control for changes in competitors' marketing strategies. Given competitive performance is correlated with competitors' current and past marketing, this approach affords a parsimonious representation of the influence of competition on marketing and sales. The alternative, an enumeration of all competitor marketing actions quickly exhausts degrees of freedom, over-parameterizes the model (a problem exacerbated in the DLM) and yields poor predictions.

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

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

$$\zeta_{ijt} = \pi_{0ij} + \pi_{1ij}\zeta_{ijt-1} + \pi_{2ij}\overline{Sales}_{jt-1} + \pi_{3ij}\overline{Sales}_{j't-1} + \omega_{ijt}, \tag{9}$$

where Z_{ijt} is the ith marketing mix instrument of brand j in week t. Equation (8) posits that observed marketing spend 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, and past performance of the focal brand and past performance of the competitors. The parameter π_{1ij} is associated with the lagged national strategy and captures inertia in the marketing spend. $Sales_{jt-1}$ is the focal brand's lagged national sales, and $Sales_{j't-1}$ for all $j' \neq j$, is the sum of competitors' lagged national sales. Thus the parameters π_{2ij} and π_{3ij} respectively capture own- and cross-performance feedback effects for the marketing mix instrument i. 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 υ_{jt}^{S} and υ_{ijt}^{Z} be correlated in order to account for common unobserved shocks in the observation equations.[2] 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 their 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, as the evolution equation is non-linear in parameters. The details of the sampling chain are provided in the Appendix.

4 Data and Variables

4.1 Data

We calibrate our model on a novel dataset provided by Information Resources Inc. (France). The data covers 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).

[2] We estimated an alternative diagonal error correlation. The log Bayes Factor (West and Harrison 1997) favored the full matrix specification over the diagonal matrix specification (log BF = 18,641.81).

Table 2: Descriptive Statistics

Category		*# New Brands*	*# Brands in Category*	*Sales Volume New Brand (x 1000)*	*Sales Volume (x 1000) Category Mean*	*Sales Value (x1000)*	*Advertising (x1000)*	*Price (per 1000)*	*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	2563.9	108.2	112.8	7.7	4.8	1.9	0.4	2.4	12.9
Beer	M	36	961	1030.4	2263.9	249.3	27.5	3.9	4.5	2.3	1.0	2.2	18.3
	SD			2330.2	26826.5	440.2	47.8	2.2	9.8	1.1	0.5	1.4	12.0
Butter	M	12	382	2183.6	2029.9	1979.7	40.9	5.0	9.7	3.0	2.0	2.7	21.1
	SD			2182.5	6609.9	2094.6	69.8	2.0	19.9	2.0	1.0	2.4	19.6
Cereals	M	7	118	647.1	2454.0	401.8	2.7	6.1	4.6	3.9	2.3	2.5	6.2
	SD			1194.0	12290.8	585.6	.	3.0	5.2	4.3	1.4	4.4	5.4
Chips	M	5	86	4143.0	6144.1	1456.2	.	2.3	9.9	5.2	4.2	2.8	13.5
	SD			8011.8	16199.5	3041.2	.	0.9	19.1	8.4	2.4	1.1	8.6
Coffee	M	16	306	93.2	1444.5	121.2	.	9.0	1.9	4.0	1.5	7.0	34.0
	SD			143.2	7309.0	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	2002.9	1861.1	1514.3	32.4	5.7	11.8	6.8	6.0	2.0	13.6
	SD			1013.1	4492.1	998.8	.	3.5	2.9	7.8	2.5	0.9	3.0
Ice Cream	M	19	211	1046.3	2465.1	805.2	2.3	5.0	8.2	6.0	1.3	2.3	11.5
	SD			1521.1	7615.9	1146.9	.	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	4773.1	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	2562.8	93.1	1.7	4.3	2.4	6.2	1.7	3.2	17.2
	SD			1675.1	17300.3	124.8	1.3	3.4	3.0	5.2	0.8	2.6	10.6
Shampoo	M	9	172	1211.9	1143.0	2013.7	89.0	9.8	22.8	6.1	1.5	1.0	7.0
	SD			1950.2	2895.2	3136.9	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	1265.2	306.1	.	8.6	6.2	1.1	1.5	0.6	6.3
Soup	M	21	333	1643.5	2244.3	584.8	31.2	3.3	8.9	6.6	1.9	1.8	12.4
	SD			3714.1	18135.0	1235.8	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			.	1720.9	.	.	.	.	.	.	.	.
Water	M	14	189	58.7	88.4	2938.6	93.6	3.4	22.0	3.5	2.6	0.7	9.9
	SD			54.2	342.1	3101.4	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			.	1990.3	.	.	.	.	.	.	.	.
Yogurt	M	8	226	534.1	10762.0	279.7	132.0	4.7	4.8	2.4	0.9	1.3	7.0
	SD			846.7	37229.1	363.7	.	1.7	6.2	0.8	0.3	0.9	6.3
Yogurt Drink	M	3	37	1777.1	5043.5	751.4	.	3.6	10.7	2.1	5.8	0.7	3.3
	SD			1248.1	14107.6	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 non-zero observations.

