Managing brands

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Preface

CLOV: Finished, it's finished, nearly finished, it must be nearly finished. (Pause) Grain upon grain, one by one, and one day, suddenly, there's a heap, a little heap, the impossible heap. (Pause) I can't be punished any more. I'll go now to my kitchen, ten feet by ten feet by ten feet, and wait for him to whistle me. (Pause) Nice dimensions, nice proportions, I'll lean on the table, and look at the wall, and wait for him to whistle me.

Endgame (1957)
by Samuel Beckett

Audiences all over the world have seen a version of "The Dissertation" on stage at some point in their lives. Here is a brief summary of this somewhat boring epic for the few who have never heard of it before. A young man in search of his next quest walks the busy streets of a city on a rainy day. All of a sudden, amid thunder and lightning, appear The Weavers of Destiny. Seated by the well of wisdom, the three men tell stories of the past, the present and the future as they thread. After hearing their stories, The Young Man decides to leave everything behind and embarks on a journey of a lifetime. Crossing the mountains and the seas, he sets ashore at a faraway land, where he begins his journey. A journey that will take him one thousand seven hundred thirty-nine days and one thousand seven hundred thirty-nine nights… A journey guided by The Mentors, accompanied by The Travelers… A journey through dark tunnels leading to a land that is believed to be a wonderland full of trees with leaves of jewels. At the end of the tunnel, await The Gatekeepers. Any man who desires to enter this land must first answer their riddles. Will The Young Man give the correct answers and be allowed to pass though? Or will he find himself back on the busy streets of the city on a rainy day?

On June 13, 2007 I had a chance to see a new production of this long standing play. If you missed this one-off performance of "The Dissertation" you have missed something very special indeed. The story might not be magnificent –it is mediocre at best-, but what made this particular production a gem was the quality of acting. Harald van Heerde as one of The Mentors deserves enormous credit for giving a very focused and disciplined performance. So does Carl Mela as the other mentor: the hint of an older brother figure in Mela's interpretation of the role added a great deal to the character. I have to commend Rita Coelho do Vale and Robert Rooderkerk (two members of The Travelers, later to become the guardian angels) for their exhilarating performances: their sheer presence was enough to light up the whole stage. There were also good performances from the other members of The Travelers (Man Wai Chow, Martijn de Jong, Fleur Laros, Jia Liu, Carlos Lourenço, and Maciej Szymanowski to name a few). The scenes with The Mates (acted skillfully by Gül Gürkan and Kanat Çamlıbel –stunning performance in his stage debut) were a real treat. The audience enjoyed outstanding performances by The Weavers of Destiny (Ümit Şenesen, Burç Ülengin, and Rik Pieters) and The Gatekeepers (Peter Leeflang, Els Gijsbrechts, Marnik Dekimpe, and Koen Pauwels). The other members of the cast fared pretty well, too. Among the standouts: Seza Doğruöz was lovely as The Friend; Özge Pala and Stefan Wuyts delivered a very good performance as The Couple waiting at the Point of Return; Ralf van der Lans was brilliant in The Young Man's voice in Dutch. Last but not least, Ayla Ataman and Osman Bilge Ataman's portrayal of the family left behind was flawless: their detailed analyses of the emotional journey these characters travel added yet another layer on this already complex staging, serving as the icing on the cake. Ultimately, Berk Ataman –as The Young Man- lived up to the challenge. Thanks to the support of his fellow actors. They are, at the end of the day, the ideal cast for any actor who attempts to take on this part.

Berk Ataman
Rotterdam, 2007

Outline

Chapter 1

Introduction

1.1 Brands, Long-term Performance and the Marketing Mix

Brands are vital for the manufacturers. They are raised, nurtured, and –when the time comes- put to sleep by the very same manufacturers that created them. Guiding the brands through this long journey is a challenging task, which requires careful planning and implementation of marketing strategies with a long-term perspective. The task is challenging as the manufacturer needs to manage the tangible (e.g., baseline sales, market share) and intangible (e.g., brand equity, brand image) brand performance components simultaneously using the same set of tools, the marketing mix instruments, over time and across space.

The marketing support a brand receives during the early phases of its lifecycle determines whether or not and how fast the brand will reach the status of an established brand, and enjoy the benefits associated with that status. Reaching that state once does not necessarily imply that the brand will remain in that position for eternity. The new challenge that awaits the manufacturer is to maintain the position, and possibly try to find ways of growing the brand further, delaying the probable decline. These evolving goals not only require adjustments in the marketing budget but also imply the need to rely on different instruments of the marketing mix at different stages of the brand's life cycle. In short, the marketing budget and the composition of the marketing mix have to evolve as the brand matures. Furthermore, the performance of a new (or a mature) brand may vary markedly across markets at a given point in time –i.e., the brand may be successful in certain geographic markets and less successful in others. This new source of performance variation adds to the challenges that manufacturers face in managing brand performance.

As product categories grow and approach saturation, markets expand and competition intensifies, brands require ever increasing levels of marketing support, hence spending, to attain and retain their positions. For example, in 2004 alone, US firms spent $648BB on their marketing communications, representing 6% of the US Gross Domestic Product (Promotion Marketing Association, 2004). Accordingly, marketing expenditures play a substantial role in the economy. The effect of these expenses on brands is of central interest to many firms. Research in marketing has made significant headway in understanding the role marketing plays in shaping demand (Bucklin and Gupta 1999). However, the bulk of our generalized knowledge pertains to the immediate effects of the marketing mix instruments on demand. Moreover, extant research solely focuses on temporal variation in brand performance leaving spatial variation as an underexplored dimension of performance. While recently there has been an increasing emphasis on the long-term effects of marketing strategy on brands (e.g., Pauwels, Hanssens & Siddarth 2002, Jedidi, Mela & Gupta 1999, Nijs, Dekimpe, Steenkamp & Hanssens 2001), there are no studies that

a) Compare the relative long-term effects of *the entire marketing mix* (pricing, promotion, product, and place) in unison,
b) Contrast the long-term efficacy of marketing spending for *new and established brands*,
c) Compile insights from *temporal and spatial* analyses of brand performance, and
d) Consider these effects over a large number of categories to generalize the findings.

Accordingly, a critical question still remains unanswered (Ailawadi, Lehman & Neslin 2003, Aaker 1996, Barwise 1993): "How are strong brands built (maintained) and which elements of the marketing mix are most critical in building (maintaining) brand equity?" This question has endured for decades because its resolution requires extensive data sets and advanced modeling techniques, which became available to the academics only very recently. The three essays in this book seek to offer a more complete and generalized understanding of managing brand performance in the long run.

1.2 Modeling Long-term Effects of the Marketing Mix

During the last decade there has been growing emphasis on the long-term effects of marketing activity on performance. This increased attention led to the development and/or application of various time series analysis techniques in marketing. These modeling techniques can be grouped under three *seemingly* alternative approaches: Time Varying Parameter Models (TVPM hereafter), which were prominent during the first half of the decade (e.g., Mela, Gupta and Lehman 1997), vector autoregressive models (VAR hereafter) that took over the place of TVPM in the second half (e.g., Pauwels, Hanssens and Siddarth 2002), and Dynamic Linear Models (DLM hereafter) that emerged towards the end of the decade (e.g., Van Heerde, Mela, and Manchanda 2004). In fact these modeling traditions are closely related because of their roots in state-space modeling. It is possible to formulate state-space analogs of transfer function models (TVPM) and VAR models, as the state-space formulation is remarkably general (see Harvey (1994) for details). The estimation of state-space models relies on frequentist statistical techniques, such as maximum likelihood. DLMs are Bayesian extensions of state-space models; therefore they subsume all earlier approaches. Like any other state-space model, DLM derives from the Kalman filter –not inherently a Bayesian technique but provides a method for forecasting that is consistent with the Bayesian inference (Harrison and Stevens 1976). The models in the following chapters build on this new –to the marketing literature- modeling tradition and extend the earlier work in various respects (see Neelamegham and Chintagunta (2003) and Bass et al. (2007) for other applications in marketing). Next we discuss a number of desirable features of DLMs and provide a brief introduction to this modeling tradition.

The Advantages of DLM

First, using DLM methodology predictions can be produced even in the case of little or no past data. Having no data does not mean having no information. The Bayesian nature of the model allows the modeler to incorporate information derived from experience through informative priors and make a sequence of predictions (Harrison and Stevens 1976). Second, extrinsic information can readily be included in the model as it becomes available. Or alternatively the modeler can intervene with subjective information. This could be done by (1) directly over-riding the prior expectations implied by the Kalman recursions, or (2) introducing subjective information through the specification of the disturbance distribution (West and Harrison 1997). Third, the DLM copes naturally with missing data. If no data are available then the posterior distribution of the model parameters (state vector) remains the same as the prior distribution. The distribution is updated only when new observations arrive (Van Heerde, Mela and Manchanda 2004). Fourth, it is possible to show that DLMs and linear time series models are equivalent, and DLM nests all ARIMA processes, even including the explosive non-stationary processes. Moreover, the Bayesian approach of DLM does not relate the evolution of the future totally to that of the past, therefore there is no requirement that the original series is stationary (Harrison and Stevens 1976). Fifth, DLM allows for a single-stage analysis of the long-term phenomenon. Alternative approaches (e.g., moving windows or before-and-after analysis) suffer a loss in statistical efficiency due to analyzing subsets of the data (Van Heerde, Mela and Manchanda 2004), whereas the DLM accommodates greater statistical efficiency. Finally, DLM and hierarchical Bayesian models can readily be integrated to accommodate cross-sectional as well as inter-temporal heterogeneity (Van Heerde, Mela and Manchanda 2004).

A Brief Introduction to DLM

Dynamic modeling has a long history, dating back to mid 1960s, in the forecasting literature (Harrison 1965). Developments in systems and control engineering on adaptive estimation and filtering theory for automatic control, paralleling the developments in the forecasting literature led to the seminal article of Harrison and Stevens (1976) on dynamic linear models. Harrison and Stevens' dynamic modeling approach comprises (i) sequential model definitions for series of observations, (ii) structuring using parametric models with easy-to-interpret parameterizations, (iii) probabilistic representation of information about all parameters and observations, and hence (iv) inference and forecasting derived by summarizing appropriate posterior and predictive probability distributions (West 1999). Pole, West, and Harrison (1994) provides an excellent introduction to the basic dynamic linear models with applications, whereas a full treatment of theory and methods of Bayesian time series analysis and dynamic linear models can be found in West and Harrison (1997).

In its simplest form a univariate normal dynamic linear model is defined by the following observation and evolution equations,

(1.1) $$Y_t = F_t \theta_t + v_t ,$$

(1.2) $$\theta_t = G_t \theta_{t-1} + \omega_t ,$$

where Y_t is the univariate dependent variable, θ_t is the state vector at time t, F_t is a known matrix of regressors, and $v_t \sim N(0,V)$ represents measurement and sampling errors. G_t is the state evolution matrix that defines the deterministic mapping of the state vectors between time periods t–1 and t. In most applications the state evolution matrix, G_t, is assumed to be constant over time and is set to identity matrix, which implies a rather restrictive random walk process for the state vector. In the studies that follow, we relax this assumption and infer the duration of adjustment as well as the persistent/transient nature of the series. The evolution error is distributed $\omega_t \sim N(0,W)$ and allows for stochastic deviations from the mapped values of the state vector (West and Harrison 1997). [1] The model has a Markovian nature as the state vector varies over time following the Markov evolution equation. Sequentially arriving data points are used in the sequential updating of the summary statistics that determine the posterior distributions. These posterior distributions are used for inference about the state vector θ_t over all observations and future values of the dependent variable. Assuming normality of the initial state vector θ_0 and assuming that the only information used in updating is the set of observed values of the dependent variable (Y_t) and the independent variables (in F_t) one obtains a closed model, wherein the information is updated via $D_t = \{D_{t-1}, Y_t\}$ and jointly normally distributed Y_t and θ_t. The sequential updating is based on the known Kalman equations (see West and Harrison (1997) for details).

The extension of the normal dynamic linear model to the multivariate case is straightforward and therefore not discussed here[2]. The normal dynamic linear model – univariate or multivariate- can further be extended by introducing deterministic terms in the evolution equation as shown in Equation (1.4).

(1.3) $$Y_t = F_t\theta_t + v_t,$$

(1.4) $$\theta_t = G_t\theta_{t-1} + h_t + \omega_t.$$

These models are known as transfer function DLMs where non-stochastic sources of variation are allowed to influence the state vector. Through this state vector

[1] The standard form of a Bayesian state-space model is $y_t = F(x_t) + v_t$ and $x_t = G(x_{t-1}) + w_t$, where $v_t \sim (0,V)$ and $w_t \sim (0,W)$. When $F(.)$ and $G(.)$ are linear and the error distributions are normal, the functions $F(.)$ and $G(.)$ are replaced by constants F_t and G_t that premultiply the state vector, and the Bayesian state-space model is called a normal dynamic linear model.

[2] There is also a class of dynamic linear models that are non-normal (non-Gaussian). Non-normality in these models can take two forms: non-normal in observations or non-normal state models. As such models are not used in the studies that follow they are nor reviewed here. The interested reader may refer to West, Harrison, and Migon (1985) and Gamerman (1998) for a detailed discussion of generalized dynamic linear models. Yet it is worth noting that non-normal (in observations) dynamic models are a generalized version of Bayesian learning models utilized in the structural modeling paradigm.

the new source of variation is transferred to the dependent observations. The models specified in Chapter 2 (non-linear transfer function) and Chapter 3 (linear transfer function) belong to this class of the DLMs.

1.3 Dissertation Overview

The goals set out in Section 1.1 imply three building blocks that uniquely define each essay in this book. These core components are: brand maturity (new versus established brands), marketing mix (pricing, promotion, product, and place), and the focal source of variation (temporal versus spatial). Considering the effects over a large number of categories is common across all essays. Next we briefly overview the three studies and visualize each in the subsequent figures. For an overview of the research goals, modeling approaches and features, and data set characteristics of the three studies in this book see Table 1.1.

Given the pivotal role of new products in firm profitability, Chapter 2, "Strategies for Building New Brands", focuses on the antecedents of *new brand* performance. Identifying the drivers of new brand success has received substantial attention in the marketing literature. Yet few studies have offered an integrated view across *the entire marketing mix* to ascertain which marketing introduction strategies have the greatest effect on the success of new brands. The study presented in Chapter 2 sheds light on this issue by ascribing the growth performance of new consumer packaged goods brands –*over time*- to firms' post-launch marketing choices (see Figure 1.1). In order to achieve this goal, we propose a marriage between the traditional diffusion models and DLMs, which leads to a non-linear transfer function DLM.

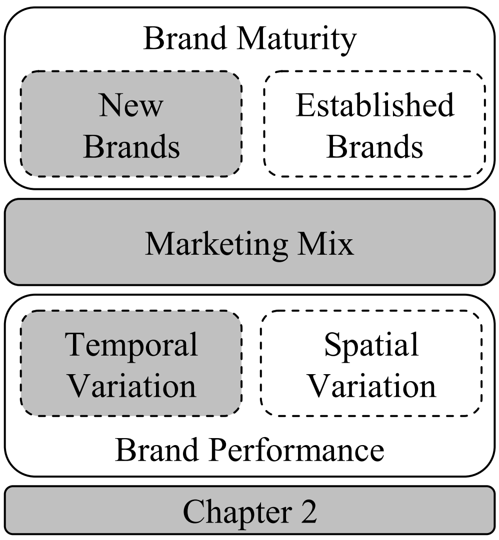


Figure 1.1: Building blocks of Chapter 2

The dominant view in traditional models of innovation diffusion is that the innovation is spread like an epidemic, implying eventual adoption by the whole population (Kalish 1985; Kuester, Gatignon and Robertson 2000). For that reason the differences between diffusion patterns are typically attributed to external factors such as economic conditions (e.g., van den Bulte 2000), market structure (e.g., Steenkamp and Gielens 2003), consumer heterogeneity (e.g., Steenkamp and Gielens 2003), and country characteristics (e.g., Tellis, Stremersch and Yin 2003). This might be the case in new product categories where consumers are faced with a lifestyle changing innovation. However, new brand introductions in already heavily populated consumer packaged goods categories are typically continuous innovations. The new brand offers products with modifications (such as new varieties, unique recipes, improved effectiveness, and/or new design, etc.) to the existing products. Yet, consumers typically use the product in the same fashion as they had before. Such new brand introductions do not change the nature of the market dramatically (Gatignon, Weitz and Bansal 1990). Especially in cases like this, one cannot view the diffusion of the new brand as an inevitable, epidemic, process.

In Chapter 2, we adopt the notion that diffusion of an innovation can be managed strategically (Kuester, Gatignon and Robertson 2000). The success of a new brand is decomposed into its ultimate market potential and the rate with which it achieves this potential. We argue that the firm offering the brand can increase the brand's market potential and/or generate growth by managing the marketing mix. Moreover, we argue that some marketing mix instruments are especially effective at accelerating brand growth while others mainly serve to retain sales at a constant long-run level. We therefore investigate how advertising, promotion, distribution, and product activities affect growth and market potential. To achieve this aim we develop a dynamic linear model in the context of a diffusion framework wherein growth and market potential are directly linked to the new brands' long-term advertising, promotion, distribution and product strategy. The analysis is performed on 225 brands from 22 product categories to generalize the findings. The data is obtained by combining advertising expenditure data from TNS Secodip and store level scanner data from Information Resources. The results 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. Overall, we find that access to distribution plays the greatest role in the success of a new brand, followed by product.

In Chapter 3, “The Long-term Effect of Marketing Strategy on Brand Performance”, we focus on *established brands*. Recent research has advanced our understanding of the long-term effects of price promotions[3] and advertising on established brands (Pauwels, Hanssens & Siddarth 2002, Jedidi, Mela & Gupta 1999, Boulding, Lee & Staelin 1994, Nijs, Dekimpe, Steenkamp & Hanssens 2001, Steenkamp, Nijs, Hanssens & Dekimpe 2005), yet much less research exists regarding the long-term effects of product and distribution strategies. Moreover, none have generalized our understanding of how *the entire mix* impacts established brands over long periods of time by reviewing its effect over many years and categories. In this chapter, we seek to obtain a more complete view of what drives performance of established brands *–over time-* by considering all four elements of marketing mix in unison (see Figure 1.2).

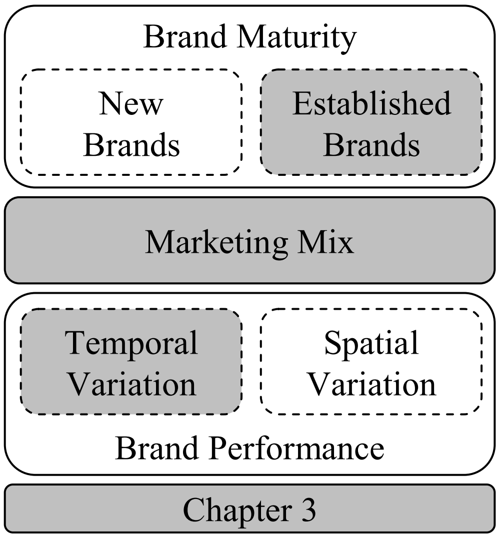


Figure 1.2: Building Blocks of Chapter 3

Using insights from brand equity literature, we measure brand performance by quantity premium and margin premium. Following others the quantity premium is operationalized as the baseline sales (Kamakura and Russell 1993). Strong brands have higher quantity premiums, i.e., they sell more than weaker brands with an identical offer. The margin premium component, on the other hand, is operationalized as the inverse of price elasticity (Nicholson 1972). Consistent with the brand differentiation view, we consider brands strong when their margin premiums are high, or in other words the elasticity magnitude is low (Boulding et al. 1994).

The analysis is based on a Dynamic Linear Model that allows us to understand how a brand’s quantity premium (baseline sales) and margin premium (inverse of price

[3] We use the terms price promotion and discount interchangeably throughout the text.

elasticity) evolve over time as a function of marketing activity. This approach offers a highly flexible means for assessing changes in model parameters over time, while, at the same time, accounting for endogeneity and simultaneity, and competitive interactions. The model is calibrated by combining detailed advertising data from TNS Secodip with weekly store-level scanner data from Information Resources, covering a time horizon of 265 weeks, 25 product categories, and 450 stores from a French national sample. The results suggest that advertising and new product activities are the primary drivers of brand performance.

In Chapter 4, "Consumer Packaged Goods in France: National Brands, Regional Chains, Local Branding" we study the size and the robustness of variation in *established brand performance across markets* (see Figure 1.3). Using data from 31 categories over 39 four-week intervals in 50 United States markets, Bronnenberg, Dhar and Dubé (2007) observe that geographic variation is the predominant source of variation in national brand market shares. We extend this surprising and heretofore undocumented result in five respects. First, we assess whether this finding generalizes to other markets, in particular France, and we replicate the result. Second, the robustness of this result to the sampling rate of the data (weekly or four-weekly), the duration of the data (39 or 66 four-week periods), and the level of aggregation (9, 22, or 96 regions) is shown. Third, we add *chain-specific effects* to assess whether variation in market shares is related to chains and observe these explain more variation in share than either time or region in France. Owing to the regional distribution of chain locales, it is suggested that this result may reflect another form of regional variation in market shares. Fourth, we consider BDD's negligible time variation results and find that the brand-time interactions explain slightly more variation than brand-region effects in France. Brand-time interactions capture variation in sales arising from weekly variation in brand-specific marketing tactics such as promotions and product line length that are not captured by time main effects considered in Bronnenberg, Dhar and Dubé (2007). Fifth, we find that time effects increase with the duration of the data, suggesting that long-term effects in marketing merit more attention and that firms should collect longer durations of data. Overall, we underscore that Bronnenberg, Dhar and Dubé (2007) have uncovered a heretofore underexploited regional variation in market shares of "national" brands. Further, we find that chain effects are another source of underexploited variation in brand shares.

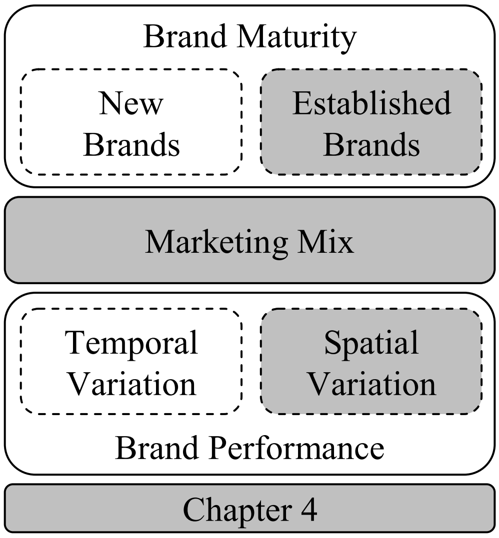


Figure 1.3: Building Blocks of Chapter 4

In Chapter 5, we summarize the findings of the three studies in this book, and draw implications for the practitioners and academicians. We also elaborate on several future research topics that emerged during the process of conducting these three studies.

Table 1.1: Overview of Chapters

	Chapter 2	Chapter 3	Chapter 4
Main Goal(s)	How does marketing support generate growth and build market potential of new brands introduced in existing CPG categories?	How does marketing support influence various components of performance of an established brand in a CPG category?	What is the largest source of variation in brand performance in CPG categories? How robust is this variance decomposition to data aggregation? Which marketing activities lead to geographic performance discrepancies?
Brand Performance Measure	Growth Rate Market Potential	Quantity Premium Margin Premium	Market Share
Source of Variation	Temporal	Temporal	Spatial & Temporal
Marketing Mix Instruments Considered	Price Promotion Product Place	Price Promotion Product Place	Promotion Product Place
Modeling Approach	Multivariate Non-linear Transfer Function DLM	Multivariate Linear Transfer Function DLM	Generalized Linear Model & Spatial Correlation Analysis
Model Features	Baseline sales evolution follows a non-linear repeat purchase diffusion structure Controls for endogeneity, and own- and cross-performance feedback	Quantity premium and margin premium evolution follows a linear structure Controls for endogeneity, competitor interaction, and own- and cross-performance feedback	NA
Number of Categories	22	25	25
Number of Brands	225 New National CPG Brands	70 Established National CPG Brands	50 Established National CPG Brands

Chapter 2

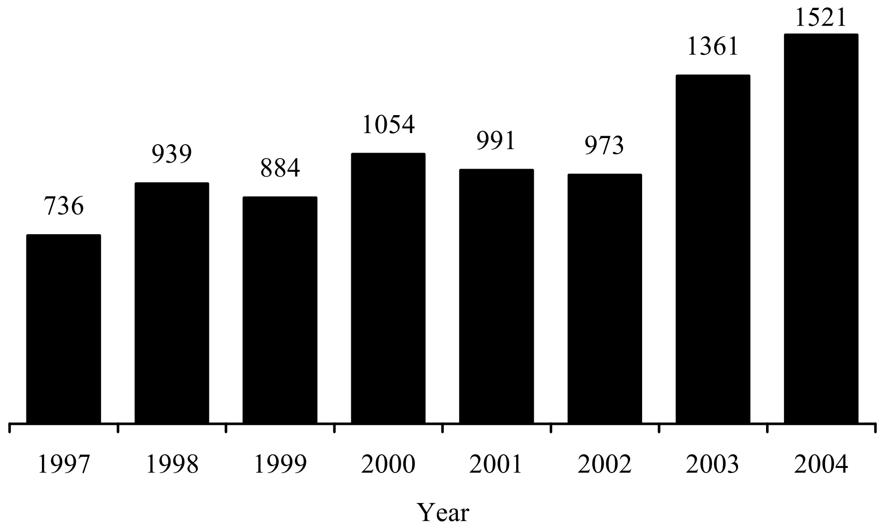
Strategies for Building New Brands[✠]

2.1 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 2.1). 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.

[✠] The article presented in this chapter is based on Ataman, M. Berk, Carl F. Mela, and Harald J. van Heerde (2007), "Building Brands," currently being revised for second review in *Marketing Science*. We benefited from comments by Jason Duan, Vithala Rao, Song Yao and audience members at 2006 INFORMS Marketing Science Conference. We would like to thank IRI and TNS Media Intelligence for providing the data, Netherlands Organization for Scientific Research for research support.

Figure 2.1: 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 chapter, 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).

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.

Table 2.1: Selected Studies from Diffusion Literature Incorporating Marketing Mix

	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.

The rest of the chapter 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.

2.2 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 the need to separate 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.

2.3 Modeling Approach

2.3.1 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 chapter, 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 that 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

$$Sales_t = \alpha_t + X_t'\beta + \upsilon_t, \tag{2.1}$$

where X_t is a matrix of regressors containing *short-term* oriented marketing activity that create 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[4]

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[4] 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,

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

$$\alpha_t = \delta\alpha_{t-1} + \gamma(\mu - \alpha_{t-1}) + \omega_t, \tag{2.2}$$

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 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 $(\gamma \to \gamma_t)$. 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 $(\mu \to \mu_t)$. 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 (2.2) we obtain,

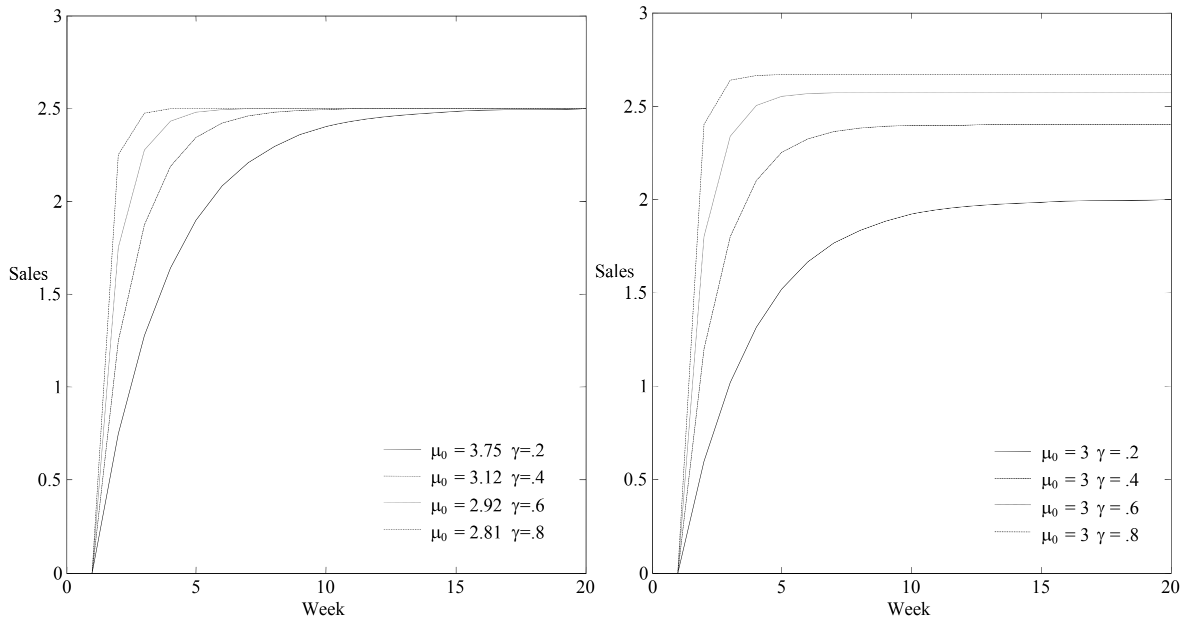
$$\alpha_t = \delta\alpha_{t-1} + Z_t'\gamma(Z_t'\mu - \alpha_{t-1}) + \omega_t, \tag{2.3}$$

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 (2.3) play a long-term role in the trajectory of brand growth as a result of the carryover implied by the recursion in Equation (2.3). Conditioned on Z_t constant at $Z_t = Z$, Equation (2.3) is a geometric decay model whose carryover is given by $\delta - Z'\gamma$. The model in Equation (2.3) 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 2.2). In sum, Equation (2.3) provides a flexible model of brand baseline sales growth which can change in response to the marketing mix.

The model defined in Equations (2.1) and (2.3) 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 2.2: Growth Trajectory Illustrations



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

2.3.2 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,

$$\overline{Sales}_{jt} = \alpha_{jt} + \overline{X}'_{jt}\beta_j + \upsilon^S_{jt}, \tag{2.4}$$

where $\overline{Sales}_{jt}$ is the 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,

$$\alpha_{jt} = \delta_j\alpha_{jt-1} + \overline{Z}'_{jt}\gamma(\overline{Z}'_{jt}\mu - \alpha_{jt-1}) + \omega_{0jt}. \tag{2.5}$$

$\overline{Z}'_{jt}$ is a vector of standardized marketing strategy variables posited to effect diffusion. The standardization assures that 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 (2.4) and (2.5) can be compactly written as,

$$Y_t = F_t\theta_t + X_t\beta + \upsilon_t, \tag{2.6}$$

$$\theta_t = G_t\theta_{t-1} + h_t + \omega_t, \tag{2.7}$$

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 (2.7). Rearranging the terms in Equation (2.5) 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 (2.7) 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.

2.3.3 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 (see Horvath et al. 2005 for a similar specification),

$$\overline{Z}_{ijt} = \zeta_{ijt} + \upsilon^{Z}_{ijt}, \tag{2.8}$$

$$\zeta_{ijt} = \pi_{0ij} + \pi_{1ij}\zeta_{ijt-1} + \pi_{2ij}\overline{Sales}_{jt-1} + \pi_{3ij}\overline{Sales}_{j't-1} + \omega_{ijt}, \tag{2.9}$$

where Z_{ijt} is the ith marketing mix instrument of brand j in week t. Equation (2.8) 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 (2.9) 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.

2.3.4 Estimation

We estimate Equations (2.8) and (2.9) together with Equations (2.4) and (2.5) 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.[5] 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 Appendix 1.

2.4 Data and Variables

2.4.1 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).

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 (2.4) is linear, we first aggregated the data from SKU-

[5] 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).

store to brand-store level in a linear fashion (discussed in 2.4.2). 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 2.2 for data descriptive statistics.

2.4.2 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 2.3 summarizes our expectations.

2.4.2.1 Sales Equation Variables

The dependent variable in Equation (2.4), $Sales_{jt}$, 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, feature or display support, and average weekly temperature. 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 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 in a similar fashion. We expect discounts and feature/display intensity to have a positive short-term effect on sales while temperature affords a parsimonious control for seasonality.

Table 2.2: Descriptive Statistics

Category		*# New Brands*	*# Brands in Category*	*Sales Volume New Brand (x 1000)*	*Sales Volume Category Mean (x 1000)*	*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

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.

Table 2.2: Descriptive Statistics (Continued)

Category		*# New Brands*	*# Brands in Category*	*Sales Volume New Brand (x 1000)*	*Sales Volume Category Mean (x 1000)*	*Sales Value (x1000)*	*Advertising (x1000)*	*Price (per 1000)*	*Distribution Breadth (%)*	*Product Line Length*	*Distribution Depth (%)*	*Discount Depth (%)*	*Feature Display (/100)*
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
WindowCleaner	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.

2.4.2.2 Evolution Equation Variables

The operationalization of the marketing mix variables in Z_{jt} in the evolution equation (2.5), 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.

Relative effects: As indicated in Table 2.1, 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.

Table 2.3: Summary of Expectations

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

2.5 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 chapter, 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 (2.4), (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 (2.5), and (iii) the marketing mix inertia and performance feedback parameters (π) in the marketing mix endogeneity model specified in Equation (2.9). We discuss each set of parameters in sequence.

2.5.1 The Sales Model

Table 2.4 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.

Table 2.4: 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 Ptile	Median	5th and 95th Ptile
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.

2.5.2 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 2.4 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 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 2.4 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.

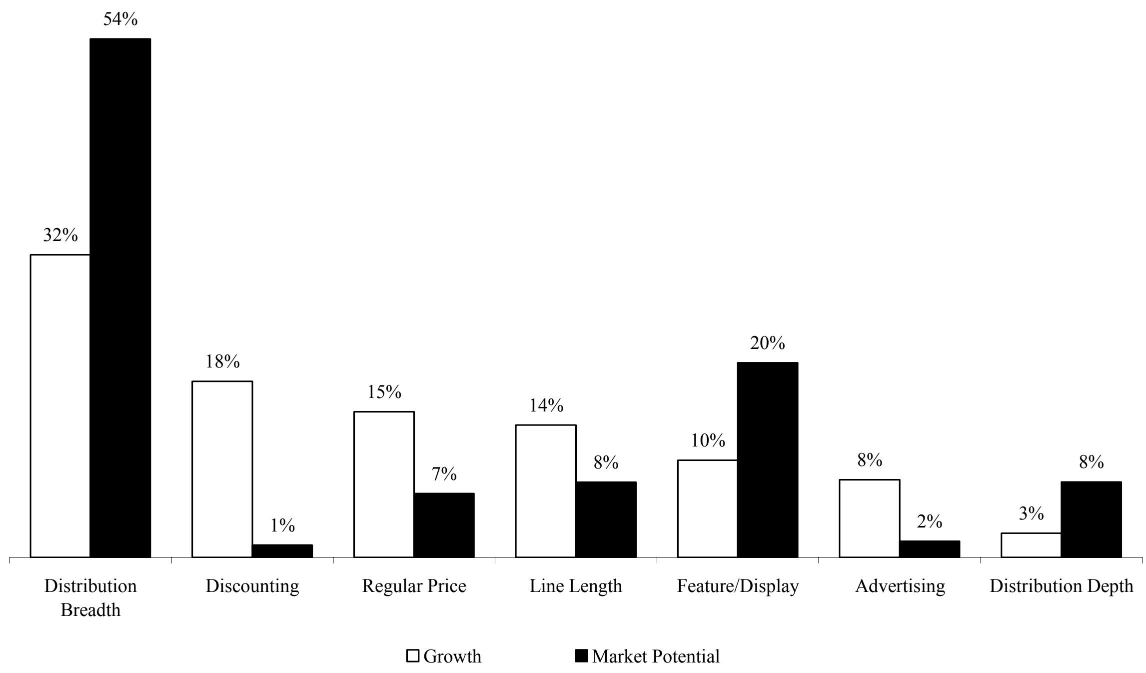
Across the 225 brands, the repeat purchase parameters, δ, range between .81 (25^{th} percentile) and .98 (75^{th} percentile), with a median of .94. The variation of repeat purchase parameter estimates across product categories does not reveal major differences. This median repeat purchase rate across 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.

2.5.3 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 2.2 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 54%) 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 building market potential 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 2.2: 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.

2.5.4 Marketing Mix Models

Lastly we summarize the results of the eight marketing instrument equations presented in Equations (2.8) and (2.9). Table 2.5 provides a summary of the inertia, own- and cross-performance feedback parameter estimates across all brands. The results reported in Table 2.5 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 2.5 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%).

2.6 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 than it redresses.

Table 2.5: 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).

2.6.1 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 2.6 summarizes the results of our policy simulation.

Findings. The first column in Table 2.6 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 2.1 also suggests these are the most often-considered instruments in past research.

Marginal Profit Analysis. Table 2.6 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 2.6 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, $((1\text{-RM})*(\text{MM})*\Delta*R_0)$ 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 $3*\Delta$. For distribution ($\Delta = .082$), 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 ($\Delta = .0024$) 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%.

Table 2.6: 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.

2.6.2 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 window of 52 weeks 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 2.7 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 2.7 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.[6] 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.

2.7 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 longstanding 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.

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[6] 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 2.7.

Table 2.7: 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 $\times 10^7$	1.05 $\times 10^8$	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

Notes: SKIMMING = Price skimming, PENETRATION = Penetration pricing, CONSTANT = Constant advertising, DECREASING = Monotonically decreasing advertising, NATIONAL = National launch, PHASED = Phased roll-out, 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.

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.

Chapter 3

The Long-term Effect of Marketing Strategy on Brand Performance[✠]

3.1 Introduction

Firms annually spend hundreds of billions of dollars to implement their marketing strategy. Much headway has been made explaining how these expenditures enhance brand performance over the short-term (Bucklin and Gupta 1999).[7] More recently, attention has been focused on the longer-term effect of marketing strategy on brand performance, particularly with respect to price and promotion (Boulding, Lee, and Staelin 1994; Jedidi, Mela, and Gupta 1999; Nijs et al. 2001; Pauwels, Hanssens, and Siddarth 2002; Steenkamp et al. 2005). Yet there has been little emphasis on the effects of product variety and place (distribution depth and breadth) on brand performance. Accordingly, a critical question remains (Aaker 1996; Ailawadi, Lehman, and Neslin 2003;

✠ The article presented in this chapter is based on Ataman, M. Berk, and Harald J. van Heerde, Carl F. Mela (2006), "The Long-term Effect of Marketing Strategy on Brand Performance," currently being revised for second review in *Journal of Marketing Research*. The authors would like to thank IRI and TNS Media Intelligence for providing the data, Marketing Science Institute and Zyman Institute for Brand Science for research support. Ataman and Van Heerde would like to thank Netherlands Organization for Scientific Research for research support. Earlier versions of this paper benefited from valuable comments of seminar participants at Northwestern University, Yale School of Management, Erasmus University Rotterdam, University of Groningen, Catholic University Leuven, Free University Amsterdam, and Tilburg University.

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

Barwise 1993; Yoo, Donthu, and Lee 2000): which elements of the marketing mix are most critical in making brands successful?

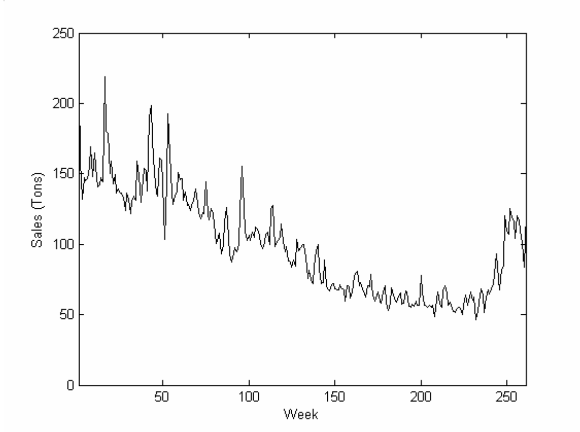
To illustrate these points, we show the historical performance of two brands over a five-year period, one that contracted dramatically (Brand C, C = Contracted), and one that grew considerably (Brand G, G = Grew). The brands and variables are from a data set that we discuss in more detail in subsequent sections. Figures 3.1 and 3.2, respectively, show sales volume, promotion activity, advertising spending, distribution depth, variety of the product offer, and distribution breadth for Brand C and Brand G over time. Comparison of sales volume between the first and second half of the data reveals a considerable 60% sales contraction for Brand C, which contrasts to an 87% growth for Brand G. This difference in performance begs the question of what strategies discriminate these brands.

To attain insights into this question, we first consider Brand C. Its downward sloping sales (Figure 3.1a) during its first four years coincide with frequent and deep discounting (Figure 3.1b), negligible advertising (Figure 3.1c), weaker shelf presence (Figure 3.1d), and lower distribution (Figure 3.1b). Of note, its sales turn around in the last year of our data. This period is characterized by increased distribution depth, product variety, distribution and advertising. Discounting was also curtailed. From this, one might infer that product, distribution and advertising help the brand, while discounting does little in the way of brand building.

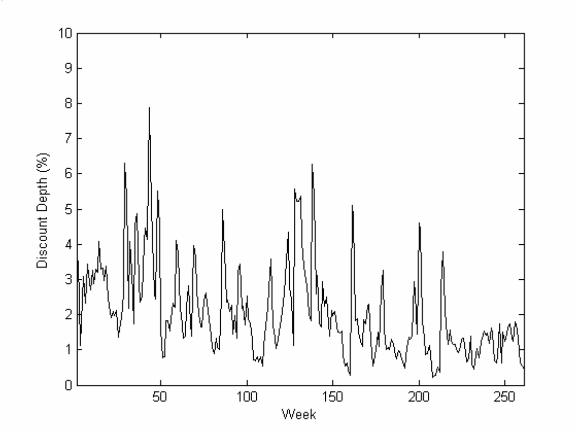
Brand G's sales (Figure 3.2a) show a marked increase shortly after week 100. This increase is characterized by heavy product activity (Figure 3.2e), high advertising spending (Figure 3.2c), increased distribution (Figure 3.2d and 3.2f) and diminished price promotions (Figure 3.2b). In the latter half of the data, sales begin to decrease slowly. This decrease is concurrent with a shift in marketing strategy – advertising spending is decreased and average discount depth is increased.

Together, these examples suggest that product, distribution, and advertising seem to enhance brand performance, while discounts do little to help brands. Yet these cases are anecdotal (and involve only two categories) and the various mix effects are confounded. In fact, the correlation in these strategies suggests that it is especially important to consider them in unison, otherwise an assessment of effects in isolation might lead one to misattribute a brands' success to the wrong strategy.

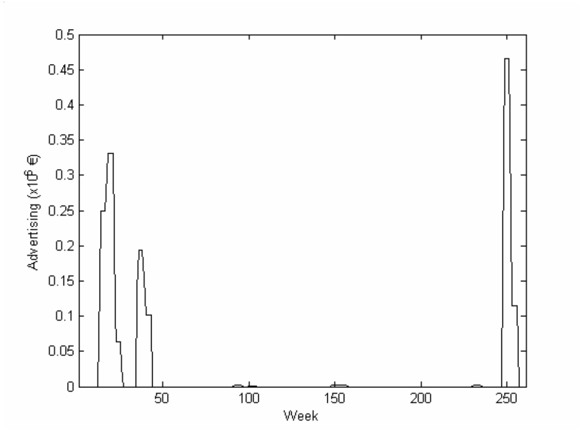
Figure 3.1: Contraction Case – Brand C



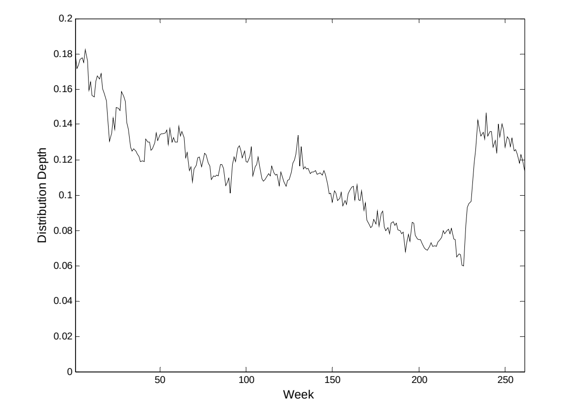
(a) Sales



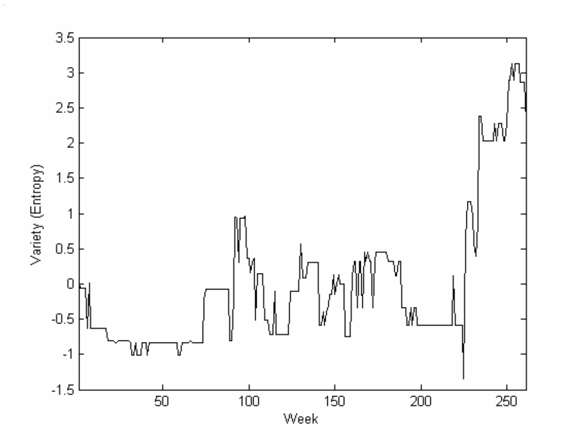
(b) Discount Depth



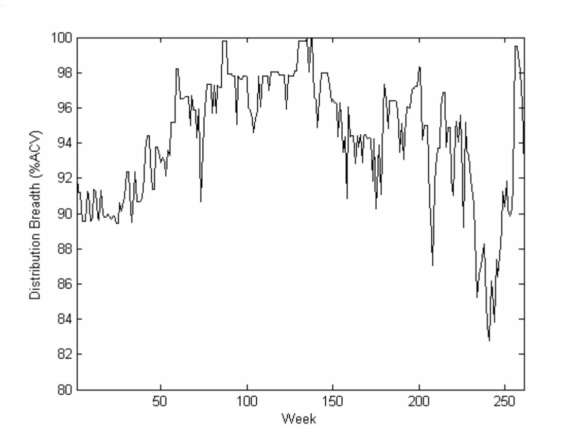
(c) Advertising Spending



(d) Distribution Depth

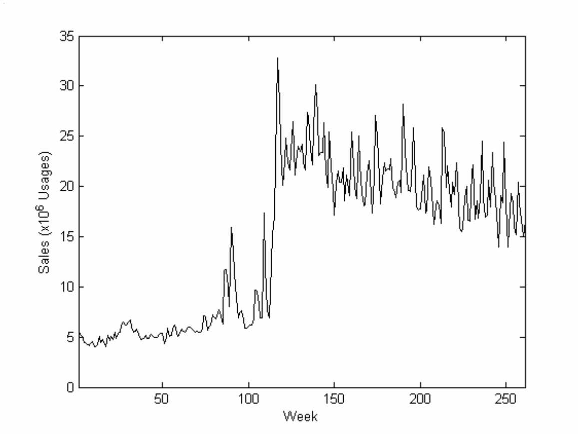


(e) Variety (Entropy)

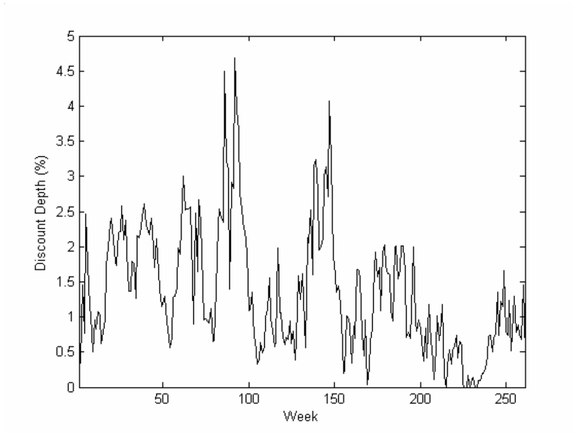


(f) Distribution Breadth

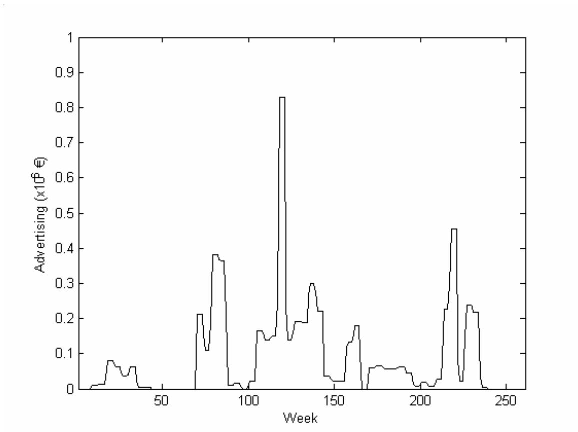
Figure 3.2: Growth Case – Brand G



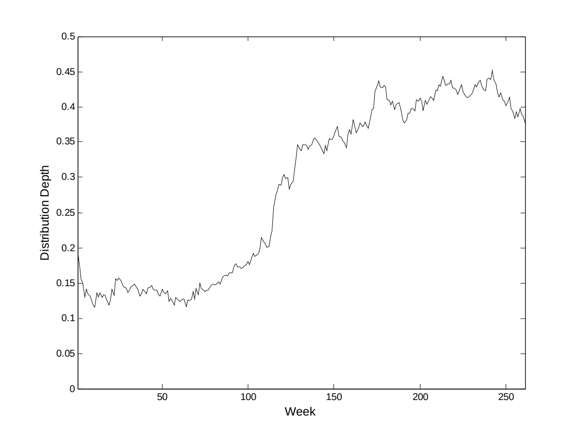
(a) Sales



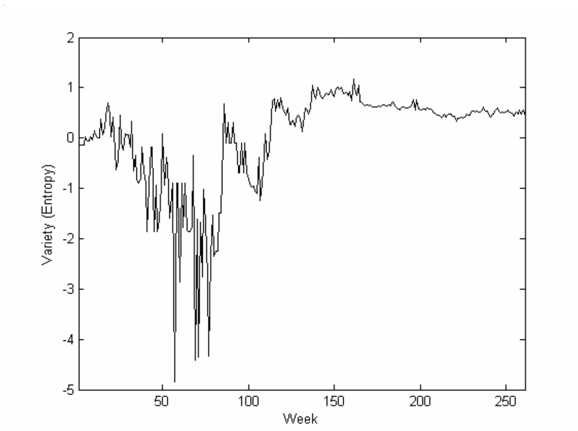
(b) Discount Depth



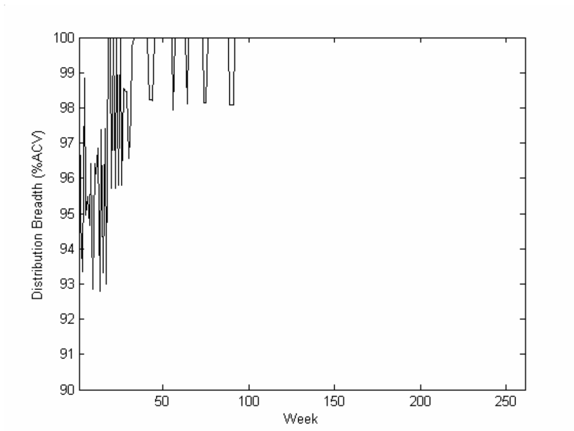
(c) Advertising Spending



(d) Distribution Depth



(e) Variety (Entropy)



(f) Distribution Breadth

Accordingly, our objective is to investigate more systematically how marketing affects brand performance in the long run. To achieve this aim we develop a time varying market response model that allows us to understand how various components of brand performance, namely sales and elasticities (discussed later in detail), evolve over time as a function of marketing activity. By combining detailed advertising data from TNS Secodip with weekly store-level scanner data from Information Resources (covering a time horizon of 265 weeks, 25 product categories, and 450 stores from a French national sample) and analyzing the weekly performance of 70 top national brands in these categories over five years, we contribute to the literature by identifying the marketing mix strategies that lead to better performance, i.e., higher sales and lower price elasticity magnitudes.