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. As 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, we then calculated an ACV weighted average of brand-store level independent variables to obtain national brand level data.

Between 1/1/1999 and 2/1/2004 we observe 365 new national brand introductions in 25 product categories. 55 of these new brands 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 approximately. On average we observe the first 152 weeks of the new brand's lifecycle, 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. See Table 2 for data descriptive statistics.

4.2 Variables

Our 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. Table 3 summarizes our expectations.

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, Gupta, and Lehmann 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 takes 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

The operationalization of the marketing mix variables in Z_{jt} in the evolution equation (5), along with our expectations regarding the role they play in growth and market potential are as follows:

Price: We define the price of a brand as the regular price in a given store-week. Consistent with previous studies (e.g. Mela, Gupta, and Lehmann 1997) we select the minimum regular price per 1000 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 whether price also affects the market potential: Bass, Krishnan, and Jain (1994) and Kamakura and Balasubramanian (1987, 1988) find no impact of 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 product 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 customer loyalty through rewards thus may help the brand to build baseline sales through increased familiarity and experience, or simply through purchase reinforcement or habit persistence (Ailawadi et al. 2007; Keane 1997). On the other hand, discounting can also have a negative long-term impact as it may erode brand equity (Ataman, Van Heerde, and Mela 2006; Jedidi, Mela, and Gupta 1999).

Features/Display: We also consider the role of non-price 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 non-price promotions make the new product salient and promote it to the shopper traffic (Gatignon and Anderson 2002). In a sense they work in the same way as 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 summing across days for the corresponding weeks (Jedidi, Mela, and Gupta 1999).

A number of studies have already 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 products, produces high awareness levels, differentiates products and builds brand equity (Aaker 1996). Thus, helps building 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) finds that advertising works better when brands are new, implying a positive growth effect.

Distribution breadth: We use ACV weighted distribution as a measure of distribution breadth (Bronnenberg, Mahajan, and Vanhonacker 2000). ACV weights a product'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 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, Mahajan, and

Vanhonacker (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 explaining 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 product 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, may generate awareness for a new brand (Eliashberg and Jeuland 1986). Therefore we expect distribution depth to facilitate growth and build market potential.

Line length: We measure the product line length by the number of SKUs a brand offers in a given week. Our discussion about the role product line length plays in the diffusion process of a new brand is rather tentative as theoretical and empirical evidence on this issue is virtually non-existent. 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 may serve more segments. Therefore we expect line length to increase market potential and facilitate growth.

Table 3: Summary of Expectations

	Growth	Market Potential
Advertising	+	+
Regular Price	-	-
Discounting	+	+
Feature and Display	+	+
Distribution Breadth	+	+
Distribution Depth	+	+
Line Length	+	+

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 consumer packaged goods categories. Therefore the relative importance of marketing instruments in building new consumer packaged goods brands is undocumented. However these effect sizes are of central interest to managers as they point out areas in which it may be more desirable to allocate marketing funds. We argue that line length, breadth and availability should assume the greatest importance simply because (i) 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 (ii) 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 lie in the second tier of critical element of the diffusion process.

5 Results

We estimate the DLM specified above using a Gibbs sampler, and run the sampling chain for 30,000 iterations (10,000 for burn-in and 20,000 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 non-stationarity in product launch provides excellent fit to the data. Across 225 brands we analyze in the paper, the average correlation between actual and predicted sales is .97 (standard deviation = .07).