Our results indicate that advertising, distribution and product play a central role in building brands while discounting is deleterious for brands. These findings arise from the application of a multivariate dynamic linear model that links brand sales to marketing strategy. The approach offers a flexible means for assessing how marketing affects intercepts and sales response parameters (e.g., elasticities) over time. Moreover, the approach i) controls for endogeneity in pricing and marketing mix instruments, ii) partials the role of past performance from marketing spend, iii) considers competitive interactions in pricing. To our knowledge, we are the first to embed these innovations into a dynamic linear model (DLM).

The chapter is organized as follows. We first discuss the literature on long run effects of the marketing mix on brand performance in order to highlight our points of difference. Second, we define brand performance more precisely using some of the literature in this research domain. Third, we discuss theories pertaining to how the marketing mix affects brand performance in the long run. Fourth, we develop our model and overview estimation. Fifth, we describe the data and variables. Sixth, we present the results. Last, we conclude with managerial implications and future research opportunities.

3.2 Literature on Long-Term Effects

Table 3.1 samples the current state of the long-term effects literature and indicates most studies focus on promotion and advertising. Those that do consider product and distribution emphasize their main effects (not the implications for elasticities) and consider only a single category. No studies integrate all elements of the mix and as such, a) cannot provide insights into their relative effects and b) risk suffering omitted variable bias as these strategies can be correlated.

Our personal interviews with senior research managers at different consumer packaged goods firms yielded a similar focus regarding the prevalence of advertising and discounting in industry research. Yet they remain unclear regarding whether this attention is misplaced in the sense that product and distribution might play a greater role in brand performance. Consequently, the question “How do the marketing mix instruments influence brand equity in the long run?” has been a top research priority of the Marketing Science Institute ever since 1988 (MSI research priorities 1988-2004).

One reason that this question has been around for so long is that answering it requires the combination of very extensive data sets and a methodology that is able to measure long-term effects while coping with the common pitfalls of empirical modeling, such as (1) endogeneity in pricing, (2) performance feedback (e.g., the effect of past sales on current marketing expenditures), and (3) competitive interactions. This research meets both requirements.

Another reason for the focus on advertising and promotion in industry pertains to their ease of measurement: it is easy to observe the immediate effect of deals on sales, but much harder to assess how product innovation affects brands in the long-term. Immediacy may also play a role, as the short-term effect of a discount is large while the effect of building distribution may take some time. As brand managers are promoted quickly, there is little incentive to invest in long-term brand building. This underscores the importance of tools to measure the longer-term effects of marketing strategy on brands, lest the emphasis on short-term metrics induces brands to weaken over time. It further underscores the importance of a large systematic study to determine whether the industry focus on discounting might be misplaced.

Table 3.1: Current Literature on Long-term Effects of Marketing Mix Instruments

	Effect of: Promotion	Advertising	Distribution	Product	Effect on (a)	Modeling Approach (b)	# Categories
Clarke (1976)		✓			BS	VPM	1
Baghestani (1991)		✓			BS	VAR	1
Dekimpe and Hanssens (1995)		✓			ChS	VAR	1
Papatla and Krishnamurthi (1996)	✓				C	VPM	1
Mela, Gupta, and Lehmann (1997)	✓	✓			C	VPM	1
Mela, Jedidi, and Bowman (1998)	✓				I & Q	VPM	1
Mela, Gupta, and Jedidi (1998)	✓	✓			MS	Mixed	1
Kopalle, Mela, and Marsh (1999)	✓				BS	VPM	1
Jedidi, Mela, and Gupta (1999)	✓	✓			C & Q	VPM	1
Foekens, Leeflang, and Wittink (1999)	✓				BS	VPM	1
Dekimpe and Hanssens (1999)	✓	✓			BS	VAR	1
Dekimpe, Hanssens, and Silva-Risso (1999)	✓				BS & CS	VAR	4
Srinivasan, Leszczyc, and Bass (2000)	✓		✓		MSh	VAR	2
Bronnenberg et al. (2000)	✓	✓	✓		MSh	VAR	1
Nijs et al. (2001)	✓				CS	VAR	560
Pauwels, Hanssens, and Siddarth (2002)	✓				I, C & Q	VAR	2
Srinivasan et al. (2004)	✓				MR	VAR	21
Pauwels (2004)	✓	✓		✓	BS	VAR	1
Van Heerde, Mela, and Manchanda (2004)				✓	MS	DLM	1
Pauwels et al. (2004)	✓			✓	FM	VAR	1
Steenkamp et al. (2005)	✓	✓			BS	VAR	442
THIS PAPER	✓	✓	✓	✓	BS & E	DLM	25

Notes: (a) BS = Brand Sales; ChS = Chain Sales; CS = Category Sales; FM = Financial Measures; MR = Margins & Revenues; I = Incidence; Q = Quantity; C = Choice; MS = Market Structure; MSh = Market Share; E = Elasticity (b) VPM = Varying Parameter Model; VAR = Vector Autoregressive model; DLM = Dynamic Linear Model

3.3 Brand Performance

Brand performance or brand equity has been conceptualized and operationalized using stock market returns (Simon and Sullivan 1993), brand sales or choice data (Kamakura and Russell 1993), and information regarding brand attitudes (Aaker 1996). Though each has its respective benefits, our research fits in the second stream. Several papers embedded in this stream propose different measures for brand equity. The first measure suggests assessment of brand equity through the quantity premium, which is operationalized as the brand intercept in a sales model (Kamakura and Russell 1993). This measure is analogous to a baseline inasmuch as it captures the incremental volume attributable to the brand over a firm with lower baseline sales. The second measure builds upon the differentiation related arguments in the brand equity literature, and proposes to use margin premium as the focal measure. A high margin premium shows a brand's ability to successfully differentiate its offerings from its competitors, which provide similar benefits (Swait et al. 1993).

The discussion on whether or not a single measure is sufficient to capture all the aspects of brand performance is a valid one. Boulding et al. (1994) argue that consumer perceptions influenced by the marketing mix will, in turn, influence not only the desirability of the offering but also the sensitivity to price. The former impact manifests as a shift in demand and corresponds to the quantity premium, while the latter impact reflects a change in the slope of the demand curve. As brand performance is often manifested along two routes, namely quantity and margin premiums, we adopt both measures.

We operationalize the quantity premium as the intercept in a sales model. Strong brands have higher quantity premiums, i.e., they sell more than weaker brands with an identical offer. The margin premium component, on the other hand, is operationalized as the inverse of the absolute price elasticity value (Nicholson 1972). In a market characterized for ease of exposition as a duopoly, where firms face a demand curve satisfying conditions of a constant elasticity framework, the percent profit margin of a firm equals the inverse of its minus price elasticity. Consistent with the brand differentiation view, we consider brands strong when their margin premiums are high, or in other words the price elasticity magnitude is low (Boulding et al. 1994)[8].

[8] It is possible to combine the quantity and margin premium to obtain a measure similar to revenue premium recently proposed by Ailawadi, Lehman and Neslin (2003), though we prefer to disentangle the effects as they are informative in their own right.

Using quantity premium and margin premium one can construct a two-dimensional performance space (see Figure 3.3), and track the movement of a brand by considering how its quantity premium and margin premium change over time. A brand can traverse this performance space as a result of its marketing actions, i.e., it can move from one point to another by managing its marketing mix accordingly. We are agnostic about the desirability of entering a particular quadrant, as each implies a different revenue and cost structure. For example, though low price elasticity magnitudes increase margins, all else equal they are associated with lower unit sales (as is common for luxury goods). Thus if one's goals are high margins, this is a good strategy. In contrast, if the goal is high revenue, one might pursue a strategy of low margins and high volume. Thus, our main emphasis is not the choice a particular brand should make, but rather the strategies that lead brands into the desired point in the space. We pursue this line of reasoning further by next outlining how various marketing strategies impact brand positions in this space.

3.4 The Effect of the Mix on Brand Performance

The following sections overview the current literature regarding the long-term effects of price promotions, advertising, distribution, and product on brands, and how they relate to margin and quantity premiums (see Table 3.2). We note that our discussion of the latter two elements of the mix is more tentative given the dearth of work in the area. We then conclude by discussing the relative efficacy of the various marketing strategies.

Figure 3.3: Performance Space

		Margin Premium	
		Low	High
Quantity Premium	High	Value Brands	Quality Brands
	Low	Cheap Brands	Luxury Brands

3.4.1 Price Promotion

While some studies in the literature suggest a negative long-term impact of price promotions on quantity premiums (Dekimpe, Hanssens, and Silva Risso 1999; Foekens, Leeflang, and Wittink 1999; Jedidi, Mela, and Gupta 1999), others suggest the opposite effect as a result of the positive effects of state dependence (Keane 1997) and purchase reinforcement (Ailawadi et al. 2005). Others have found only a fleeting negative effect (Pauwels, Hanssens, and Siddarth 2002). Overall, it is not clear to us whether the positive effect dominates the negative effect on equity, and a large-scale generalization seems necessary in this regard.

In contrast, discounting policies are typically found to increase price sensitivity (decrease margin premiums) by focusing consumers' attention to price-oriented cues (Boulding et al. 1994; Mela, Gupta, and Lehmann 1997; Papatla and Krishnamurthi 1996; Pauwels et al. 2002).

3.4.2 Advertising

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

Two different schools of thought in economic theory, namely information and market power theories, offer alternative explanations for the impact of advertising on the margin premium component of brand equity. The information theory suggests that advertising may increase competition by providing information to consumers about the available alternatives, thus increase price sensitivity, whereas the market power theory argues that advertising may increase product differentiation, thus reduce price sensitivity (Mitra and Lynch 1995). Related, Kaul and Wittink (1995) indicate that brand-oriented advertising decreases price elasticity magnitude while price-oriented advertising increases it. Mela, Gupta, and Lehmann (1997) note that national brand television advertising is predominantly brand-oriented. Accordingly, we expect national television advertising such as we observe in our data will reduce price elasticities and thereby increase margin premiums.

3.4.3 Product

Research regarding the long-term effect of product (e.g., innovations, changes in form, etc.) on brand performance is very limited (Table 3, Bucklin and Gupta 1999), hence our expectations regarding the effects of increasing the variety of items offered within a product line are tentative. The effect of increased product variety on quantity premiums is incumbent upon the degree to which cannibalization offsets incremental sales garnered by serving mode segments. In general, we argue novelty has a small but positive effect on quantity premium because we do not expect cannibalization to entirely offset the increased demand. We expect that more differentiated or customized alternatives lower price sensitivity (and increase margin premium) because strongly differentiated items can serve loyal niches.

Related, repetitive or "me too" additions to the product line, a phenomenon known as product proliferation, can have an adverse effect on demand (Gourville and Soman 2005); suggesting care must be taken when defining product innovation, a point we revisit when defining our measures. Interestingly, variants that increase proliferation can still have a positive effect on sales via their role in appropriating shelf space, a point we address next.

3.4.4 Distribution

Distribution breadth (the percent of distribution that carries a brand) and depth (a brand's share of the total number of SKUs in a category in a store) can affect brand performance, but as with product, theoretical and empirical evidence for these effects are limited. We expect that increases in the breadth and depth of distribution lead to higher quantity premiums as the wider availability facilitates consumers' ability to find the brand (Bronnenberg, Mahajan, and Vanhonacker 2000).

Two competing expectations can be formulated for the effect of distribution breadth on margin premiums. First, broader distribution may increase the chance of within-brand price comparison across stores, commonly called "cherry picking" (Fox and Hoch 2003). This leads to an increased emphasis on price and an attendant decrease in the margin premium. In contrast, broader distribution signals manufacturer commitment to the brand and potentially its success in the marketplace. A similar signaling effect is also observed for advertising (Kirmani and Wright 1989). Moreover, increased shelf-facings may induce an "advertising effect" that lowers elasticities and increases margin premiums. Given the competing arguments, we treat the effect of distribution breadth on margin premium as an empirical question. Finally, we argue that deeper distribution increases a brand's control over the shelf space, preempts competition, reduces emphasis on price and lowers price sensitivity, thereby increasing margin premium. Table 3.2 summarizes the expected effects of marketing on brand performance.

3.4.5 Relative Effects

Of interest is the relative magnitude of these effects. To our knowledge, no research incorporates all of these effects into a single framework over a large number of categories, so any discussion of the relative magnitude of these effects is necessarily speculative. Our personal communications with firms and colleagues suggest most individuals expect distribution and product innovation to have the greatest long-term effects on brands. As a higher percentage of a store's shelf space is covered by one brand, competition is substantially mitigated. Product innovation is also likely to have considerable effects, especially on elasticities, as it is a core source of differential advantage. We believe that product strategies, by virtue of their ability to change buying patterns, might play the greatest role in driving the success of brands (Van Heerde, Mela, and Manchanda 2004). In contrast, advertising and pricing are limited in their ability to differentiate goods. In sum, we expect product and distribution to matter most.

Table 3.2: Expected Marketing Mix Effects on Quantity and Margin Premium

Variable	Operationalization	Predicted Effect on	
		Quantity premium (=intercept)	Margin premium (=1/-elasticity)
1. Price variable			
Discounting	Discount depth	?	Negative
2. Advertising variable			
Spending	Dollars	Positive	Positive
3. Product variable			
Variety of assortment	Index for newness (entropy)	Positive	Positive
4. Distribution variables			
Breadth	%ACV weighted distribution	Positive	?
Depth	%SKUs in the category	Positive	Positive

3.5 Modeling Approach

3.5.1 Overview

We seek to allow the margin and quantity premium to vary over time as a function of marketing strategy. Dynamic Linear Models (DLM) (Van Heerde, Mela, and Manchanda 2004; West and Harrison 1997) are well suited to this problem. The general multivariate form of our model is:

(3.1a) $$Y_t = F_t \theta_t + \upsilon_t$$

(3.1b) $$\theta_t = G\theta_{t-1} + Z_t'\gamma + \omega_t$$

where Y_t is a vector in which the log sales of brand j in chain s belonging to category k at time t is stacked across brands and chains. F_t is a matrix of regressors, such as log price, that affect sales. We assume $\upsilon_t \sim N(0,V)$, where V is the covariance matrix of error terms in (3.1a). The *observation equation* (3.1a) models the short-term effect of marketing activities on sales. Note that this equation yields period-specific estimates for price elasticities (the inverse of minus the margin premium) and intercepts (the quantity premium). We allow these to vary over time as described by the *system equation* (3.1b) in order to measure the long-term effect of marketing strategies on the quantity and margin premiums. These strategies, Z_t, can include advertising, promotional policies, new product introductions, and distribution strategies. The system evolution matrix G measures the duration of these strategies – for example the rate of advertising memory. The stochastic term ω_t are assumed to be distributed $N(0,W)$.

In the next section, we elaborate upon this basic specification and detail how it can be extended to control for (1) endogeneity in prices and marketing mix, (2) performance feedback, and (3) competitor interactions. To our knowledge, this is the first application of the DLM to address all three issues.

3.5.2 Model Specification

<u>Observation Equation: Sales</u>. Similar to Van Heerde, Mela, and Manchanda (2004) and others, we use a log-log model to capture the short-term effect of marketing activity on a brand's sales in a given chain:

(3.2) $$\begin{aligned} \ln \overline{SALES}_{jskt} &= \alpha_{jkt} + \beta_{jkt} \ln \overline{ACTPR}_{jskt} + \phi_{jk} \overline{FND}_{jskt} \\ &\quad + \sum_{\substack{j'=1 \\ j' \neq j}}^{J} \rho_{j'j} \ln \overline{CPR}_{j'skt} + \sum_{i=1}^{I} \tau_{ik}^{s} SD_{ikt} + \upsilon_{jskt}^{S}, \end{aligned}$$

where $\ln\overline{SALES}_{jskt}$ represents the log sales of brand *j* in chain *s* in category *k* in week *t*, $\ln\overline{ACTPR}_{jskt}$ is the log inflation adjusted actual price, $\overline{FND}_{jskt}$ indicates whether there was a feature and/or display without a price discount, $\ln\overline{CPR}_{j'skt}$ is log cross price, and the monthly dummies, SD_{ikt}, are used to model seasonal variation in sales. The super-scripted bar indicates that variables are mean centered across brands and chains in order to control for brand-chain-fixed effects. υ^{S}_{jskt} is an error term, which is assumed to be distributed normal and independent across time. α_{jkt} is the brand-category specific intercept, which can be construed as the quantity premium[9]. The brand-category specific price elasticity coefficient β_{jkt}, is the second central parameter and reflects the inverse of minus the margin premium. We also incorporate a number of control variables in the model; ϕ_{jk} is the feature and/or display log multiplier, $\rho_{j'j}$ is the cross price elasticity, and τ^{s}_{ik} ($i = 1,\ldots,I$) capture the seasonal variation, if any.

<u>System Equation: Long-term Effects</u>. A core contention of our research is that firms' positions in the performance space of margin premium and quantity premium vary over time. To test these conjectures, we specify the long-term effect of marketing strategies on the margin premium and quantity premium to be as follows:

(3.3a) $$\alpha_{jkt} = \delta^{\alpha}_{0jk} + \lambda^{\alpha}_{k}\alpha_{jkt-1} + Z'_{jkt}\gamma^{\alpha} + \omega^{\alpha}_{jkt},$$

(3.3b) $$\beta_{jkt} = \delta^{\beta}_{0jk} + \lambda^{\beta}_{k}\beta_{jkt-1} + Z'_{jkt}\gamma^{\beta} + \omega^{\beta}_{jkt}.$$

The γ measure the effect of marketing mix elements Z_{jkt} on the quantity and margin premiums. These are the central parameters of interest in our analysis as they measure the effect of marketing strategy on brand performance.[10] The λ's represent the decay rate of these effects, where λ is between 0 and 1. A value near 0 implies the effect is brief whereas a value of 1 implies the effect of the strategy is enduring. We assume all

[9] We label baseline sales, α_{jkt}, as quantity premium following our discussion in Section 3.3. As an alternative we could have used the term "quality premium" for labeling this brand performance dimension. We choose quantity premium over quality premium as the latter implies the former i.e., high quality brands *ceteris paribus* enjoy higher baseline sales levels.

[10] Note that the marketing mix effects on quantity premium and margin premium are pooled (across all brands) estimates as our main focus is on central tendencies. However, we believe that a parsimonious model that allows for between brand and/or category differences (e.g., a hierarchical Bayes random coefficients model with brand- and category-level covariates layered upon the multivariate DLM) might provide additional useful insights. We acknowledge this possibility but leave it as a fruitful avenue for future research.

ω's are independently distributed, yet brand specific, with zero mean and a diagonal covariance matrix W.[11]

Price Endogeneity. A recent meta-analysis by Bijmolt, Van Heerde, and Pieters (2005) indicates price endogeneity plays a major role in price response estimates. To control for this bias, we begin by assuming that a brand's price in a particular chain ($\ln \overline{ACTPR}_{jskt}$) is a manifestation of its (latent) national pricing strategy μ_{jkt}. Deviations from this strategy arise from seasonal and random effects. We model this phenomenon by constructing the following equation:

$$\ln \overline{ACTPR}_{jskt} = \mu_{jkt} + \sum_{i=1}^{I} \tau_{ik}^{p} SD_{ikt} + \upsilon_{jskt}^{P}. \tag{3.4}$$

We estimate Equation (3.2) and (3.4) simultaneously and let error terms, υ_{jskt}^{S} and υ_{jskt}^{P}, be correlated in order to account for price endogeneity in the observation equation. The associated system equation is as follows,

$$\mu_{jkt} = \delta_{0jk}^{\mu} + \lambda_{k}^{\mu} \mu_{jkt-1} + \gamma_{k}^{\mu} S_{jkt-1} + \omega_{jkt}^{\mu}.$$

This is analogous to the instrumental variable approach to the endogeneity problem. As in such models, we replace the true supply side model with a linear specification including instrumental variables as the independent variables. We allow for correlation between the demand side error term and the supply side error term. We use the lagged strategy, μ_{jkt-1}, as an instrument for itself as commonly applied (Yang, Chen, and Allenby 2003). This specification also allows us to control for performance feedback, since the national-level strategy is not only based on past national strategy but also the previous period's national brand sales, S_{jkt-1}.

Competitor Interactions. Jedidi et al. (1999) find that competitive adjustments in price matter over the long run. As such, it is desirable to control for these behaviors, especially when forecasting the effect of future changes in marketing activity on firm sales. One can incorporate interaction between competitors' pricing strategies by modifying the preceding equation in the following manner[12],

[11] We checked the stability of our results by estimating a model with random coefficients in the state equation and found that the substantive conclusions remain the same.

[12] Extensive simulation exercises support the estimation procedure's ability to recover the true parameters in a data generating process defined by Equations (3.2)-(3.5). Detailed information on these simulations is available upon request from the first author.

(3.5) $$\mu_{jkt} = \delta_{0jk}^{\mu} + \lambda_k^{\mu} \mu_{jkt-1} + \sum_{\substack{j'=1 \\ j' \neq j}}^{J} \vartheta_{jj'k}^{\mu} \mu_{j'kt-1} + \gamma_k^{\mu} S_{jkt-1} + \omega_{jkt}^{\mu}, \quad j \neq j'.$$

The term $\vartheta_{jj'k}^{\mu}$, captures firm j's response to the action of firm j'.

Marketing Mix Endogeneity and Performance Feedback. The previous section deals with price endogeneity alone. However, remaining marketing mix instruments, namely advertising expenditure, distribution breadth, discount depth, line length, and distribution depth, might also be determined endogenously. To control for endogeneity, we specify an additional DLM for each marketing mix instrument. The specification also allows us to control for performance feedback in the marketing spend. Otherwise, the link between marketing spend and brand performance may be an artifact of the effect that past performance has on marketing spend. Another key advantage of this approach is that it controls for changes in long-term marketing strategies of competing brands, because the sales of these brands is a function of these strategies (Horvath et al. 2005). To redress this issue, we include the following regression equation in our DLM for all five marketing mix instruments:

(3.6) $$Z_{ijkt} = \pi_{0ijk} + \pi_{1ik} S_{jkt-1} + \pi_{2ik} S_{j'kt-1} + \upsilon_{ijkt}^{Z},$$

where Z_{ijkt} is the *i*th marketing mix instrument of brand *j* in category *k* during week *t*. S_{jkt-1} is the focal brand's national sales from the previous period, and $S_{j'kt-1}$, for $j' \neq j$, is lagged sum of competitors' national sales. The parameters π_{1ik} and π_{2ik} capture, respectively, the own- and cross-performance feedback effects for marketing mix instrument *i*. This specification builds on the results in Horvath et al. (2005), which show that own- and cross-performance feedback is more informative than inertia and direct competitive action in the prediction of marketing mix activity. We estimate Equation (3.6) together with Equations (3.2) and (3.4) and let error terms υ_{jskt}^{S}, υ_{jskt}^{P}, and υ_{ijkt}^{Z} be correlated in order to account for common unobserved shocks in the seven observation equations.

Note that some of the parameters in Equation (3.2)-(3.6) are specified as non-time varying. The state-space enlarges exponentially with additional time varying parameters and we found the model to yield poor reliability and convergence when all parameters, including those for control variables in Equation (3.2) and (3.4), and all parameters in Equation (3.6), were allowed to vary. To be more precise, Equation (3.2)-

(3.6) yield 54,810 state-space parameters. When extended to allow all parameters to be time varying, there are 408,204 state-space parameters. Though the resulting degrees of freedom in Bayesian DLM models are difficult to assess and data dependent due to the precision of the likelihood and priors, it is evident that strong and perhaps unpalatable assumptions would be necessary to identify time-varying parameters for all the regressors.

3.6 Model Estimation

By stacking all observations, Equations (3.2)-(3.5) can be combined in a single model, which is still a multivariate dynamic linear model, and estimated simultaneously conditional on Equation (3.6). Let $j = 1,...,J$ denote the brand, $s = 1,...,S$ denote the chain, $k = 1,...,K$ denote the category and $t = 1,...,T$ denote the time. Then the combined model can be written as

(3.7a) $$\mathrm{Y}_t = \mathrm{F}_t \Theta_t + \upsilon_t,$$

(3.7b) $$\Theta_t = \mathrm{G}\Theta_{t-1} + \mathrm{h}_t + \omega_t.$$

In Equations (3.7a)-(3.7b) Y_t is a $MJS \times 1$ vector of dependent variables including log sales, and M endogenous variables (log actual price in our application). F_t is a $MJS \times NJ$ matrix of regressors where N is the total number of explanatory variables with a time varying parameter (one intercept for all dependent variables and log own-price). Θ_t is a $NJ \times 1$ vector of brand specific time varying parameters, υ_t is a $MJS \times 1$ vector of observation equation errors. G is a $NJ \times NJ$ matrix defining system evolution, and ω_t is a $NJ \times 1$ vector of system errors. The $NJ \times 1$ vector $\mathrm{h}_t = \delta + \mathrm{Z}'_t \gamma$ includes the marketing mix and lagged national sales effects, as well as the system equation intercepts. Both Y_t and Θ_t have multivariate normal distributions, and so do the associated error terms. We assume that $\upsilon_t \sim N(0, \mathrm{V})$, where the variance matrix V, of size $MJS \times MJS$, is time invariant and block diagonal. We correlate sales and price error terms of each brand across chains. This allows us to capture unobserved shocks that cause endogeneity. The system errors are distributed multivariate normal, $\omega_t \sim N(0, \mathrm{W})$, where W is a diagonal matrix of size $NJ \times NJ$.

We obtain the time varying parameters of this combined model by a series of Bayesian updating equations conditional on known variance matrices and other parameter vectors. We estimate these variance matrices and all other parameters using

MCMC techniques. A detailed illustration of the model and the steps of the estimation procedure can be found in the Appendix.

3.7 Empirical Analysis

3.7.1 Data

We use a novel data set provided by Information Resources Inc. (France) to calibrate our model. These data include five years (1/1/1999 to 1/1/2004) of weekly SKU-store level scanner data for 25 product categories sold in a national sample of 560 outlets representing 21 chains. The 25 categories are chosen to vary across dimensions such as food/nonfood, storable/nonstorable, new/mature, etc. In addition, TNS Media Intelligence (France) provided the matching monthly brand-level advertising data. Accordingly, the data includes temporal and cross-sectional changes in (i) advertising strategies, (ii) product offerings, (iii) distribution coverage, and (iv) pricing strategies. One reason we selected France over the United States is that it does not suffer from measurement problems induced by Wal-Mart. Given Wal-Mart sales are growing and IRI does not cover that chain, parameter paths could reflect these changes.

The data's long duration, coverage of the entire mix and manifold categories make the data well suited to addressing our core research questions. On the other hand, its massive size makes estimation of an SKU-store level model specification infeasible (our brand-chain model takes 3 weeks to estimate using a 3.06GHz workstation). As such, the data are aggregated to the brand-chain level. We aggregate to the brand level as our central interest pertains to the effect of marketing on brands and we aggregate to the chain-level as pricing and other marketing policies tend to be fairly consistent within chains in our data. Data are aggregated from the SKU-store level to brand-chain level following the procedures outlined in Christen et al. (1997) to avoid any biases due to aggregation. We limit our analyses to the top four chains (184 stores), accounting for approximately 75% of the total turnover across all categories, and to three top-selling national brands.[13] However there are three categories – dominated by private labels – in which we observe less than three national brands being sold in the top four chains over the entire sample period. This leaves us with 70 national brands in total. The total market share of the top three national brands ranges between 26.1% (Oil) and 79.1% (Carbonated Soft Drinks).

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

3.7.2 Observation (Sales) Equation Variables

Sales. The dependent variable of the observation equation is sales volume, calculated as the ACV weighted geometric average of total sales of a brand in a given store-week, across stores in a given chain.

Price. We define price for a brand as the actual shelf price, and calculate it similar to Mela, Gupta, and Lehmann (1997). We use the minimum price per 1000 volume units across SKUs of a brand in a given store and week as the price for that brand. This measure has the added benefit of not being sensitive to the particular sales weighting scheme selected. Moreover, it exploits price variation in the data that might be understated in the event one major SKU lowers its price. We calculate average chain level brand price in a nonlinear fashion. We assume that a brand is on feature or display if any SKU of that brand is on feature or display in a given store and week. Chain-level feature and display variables are calculated by taking the ACV weighted arithmetic average across stores in a given week (see Christen et al. 1997). The feature and display variable are set to zero when there is a price discount of five percent or more. The benefit of this transformation is a considerable reduction in correlation between price and the variable for feature and display (Van Heerde, Leeflang, and Wittink 2000).[14] As such the feature and display variable measures the effects of these activities in the absence of a price cut, while the price variable measures the impact of price changes that are possibly communicated via feature and display. Finally we use monthly dummies in the observation equation to account for any seasonal patterns inherent in sales.

We standardize all variables within store-chain-brand to control for unobserved fixed effects because our focus is on changes in brand position across time. Moreover, this standardization facilitates comparison of effect sizes across the mix and categories (where price is typically expressed in different equivalency units such as liters or grams).

3.7.3 State Equation Variables

We operationalize long-term marketing strategies from the following weekly measures. The model then creates a geometric-decay weighted average of the weekly variables to capture their long-term effect (see Equations 3.3a and 3.3b).

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

Pricing: Price promotion is measured as one minus the ratio of the actual to the regular price. National level averages are calculated across stores and chains in a linear fashion.

Advertising: We construct a weekly advertising expenditure variable from our monthly data by dividing the monthly figures by the number of days in a month, and then summing across days for the corresponding weeks (Jedidi, Mela, and Gupta 1999).

Distribution Breadth: Following Bronnenberg, Mahajan, and Vanhonacker (2000), we use ACV weighted distribution as a measure of breadth of distribution. ACV weights a product's distribution by the total dollar volume sold through a particular store. Thus, ACV gives more distribution credit for an item that is carried in a large dollar volume store than it does for a small dollar volume store.

Distribution Depth: We measure distribution depth as the number of SKUs a brand offers in the category relative to the total number of SKUs in that category. Average-items-carried 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 chain level and then calculate national averages.

Product: We consider the uniqueness of a brand's items as the only product variable. Using insights from assortment variety literature we calculate weekly variation in a brand's product offer. The set of SKUs that a brand offers is said to be varied when the attribute levels are dispersed. Each time a new SKU is introduced or deleted a change in dispersion takes place. We use entropy as a measure of dispersion for categorical variables (Van Herpen and Pieters 2000). Assuming that the items in category k can be identified by N^k attributes each with L_n^k levels, the intra-brand entropy is given by,

$$E_{jkt} = -\sum_{n=1}^{N^k} \sum_{l_n^k=1}^{L_n^k} P_{l_n^k,jkt} \ln P_{l_n^k,jkt} \tag{3.8}$$

where $P_{l_n^k,jkt}$ is the proportion of SKUs in the assortment of brand j in week t with attribute level l_n^k. A desirable aspect of this measure is that redundant SKUs decrease entropy, consistent with the notion that product proliferation is deleterious to brands. We use IRI's product definition libraries for the attributes and their levels. Following Fader and Hardie (1996) we select the product attributes such that they satisfy (i) consumer recognizability, (ii) objectivity, and (iii) collective exhaustiveness conditions.

3.8 Results

We first discuss results of the short-term sales model and then detail the long-term effects of the marketing mix on the quantity and price premiums. We conclude with results pertaining to the competitor price interactions and performance feedback models.

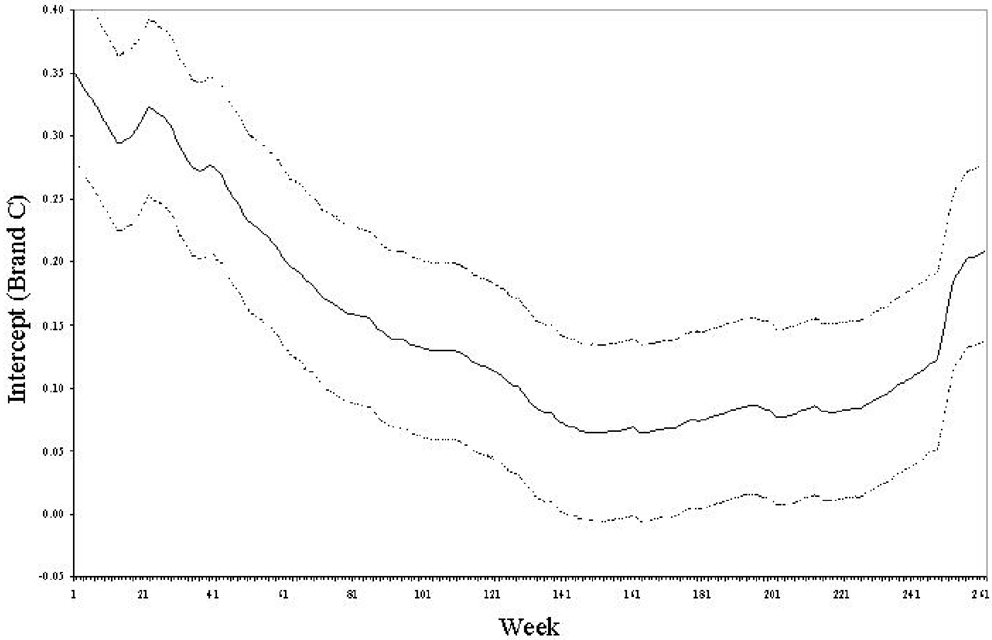
3.8.1 The Sales Model

We consider two sets of parameters in the sales model (Equation 3.2) for each of the 70 brands; i) the time varying parameters (the intercepts and elasticities), and ii) the control variable parameters (feature/display multiplier, cross-price elasticities, and seasonality parameters). The average price elasticity over all time periods and across brands is –1.78, and the distribution of price elasticities are consistent with the results of a recent meta-analysis by Bijmolt, Van Heerde, and Pieters (2005). However, our greater interest lies in how these change over time.

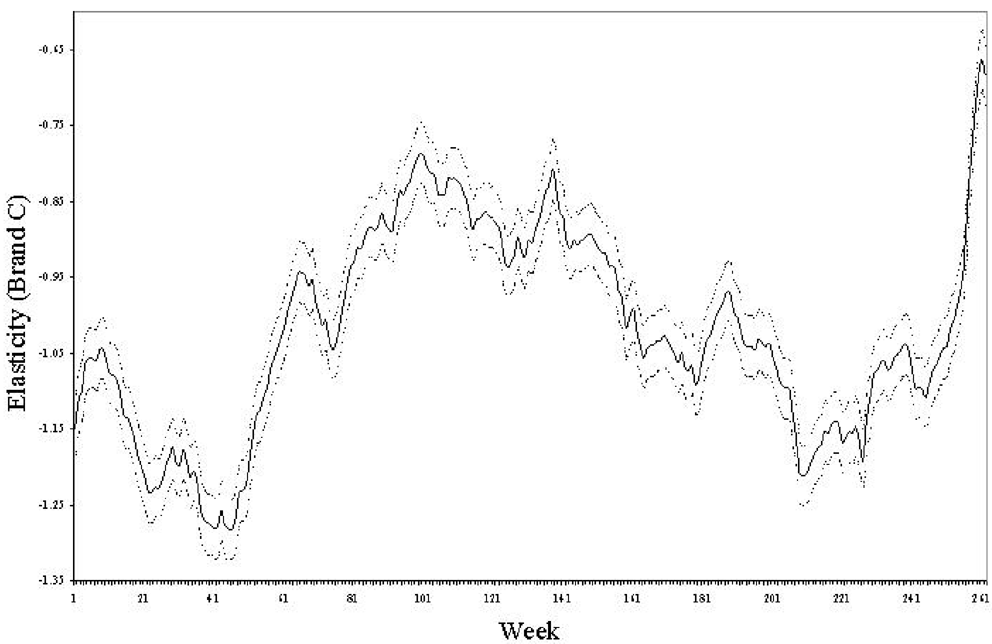
Figure 3.4 presents a sample intercept and elasticity path for Brand C (Panel a and b) and Brand G (Panel c and d) discussed in the Introduction. Consistent with the example, we see the intercept decreasing for brand C until the last year, when sales turn around. Brand G shows a small increase in its intercept attendant with its increase in sales, and a more marked decrement in its elasticity during a period of heightened brand introduction activity. Figure 3.4 suggests our model appears to discriminate the changes indicated in Figures 3.1a and 3.2a. Given the marketing strategies of Brand G are so highly correlated, it is interesting to ascertain what might lie at the root of this change, and our long-term effects model seeks to accomplish this.

The mean of the feature and display multipliers, obtained by taking the anti-log transformation, is 1.14, which is comparable to other results in the literature (Van Heerde, Mela, and Manchanda 2004). The significant cross-price elasticity estimates are all positive and average .12 across all brands, which is also consistent with other results in the literature (Sethuraman, Srinivasan, and Kim 1999). Finally, the coefficients of the eleven month dummies included in the model are significant only in product categories where sales is expected to exhibit a seasonal pattern (i.e., reaching a peak during summer months in categories like ice cream and carbonated soft drinks, and during winter months in categories like soup and coffee), and insignificant in the others (95% posterior density interval includes zero).

Figure 3.4: Intercept and Elasticity Path for Brands C

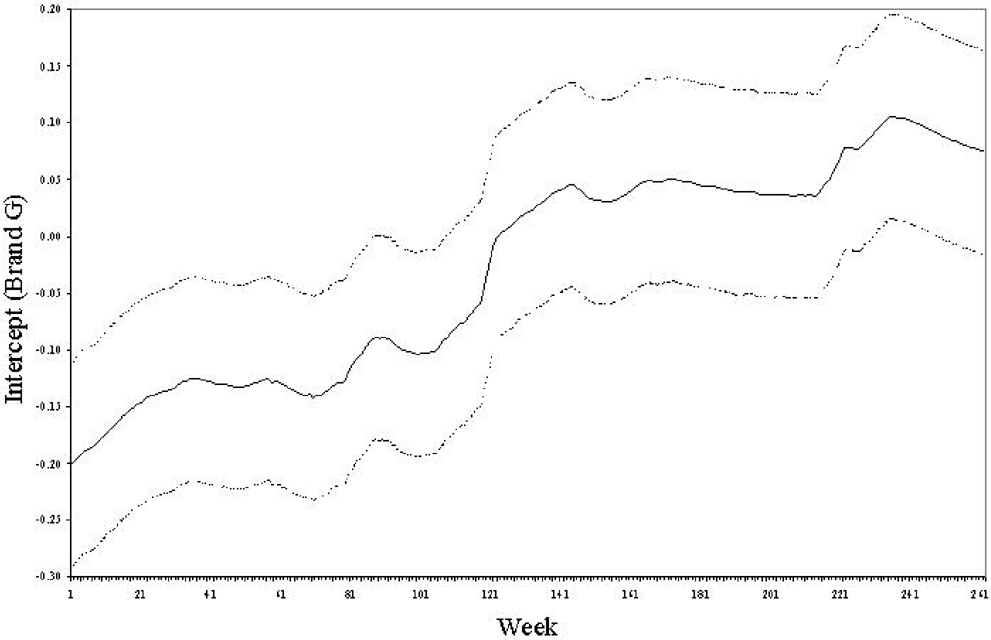


(a) Intercept (Brand C)

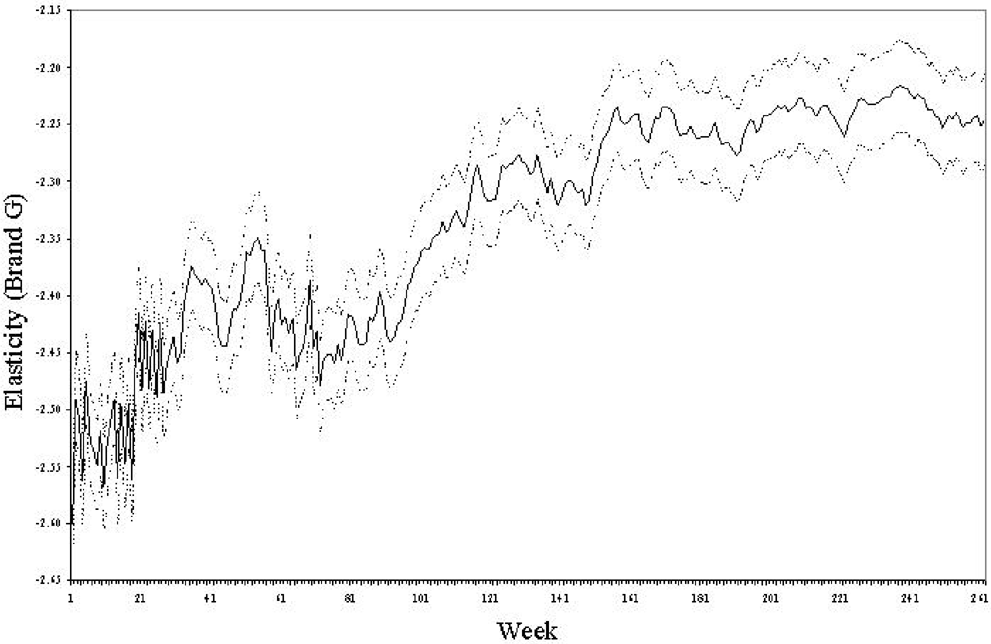


(b) Elasticity (Brand C)

Figure 3.4: Intercept and Elasticity Path for Brands G (Continued)



(c) Intercept (Brand G)



(d) Elasticity (Brand G)

3.8.2 The Long-term Effect of the Marketing Mix on Brand Performance

The Long-term Effects: Of central interest are the long-term effects of marketing strategy on the quantity and margin premiums (Equations 3.3a and 3.3b), and these effects are given by γ^{α} and γ^{β} respectively.

Results, reported in Table 3.3, indicate advertising spending and product variety increase quantity premiums, as expected. The negative effect of discounting reflects that the negative effects on brand perceptions dominate the positive state-dependence effects. The effects of distribution depth and breadth on the brand intercepts are negligible. Advertising and product variety appear to be the most effective tools for increasing quantity premium. A major surprise to us is that distribution breadth has little effect on quantity premiums for mature brands. We speculate that when products are sufficiently well available (as is often the case for the larger mature brands), incremental availability plays little role because consumers can readily find their desired brands.

Table 3.3 further indicates that product variety decreases price sensitivity, thereby increasing the margin premium. The finding is consistent with the notion that variety leads to greater differentiation, thereby enhancing the likelihood a consumer finds a preferred variant and leading to a focus away from price. In addition, both distribution depth and breadth decrease price sensitivity and increase the margin premium.

Table 3.3: Marketing Mix Effects on Intercepts and Elasticities

	Intercept		*Elasticity*	
Effect…	Hypothesized	Estimated	Hypothesized	Estimated
Effect of…		*Median*		*Median*
Discounting	?	-0.0011***	Negative	-0.0119**
Advertising spending	Positive	0.0022***	Positive	-0.0043
Variety of assortment	Positive	0.0008**	Positive	0.0148***
Distribution breadth	Positive	-0.0002	?	0.0269***
Distribution depth	Positive	-0.0003	Positive	0.0149***

*** The 95% interval of the posterior distribution excludes zero.
** The 90% interval of the posterior distribution excludes zero.

Note: Following the operationalization of margin premium (reciprocal of minus price elasticity), a reduction in price elasticity (an increase in price sensitivity) is equivalent to a reduction in margin premium.

These results support the argument that deeper penetration into the category mainly serves to pre-empt competition and more intensive distribution increases the value consumers get from purchasing the brand.

Moreover, we find discounts decrease price elasticities and lower the margin premium. This discounting result is also consistent with previous research (Kopalle, Mela, and Marsh 1999). The effect of advertising on margin premium is not significant as the 90% posterior density interval includes zero. These results suggest that the key tools available to managers to avoid price erosion are product innovation, intensive distribution, and a diminution of discounts.

Dynamics: Also of interest is the duration of these effects, parameterized by λ in our model (Equations 3.3a and 3.3b). Given that a brand has done well, one might wonder how long positive effects linger. Conversely, given a brand has done poorly the question is how long it takes to resuscitate it. Across the 70 brands, the intercept decay parameters range between 0.15 (25^{th} percentile) and 0.98 (75^{th} percentile), with a median of 0.71. This implies that 90% duration interval of marketing activity (Leone 1995) range from 1.2 to 135.9 weeks with a median of 6.8 weeks. The median decay for price elasticity is 0.53, ranging between 0.16 (25^{th} percentile) and 0.67 (75^{th} percentile), and the implied 90% duration interval range from 1.3 to 5.7 weeks with a median of 3.7 weeks. This implies that the adjustment in margin premium is slightly faster than the adjustment in quantity premium. In five categories the effects of the marketing mix appear to be persistent (non-stationary) since the posterior density intervals for decay parameters include 1 (Dekimpe and Hannsens 1999). Overall these dynamics imply it is generally possible to recover from a weak position within a couple of months. However, in some instances it can take ½ year or more to resuscitate a brand.

Relative Effects Across the Mix: Next, we compare the relative effects of the marketing mix by first computing the absolute value of the standardized coefficient for long-term marketing effect k (e.g., advertising) on parameter p (e.g., price elasticity), $\hat{\gamma}_k^p$, and then taking the ratio of each effect to the sum of these effects, that is $\hat{\gamma}_k^p / \sum_k \hat{\gamma}_k^p$ (we caution this approach ignores the covariation in parameter estimates, though these are not large in our application). Figure 3.5 presents a pie chart of these relative mix effects.

Figure 3.5 indicates that advertising explains most of the variation in the quantity premium, followed by discounting and product variety. Further, Figure 3.5 indicates that the positive effects of variety, distribution depth and breadth are larger than the negative effect of discounting on price elasticity. In sum, advertising and discounting play the greatest role in repositioning brands in the quantity premium but product and distribution play the greatest role in positioning along the margin premium dimension.

3.8.3 The Price and Performance Feedback Models

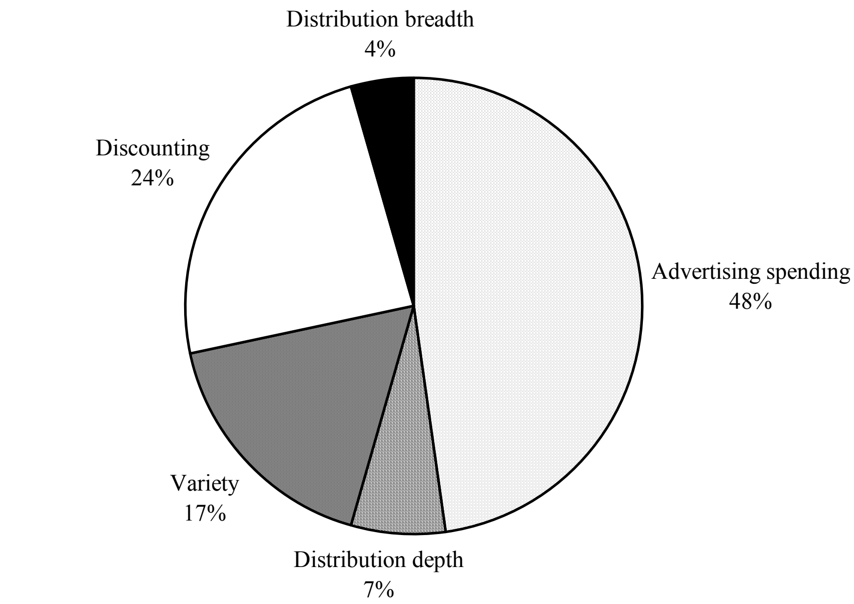
Competitor Interactions. Finally, we summarize the price DLM (Equations 3.4 and 3.5b) and the five marketing mix equations (Equation 3.6) findings. The results of the price DLM suggest that the dominant form of competitor interaction in the latent national pricing measure is no interaction (75% of all brands). When interaction exists, prices typically are positively correlated (19%) and in rare cases are negatively correlated (6%). These are in line with the findings in Steenkamp et al. (2005).

Performance Feedback. In 56% of the cases there is no own-sales performance feedback effect on pricing (Equation 3.5). When past sales do influence current prices the effect is mostly negative (28%). This result suggests large firms are more effective at getting retailers to pass through their discounts. The median 90% duration interval of these effects is 20 weeks.

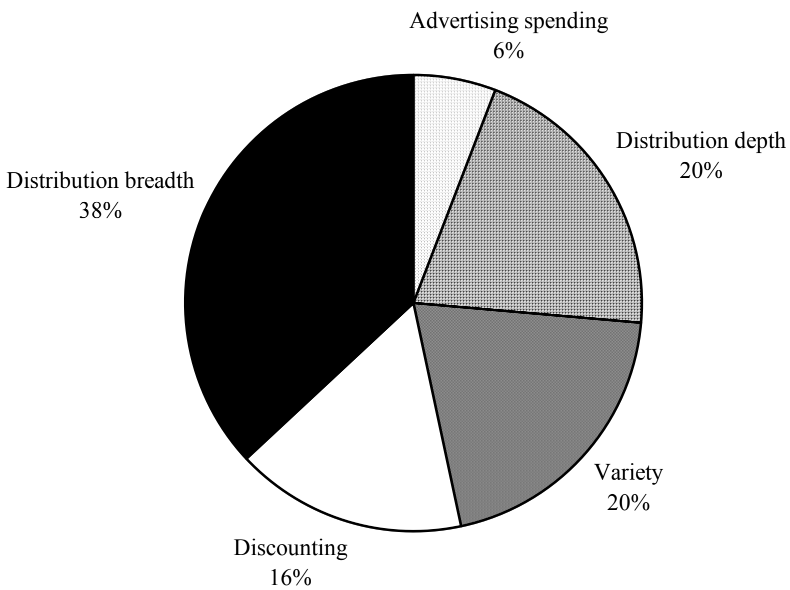
Own-sales performance feedback effects are positive in 75% of the cases for advertising, 54% of the cases for product variety, 76% of the cases for price promotion, 56% of the cases for distribution depth, and 78% of the cases for distribution breadth. Therefore, we surmise better historical performance generally leads to greater marketing spend. This result suggests it is critical to control for performance feedback, lest these feedback effects be ascribed to the role of marketing on sales.

The cross-sales performance feedback effects are mostly negligible for advertising (52%), discounting (65%) and distribution breadth (60%). In contrast, we observe negative cross-performance feedback effects for distribution depth (70%), indicating that better performing brands are able to capitalize on competitive weakness by increasing shelf-space.