For all 225 brands we consider three sets of parameters: (i) the short-term marketing effects (β) on sales model specified in Equation (4), (ii) the long-term marketing strategy effects on growth (γ) and market potential (μ), as well as the repeat purchase rate parameter (δ) in the baseline sales evolution model as shown in Equation (5), and (iii) the marketing mix inertia and performance feedback 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 as each stimulates same-week sales. 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 regarding the evolution of baseline sales (α_t), including (i) repeat purchase effects (δ), how marketing mix instruments correlate to sales growth (γ) for new brands, and (ii) the role these instruments play in the market potential (μ) for a new brand. Table 4 indicates that increases in advertising support, distribution breadth, product 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

Table 4: Parameter Estimates (Sales Model)

Observation Equation Parameters [a]				
Category	Discounting	Feature/Display	Temperature	Repeat Rate
Bath Products	.01	.10	.00	.90
Beer	.00	.07	.00	.87
Butter	.00	-.04	-.02	.84
Cereals	.02	-.02	-.01	.92
Chips	.08	-.03	-.01	.98
Coffee	.05	.10	.00	.99
Feminine Needs	.04	.02	-.01	.92
Frozen Pizza	.21	.02	-.01	.95
Ice Cream	.03	.01	.00	1.00
Mayonnaise	.02	.22	.00	.90
Mineral Water	.05	.10	.00	.95
Paper Towel	.29	.07	.01	.91
Pasta	.03	.05	-.01	.93
Shampoo	.05	.05	.00	.97
Shaving Cream	.01	-.02	.00	.95
Soup	.01	-.02	-.01	.95
Tea	.02	.09	-.01	.94
Toothpaste	.02	-.05	-.01	1.02
Water	.00	.00	.00	1.02
Window Cleaner	.06	.20	.02	1.00
Yogurt	.03	.03	-.01	.97
Yogurt Drink	.00	.04	.00	.97

Growth and Market Potential Parameters [b]				
	Growth		Market Potential	
Marketing Activity	Median	5th and 95th Percentile	Median	5th and 95th Percentile
Constant	**.0979**	**.0908; .1056**	**.1076**	**.0808; .1338**
Advertising	.0064 [c]	-.0015; .0145	.0243 [c]	-.0041; .0560
Regular Price	**-.0120**	**-.0154; -.0085**	**-.0955**	**-.1272; -.0628**
Discounting	**.0145**	**.0110; .0187**	-.0184 [c]	-.0400; .0024
Feature and Display	**-.0080**	**-.0099; -.0062**	**.2903**	**.2470; .3316**
Distribution Breadth	**.0249**	**.0209; .0289**	**.7735**	**.7229; .8286**
Distribution Depth	-.0020	-.0059; .0019	**.1125**	**.0839; .1429**
Line Length	**.0109**	**.0065; .0153**	**.1122**	**.0774; .1445**

Notes: (a) Variance weighted average of median estimates across brands. (b) Bold indicates that 90% posterior confidence interval excludes zero. (c) The growth effect of advertising crosses zero at 91st percentile, the market potential effect of advertising at 92nd percentile, and the market potential effect of discounting at 93rd percentile.

expectations. The effect of distribution depth on growth is negligible. Surprisingly, we find that feature and display intensity *slows* diffusion of new brands though 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 advertising, feature and display activity, product line length, distribution breadth, and distribution depth correlate positively with market potential for new brands. As expected, high prices are associated with lower market potential. Consistent with the literature on the long-term effect of discounts, the effect of discounting on market potential is negative (Mela, Gupta and Lehmann 1997). It is interesting to note the dual role of discounts in leading to faster growth but lower long-term sales.