Figure 3.5: Relative Effects across the Mix
Based on Standardized Regression Coefficients



(a) Effect on Quantity Premium



(b) Effect on Margin Premium

3.9 Managerial Implications

3.9.1 Better Measures and Data are Required to Manage Brands Over the Long Run

The foregoing analyses lend insights regarding the relative role the marketing mix instruments play in building brand equity. Empirical findings show that distribution, product innovation and advertising play a major role in building brands, while discounts serve to decrease price elasticity and quantity premiums. This result seems inconsistent with a singular emphasis on long-term effect of price promotions often observed in scanner-based marketing modeling (Bucklin and Gupta 1999) and at the firms we interviewed. One plausible reason that many firms adopt a short-term emphasis on promotions is that they have a large-short term effect that is easy to measure (Bijmolt, Van Heerde, and Pieters 2005, Kalra, Rajiv and Srinivasan 1998). The longer-term effects of product and distribution on brands are also less readily measured and take months or years to manifest (see also Lodish et al. (1995) for a similar discussion regarding the long-term effects of advertising). Compounding this problem, brand managers have a brief tenure in which to be promoted, often spending a year before moving to the next assignment. As such, long-term effects benefit their successor, while short-term effects benefit them. Since there is little incentive to invest in long-term brand building, brand managers may choose to ignore the instruments that do lead to beneficial long-term effects, such as advertising, new product introductions, and broader and deeper distribution.

While short-term sales and profits play an important role in firm strategy, it is desirable to develop longer-term equity based measures of brand performance to discourage the potential for harvesting major brands. Along these lines, firms can determine the desired position in the performance space for each of the brands in the firm's portfolio. Brand managers can then be judged in part on the extent to which they achieve these aims. Necessary conditions to create such an assessment scheme is (i) storage of multiple years of data on sales, prices, and other marketing activities, and (ii) estimation of the model proposed in this chapter. When both conditions are satisfied, the Bayesian nature of our model estimation allows management to update parameters whenever a new assessment is required. Surprisingly, purveyors of research such as IRI and AC Nielsen are moving in the opposite direction – compiling increasingly shorter spans of data that are sampled more frequently (e.g., IRI's Drivers on Demand), thus leading to an increased emphasis on discounting and short-term performance. This is further increasing the emphasis on short-term strategy. Ironically, these same firms, when queried about their beliefs regarding the drivers of brand strength suggest that product and distribution play the greatest role. Our solution is to supplement these shorter-term measures with longer-term ones.

3.9.2 Managing Brand Performance

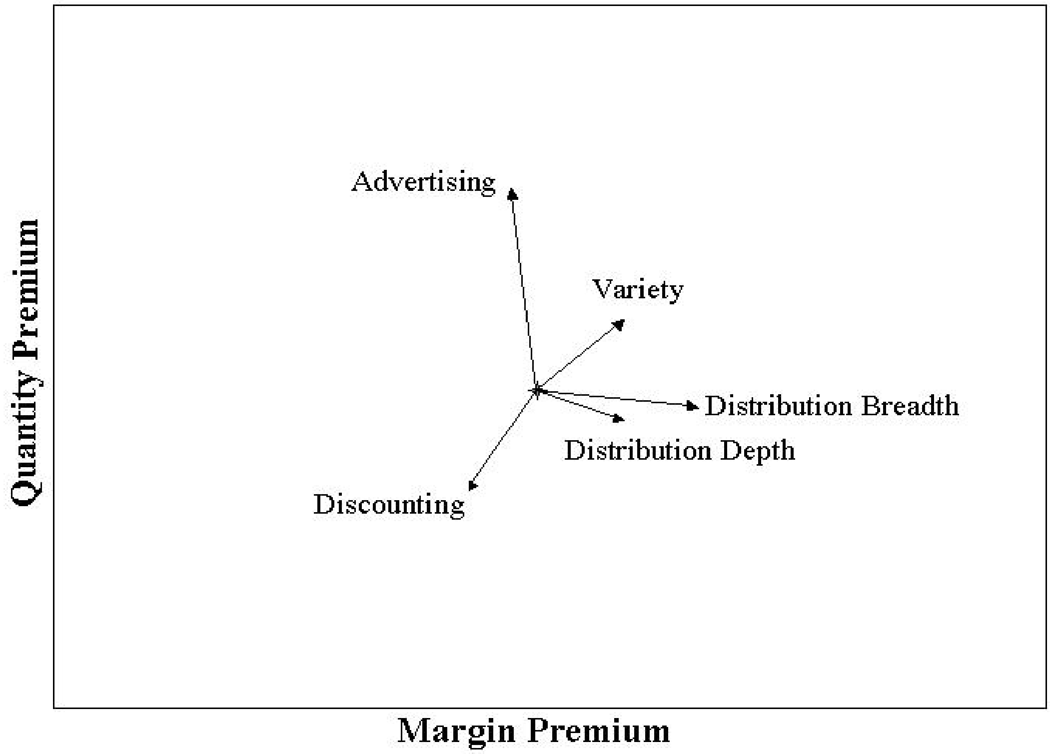
Our analysis provides insights on how price promotion, advertising, product, and distribution strategies can be managed over time to move over a performance space defined by multiple components of brand equity in Figure 3.6.

By manipulating the marketing mix and the estimates of our model, we can extrapolate how effective various strategies are in re-positioning brands in the equity space. Figure 3.6a exhibits the different effects of a one-period, one standardized unit change in each of the marketing mix instruments. Figure 3.6b depicts the net effect after one time period by summing these values. Figure 3.6c represents the net effect of a permanent change in marketing strategy, yielding a new position reflecting higher values on both dimensions of brand strength. In contrast, Figure 3.6d display the trajectory of a temporary change over several periods, showing that temporary investments do not lead to a new position in the long run.

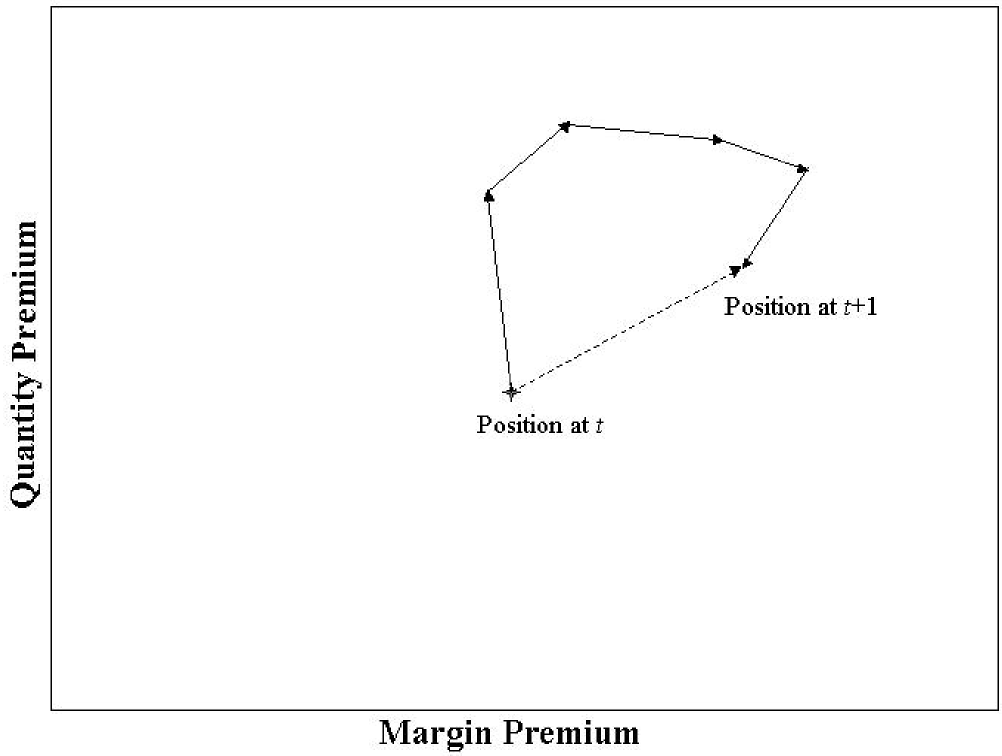
Next, we elaborate on the movement of brands across the performance space. Figure 3.7 depicts the trajectory of Brand G and Brand C, over five years. Brand G's success in increasing quantity and margin premiums can be ascribed to its policy of increased advertising and distribution (see Figure 3.2). In Figure 3.7, we also observe the turnaround of Brand C. At first, its margin and quantity premiums decrease owing to decreased distribution depth, low variety and low advertising. In the last year, the brand moves far and fast as a result of increased product activity, distribution and advertising coupled with a diminution in promotions.

In sum, we observe that marketing strategies relate to the long-term performance of brands. Moreover, it is worth noting that many of these strategies are coinciding. For example, Brand G accompanies its new variants with promotions. Were an analysis of Brand G's performance over time to exclude the product component, as commonly done in prior research, the deleterious effects of discounts could be understated as they were accompanied by more innovation. These examples demonstrate the desirability of considering these strategies in an integrated framework.

Figure 3.6: Visualizing Marketing Mix Impact

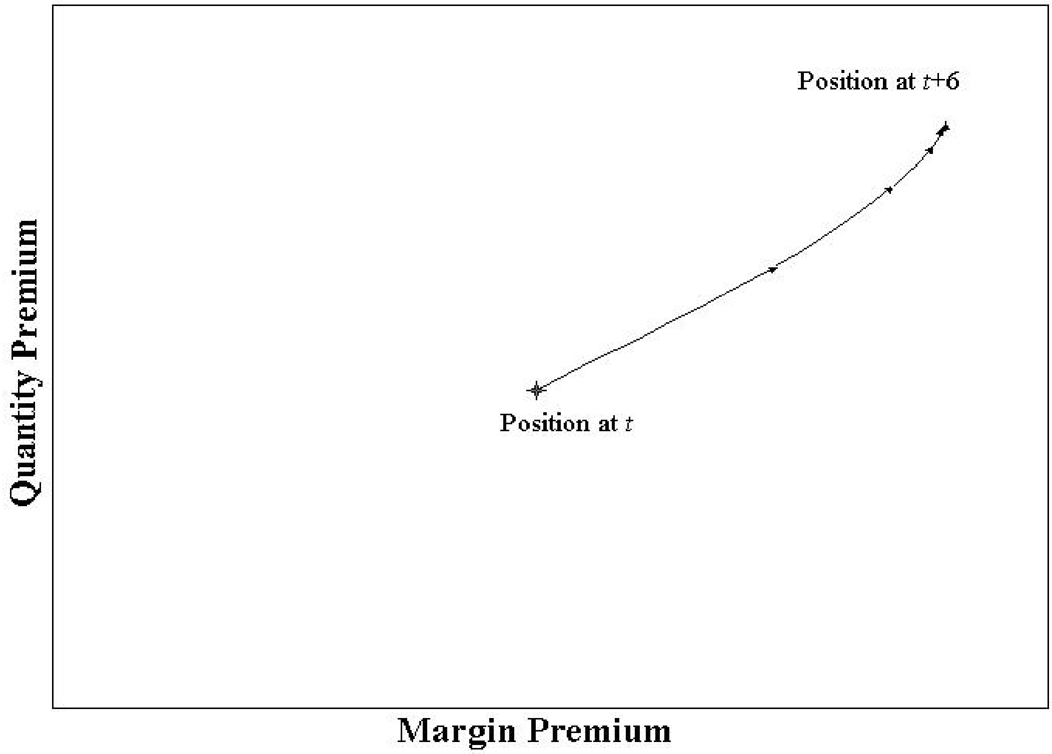


(a) Effects of one-period standardized changes in marketing instruments

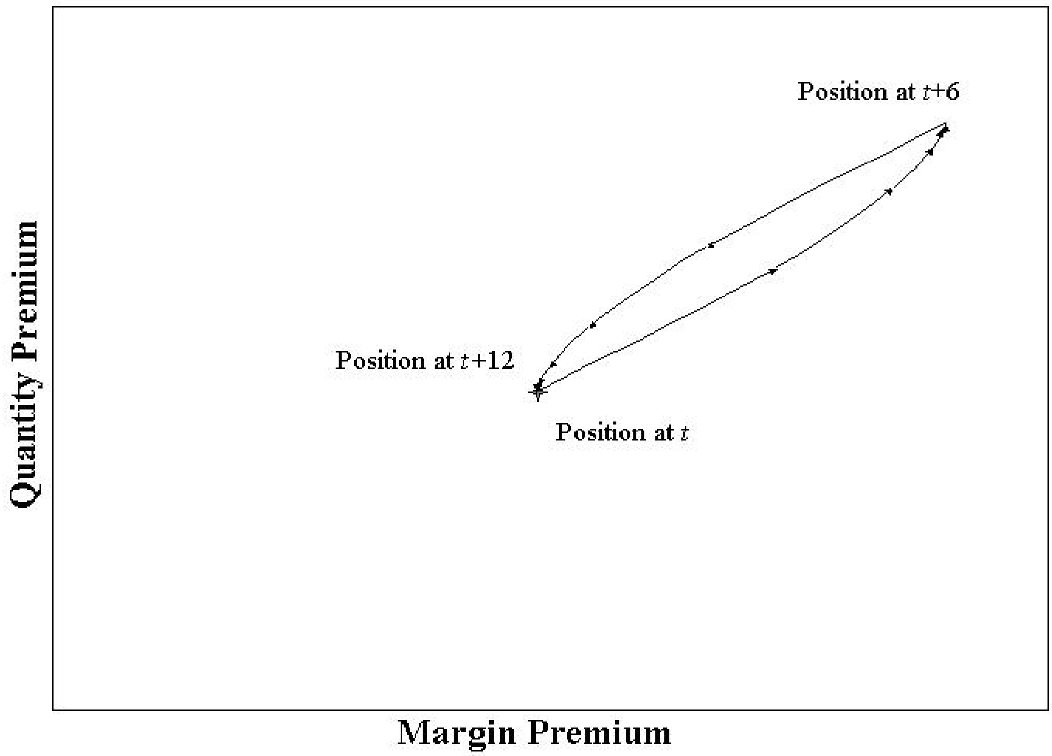


(b) Net sum of one-period changes across instruments

Figure 3.6: Visualizing Marketing Mix Impact (Continued)

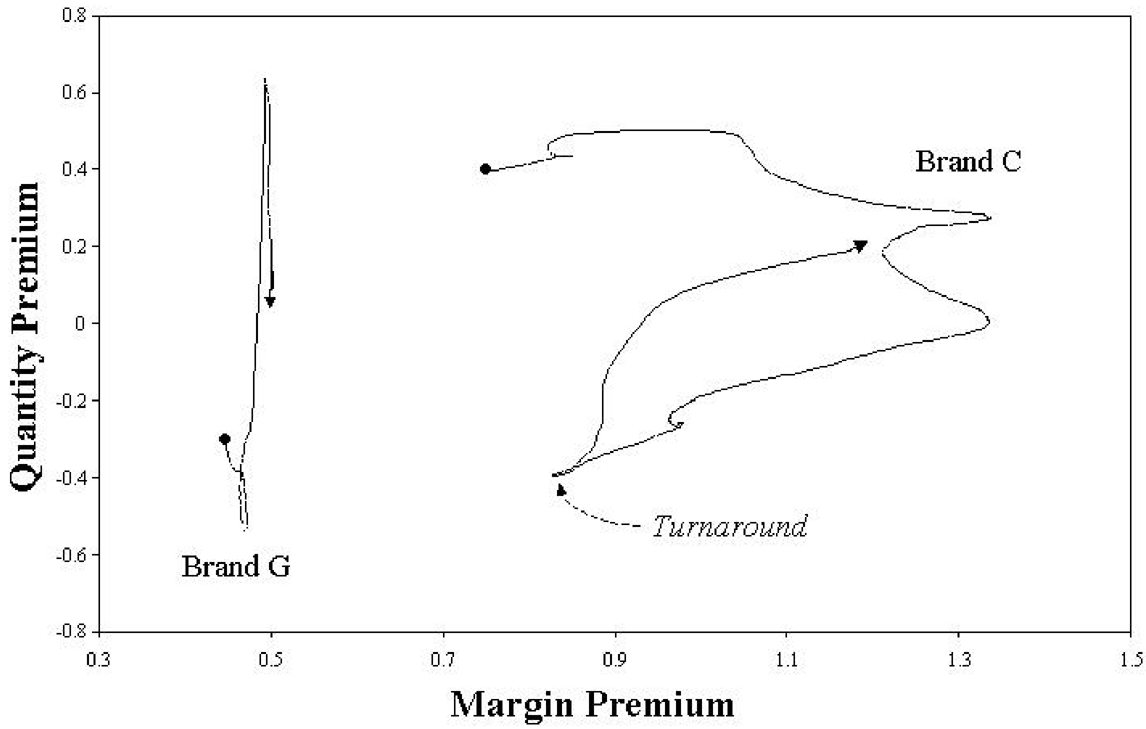


(c) Trajectory due to permanent changes in instruments



(d) Trajectory due to one-period changes in instruments

Figure 7: Trajectory on the Performance Space [a]



a. The figure is based on two-monthly moving averages of median intercept and elasticity estimates.

3.10 Summary and Conclusions

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

This study attempts to address both the data and the modeling requirements. We use five years of weekly data across 184 stores, 25 categories, and 70 brands. By observing brands that perform on the continuum from poor to well, and relating that performance to the brands' entire marketing mix strategy, insights are obtained regarding which strategies are most likely to lead to long-term advantages for brands. We apply our data to a Dynamic Linear Model (DLM), which allows us to model both sales and the marketing mix as dependent variables, which help us to address the three common pitfalls mentioned in the previous sections; endogeneity, performance feedback, and competitor pricing interactions.

Using the DLM, we link marketing strategy to two components of brand performance, quantity and margin premiums and find:

- Product variety, which serves to differentiate brands, is the only marketing mix instrument that can increase both quantity and price premiums. Discounts are the only element that decrease both.
- Overall, the effect of advertising and discounting on quantity premium are considerably larger than the effect of product and distribution, while the opposite holds for the margin premium.
- Adding new SKUs to the product line may strengthen shelf presence by increasing distribution depth. However the composition of the product line is important. Me-too SKUs can lower product entropy. This suggests gains from increased distribution depth can be countervailed by decreased variety. Ergo, it can be more desirable to offer a modest set of distinct alternatives than a large set of similar ones.
- Distribution breadth has little long-term effect on the quantity premiums of major national brands, perhaps because they are already widely distributed. On the other hand, it has the largest (positive) long-term effect on margin premium.

This study has a number of strategic implications for firms. We recommend brands supplement their short-term analyses (such as the effect of discounts on sales) with longer-term ones (e.g., their effect on baselines). When the long-term marginal effect of promotions is less than that of other mix elements, we recommend that more attention be allocated to other aspects of the marketing mix, especially product. Surprisingly to us, the major CPG firms we interviewed indicate their marketing and research budgets emphasize discounting and advertising even though they believe product and distribution matter more. This mirrors the trend to allocate attention to discounting and advertising in the marketing literature (Bucklin and Gupta 1999).

These findings are subject to several notable limitations, some of which point out several future research opportunities:

- The DLM is well suited to linking marketing activity to intercepts and elasticities but can not be scaled to a large number of variables, periods and observations because a) the state-space explodes and, along with it, the computer memory needed for estimation, and b) convergence of each model run takes weeks. Therefore our use of the DLM amplifies the trade-off between model parsimony and completeness. Accordingly, we have made a number of assumptions to render analysis feasible, including:

- Our model does not allow for different decay factors for different marketing mix instruments. One can write a canonical transfer function DLM to overcome this limitation and estimate different decay parameters for each marketing mix instrument using a data augmentation step in the Gibbs sampler.
- Several potential interactions exist in the marketing mix. For example, advertising itself may facilitate new distribution. We control for these effects indirectly via lagged performance feedback, which embed the marketing actions pursued by firms in preceding periods.
- We presume the effects of feature and display are fixed over time. Undoubtedly, these effects can change over time with marketing strategy. Expansion of the model to accommodate these effects would render such insights unreliable as a result of increased multicollinearity and model complexity. In an analysis not reported herein, we estimate a simpler version of the DLM wherein all parameters are time varying but the time paths are not specified to vary with the marketing mix. The estimated parameter paths for price and the intercept are largely the same as observed in our model, suggesting that the omission of time varying effects for feature and display do not bias our results. West and Harrison (1997, p. 97) discuss the robustness of the DLM to the specification of the observation equation as a result of local observability.
- We do not distinguish between discount and regular prices. Though most prior research does the same, it would be interesting to relax the model to accommodate potential differences. Yet Blattberg, Briesch, and Fox (1995) indicate evidence is mixed that these elasticities are actually different. Moreover, the equilibrium implications of increased discount elasticities are similar to increased price elasticities; a higher elasticity again implies lower margins. Hence, the insights from this adjustment are not likely to offset the additional cost of modeling them.
- We aggregate data to the chain level. It would be desirable to extend this research to the store level, as the chain level measures are noisier and the reduction in observations reduces power. As a result, our research is a conservative test of our hypotheses. Chain-level analysis is not uncommon in mar-

keting, perhaps because marketing activity tends to be correlated across stores within a chain.

  - We impose two restrictions on the nature of competitor interaction (Equation 5). First, we only consider interactions for like instruments. Second, we do not directly model contemporaneous response to the competitor's actions as there is some response latency. Results in Leeflang and Wittink (1992, 1996) suggest that these two assumptions are reasonable.
  - We consider the top 4 chains and the largest 3 brands in each category. As such, our results should be interpreted from the perspective of managers with large brands selling through predominantly large chains. It would be interesting to consider whether the results generalize to smaller niche brands and outlets.

  Most of these extensions are tangential to our central research objectives. Yet we believe they would form the basis for future work to further enhance our comprehension of the role marketing plays on performance in the long-term.

- Second, this chapter focuses upon mature brands. An analogous problem pertains to the management of recently introduced brands. One might observe reversals of some results reported in this chapter. For instance, for new brands price promotions could also help building quantity premiums, since these promotions may encourage trial purchases, and transform first-time buyers to repeat buyers. Moreover, for mature brands distribution is wide-spread. For new brands, this is not the case, which suggests that distribution may play a greater role.

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

Chapter 4

Consumer Packaged Goods in France: National Brands, Regional Chains, Local Branding[*]

4.1 Introduction

Do top national brands perform equally well in all geographic markets they are sold? Scanner-panel data based empirical studies in marketing that exclusively focus on a few top national brands also use data from a single, rather isolated, market and rely mainly on time series variation for estimating effectiveness of marketing mix instruments and making strategic recommendations. The implicit assumption behind this practice is the selected single market is a representative, scaled down version of the national market reality. However this assumption may not be a valid one. A recent study by Bronnenberg, Dhar and Dubé (2007) –BDD hereafter- provides solid evidence against this assumption, and even casts doubt on the concept of a national brand.

Using data from 31 categories over 39 four-week intervals in 50 United States markets, BDD observe that geographic variation is the predominant source of variation in national brand market shares. This phenomenon is shown to be brand specific, sug-

[*] This chapter is an extended version of the article Ataman, M. Berk, Carl F. Mela, and Harald J. van Heerde (2007), "Consumer Packaged Goods in France: National Brands, Regional Chains, Local Branding," *Journal of Marketing Research*, 44 (February), 14-20.

gesting a different market structure in each geographical region. Moreover these brand-market effects explain almost all the variation in market shares, indicating the practically negligible role time plays in explaining total variation in shares. This provocative observation is long overdue and points out that marketing has been too inattentive to this phenomenon.

Our goals in this chapter are threefold. First, we seek to assess whether this result generalizes to other markets, in particular France. France is an especially desirable market to contrast with the United States because more than a third of its retail chains and the bulk of its advertising are nationally-oriented. Moreover, France, like all European countries except for Russia, is smaller than the United States; the area of France is 7.2% of the conterminous United States land area (somewhat larger than a triangle whose vertices are formed by New York, Chicago and Atlanta) and the population of France is 21% of that in the United States. Therefore, one might expect that the results of BDD do not extend beyond the United States. Surprisingly, we find BDD's findings are robust in France. Whereas BDD find that brand-market interactions explain 92% of the total variation in share in the United States, we find these effects are also dominant in France, explaining 77% of the total variation in market share in France. This result is robust to the sampling rate of the data (weekly or four-weekly), the duration of the data (39 or 66 four-week periods), and the level of aggregation (9, 22, or 96 regions). Like BDD we find market shares exhibit spatial dependence. However, the spatial dependency in market shares is lesser in France presumably due to greater variation in local culture.

Second, we assess whether variation in market shares is related to chain effects. We consider chain variation for two reasons. The first reason is that many chains operate locally; therefore they represent another source of spatial variation in sales. The second reason is that the chains are an interesting phenomenon in their own right, and this issue has seen scant attention in the literature than the regional variation in market shares described by BDD. In contrast to the United States, where Bronnenberg, Dhar and Dubé (2006) find region effects dominate chain effects, we find chain structure explains more variation in market share than either regions or time in France. Moreover, the addition of chains attenuates the combined market and brand-market effects by 27%. It is interesting to speculate the degree to which this diminution in region-specific effects arises from regional differences in demand or marketing manifested at the chain level or whether it arises from differences in chains' strategies.

Third, we consider BDD's finding of negligible time variation in shares. Using the same duration, frequency and model as BDD, we replicate their finding that time effects are small (7% of the total variation in France compared to 1% in the United States). However, using a longer time horizon and higher sampling rate coupled with a brand-by-time interaction, we find that the proportion of explained variation in market shares due to brand-time effects in France (20%) is slightly larger than brand-region effects (18%). The weekly brand-by-time interactions can capture market share variation arising from brand-specific time-varying strategies such as promotions or advertising. One interesting prescription arising from this finding is that longer-term data are needed to properly assess time-variation in market shares.