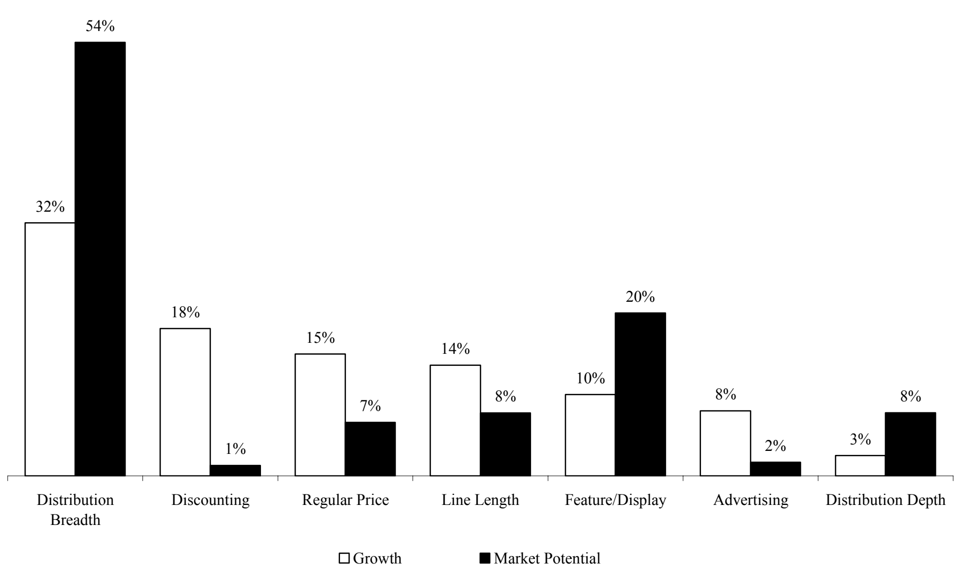
Across the 225 brands, the repeat purchase parameters, δ, range between .81 (25^{th} percentile) and .98 (75^{th} percentile), with a median of .94. The variation of repeat purchase parameter estimates across product categories does not reveal major differences. This median repeat purchase rate across 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 (i) the standardized coefficient for a given marketing mix instrument to (ii) the sum of all marketing mix effects. In the calculation we use the absolute values of the standardized coefficients for the growth and market potential parameters respectively. Figure 2 presents the relative effects of the marketing mix instruments.

Figure 2 makes it apparent that distribution breadth is the single most important marketing mix instrument in generating growth (relative effect of 32%) and building market potential (relative effect of 52%) for a new brand. Although the result is not altogether surprising (a brand can not have sales without distribution), the precise effect size relative to other variables is less obvious as i) *the effect of distribution exceeds all other strategies combined* in generating growth and ii) it is also the case that a brand can not have sales without product, yet this effect is not as considerable. Distribution breadth and depth assume greater importance in building market potential (jointly 62%) than accelerating growth (jointly 35%). After distribution, discounting has the second largest impact on growth (18%). Feature and display have the second largest effect on market potential (20%), which implies their short-term effect on weekly sales is supplemented by their ability to build long run demand for new brands.

Figure 2: 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.

5.4 Marketing Mix Models

Lastly we summarize the results of the eight marketing instrument equations presented in Equations 8 and 9. Table 6 provides a summary of the inertia, own- and cross-performance feedback parameter estimates across all brands. The results reported in Table 5 indicate that inertia in advertising spending, regular price, discount depth, distribution breadth, distribution depth, feature/display and line length is positive in 93%-100% of the cases. For feature/display intensity we find that inertia is negligible in 24% of the cases, suggesting less state dependence.

Own-performance feedback effects on all marketing mix instruments are negligible for more than half of the brands except for distribution breadth where performance feedback effects are substantial. When own-performance feedback differs from zero, the effects are mostly positive; for discounting (31%), feature/display intensity (32%), distribution breadth (63%), distribution depth (33%), and line length (38%). Therefore we can conclude that better historical performance leads to greater marketing support for the recently introduced brand. For regular price we find that better performance leads to lower regular prices in 21% of the cases and to higher regular prices in 15% of the cases.

Table 5 further indicates that cross-performance feedback (or competitor effects) is predominantly zero for the marketing mix instruments. Steenkamp, Nijs, Hanssens and Dekimpe (2005) observe a similar result in the context of advertising and pricing for mature brands. The cross-performance feedback effects we observe are mostly negative for distribution depth (16%) and breadth (16%) suggesting new brands are able to strengthen their shelf presence at the expense of others when the others fare less well. The cross-performance feedback effects are mostly positive for discounting (11%) and feature/display (15%).

Table 5: Marketing Mix Models

	Inertia (%)			Own-performance Feedback (%)			Cross-Performance Feedback (%)		
	-	0	+	-	0	+	-	0	+
Advertising	0	0	100	2	96	2	0	98	2
Regular Price	0	2	98	21	64	15	8	83	9
Discounting	0	7	93	5	64	31	6	83	11
Feature and Display	4	24	72	6	62	32	7	78	15
Distribution Breadth	0	0	100	2	35	63	16	80	4
Distribution Depth	0	2	97	11	56	33	16	75	9
Line Length	1	3	96	2	60	38	9	82	9

Notes: The 90% posterior confidence intervals of marketing mix equation intercepts include zero as all variables are standardized. The entries in the table are the percentage of parameters, across all brands, estimated as negative, zero, or positive (based on 90% posterior confidence interval).