The remainder of the chapter is organized as follows. In the next section, we describe the data set used in the chapter. Then, we summarize the sequence of models used to replicate BDD's results and extend their findings. The last section concludes the chapter.

4.2 Data

We use data provided by Information Resources Inc. (France). These data include just over five years (1/1/1999 to 1/31/2004) of weekly SKU-store level scanner data for 25 product categories sold in a national sample of 443 outlets representing 23 chains. While BDD use Nielsen designated Scantracks, there is no equivalent to designated market areas in France (or elsewhere in European Union, except the U.K.). Accordingly, we consider three sets of market definitions using geographic and administrative divisions in France. First we consider the nine main geographic regions in France (average population = 6,473,172 / average area = 22,964 mi^2). We also study a second market definition with twenty-two regions (average population = 2,659,943 / average area = 9,547 mi^2). These regions are also the main administrative units of the French government (somewhat like states in United States, although with less independence). The regional characteristics are quite pronounced in this breakdown as people promote and preserve valued traditions, from clothing to local types of food. These twenty-two regions are then subdivided into ninety-six departments (counties), which form the third market definition (average population = 609,570 / average area = 2,188 mi^2)[15]. Note that the nine-region breakdown is closest to the United States sample

[15] To be precise, we use 21 markets in the 22-region breakdown, as the island of Corsica is not included in the analysis. Furthermore, we observe stores located in 79 departments in the 96-region breakdown.

(BDD) with regard to the number of stores sampled per region, whereas the twenty-two-region breakdown is closest in terms of population per region. To make our sample most comparable to BDD and to decrease the covariation between chain location and region, we use the most aggregated market definition for our analysis (9 regions), though we consider the other two market definitions to explore the effect of regional aggregation.

We seek to make our data further comparable to BDD in terms of duration, sampling rate, and level of aggregation. Therefore, in each category we aggregated data from SKU-store-week level to the brand-four week-region level. Like BDD, we consider the variation over time in the volume share of the two largest national brands in each category. To make the data duration comparable, we initially focus only on the last 39 four-week time periods. Subsequently, we relax the duration, sampling rate, and level of aggregation restrictions to explore their effects.

Table 4.1 contains descriptive statistics for the market shares of the selected 50 brands (2 brands in 25 categories) based on the last 39 four-week periods. We report descriptive statistics for the market shares calculated using either data from all chains, local chains only, or from national chains only. We define a chain as national if it is present in all nine regions and local otherwise. The local chain only row mimics United States data wherein national chains such as Target and Wal-Mart are often excluded.

Table 4.1: Description of the Top Selling 2 Brands across 25 Categories

(a) All Chains					
	National Share	Dispersion	Range	Minimum	Maximum
Mean	.203	.132	.073	.162	.235
Std Deviation	.099	.087	.052	.086	.112
(b) Local Chains Only					
	National Share	Dispersion	Range	Minimum	Maximum
Mean	.199	.158	.091	.157	.249
Std Deviation	.098	.100	.061	.086	.121
(c) National Chains Only					
	National Share	Dispersion	Range	Minimum	Maximum
Mean	.194	.118	.064	.162	.226
Std Deviation	.097	.078	.043	.088	.109

Table 4.1 Panel A indicates that average national market share in the United States (BDD) and French samples are similar and around 20%. However, the standard deviation of national market shares across regions is lower in the French sample (.10 vs. .15 in the United States) and the dispersion is considerably smaller (.13 vs. .72 in the United States). This smaller dispersion may reflect the smaller size of the French market. It may also in part be due to the presence of retail chains operating nationally in the French data and brands operating locally in United States data. When considering only i) local chains and ii) nationally distributed brands in both data, the difference in dispersion between France and the United States becomes smaller (.16 vs. .43 in the United States). The increase in dispersion when national chains are omitted suggests that national distribution in France plays a role in the relatively low dispersion there. In addition, advertising expenditure data provided by TNS Media Intelligence (France) reveal that the bulk of brands in our sample do not spend money on regional advertising which is also consistent with BDD's speculation that local advertising may play a role in creating regional variation in market shares[16].

Figure 4.1 plots brands' regional shares against their national shares providing visual evidence in regional vs. national market share disparity. The figure also indicates that regional vs. national share disparity widens as national market shares increase (the correlation between brands' national market shares and variation of brands' shares across markets is .687 and significant).

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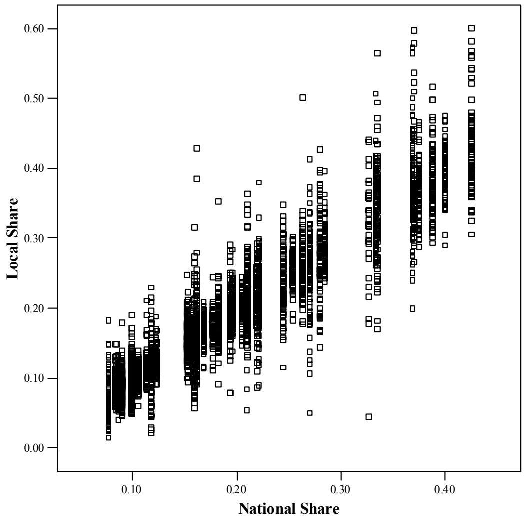
[16] Using endogenous sunk costs theory of market structure Bronnenberg, Dhar and Dubé (2006) attribute geographic long run performance differences between brand shares to strategic entry advantages, specifically to the advertising support early entrant's brand receives. The authors posit that first entrants invest more in advertising than the subsequent entrants, and this advertising investment creates a form of vertical product differentiation. The highest quality firm always garners market share and make positive economic profits. Performance variation across markets exists, and persists, when entry and advertising decisions are made at the geographical market level. This is possible to the extent that isolated advertising markets exist. As mentioned earlier, vast majority of advertising buying is national in France. However local buys are still observed within local media. Although regional advertising spending is negligibly small, we investigate, in a descriptive sense, the possibility that regional advertising may lead to regional differences in brand performance. In order to achieve this we use advertising expenditure data provided by TNS Media Intelligence with an exhaustive media breakdown. Press, television and radio advertising is further split into national and regional spending in these data. However the regional advertising activity cannot be included in the models estimated in this study as a covariate due to data unavailability. The TNS data breakdown doesn't specify how much is spent in each region. For the 50 brands in our sample we find that 41 brands spend 100% and 7 brands spend more than 99% of their annual advertising budgets nationally. However, in the beer category, where regional share variation is highest, the top two brands Kronenbourg and Heineken allocate approximately 10% of their annual advertising budgets to regional press, television and radio. Although we cannot formally conclude that local advertising activity is the primary cause of regional market share variation, regional advertising support a brand receives can be taken as a contributing factor, confirming the conjecture of Bronnenberg, Dhar and Dubé (2006).

Figure 4.1: Local vs. National Share



4.3 Approach

To assess whether regional differences dominate market share variation in France, and how robust this finding may be to factors such as data aggregation and duration, we estimate a sequence of generalized linear models as outlined in Figure 4.2. Using this approach, we explore the robustness of the dominance of regional effects to

(1) data duration;

(2) time aggregation;

(3) regional aggregation;

(4) chain aggregation;

(5) the addition of brand-by-chain interactions; and

(6) the addition of brand-by-time interactions.

We consider (5) because chains differ in their locations across regions and because chain-specific effects are an interesting consideration in their own right. Chain variation in shares can arise from differences in their clientele's preferences, or differences in retailer and manufacturer marketing support for a given brand across chains. To exemplify the role of chains in explaining variation in market shares, we consider Kellogg's cereal shares in two French chains denoted Chain 1 and Chain 2. Most of Chain 1's outlets are in the northeast of France while Chain 2's outlets are present in almost all regions. Kellogg's has low share in Chain 1 across its entire territory and tends to have a high share in Chain 2 across its territory (see Figure 4.3).

Figure 4.2: Analysis Steps

M0: Replicate analysis of BDD

Data: Brand – Market – Four Weekly – 39 periods
Approach: Linear (One factor at a time in ANOVA)
Model: Brand, Market, Time, Brand x Market
Market definition: 9 regions

M1: Translate BDD to all factors in ANOVA approach

Data: Brand – Market – Four Weekly – 39 periods
Approach: Linear (All factors in ANOVA)
Model: Brand, Market, Time, Brand x Market
Market definition: 9 regions

M2: Sensitivity to Duration

Data: Brand – Market – Four Weekly – 66 periods
Approach: Linear (All factors in ANOVA)
Model: Brand, Market, Time, Brand x Market
Market definition: 9 regions

M3a: Sensitivity to Time Aggregation

Data: Brand – Market – Weekly – 5 years
Approach: Linear (All factors in ANOVA)
Model: Brand, Market, Time, Brand x Market
Market definition: 9 regions

M3b and M3c: Sensitivity to Regional Aggregation

Data: Brand – Market – Four Weekly – 66 periods
Approach: Linear (All factors in ANOVA)
Model: Brand, Market, Time, Brand x Market
Market definition: 22 regions (M3b) and 96 regions (M3c)

M4: Sensitivity to Chain Aggregation

Data: Brand – Chain – Market – Weekly – 5 years
Approach: Linear (All factors in ANOVA)
Model: Brand, Market, Time, Brand x Market
Market definition: 9 regions

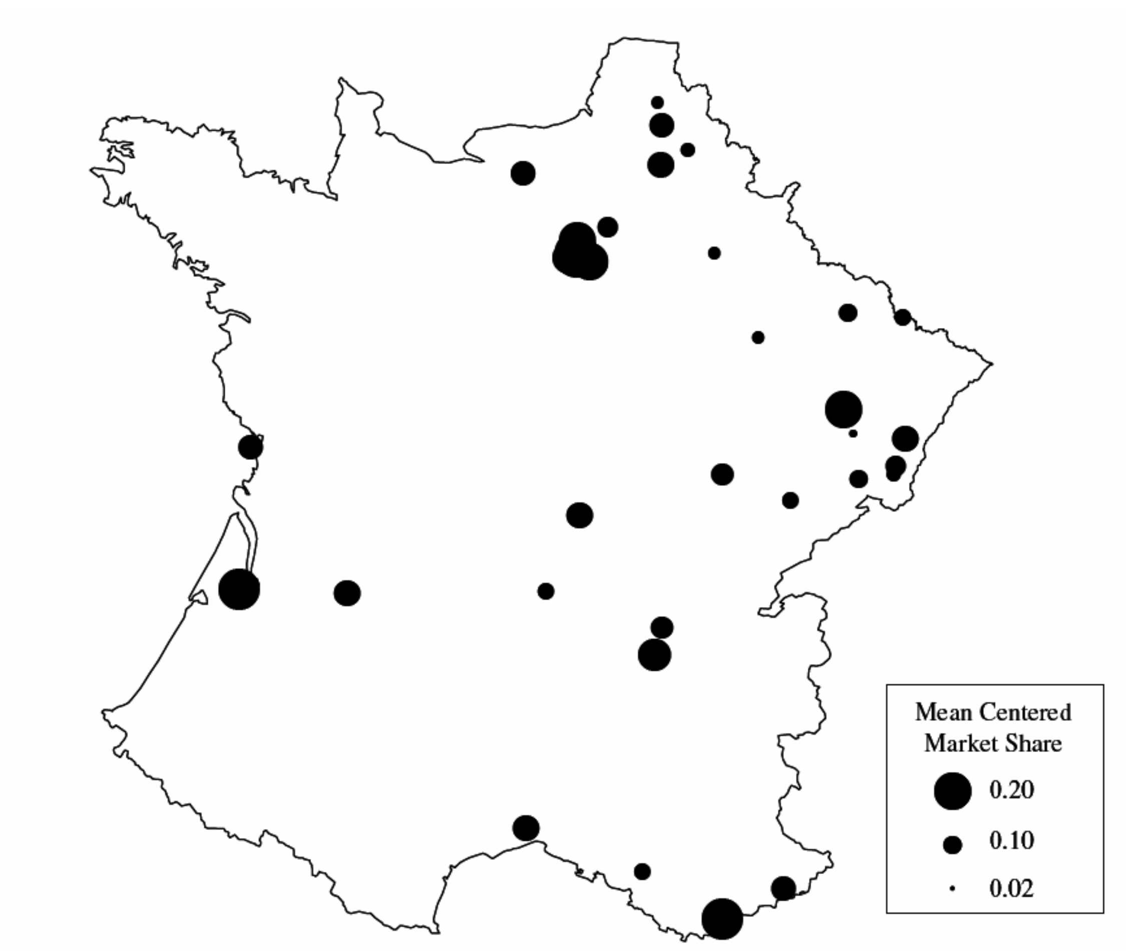
M5: Add Chain Effects

Data: Brand – Chain – Market – Weekly – 5 years
Approach: Linear (All factors in ANOVA)
Model: Brand, Chain, Market, Time, Brand x Chain, Brand x Market
Market definition: 9 regions

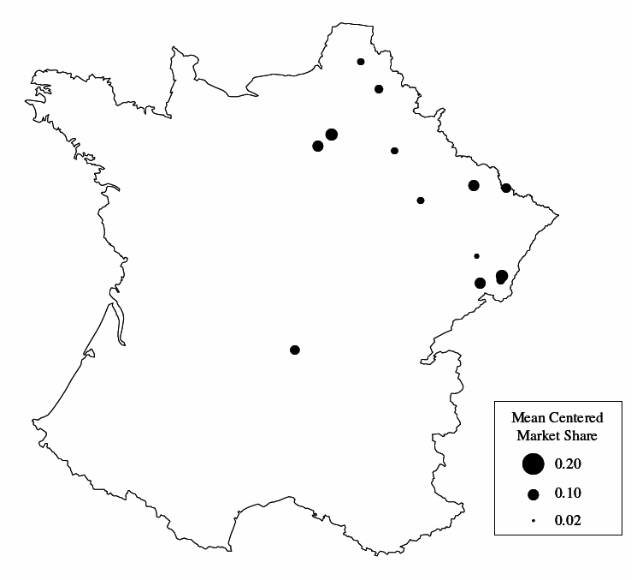
M6: Add Brand-Time Effects

Data: Brand – Chain – Market – Weekly – 5 years
Approach: Linear (All factors in ANOVA)
Model: Brand, Chain, Market, Time, Brand x Chain, Brand x Market, Brand x Time
Market definition: 9 regions

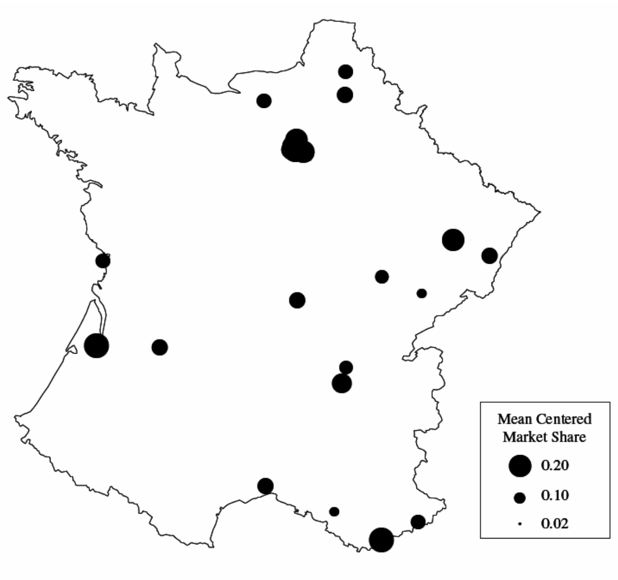
Figure 4.3: Market Shares of Kellogg's Cereals by Chain



(a) Two chains



(b) Chain 1



(c) Chain 2

This has a couple of key implications. First, when considering the very northernmost part of France (such as Nord Pas-de-Calais or Paris), the overlap of chain 1 and 2 in the same region leads to considerable within-region variation in market shares. This suggests that chain variation is an important component of market shares. Second, in regions where chains 1 and 2 do not overlap, such as Bordeaux in the southwest of France (wherein only chain 2 operates), it is unclear whether the high share for Kellogg's can be ascribed to a chain effect or a region effect. Therefore it is desirable to control for chain effects when measuring region effects, and the overlap of chains within at least some of the regions enables one to disentangle these effects (such as in our 9 and 22 region data). Figure 4.3 illustrates this point by plotting the deviations from the national market share of Kellogg's cereal across the two chains in France.

We consider (6), brand-time interactions, because time effects may be brand-specific due to brand-specific promotions or advertising. Time main effects (as included by BDD) may not explain much variation in share since share gains for one brand often come at the expense of another. This suggests the combined share of the top two brands might not vary much over time (were all brands included, constraints on the sum of market shares mitigate any over time variation).

4.4 Results

4.4.1 Market Share Analysis of Variance

Table 4.2 reports the results of each model. M0, reflective of the approach used by BDD, indicates (1) market main effects explain much more market share variation than time main effects (14.2% vs. 6.5%), (2) brand-market interactions explain more variation than the sum of their main effects (76.5% > 51.3% + 14.2%). These results reaffirm BDD's findings that there is a large, brand-specific geographic dispersion in market shares that dominates time main effects.

M1 replaces the "one-at-a-time" ANOVA of BDD wherein each factor is considered separately with a simultaneous ANOVA wherein all factors are simultaneously present. This controls for non-orthogonality in the design variable, as a very small number of brand-region-time combinations are not present in our data. M1 indicates the combined brand, market, and brand-by-market effect constitutes 50.9% + 14.1% + 11.1% = 76.1% of the total variation (similar to M0's 76.5%).

In M2 we assess the robustness of the findings to a 69% increase in the data duration (from 39 to 66 four-weekly periods). As indicated by BDD, more observations over time accommodate the possibility of an increase in time variation. Confirming their conjecture, the total variation accounted by time effects increases from 6.4% to 9.9% and the sum of brand, market, and brand-by-market effects drops somewhat to 71.3%. It is interesting to note that the *time variation increases in proportion to the data length*, suggesting that it is important for firms to collect long periods of data to assess the long-term effects of their strategies on market share (Ataman, Van Heerde, and Mela 2006).

The sensitivity of our results to time and regional aggregation is considered next. Regional differences as a percent of total variation become slightly more pronounced as we disaggregate markets: 71.3% for 9 regions (M2) vs. 69.5% for 22 regions (M3b) and 64.7% for 96 regions (M3c). Similarly, time effects become slightly less pronounced as a percent of total variation as time aggregation increases: 10.5% for weekly periods (M3a) vs. 9.9% for four-weekly periods (M2). Overall, the regional effects are largely robust to aggregation across time and region. Our subsequent analyses proceed using the most disaggregated time- (i.e., 264 weeks) and the most aggregated region levels (i.e., 9 regions) because the larger regions offer the most orthogonal design to disentangle region and chain effects and because the 264 weeks provides more information regarding time effects.

M4 considers chain aggregation by disaggregating the data from the brand-region-time level to the brand-region-time-chain level. The percent of total variation explained (39.8%) by the same four factors (market, brand, time, and brand-by-market) is much lower compared to M3a (77.4%) because of added variation in the data arising from unobserved chain-time-region-brand factors. Stated differently, adding observations but not regressors to the ANOVA decreases the explained variation in the model. This makes it difficult to compare the regional effects across the different data sets as the explained variation generally falls with more observations. To address this issue, we introduce another metric; *percent of explained variation* (as opposed to percent of total variation). The brand and market factors in M4 constitute (4.5% + 27.6% + 4.3%) / (4.5% + 27.6% + 4.3% + 3.4%) = 91.5% of the *explained variation* compared to 86.4% in M3a, 89.4% in M3b, 92.4% in M3c, 87.8% in M2, and 92.2% in M1. As these percentages are all roughly comparable, we conclude that regional effects are robust to aggregation across chains, markets, and time in terms of their relative importance in explaining variation in market share.

M5 adds chain and brand-by-chain effects to M4. We add chain effects as there is considerable regional variation in the location of chains as discussed above and because we conjecture these effects may explain considerable variation in market shares. Results of M5 indicate that chain effects (8.8%) explain more share variation than market (3.3%) or time main effects (3.3%) in France. Second, when we add chain and brand-by-chain effects we observe that the explained variation arising from the combined chain, brand, and brand-by-chain effect is larger than the combined brand, market, and brand-by-market effect (28.9% vs. 18.3%). Both factors appear to dominate time effects. Related, the percent of *explained variation* arising from brand, market and brand-by-market effects decreases from 91.5% in M4 to 47.4% in M5 because the variation explained by chain effects is considerable and because some of the regional variation in shares can be ascribed to chains. Reflective of this latter point, the percent of total variation explained by the combined region and brand-by-region effects decreases from 8.8% to 6.4% (a decrease of 27%) when we add chain effects, suggesting that it is desirable to control for chain effects when estimating region effects. From model M5 we conclude that not only do spatial variation in market shares merit additional attention, so too do variation in shares across chains.

M6 adds brand-by-time effects. In this model the combined brand, market, and brand-by-market effect accounts for 18.3% of the total variation, the combined brand, chain, and brand-by-chain effect accounts for 28.8% of the total variation; and the combined brand, time, and brand-by-time effect for 20.2% of the total variation in market shares.[17] Therefore, brand-time effects are somewhat larger than brand-region effects in France and constitute a key source of variation in market shares.[18]

[17] When adding a brand-by-time interaction to M0 (denoted M0a), we find the percent of total variance explained by market, brand, time, brand-by-market and brand-by-time are 14.0%, 50.9%, 6.9%, 11.1% and 12.5% respectively. This indicates that brand and time effects as a percent of total variance (70.3%) are smaller than combined brand and region effects (76.0%) in France, but still sizable. The increasing relative importance of time effects at the chain-week level may reflect chain-level differences in promotional strategy.

[18] We also estimated a MANOVA of the two brand shares on brand, chain, region, and time. This analysis controls for within-chain covariation of brand shares for a given chain-region-period. In the betweens subject block, market, chain and time explain 12.3%, 27.2%, and 11.1% of the total variation whereas in the within subject block the market, chain and time effects explain 7.6%, 15.8% and 11.1% of the total variation. The brand effect is 23.4%, thus brand effects are dominant on within chain differences in brand shares and chain effects are dominant on mean share differences across markets. Related, time effects exceed region effects within chains, while the region effect exceeds the time effect across chains. This

Table 4.2: Percent of Variance Explained (Average Across 25 Categories)[a]

Model	Data (Duration / Market definition)	Market	Chain	Brand	Time	Brand x Market	Brand x Chain	Brand x Time
M0	Brand-Market-Four week *(39 time periods / 9 regions)*	14.2%	-	51.3%	6.5%	76.5%	-	-
M1	Brand-Market-Four week *(39 time periods / 9 regions)*	14.1%	-	50.9%	6.4%	11.1%	-	-
M2	Brand-Market-Four week *(66 time periods / 9 regions)*	12.5%	-	48.5%	9.9%	10.3%	-	-
M3a	Brand-Market-Week *(265 time periods / 9 regions)*	11.3%	-	46.2%	10.5%	9.4%	-	-
M3b	Brand-Market-Four week *(66 time periods / 22 regions)*	12.2%	-	43.4%	8.2%	13.9%	-	-
M3c	Brand-Market-Four week *(66 time periods / 96 regions)*	13.8%	-	35.3%	5.3%	15.6%	-	-
M4	Brand-Chain-Market-Week *(265 time periods / 9 regions)*	4.5%	-	27.6%	3.4%	4.3%	-	-
M5	Brand-Chain-Market-Week *(265 time periods / 9 regions)*	3.3%	8.8%	11.9%	3.3%	3.1%	8.2%	-
M6	Brand-Chain-Market-Week *(265 time periods / 9 regions)*	3.3%	8.8%	11.9%	3.1%	3.1%	8.1%	5.2%

[a] We report the average eta-squared for all models. Note that M0 results are comparable to BDD as eta-squared and R-squared statistics are identical in models with a single fixed effect.

4.4.2 Spatial Dependence

Following BDD, we estimate the spatial autocorrelation in market shares using the non-parametric approach of Conley and Topa (2002). The dependence between the observations is assumed to be a function of the physical distance between pairs of regions. Denoting the observed market share data by s_m, indexed by region m with coordinates ω_m in an Euclidean space, the spatial autocovariance function can be defined as,

(4.1) $$\mathrm{cov}(s_m, s_{m'}) = f\left(D_{mm'}\right),$$

where

(4.2) $$D_{mm'} = \left\|\omega_m - \omega_{m'}\right\|$$

implies that it is between-subject variation in market shares that is the predominant source of regional variation in shares.

is the Euclidean distance between regions *m* and *m'*. Conley and Topa (2002) propose estimating the autocovariance function in (4.1) non-parametrically using Kernel-smoothing over a grid of distances. At each grid point, δ, the estimated spatial autocovariance is given by

$$\hat{f}_s(\delta) = \sum_{m,m'\neq m} W_N \left\| \delta - D_{mm'} \right\| \left(s_m - \bar{s}\right)\left(s_{m'} - \bar{s}\right), \tag{4.3}$$

where $W_N\| \delta - D_{mm'} \|$ are weights. If a uniform Kernel with a bandwidth of η is used, as commonly applied, then the weights are given by

$$W_N \left\| \delta - D_{mm'} \right\| = \begin{cases} \dfrac{1}{N_\delta} & if \ \left\| \delta - D_{mm'} \right\| < \eta \\ 0 & otherwise \end{cases}, \tag{4.4}$$

where N_δ is the number of region pairs within $\delta \pm \eta$ distance. Finally, to obtain the spatial autocorrelation function (4.3) is standardized by the sample variance of shares,

$$\hat{\rho}_s(\delta) = \frac{\hat{f}_s(\delta)}{\mathrm{var}(s)}. \tag{4.5}$$

We estimate spatial autocorrelation using each brand's mean market shares across 50 markets and a uniform Kernel with a bandwidth of η = 50 miles, which is approximately 25% of distance distribution's inter-quartile range for each level of regional aggregation. We obtain the acceptance regions of the autocorrelation functions using a bootstrap procedure, wherein data are re-sampled from the empirical marginal distribution with replacement and locations are fixed. See Figure 4.4 for selected spatial autocorrelation function examples and Figure 4.5 for the distribution of spatial independence distances.

Figure 4.4: Selected Spatial Autocorrelation Function Examples

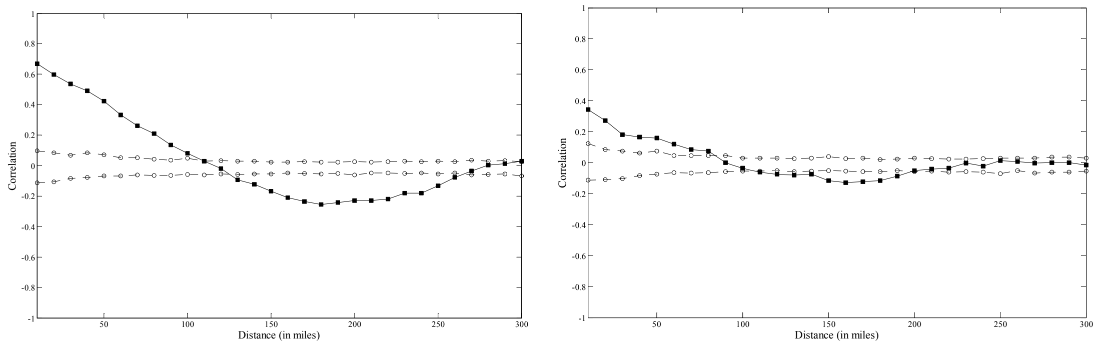
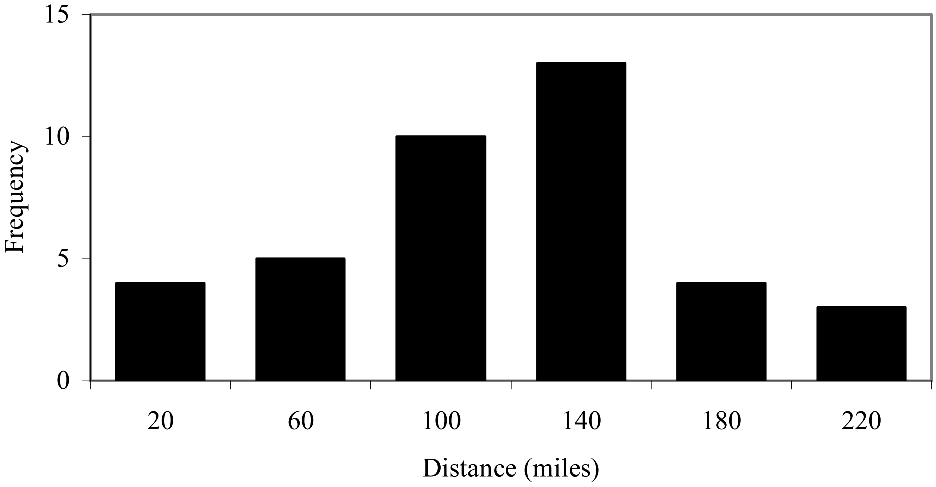
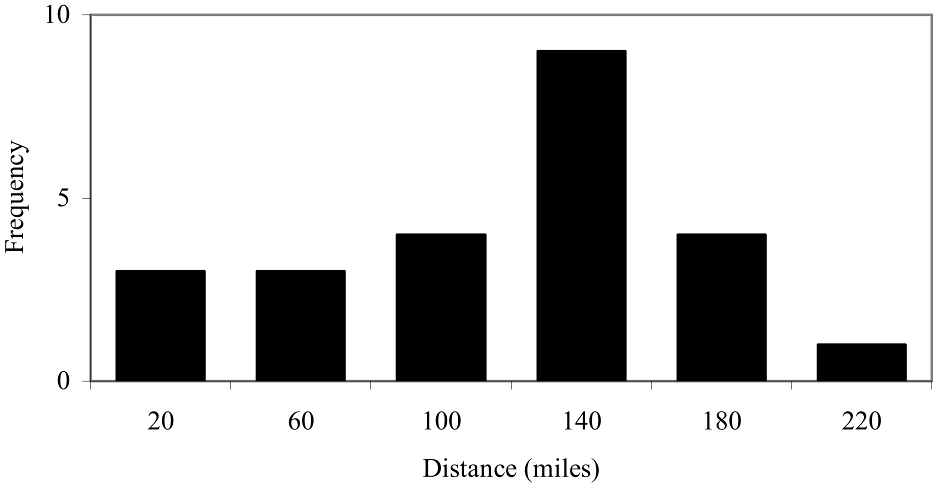


Figure 4.5: Distribution of Spatial Independence Distances (Exclusive of zeros)



(a) 96-region breakdown



(b) 22-region breakdown

We find significant spatial autocorrelation primarily in the lowest level of regional aggregation (the spatial autocorrelation is significantly different from zero for 78%, 48% and 10% of brands in the 96, 22, and 9 region levels respectively). We find that brand shares are correlated in regions separated on average by 96, 58 and 9 miles in the 96, 22, and 9 region levels respectively (inclusive of zero distances). The finding of lower levels of spatial autocorrelation in France may reflect greater regional heterogeneity in customs and culture in France (like many countries) relative to the United States. For example, the eastern-most regions of Alsace-Lorraine and Moselle are influenced by German-speaking cultures, Flemish culture is prevalent in the far northeast, Italian influences are present in the far south-east, Celtic influences are common in Bretagne in the northwest, and Catalan and Basque culture are evidenced along Spanish border. This suggests that spatial covariation is most likely to manifest at the most local level. Consistent with this conjecture, much of this spatial covariation is attenuated when aggregating across regions.

4.6 Conclusion

In this chapter we show that the findings of BDD regarding the central role played by regional variation in market shares are replicated in France. In short, the important source of market share variation documented by BDD that has heretofore been under-attended by marketing research is robust across different levels of time and region aggregation and time duration. Moreover, spatial dependence in market shares appears to be a common phenomenon in France and the United States. Second, we find that a large portion of the explained market share variance in France is due to chain effects. Importantly, these chain effects exceed region and time effects suggesting that there is another important component to market shares that has been largely underattended by the field. An interesting avenue for future research would be to assess whether these chain differences are another manifestation of regional variation in shares arising from manufacturer policy or local consumer preferences, or whether they are related to other chain-specific factors. Third, by extending the analysis of BDD to the chain-weekly level over five years and adding brand-time interactions, we find that brand-time effects are larger than brand-region effects in France. We also find the time variation in share increases with the duration of the data and therefore recommend that firms work to collect data over increasingly long durations to better understand how brands garner enduring share advantage.

Given the plethora of research pertaining to explaining brand-time variation, we find the relative dearth of research regarding spatial and chain effects to be surprising, and commend BDD for their pioneering research in this area.

Chapter 5

Concluding Remarks and Directions for Future Research

5.1 Where are we now?

Managing brands throughout their lifecycle is a complex task in today's highly competitive markets. The complexity arises from the need to balance the short- and long-term goals regarding the brand. However, (1) the ever increasing amount and frequency of performance data available to the market players, (2) the litany of short-term sales response models continuously promoted by large market research agencies, and (3) the brand managers' brief tenure periods have shifted the focus of brand management from a strategic (long-term) perspective to a tactical (short-term) perspective (Lodish and Mela 2006).

Despite the emphasis on short-term performance prevalent in the industry and the academia, the essays in this book focus on the long-term performance of brands. Although recent research has advanced our understanding of the long-term effects of certain marketing mix instruments on brand performance, no study has considered the entire marketing mix in unison and generalized the findings. We investigate how the 4Ps (price, promotion, product, and place) simultaneously affect the long-term performance of brands, and offer a more complete and generalized understanding of managing brand performance in the long run. Next, we present a summary of the main findings, followed by implications for managers and research in marketing. Finally, we discuss a number of future research opportunities.

5.1.1 Summary of Findings

The first essay of this book investigated which marketing strategies are most effective for introducing new brands and sheds light on this issue by ascribing growth performance to firms' post-launch marketing choices. The success of a new brand is decomposed into its ultimate market potential and the rate with which it reaches this potential. To achieve this aim we formulated a Multivariate Bayesian Dynamic Linear Model of repeat purchase diffusion wherein growth and market potential are directly linked to the new brands' long-term advertising, promotion, distribution, and product strategy. In the second essay we sought to obtain a more complete view of what drives performance of established brands by considering all four elements of the marketing mix in unison. Using insights from the brand equity literature, we decomposed brand performance into quantity premium (baseline sales) and margin premium (reciprocal of price elasticity in absolute terms), and analyzed how these performance measures evolve over time as a function of marketing activity. The analysis was again based on a Multivariate Bayesian Dynamic Linear Model.[19] In the final essay we investigated the spatial variation in the performance of established brands assuming that regional differences are a manifestation of long-term marketing effects. This essay, written as a response to Bronnenberg, Dhar and Dubé (2007a), showed that geographic variation is the predominant source of variation in national brand market shares, and that the result is robust to the sampling rate of the data, the duration of the data, and the level of aggregation. Role of other factors were also entertained.

In these three studies we systematically analyzed the performance of 295 brands in 25 different product categories, using a maximum of five years of weekly data and a nearly exhaustive set of marketing mix instruments. We found:

[19] A natural alternative to the multivariate DLM estimated in Chapter 3 is the matrixvariate dynamic linear model (Quintana and West 1987). This class of DLMs is especially useful when modeling multiple multivariate series that are viewed as structurally similar, such that they share common defining elements F_t, G_t, and W. The matrixvariate DLM offers a parsimonious way of modeling covariation among observations. However identification of model parameters is a crucial issue when the time series are structurally dissimilar, e.g., the series do not share a common state evolution matrix. In that case a column vectorized form of the matrixvariate DLM may be preferred to overcome the identification issue. The DLM used in Chapter 3 is an example of this approach.

- Discounts help new brands grow faster but they eventually lower the market potential of these brands. The net effect on long-term performance is small yet negative. Moreover, discounts decrease the quantity premium and the margin premium that established brands enjoy. These findings taken together indicate that discounting has negative long-term consequences for brands regardless of their position on the brand lifecycle curve.
- Advertising builds market potential for a new brand and facilitates faster growth. When the brand reaches the status of an established brand, advertising support increases quantity premium, however its effect on margin premium is negligible.
- Features, displays and other in-store communication tools not only boost brand sales in the short run but also build market potential for new brands by advertising their existence and unique features. Their long-term effects on the two components of established brand performance (quantity premium and margin premium) are yet to be explored.
- Two understudied correlates of brand performance, product line length and composition, appear as crucial factors. New brands carrying longer lines obtain higher equilibrium sales and reach the steady state faster than brands that offer a low number of alternatives. Product line composition, i.e., the variety of the brand's product line, which serves to differentiate brands, increases both quantity and margin premium of an established brand.[20]
- Distribution breadth and depth, also understudied determinants of brand performance, are crucial for new as well as established brands. The effect of distribution breadth exceeds the combined effect of all other marketing effects that determine market potential for a new brand. It is also the most important marketing mix instrument that governs the rate of growth. Moreover, broad availability enhances the efficacy of other marketing mix instruments. However distribution breadth has little long-term effect on the quantity premium of a major

[20] The reader might have noticed the discrepancy concerning the product variables in Chapter 2 and Chapter 3. It is plausible to expect that the composition of the product line, in addition to product line length, plays a role in the growth process of new brands. The model in Chapter 2 was estimated with a new variable 'uniqueness', a simple attribute matching based measure of brand dissimilarity, to accommodate line composition. However, uniqueness had a negligible effect compared to other instruments of the marketing mix. The substantive findings regarding other marketing mix instruments in both models were virtually identical. The long-term effect of product line length on quantity premium and margin premium are yet to be tested.

national brand, because they are already widely distributed and the additional distribution is most likely from marginal chains. On the other hand, distribution breadth has the largest (positive) long-term effect on margin premium. Finally, distribution plays a central role in explaining differences in sales across geographic regions in France.

In sum, we found –contrary to the emphasis on advertising and discounting- that product and distribution are the main drivers of a brand's long-term success.[21]

5.1.2 Implications

The findings in the three essays have a number of implications for managers and research in marketing. We start by discussing the managerial implications and then offer implications for marketing research.

Broad Distribution Coverage Is Vital for Brands

Brands have base performance levels and weekly/quarterly sales figures are just noisy manifestations of the underlying performance, masking the true performance. This performance, which can be decomposed into various components, is dynamic and determined by the long-term marketing support. Gaining access to distribution – increasing distribution breadth- is the most critical determinant of long-term brand performance and therefore needs to be on the top of a brand manager's checklist. As returns from adding new points of sale are decreasing, the manufacturer has to rely on other instruments of the marketing mix, such as advertising or line extensions, to ensure further growth. However, keeping distribution coverage constant at a certain level is crucial for stasis, as a performance decline results in distribution coverage erosion.

Brands Need Product Line Extensions that Increase Variety

Product line length and its composition are two other crucial determinants of a brand's long-term performance. A firm can strengthen its brand's position in the market by increasing product line length because adding new SKUs to the product line increases the likelihood of that brand being selected in the category and because the extension strengthens shelf presence by increasing distribution depth. The effect materialized through these two routes is beneficial for new brands as well as established brands. However, the composition of the product line is also crucial. The variety offered by the brand declines when me-too SKUs are added to the product line. This in return can

[21] Note that, these findings are mean tendencies and the results may vary by category. Future research should investigate whether and how long-term effects change by category.

countervail the gains from increased line length and distribution depth. Therefore, the manufacturers have to consider these opposing forces when designing their product lines.

Align the Brand's and the Brand Manager's Agendas

The tactical moves –especially offering deep and frequent discounts- that brand managers make to boost brand performance in the short run and to prove themselves worthy of a promotion, lower brand performance in the long-run. Brand managers may choose to ignore marketing mix instruments that lead to beneficial long-term effects – such as advertising, new product introductions, and broader and deeper distribution- as there is little incentive to invest in long-term brand building –because long-term effects of their actions benefit their successors. Manufacturers, on the other hand, seek to carry brands with strong sustainable positions in the market. A remedy for this manufacturer-brand manager goal incompatibility would be to judge brand managers on the extent to which they achieve the long-term targets set by the firm in addition to their short-term targets.

Adopt New Sales Response Models

Brand managers may also refrain from investing in long-term brand building instruments as there is little evidence regarding their effects (it may take months or years to manifest), and adopt a short-term emphasis on discounts because their effects are large and easily measured. Developing and/or adopting a brand health assessment system that supplements short-term analyses with longer-term ones could provide the needed motivation for investing in long-term brand building instruments. A necessary condition for adopting such an assessment system is storage of multiple years of data on sales and marketing activities, which are already present in the databases of research agencies. Once equipped with that data the management could estimate the models developed in this book, and update their predictions whenever new data becomes available (or a new assessment is required) using the Bayesian nature of our models.

Product and Place as Information Cues for a Bayesian Learner

The evolution of literature streams on the long-term effect of marketing strategy using aggregate data and disaggregate data are coincidental. The strong interest in discounts and advertising in the former stream of literature is shared by the latter, wherein consumers use pricing and/or advertising signals as diagnostic information. However, if consumers are rational economic agents who observe firms' behaviors and act as Bayesian learners, then they should be able to process product and distribution cues in addition to pricing and advertising cues. Assuming that the aggregate models are able to capture at least a part of the underlying individual level dynamics, our findings suggest that consumers use product and distribution signals as even more diagnostic information cues. Therefore it is important to extend the dynamic choice modeling stream to other aspects of the marketing mix.

Exploit Variation across Markets as a New Source

Extant modeling research uses data on a national brand from a single, rather isolated, market and relies mainly on time series variation for estimating effectiveness of marketing mix instruments and making strategic recommendations. Here, the implicit assumption is that the selected single market is a representative, scaled down version of the national market reality. However this assumption is not a valid one as national brands perform differently in regional markets. As performance, therefore marketing activity, varies markedly across markets, results based on an analysis of a single isolated market are not generalizable. Academic and industry research should also exploit this recently documented source of variation.

5.2 Where do we go from here?

The following sections discuss several avenues for future research that emerged while the three studies in this book were being conducted. We address the substantive issues, try to discuss the modeling challenges, and outline the proposed solutions as much as possible. Unless otherwise mentioned, the adopted modeling approach mainly follows the Dynamic Linear Models and Bayesian forecasting tradition and extends this framework in various respects.

5.2.1 Long-term Drivers of Store Equity

As pointed out in a number of recent studies, building and maintaining equity is imperative for retail chains as it is for manufacturers (Ailawadi and Keller 2004; Hartman and Spiro 2005). The studies that conceptualize store equity call for empirical research on measuring and identifying the drivers of store equity.

The first issue that needs to be addressed is how one can measure store equity. Both Hartman and Spiro (2005) and Ailawadi and Keller (2004) parallel the definition of store equity with that of brand equity. Therefore it might be possible to use one (or a combination) of the proposed brand equity measures in the literature. A thorough review of related studies suggests that revenue premium (Ailawadi, Lehmann and Neslin

2003) as a measure of brand equity can indeed be used to measure store equity. Revenue premium, in a goods context, is defined as the difference between the revenue of a branded product and a corresponding private label. If the reference point is chosen as a hypothetical unbranded product as in Swait et al. (1993), implying zero revenue, the brand's revenue at a given point in time serves as the measure of brand equity. Replacing "product" with "store" one can use this measure of equity also for retail stores. Provided that one wishes to use this equity figure to compare stores, it is necessary to standardize this measure by store size. This standardized equity is directly related to a previously used measure of store performance, revenue per square meters, a productivity based retailer performance measure adopted by Reinartz and Kumar (1999) and Kumar and Karande (2000).

The second issue we would like to address is the drivers of store equity. Extant research has analyzed the impact of store-level marketing activity on store performance. Yet again the marketing variables were considered only in isolation (e.g., Kumar and Leone 1988; Walters 1991; Lam et al. 2001; Rhee and Bell 2002; Gijsbrechts, Campo and Goossens 2003) and none of the studies adopted a long-term perspective (a notable exception is Srinivasan et al. 2004). Provided that equity (of a brand or of a store) is the accumulation of marketing investments over many years, taking a long-term perspective and focusing on a large set of store level marketing variables is desirable. A quick review of the literature yields as some of the drivers feature promotions, displays and other in-store communication activities, breadth and depth of discounting, assortment breadth, assortment depth, and the store's private label program. Using this exhaustive set of store-level marketing variables, we can offer a more complete understanding of how store equity is built in the long run and which instruments matter the most. These insights may help retail managers make better decisions when allocating resources, making trade-offs between various instruments, under tight budget constraints.

Furthermore it is interesting to generalize the findings of this study by conducting the analyses across many stores and chains. However such generalizations require the use of large data sets (e.g., hundreds of stores operated by tens of different chains). Provided that Bayesian models of long-term marketing effects are computationally very demanding, the modeler faces a challenge of reducing the complexity of the problem. At least two modeling alternatives exist that deal with the high dimensionality problem: a hierarchical DLM specification (*à la* Gamerman and Migon 1993) and a factor analytic DLM specification (*à la* Lopes, Salazar and Gamerman, 2006). Next we briefly discuss these specifications and point out the new model features.

First, one can specify a hierarchical DLM to reduce the dimensionality of the model. Recent research in Bayesian forecasting proposed an extension to DLM that concerns analysis of a time series of cross-sectional data. This generalization of multivariate DLMs comprises stratified parametric linear models where relations between cross-sectional data points are structured within the model. The observation and evolution equations (5.1) and (5.3) are coupled with one (or more) structural equation(s) (5.2) that describe(s) the structure of parameter hierarchy (Gamerman and Migon 1993).

(5.1) $$Y_t = F_{1t}\theta_{1t} + v_{1t},$$

(5.2) $$\theta_{it} = F_{i+1t}\theta_{i+1t} + v_{i+1t}, \text{ where } i = 2,...,k-1,$$

(5.3) $$\theta_{kt} = G_t\theta_{kt-1} + \omega_t.$$

Dimension of the state vector reduces progressively as one goes up the parameter hierarchy. This makes estimation a less computationally demanding process as the evolution of the state vector is defined at the highest level of the hierarchy[22]. I propose extending this framework by incorporating the spatial structure in the data.

As with any DLM we start by specifying the observation equation. A simple linear model with a time varying intercept, $RP_{cst} = \pi_{cst} + \upsilon_{1cst}$, is sufficient at this stage. The dependent variable RP_{cst} is the revenue in week t, store s, chain c and $\upsilon_{1cst} \sim N(0,V_1)$. In the first level of the hierarchy we eliminate the store dimension by specifying a structural equation that imposes $\pi_{cst} \sim N(\pi_{ct}, V_2)$, where $V_2 = \tau^2 R_\phi$ and R_ϕ is a distance-based correlation matrix that takes into account the spatial dependence among observations (Duan and Mela 2006). In the second level of the hierarchy we further reduce the dimension of the state vector by specifying a second structural equation as $\pi_{ct} \sim N(\pi_t, V_3)$, where $V_3 = \sigma^2 R_\delta$ and R_δ is a matrix that captures the relationship between retailers, such as percentage of overlapping markets. The system equation is specified as follows: $\pi_t = \lambda\pi_{t\text{-}1} + h_t + \omega_t$, where $\omega_t \sim N(0,\rho^2)$. If we specify a similar model for all store level marketing variables (μ_t) and stack all time varying parameters in θ_t, $\theta_t = (\pi_t', \mu_t')'$, then we can estimate the system equation $\theta_t = G\theta_{t\text{-}1} + h_t + \omega_t$, where $\omega_t \sim N(0,W)$,

[22] Landim and Gamerman (2000) provide an extension of the hierarchical models by further generalizing it to a multiple multivariate time series case. Inference about error variances is somewhat of a problem in these hierarchical DLMs. However the standard DLM recursions are not affected as updating is conditional on known variance matrices.

at the highest level of the hierarchy. The error covariance matrix W is full, capturing immediate effects and common unobserved shocks that may cause endogeneity. The system evolution matrix G is also full, and its diagonal elements capture inertia or carryover effects, first row captures the long-term impact of marketing on store equity, first column captures feedback effects, and off-diagonal elements –other than the ones in the first row and first column- dynamic dependencies among the marketing variables.

The second alternative specification accommodates a direct dimension reduction approach. Recent advances in time series models for large data sets propose using factor analytic procedures (see Pauwels, Naik and Mela 2004 for the first application in marketing). Such a factor analytic model could overcome the dimensionality problem in this study. We take a slightly different angle from Pauwels, Naik and Mela (2004) and once more propose bringing in the spatial structure inherent in the data. This leads to a fusion between spatial factor models and spatial DLMs, resulting in a dynamic spatial factor model recently proposed by Lopes, Salazar and Gamerman (2006). In these models, the observations from the sampled locations are grouped together in m common factors based on the similarities among locales. The columns of the factor loadings matrix are used to introduce the spatial dependence –as factor loadings are directly related to correlations between observations- which is achieved by using spatial Gaussian processes.

Taking a one-factor model (m = 1) for ease of exposition, one can specify $RP_{cst} = \beta f_t + \upsilon_{cst}$, where RP_{cst} is the revenue in week t store s chain c and $\upsilon_{cst} \sim N(0,V)$. V is a diagonal matrix implying that all covariance structure is captured by the underlying factor. The spatial dependence is introduced through the factor loadings, such that $\beta \sim N(\mu,\tau^2 R_\phi)$ and R_ϕ is a distance-based correlation matrix. The evolution of the common factor is specified as $f_t = \lambda f_{t\text{-}1} + \omega_t$, where $\omega_t \sim N(0,\rho^2)$. Following the logic outlined in the hierarchical DLM we propose specifying similar spatial factor models for all store-level marketing variables and estimating $F_t = \Lambda F_{t\text{-}1} + \omega_t$, where F_t is a vector that stacks all common factors, $F_t = (F_t^{RevPre\prime},F_t^{MMix\prime},)'$, and Λ is a full system evolution matrix capturing inertia, performance feedback, dynamic dependencies, and long-term effects.

Finally, note that the dynamic spatial factor model outlined above only considers spatial dependence over a two-dimensional Euclidean space but not other types of dependence. A natural extension would be to incorporate other forms of spatial dependence such as inter-retailer linkages discussed earlier.

5.2.2 Cross-sectional and Temporal Heterogeneity in Spatial Dependence

Two similar –yet not identical- brands, within the same price-quality tier, that are sold in exactly the same geographical markets may exhibit different levels of spatial dependence, indicating some form of cross-sectional heterogeneity (e.g., Brand A's markets become spatially independent after 100 km, whereas Brand B's after 70 km). Moreover, for a given brand the degree of spatial dependence may also change over time, indicating temporal heterogeneity (e.g., five years ago Brand A's markets became spatially independent in 60 km). The dispersed distributions of (1) the spatial independence distances in Bronnenberg, Dhar and Dubé (2007a), (2) the spatial independence distances reported in Chapter 4, and (2) the estimated values of the spatial autocorrelation function at zero distance in Bronnenberg, Dhar and Dubé (2006) provide solid evidence for cross-sectional heterogeneity. Yet, we lack evidence in support of temporal heterogeneity, as the temporal evolution of spatial dependence for a given brand has not been documented in the marketing literature so far. Therefore documenting the magnitude of cross-sectional and temporal variation in spatial dependence and understanding the sources of inter-market linkages through a dynamic analysis of spatial correlation magnitudes constitute a fruitful area for future research.