6 Managerial Implications

We next consider the ramifications of our analysis for new product launch marketing strategies. As a prelude, we note limits inherent in the archival data analysis that we propose, namely that parameter estimates may 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 percent sales change due to 10% permanent marginal increase in marketing spending by comparing the sales level of the new case to the base case $((S_1\text{-}S_0)/S_0) \equiv \Delta$. In these calculations, we considered only the first 52 weeks post-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.

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

	Mean	Standard Deviation	Minimum	1st Quartile	2nd Quartile	3rd Quartile	Maximum
Advertising Spending	.24	.26	.01	.07	.15	.27	1.02
Regular Price	-7.09	5.34	-39.83	-9.24	-6.00	-3.70	-.07
Distribution Breadth	8.19	4.99	.42	5.18	7.00	9.50	30.21
Line Length	2.35	1.85	.16	1.19	1.81	2.86	10.60
Distribution Depth	2.95	2.14	.16	1.60	2.41	3.46	15.82
Discount Depth	-.14	.84	-12.56	-.10	-.06	-.03	-.00
Feature/Display	1.74	1.54	.09	.80	1.27	2.31	11.06

Notes: As a result of a 10% permanent increase in regular prices sales reaches a 7.1% lower equilibrium level than it would have reached had the price been kept constant at its mean.

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 groups of equally efficacious marketing mix strategies. The most effective group comprises distribution breadth increases (a 10% arc elasticity of 8.2%), and regular price decreases (7.1%). Nevertheless, the implied average regular price elasticity (0.71) is low relative to meta-analytical results for regular prices and new brands (Bijmolt, Van Heerde, and Pieters 2005). This result may in part be attributed to our controls for other aspects of launch strategy, which are sometimes correlated with price. When omitted as in prior research, these factors can amplify the effect of price. The second most effective array of marketing mix instruments includes distribution depth, line length and feature/display (1.5%-3.0%). 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 inasmuch as Table 1 also suggests these are the most often-considered instruments in past research.

Marginal Profit Analysis. Table 6 further illuminates a "back of the envelope" marginal profit approximation. Let C_0 denote the cost 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 given by $\Pi_0 = (1\text{-RM})*(\text{MM})*R_0 – C_0$. With a 10% increase in the marketing expenditure, the new level of profits are given by $\Pi_1 = (1+ \Delta)*(1\text{-RM})* (\text{MM})*R_0 – (1+.10)*C_0$ (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)*Δ*R_0) is greater than the resulting increase in marginal cost, .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 $3*\Delta > C_0/R_0$.

Stated differently, the marginal profits of investing in marketing become positive when costs as a percent of retail revenue exceed 3*Δ. For distribution (Δ = .082), this implies it is profitable on the margin to invest in distribution when distribution costs are less than 24% of retail revenue. On the other end of the spectrum, it is only profitable to advertise (Δ = .0024) when the marginal cost of advertising is less than 0.7% 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 there is sufficient variation across categories that different strategies dominate in different categories). The thresholds for line length and distribution depth are 7% and 9% respectively, while the threshold for feature display is 5%.

6.2 Strategic Launch Options

Firms often face strategic trade-offs when introducing brands. We compare the sales impact of various strategic marketing choices (Skimming versus Penetration Pricing, Constant Advertising versus Decreasing Advertising, National Distribution versus Phased Roll-out, and Simultaneous versus Phased Product Line Entry) as enumerated in the diffusion literature.

Price Skimming vs. Penetration Pricing. Penetration pricing is regarded as the best strategy for new durable goods (e.g. Horsky 1990, Kalish 1985). When repeat purchase goods are considered, the pricing strategy is incumbent upon the diffusion process (e.g. Mesak and Berg 1995). Collective evidence suggests that price skimming may be favored when markets are oligopolistic, word-of-mouth influence is not strong, trial is rather inexpensive; all characteristics of consumer packaged goods markets. Accordingly, we consider the role of pricing strategy on sales in the context of consumer packaged goods brands.

Constant vs. Monotonically Decreasing Advertising Spending. The presence of decreasing returns to scale in advertising favors a monotonically decreasing advertising strategy for durable goods (Dockner and Jørgensen 1988; Horsky and Mate 1988; Kalish 1985). Such a strategy causes the peak in sales to be higher and occur earlier than it would have been without any advertising support (Horsky and Simon 1983). We assess whether such sales effects manifest when advertising is monotonically decreased.

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 brands diffusion (Bronnenberg and Mela 2004). Jones and Ritz (1991) argue that if the initial retail distribution is broad (typical for fast moving consumer goods) the growth pattern is exponential, and it assumes the commonly observed S-shaped pattern when the distribution is limited. The foregoing literature indicates that the timing of penetration into retail distribution plays a role building brands. Accordingly, we compare both strategies.

Simultaneous vs. Phased Product Entry. When brands develop an array of variants in their product line, manufacturers are confronted with the choice launching all alternatives concurrently or extending the product line over time as the brand matures. In the context of durable goods, Wilson and Norton (1989) argue it is desirable to introduce all alternatives earlier in the life cycle when the new products stimulate a rapid diffusion of information. Moorthy and Png (1992), on the other hand, argue that sequential product introduction is better than simultaneous introduction when cannibalization is an issue. Little research considers the issue in the context of repeat purchase goods. Accordingly, we consider the effect of the simultaneous and phased strategies on sales.

Simulation Design. We generate a 2 (Skimming / Penetration Pricing) × 2 (Constant Advertising / Decreasing Advertising) × 2 (National Distribution / Phased Roll Out) × 2 (Simultaneous / Phased Product Entry) design to measure the effect of the various marketing strategies on sales as well as the potential for interactions in marketing strategies. We consider a 52-week duration as most brands reach their maximum sales by this time.

The skimming/penetration condition contrasts (i) 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 (ii) a price strategy that begins one standard deviation below the mean and ends one standard deviation above the mean (penetration). The constant/decreasing advertising condition contrasts (i) advertising held at one standard deviation above its historical mean (constant) to (ii) a case where advertising decreases from one standard deviation above the mean to one standard deviation below (decreasing). The national launch/regional condition roll-out contrasts the effects of (i) holding distribution at one standard deviation above its historical mean (national launch) to (ii) increasing distribution from one standard deviation below the mean to one standard deviation above the mean (phased roll-out). In the simultaneous/phased entry manipulation we compare (i) an increase from one standard deviation below the mean to one standard deviation above the mean (phased) to (ii) a constant level of product line length held at one standard deviation above the historical mean observed in the data (simultaneous). In all instances we initialize new product sales at zero and then forecast the subsequent demand for all 225 brands over the 52 weeks after launch using the parameters estimated in our model.

Table 7 reports the sales and growth effects of the strategic launch options. The sales effects are 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 growth effects as the difference between the time it takes a brand to reach 90% of maximum sales in the base case and the time to reach 90% of maximum sales under an alternative strategic option. Panel B summarizes the main effects of the marketing strategies holding other strategies at their historical mean and Panel C reports the interactions. Sales arising from a national roll-out are 48% greater than sales from a phased roll out and simultaneous product entry enhances cumulative sales by

7% over a more conservative phased strategy. Changes in advertising and pricing strategies have little sales impact; around 2%. In addition, the strategies can accelerate time to peak sales by more than half a year (for national versus phased roll-out) or less than one week (continuous versus monotonically decreasing advertising). Although product roll-out appears to have the second largest sales impact, pricing assumes this role in the growth impact. Though a national launch with a concurrent deployment all product variants is more effective at generating sales, it is also more expensive. Using our analysis, a manager can contrast the cost of a national launch with that of a roll-out to make a more informed decision regarding the merits of the two strategies.

Panel C of Table 7 indicates that, as one might expect, the fastest growth is achieved with the penetration pricing, early advertising, national launch and simultaneous product line entry combination. Surprisingly, this specific combination does not yield the highest sales impact as cuts in advertising support eventually reduce the market potential of a brand. Rather, altering this combination to replace early up advertising with constant advertising yields the greatest sales. Some specific interactions are worthy of note. National launch interacts with low price to enhance market potential. Likewise, national launch interacts with both broader product line and initially high (and next decreasing) advertising to facilitate growth.[3] Taken together, these interactions suggest broad access to distribution is a necessary condition for effective marketing. The forgoing results can also be combined with cost estimates to make informed strategy trade-offs in the face of constrained launch budgets. For example, firms might explore a price skimming strategy and use the additional cash flow to finance a national launch as the effect of skimming on growth is less material in the face of a national launch and full product line roll-out.

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

Table 7: Sales and Growth Impact of Strategic Trade-offs

Panel A: Base Case

Marketing Mix Instruments				Sales		Growth	
Pricing	Advertising	Distribution	Product Line	M	SD	M	SD
AT MEAN	AT MEAN	AT MEAN	AT MEAN	4.01×10^{7}	1.05×10^{8}	14	-

Panel B: Main Effects (relative to base case)

Marketing Mix Instruments				Sales Impact		Growth Impact	
Pricing	Advertising	Distribution	Product Line	M	SD	M	SD
PENETRATION	-	-	-	1.3	.3	-2.3	.6
SKIMMING	-	-	-	-1.2	.2	6.8	4.1
-	DECREASING	-	-	.7	.1	-1.3	.5
-	CONSTANT	-	-	2.8	1.2	-1.0	-
-	-	NATIONAL	-	45.2	25.0	-2.0	.0
-	-	PHASED	-	-2.9	.6	29.0	4.0
-	-	-	SIMULTANEOUS	5.9	2.9	-1.0	-
-	-	-	PHASED	-1.0	.2	6.3	4.0

Panel C: Interaction Effects (relative to base case)

Marketing Mix Instruments				Sales Impact		Growth Impact	
Pricing	Advertising	Distribution	Product Line	M	SD	M	SD
PENETRATION	DECREASING	NATIONAL	SIMULTANEOUS	54.7	29.6	-4.9	.3
PENETRATION	CONSTANT	NATIONAL	SIMULTANEOUS	57.7	31.3	-4.7	.5
PENETRATION	DECREASING	NATIONAL	PHASED	46.2	25.3	-3.1	.3
PENETRATION	CONSTANT	NATIONAL	PHASED	49.2	26.9	-3.0	-
SKIMMING	DECREASING	NATIONAL	SIMULTANEOUS	52.2	28.8	-.5	.9
SKIMMING	CONSTANT	NATIONAL	SIMULTANEOUS	55.3	30.5	1.6	2.1
SKIMMING	DECREASING	NATIONAL	PHASED	43.6	24.6	7.0	4.2
SKIMMING	CONSTANT	NATIONAL	PHASED	46.8	26.3	9.9	5.2
PENETRATION	DECREASING	PHASED	SIMULTANEOUS	3.6	1.8	26.4	5.0
PENETRATION	CONSTANT	PHASED	SIMULTANEOUS	6.4	3.3	27.3	4.6
PENETRATION	DECREASING	PHASED	PHASED	-2.8	1.0	28.2	4.3
PENETRATION	CONSTANT	PHASED	PHASED	-.1	.5	28.8	4.0
SKIMMING	DECREASING	PHASED	SIMULTANEOUS	3.0	2.4	29.4	3.7
SKIMMING	CONSTANT	PHASED	SIMULTANEOUS	5.8	3.9	29.9	3.4
SKIMMING	DECREASING	PHASED	PHASED	-3.0	.1	30.5	3.2
SKIMMING	CONSTANT	PHASED	PHASED	-.2	1.6	30.8	3.0

- Price: SKIMMING = Price skimming, PENETRATION = Penetration pricing,
- Advertising: CONSTANT = Constant advertising, DECREASING = Monotonically decreasing advertising,
- Distribution: NATIONAL = National launch, PHASED = Phased roll-out
- Product: SIMULTANEOUS = Simultaneous product entry, PHASED = Phased product entry.

The "Sales Impact" is the cumulative first year sales impact expressed as percentage deviation from the base case where all marketing mix instruments are kept at their historical means, while the "Growth Impact" is the growth impact expressed as number of weeks. M (mean) and SD (standard deviation) are computed across 225 brands. For example with penetration pricing alone, an average brand enjoys 1.3% more sales in the first year, and reaches the 90% mark 2.3 weeks earlier than it does in the base case.

7 Conclusions

Though 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 in order 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 employ 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 Dynamic Linear Model of repeat purchase diffusion. The methodology extends the literature on repeat purchase diffusion models (e.g., Lilien, Rao and Kalish 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 8%, line length 8%, regular price 8%, advertising 2% and discounting 1%. Thus, over the range of our data, the effect of distribution exceeds the combined effect of all other marketing effects. This underscores the importance of obtaining distribution for new brands. This finding supplements that of Ataman, Mela and Van Heerde (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 (Rao and Sudhir 2006) and suggests the study of penetration into distribution is an substantially under-researched area in marketing (we suspect this may be in part due to a lack of good data).

- The relative effect sizes of the various strategies on the time required to reach 90% of the equilibrium market potential (standardized to sum to one) are as follows: distribution breadth 32%, discounting 18%, regular price 15%, line length 14%, feature/display 10%, advertising 8%, and distribution depth 3%.
- 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.
- Distribution 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 and product line length and highest for advertising, discounting and feature/display. This result further suggests the utility of additional analyses pertaining to the role of product and distribution on the marketing of new brands.

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 tradeoff 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 becomes 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 exclusively focus 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, 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. Third, to enhance the parsimony of our model specification we abstract away from the inclusion of additional regressors, such as interactions between the marketing mix instruments in the growth equations and a complete enumeration of competitive instruments. Yet our model is sufficiently flexible to accommodate strategic interactions as indicated by our findings in the previous section. Moreover, more regressors can only have negligible impact on model performance as the average correlation between our model sales predictions and the actual sales is 0.97 and their inclusion may even worsen forecasts.

Our analysis is a step towards a more complete view regarding the role of post-launch marketing strategy on the diffusion of frequently purchased consumer packaged goods brands. In light of our findings and the foregoing limitations, we hope this research will stimulate further research on new product 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, …, 225) are,

(A.1) $$Y_{jt} = F_{jt}\theta_{jt} + X_{jt}\beta_j + \upsilon_{jt},$$

(A.2) $$\theta_{jt} = G_{jt}\theta_{jt-1} + h_{jt} + \omega_{jt},$$

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 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 $\upsilon_t \sim N(0,V)$ 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 (A.2).

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 $t = 1,...,T$ we forward filter to obtain the moments m_t and C_t. Conditional on $\tilde{Y}_t, V, W, \beta, G_t, h_t$ and $\theta_0|D_0 \sim N(m_0, C_0)$, where $\tilde{Y}_t = Y_t - X_t'\beta$:

- The prior at time t is $\theta_t|D_{t-1} \sim N(a_t, R_t)$, 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 $\tilde{Y}_t|D_{t-1} \sim N(f_t, Q_t)$, 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 $m_t = a_t + R_t F_t' Q_t^{-1}(\tilde{Y}_t - f_t)$, 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 backwards for $t = T-1,...,1$ 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 $C_0 = .1$ 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 $S_{V0} = .001\times I_{M+1}$.

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 $S_{W0} = .001$.

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 only discuss 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 *m*th 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

(A.3) $$\alpha = \frac{\pi\left(\delta_j^{(m)} \mid \theta_t, W, \phi, \mu\right)}{\pi\left(\delta_j^{(m-1)} \mid \theta_t, W, \phi, \mu\right)},$$

and $\pi(\cdot)$ is conditional likelihood of Equation (A.2) evaluated at each draw.

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

In order to obtain the conditional posterior distribution of the brand specific evolution equation parameters associated with the i^{th} marketing mix instrument (π_i) we define $K_{iT} = [1_{T\text{-}1}\ \zeta_{iT\text{-}1}\ Sales_{jT\text{-}1}\ Sales_{j'T\text{-}1}]$ 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 $\pi_i \sim N(\overline{\mu}_\pi \overline{\Sigma}_\pi)$, where

$\overline{\mu}_\pi = \overline{\Sigma}_\pi \{\underline{\Sigma}_\pi^{-1} \underline{\mu}_\pi + [K_{iT} W_{iT}^{-1} \zeta_{iT}]\}$, and $\overline{\Sigma}_\pi = \{\underline{\Sigma}_\pi^{-1} + [K_{iT} W_{iT}^{-1} K'_{iT}]\}^{-1}$.

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

In order to obtain the brand-specific conditional posterior distribution of the non-time varying observation equation parameters β, we define $\overline{Y}_t = Y_t - F_t \theta_t$ and $\mathrm{V}_T = \mathrm{V} \otimes I_T$. 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 $\beta \sim N(\overline{\mu}_\beta \overline{\Sigma}_\beta)$, where $\overline{\mu}_\beta = \overline{\Sigma}_\beta \{\underline{\Sigma}_\beta^{-1} \underline{\mu}_\beta + [X_t V_T^{-1} \overline{Y}_t]\}$, and $\overline{\Sigma}_\beta = \{\underline{\Sigma}_\beta^{-1} + [X_t V_T^{-1} X'_t]\}^{-1}$