Prior to assigning a substantive meaning to the cross-sectional heterogeneity in spatial correlation estimates, we have to consider whether the differences arise as a result of data aggregation. Thus far only brand level spatial dependence has been investigated in the literature. As brand level data are typically obtained by aggregating SKU level data, spatial dependence that SKUs exhibit will be transferred to the brand level through the aggregation process. More specifically, we could argue that aggregation of heterogeneous units is partly responsible for cross-sectional heterogeneity. Following the tradition of using analogies from the analysis of sequentially observed data points to describe properties of spatially observed data points we base our discussion on how long memory can arise in time series. Time series with a long memory, a.k.a. fractionally integrated series, arise from the aggregation of basic processes each of which has short memory (Granger 1980; Granger and Joyeux 1980). More specifically, the aggregation of k independent cross-sectional first order Markov processes, whose autoregressive parameters are independent draws from a beta distribution, approaches a fractionally integrated process as $k \rightarrow \infty$ –provided that there is no accidental cancellation of lag operators. As brands carry different SKUs at different locations, exhibiting various first order Markov processes over the space, aggregation of these units to the brand level will cause variation in the estimated brand-level spatial memory. Moreover, brands' ever changing product lines will be partly responsible for the temporal variation in spatial correlation estimates inasmuch as the SKU to brand aggregation is a source of spatial correlation variation across brands.

One reason why we might observe spatial correlation could be the similarity of consumer preferences in geographically close markets. If consumer preferences for two brands are different across these markets then observing a difference between spatial correlation magnitudes, after controlling for the aggregation effect, is not surprising. Then the question is why do the preferences of consumers in geographically close markets differ between brands? One reason might be the existence of regional brands of local manufacturers or store brands of retail chains operating regionally. On the other hand, marketing –by the focal firm and its competitors- manifested at the regional level can have also an impact on preference in a given locale. A systematic analysis of the determinants of spatial dependence can improve our understanding of geographic marketing and aid manufacturers in managing their brands across markets.

Finally, one challenge specific to this topic is the definition of a market (also see Bronnenberg, Dhar and Dubé (2007b) for a related issue). The discussion above builds on the assumption that clear market boundaries –due to local advertising markets or geographic discontinuities- exist. However the fact that advertising is not local does not imply that a brand's market is national. Distinct markets may exist but hard to observe in many data sets. Then identifying independent markets when majority of distribution channels are national and local advertising activity is virtually non-existent is challenging and provides another fruitful area for future research.

5.2.3 Who Benefits from Brand Exits?

Brands are introduced, built, managed during their maturity and withdrawn from the market at some point in time. A new product failure rate of 55% indicates that these exits are a common phenomenon. Moreover, individual items in a brand's product line frequently disappear from the market place because retailers decide to reduce their assortment (Boatwright and Nunes 2001), or because the manufacturers identify these items as candidates for elimination (Avlonitis 1985). The main question that needs to be answered is what happens after brand withdrawal, specifically who benefits from this elimination, and why? Although we only discuss brand eliminations in the subsequent paragraphs, the framework can easily be adjusted to analyze the impact of individual item withdrawals.[23]

When brands are eliminated consumers may (i) reallocate their purchases among the remaining brands available in the store immediately, (ii) delay the purchase and reallocate later, or (iii) shop around temporarily to find out whether their preferred brands are available in other stores and upon not finding them they may purchase other brands in other stores. Among which brands they reallocate their purchases and why they prefer those brands over others are two important questions for both manufacturers and retailers. The possibility that consumers may delay their purchases implies the need to make a distinction between immediate and long-term effects of eliminations. The time it takes this long-term effect –if exists at all- to be realized is also of interest.[24] Next we briefly discuss a model specification that accommodates all of the above mentioned possibilities.

The basic premise of the model is that elimination frees-up demand, which is reallocated between the remaining brands. We propose a model that treats this excess demand as a factor influencing the remaining brands' market potentials. In that respect, the model is an extension of the repeat purchase diffusion model developed in the second chapter of this book. Formally, the market potential of a remaining brand can be defined by $\mu_t = \mu_0 + \mu_1 \mathrm{I}_{t=\tau} + \mu_2 \mathrm{I}_{t>\tau} + \phi Z_t$, where τ is the week in which the competing brand exits the market. I is an indicator function and Z_t is a vector of marketing mix instruments, which allows us to control for their influence on market potential. In addition to the marketing support, one also has to control for the effect of other variables (could be included in Z_t), such as new product introductions by competitors, at the time

[23] Assortment reduction studies might shed some light on this issue as some brands totally disappear after the elimination (Borle et al. 2005; Sloot, Fok and Verhoef 2006). However these studies exclusively focus on the category level effects. A notable exception is the study by Zhang and Krishna (2006) which investigates the brand level effects of an assortment reduction. Yet the study does not answer the question why certain brands benefit from the elimination. The results of Zhang and Krishna (2006) raise another interesting question. In Zhang and Krishna (2006) consumers become more price sensitive after the assortment reduction. If assortment reduction is purely designed to reduce the clutter in the sales environment by eliminating items with overlapping attributes and make choice an easier task for the consumers then we should be observing the opposite effect on elasticities. This contradiction may point out another future research avenue.

[24] Assortment reduction studies typically consider data that spans six months prior to and six months after the reductions. Longer time series might be needed to properly evaluate the long run impact of such a shock.

of the exit, as any decrease in market potentials of the remaining brands could be misattributed to the exit. The parameters μ_1 and μ_2 are the immediate and the long-term impact of the exit, respectively. In the short run brands within the same store as well as brands in other stores can enjoy extra sales due to the elimination. As consumers are reluctant to change their main shopping outlets I expect to observe the cross-store effect only in the short run (Rhee and Bell 2002). Moreover, this cross-store effect may differ across categories. Consumers may be less likely to switch stores to buy their preferred brands in low involvement categories but they might be willing to shop around for brands in high involvement categories. Yet, it might be quite difficult to identify cross-store effects as findings in both out-of-stock literature (e.g., Campo, Gijsbrechts and Nisol 2000) and assortment reduction literature (e.g., Broniarczyk et al. 1998) report that store switching can be negligible.

Furthermore, it is possible to test whether the distribution of the freed-up demand across the remaining brands, in the short run as well as in the long run, is random or it follows a systematic pattern. This could be achieved with the help of an attribute based similarity matrix that identifies brands with similar –to the deleted brand- product line composition. Also of interest are the marketing mix instruments that convert this excess market potential into actual sales. For instance, brands that are on display, offer discounts, or introduce new varieties when the elimination takes place could share the entire freed-up demand in the short run as these marketing activities typically attract attention and encourage trial. The portion that they will receive from this excess demand may also depend on factors such as their product line similarity.

Two other issues need further consideration. First, this possibly exogenous –to the remaining brands- change in the category assortment may have an effect on how manufacturers set their marketing spending level as the exit may influence the competitive structure. Second, the time when reallocation of demand starts to take place may not correspond to the time when the exit takes place. The manufacturer exiting the market will try to exploit the maximum revenue during this phase and pushing the existing stocks without any marketing support or any other additional cost. This cut in the marketing support may indeed mark the beginning of the elimination process. However the full effect of the exit will be realized after the last item on the shelf is sold.

The conclusions drawn from this study are likely to have implementation implications for assortment reduction decisions. A large scale one time assortment reduction is big systematic change in the market that changes behaviors of the consumers, who act as Bayesian learners, forcing them to review their decision rules, attribute weights, etc. The results may show that the negative consequences of a one-time large scale elimination –e.g., observed for private labels (Zhang and Krishna 2006)- could be mitigated by sequential elimination or smooth transition.

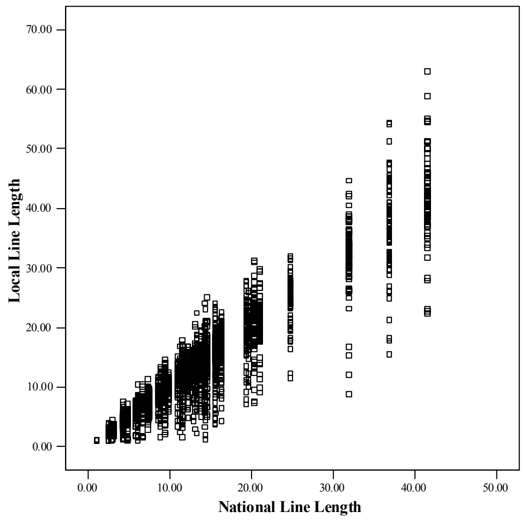
5.2.4 Local Product Line Decisions

As discussed in Chapter 4 performance of brands varies markedly across markets. Brand specific market effects account for 92% of market share variation in the United States (Bronnenberg, Dhar and Dubé 2007a) and 77% in France (Ataman, Mela and Van Heerde, 2007). Among possible causes of this empirical regularity are brands' local product line decisions.

Brands offer multiple items, SKUs, at each point of distribution. Holding everything else constant having a long product line at a certain location increases a brand's choice probability. The sales or share premium a brand enjoys due to its product line length may cause variation in regional market shares inasmuch as the brand offers different assortments in different locales –e.g., few core SKUs in all markets and more customized alternatives in some other markets. Figure 5.1 plots the distribution of line length for each brand across markets. On average brands offer 12.4 SKUs nationally with quite large regional differences. The *range* of local product line length distribution averages around 13.4, bounded by a minimum of 1 and a maximum of 41. This pattern greatly resembles that of regional market share variation (see Figure 4.1). To assess whether local product line length is a correlate of regional market share variation we estimated an extended version of the last model (M6) in Chapter 4. Using data from 96-region breakdown we calibrated a generalized linear model after adding the number of SKUs a brand offers in a given market-chain-week as a covariate. The results show that the main effect of chain still assumes the greatest importance in explaining market share differences. The addition of brand-market-chain-week specific line length variable explains away a portion of the brand, market, and brand-by-market effects and the chain, brand, and brand-by-chain effects as they are collinear with the new covariate.

Provided that this empirical regularity is observed across many brands and categories we can further explore whether other variables, such as variety and distribution depth, relate to this performance variation. As a brand's line length varies across markets, the variety of the brand's offer also changes from one market to another. In that case, one needs to assess whether the variety a brand offers across markets is random or follows a systematic pattern. If the local product line composition is not random, then we need to understand how the brand constructs these regional product lines. By studying the behavior of firms we can further advance our understanding of relationship between local brand performance and its correlates –product line length, variety, and distribution depth. This could be achieved by modeling the spatial and temporal evolution of a firm's local market entry decision using data from line extensions by established brands.

Figure 5.1: Local vs. National Product Line Length



5.2.5 Multi-tier Private Labels

In the first chapter of this book we exclusively focus on recently introduced national consumer packaged goods brands and their growth trajectories. While a similar analysis of private label growth trajectories would further enhance our understanding of how new brands are built, a rather more interesting question remains unanswered in this domain. That is how does a retailer decide to introduce a private label in the first place? However the retailer's decision concerns the second –and/or third- private label of the retail chain.

Private labels have received a great deal of attention in the marketing literature (e.g., Pauwels and Srinivasan 2004, Chintagunta, Bonfrer and Song 2002). Various normative studies investigated why a retailer carries her own brands and how these brands are strategically positioned vis-à-vis the national brands (Choi and Coughlan 2006, Du, Lee and Staelin 2004, Sayman, Raju and Hoch 2002). It has been argued that retailers carry private labels to compete profitably in the price sensitive segment (Hoch and Banerjee 1993), to get better deals from the manufacturers (Mills 1995, Narasimhan and Wilcox 1998, Scott Morton and Zettelmeyer 2004), and to build store loyalty (Corstjens and Lal 2000). Achieving these goals depends on the strategic positioning of the private label. For instance, Corstjens and Lal (2000) show that low priced high quality private labels help retailers build store loyalty. Scott Morton and Zettelmeyer (2004) argue that the retailer is able to negotiate better supply terms when the private label is positioned close to the leading national brand.

The retailer may wish to achieve these goals at the same time. This calls for a multi-tier private label strategy, i.e., a low priced product line (low-tier) that appeals to the price sensitive consumers, a me-too product line (mid-tier) to negotiate better supply terms from the manufacturers, and a more expensive premium product line (high-tier) to differentiate itself from other retailers. However none of the above mentioned studies allows the retailer to carry more than one –horizontally and/or vertically differentiated- private label, and mainly treat private labels as single brands carrying a line of inferior alternatives. Three notable exceptions in the marketing literature are (1) Dhar and Hoch (1997) as they acknowledge the distinction between premium private labels and regular private labels in explaining store brand performance, (2) Sayman and Raju (2004) who analyze how category characteristics influence retailer's decision to carry more than one store brand, and (3) Geyskens, Gielens and Gijsbrechts (2006) who investigate the effects of switching from a single-tier private label strategy to a multi-tier strategy on brand choice. Yet empirical evidence on why retailers introduce second (and third) store brand is missing.

The data set used in this book includes nearly 500 new brand introductions. Approximately 25% of these new brands are private labels indicating that we observe multiple retail chains introducing their second (and third) private label in various product categories. This data offer an excellent opportunity to test various hypotheses on the drivers of a retailer's decision to introduce these brands.

We can argue that a retailer's decision to adopt a multi-tier private label program might be driven by three groups of factors, namely consumer, retailer, and national brand manufacturer related factors. First of all, the retailer's decision might be driven by consumer needs. The chain may try to position the second private label such that the new brand fills a gap in the attribute space, in other words it targets a specific segment, or creates a compromise option. Second, national (regional) brand manufacturers continuously introduce new brands and/or alternatives in the product categories. As retailers use private labels to get better deals from the manufacturers by positioning them close to the national brands, manufacturers' continuous innovations will force the retailer to introduce new alternatives and position these fighters at different locations of the market. Finally, a retailer is in direct contact with other retailers operating in its markets. As retail chains also use private label programs to differentiate themselves from the competition and build store equity, their rivals' decisions to introduce new private labels can also have an influence on the focal chain's decision.

Provided that retailers may use their second (and third) private labels to target specific segments that are almost exclusively located in certain geographic markets, to compete with strong regional brands and other retailers operating in the same markets a market-chain level analysis of the phenomenon seems appropriate.

Appendix 1

MCMC Sampling Chain for Chapter 2

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

(A1.1) $$Y_{jt} = F_{jt}\theta_{jt} + X_{jt}\beta_j + \upsilon_{jt},$$

(A1.2) $$\theta_{jt} = G_{jt}\theta_{jt-1} + h_{jt} + \omega_{jt},$$

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 (A1.2).

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 $\Phi = \{\widetilde{Y}_t, V, W, \beta, \delta, \gamma, \mu, \pi\}$ and $\theta_0|D_0 \sim N(m_0, C_0)$, where $\widetilde{Y}_t = Y_t - X_t'\beta$:

- The prior at time t is $\theta_t|D_{t-1} \sim N(a_t, R_t)$, 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 $\widetilde{Y}_t|D_{t-1} \sim N(f_t, Q_t)$, 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 $C_t = R_t - R_t F_t' Q_t^{-1} F_t R_t$.

Next we apply the backward sampling algorithm:

- At $t = T$ we sample a matrix of evolution parameters from the distribution $N(m_t, C_t)$.
- Next we sequence backwards for $t = T-1,\ldots,1$ sampling from $p(\theta_t|\theta_{t+1}, rest)$ $\sim N(q_t^*, Q_t^*)$, 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.

The DLM recursions derived above are conditional on $\Phi = \{\widetilde{Y}_t, V, W, \beta, \delta, \gamma, \mu, \pi\}$. In reality these parameters are unknown, thus they have to be inferred. In order to carry out the inference for these unknown parameters we have to derive the posterior distribution. However sampling from such a posterior distribution is not tractable. Therefore, we use a Gibbs sampler, which allows us to simulate iteratively from the full conditional posteriors.

Step 2: $V \mid \theta, \Phi_{(-V)}$

For a given brand, we assume that the observation equation error variance matrix, of size $(M+1)\times(M+1)$, is full as we allow for correlation between the error terms for sales, prices and marketing mix instruments of a brand. We place an Inverse Wishart prior on the error correlation matrix. The full conditional posterior distribution is given by

(A1.3) $$p(V \mid \theta, \Phi_{(-V)}) \propto p(V) p(\mathrm{Y} \mid \theta, \Phi_{(-V)}).$$

Take prior degrees of freedom n_{V0} and a $(M+1)\times(M+1)$ positive definite matrix S_{V0}, then the full conditional posterior distribution, also Inverse Wishart, has

(A1.4) $$n_{V1} = n_{V0} + T,$$

(A1.5) $$S_{V1} = S_{V0} + \sum_{t=1}^{T}(Y_t - X_t'\beta - F_t\theta_t)'(Y_t - X_t'\beta - F_t\theta_t).$$

We use a diffuse prior with $n_{V0} = (M+1)+2$ and $S_{V0} = .001 \times I_{M+1}$.

Step 3: $W \mid \theta, \Phi_{(-W)}$

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

(A1.6) $$n_{W1} = n_{W0} + T - 1,$$

(A1.7) $$S_{W1} = S_{W0} + \sum_{t=1}^{T}(\theta_t - G_t\theta_{t-1} - h_t)'(\theta_t - G_t\theta_{t-1} - h_t).$$

We use a diffuse prior with $n_{W0} = 3$ and $S_{W0} = .001$.

Step 4: $\delta \mid \theta, \Phi_{(-\delta)}$, $\gamma \mid \theta, \Phi_{(-\gamma)}$, and $\mu \mid \theta, \Phi_{(-\mu)}$

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

(A1.8) $$\alpha = \frac{\pi\left(\delta_j^{(m)} \mid \theta_t, W, \phi, \mu\right)}{\pi\left(\delta_j^{(m-1)} \mid \theta_t, W, \phi, \mu\right)},$$

and $\pi(\cdot)$ is conditional likelihood of Equation (A.1.2) evaluated at each draw.

Step 5: $\pi \mid \theta, \Phi_{(-\pi)}$

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 $K_{iT-1} = [1_{T-1}\ \zeta_{iT-1}\ Sales_{jT-1}\ Sales_{j'T-1}]$ and $W_{iT-1} = W_i \otimes I_{T-1}$, where T and T-1 indicate that the observations are stacked across time in vectors, running from t = 2,…,T and t = 1,…,T-1 respectively. 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

(A1.9) $$\overline{\mu}_\pi = \overline{\Sigma}_\pi \{ \underline{\Sigma}_\pi^{-1} \underline{\mu}_\pi + [K_{iT} W_{iT}^{-1} \zeta_{iT}] \},$$

(A1.10) $$\overline{\Sigma}_\pi = \{ \underline{\Sigma}_\pi^{-1} + [K_{iT} W_{iT}^{-1} K_{iT}'] \}^{-1}.$$

We use a diffuse prior $\underline{\mu}_\pi = 0$ and $\underline{\Sigma}_\pi = 100$.

<u>Step 6:</u> $\beta \mid \theta, \Phi_{(-\beta)}$

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

(A1.11) $$\overline{\mu}_\beta = \overline{\Sigma}_\beta \{ \underline{\Sigma}_\beta^{-1} \underline{\mu}_\beta + [X_t V_T^{-1} \overline{Y}_t] \},$$

(A1.12) $$\overline{\Sigma}_\beta = \{ \underline{\Sigma}_\beta^{-1} + [X_t V_T^{-1} X_t'] \}^{-1}.$$

We use a diffuse prior $\underline{\mu}_\beta = 0$ and $\underline{\Sigma}_\beta = 100$.

Appendix 2

MCMC Sampling Chain for Chapter 3

We use a log-log sales model to capture the short-term effect of marketing activity on a brand's sales in a given chain:

$$\text{(A2.1)} \quad \begin{aligned} \ln \overline{SALES}_{jskt} &= \alpha_{jkt} + \beta_{jkt} \ln \overline{ACTPR}_{jskt} + \phi_{jk} \overline{FND}_{jskt} \\ &+ \sum_{\substack{j'=1 \\ j' \neq j}}^{J} \rho_{j'j} \ln \overline{CPR}_{j'skt} + \sum_{i=1}^{I} \tau_{ik}^{s} SD_{ikt} + \upsilon_{jskt}^{S}, \end{aligned}$$

where $\ln \overline{SALES}_{jskt}$ represents the log sales of brand j in chain s in category k in week t, $\ln \overline{ACTPR}_{jskt}$ is the log inflation adjusted actual price, $\overline{FND}_{jskt}$ indicates whether there was a feature and/or display without a price discount, $\ln \overline{CPR}_{j'skt}$ is log cross price, and the monthly dummies, SD_{ikt}, are used to model seasonal variation in sales. The super-scripted bar indicates mean centering across brands and chains. α_{jkt} is the brand-category specific intercept and β_{jkt} is the price elasticity coefficient. We specify the long-term effect of marketing strategies on the intercept and price elasticity as follows:

$$\text{(A2.2)} \quad \alpha_{jkt} = \delta_{0jk}^{\alpha} + \lambda_{k}^{\alpha} \alpha_{jkt-1} + Z'_{jkt} \gamma^{\alpha} + \omega_{jkt}^{\alpha},$$

$$\text{(A2.3)} \quad \beta_{jkt} = \delta_{0jk}^{\beta} + \lambda_{k}^{\beta} \beta_{jkt-1} + Z'_{jkt} \gamma^{\beta} + \omega_{jkt}^{\beta}.$$

We assume that a brand's price in a particular chain ($\ln \overline{ACTPR}_{jskt}$) is a manifestation of its (latent) national pricing strategy μ_{jkt} and deviations from this strategy arise from seasonal and random effects. We construct the following equation:

(A2.4) $$\ln \overline{ACTPR}_{jskt} = \mu_{jkt} + \sum_{i=1}^{I} \tau_{ik}^{p} SD_{ikt} + \upsilon_{jskt}^{P},$$

which we estimate simultaneously with (A2.1) and let error terms, υ_{jskt}^{S} and υ_{jskt}^{P}, be correlated. The associated system equation is as follows,

(A2.5) $$\mu_{jkt} = \delta_{0jk}^{\mu} + \lambda_k^{\mu} \mu_{jkt-1} + \sum_{\substack{j'=1 \\ j' \neq j}}^{J} \vartheta_{jj'k}^{\mu} \mu_{j'kt-1} + \gamma_k^{\mu} S_{jkt-1} + \omega_{jkt}^{\mu}, \quad j \neq j'.$$

Using these (A2.1)-(A2.5) we define the following multivariate DLM For a given category *k*:

(A2.6) $$\mathrm{Y}_{\mathrm{t}} = \mathrm{F}_{\mathrm{t}} \Theta_{\mathrm{t}} + \upsilon_{\mathrm{t}},$$

(A2.7) $$\Theta_{\mathrm{t}} = \mathrm{G} \Theta_{\mathrm{t-1}} + \mathrm{h}_{\mathrm{t}} + \omega_{\mathrm{t}},$$

which has the following form,

(A2.8) $$\begin{bmatrix} \ln \overline{\overline{SALES}}_t \\ \ln \overline{ACTPR}_t \end{bmatrix} = \begin{bmatrix} I_J \otimes 1_S & \ln \overline{ACTPR}_t & 0 \\ 0 & 0 & I_J \otimes 1_S \end{bmatrix} \cdot \begin{bmatrix} \alpha_{jt} \\ \beta_{jt} \\ \mu_{jt} \end{bmatrix} + \begin{bmatrix} \upsilon_t^S \\ \upsilon_t^P \end{bmatrix},$$

$$\begin{bmatrix} \alpha_{1t} \\ \alpha_{2t} \\ \alpha_{3t} \\ \beta_{1t} \\ \beta_{2t} \\ \beta_{3t} \\ \mu_{1t} \\ \mu_{2t} \\ \mu_{3t} \end{bmatrix} = \begin{bmatrix} \delta_{01}^{\alpha} \\ \delta_{02}^{\alpha} \\ \delta_{03}^{\alpha} \\ \delta_{01}^{\beta} \\ \delta_{02}^{\beta} \\ \delta_{03}^{\beta} \\ \delta_{01}^{\mu} \\ \delta_{02}^{\mu} \\ \delta_{03}^{\mu} \end{bmatrix} + \begin{bmatrix} \lambda^{\alpha} & 0 & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & 0 \\ 0 & \lambda^{\alpha} & \ddots & & & & & & \vdots \\ \vdots & \ddots & \lambda^{\alpha} & \ddots & & & & & \vdots \\ \vdots & & \ddots & \lambda^{\beta} & \ddots & & & & \vdots \\ \vdots & & & \ddots & \lambda^{\beta} & \ddots & & & \vdots \\ \vdots & & & & \ddots & \lambda^{\beta} & 0 & \cdots & 0 \\ \vdots & & & & & 0 & \lambda^{\mu} & \vartheta_{12} & \vartheta_{13} \\ \vdots & & & & & \vdots & \vartheta_{21} & \lambda^{\mu} & \vartheta_{23} \\ 0 & \cdots & \cdots & \cdots & \cdots & 0 & \vartheta_{31} & \vartheta_{32} & \lambda^{\mu} \end{bmatrix} \begin{bmatrix} \alpha_{1t-1} \\ \alpha_{2t-1} \\ \alpha_{3t-1} \\ \beta_{1t-1} \\ \beta_{2t-1} \\ \beta_{3t-1} \\ \mu_{1t-1} \\ \mu_{2t-1} \\ \mu_{3t-1} \end{bmatrix}$$

(A2.9) $$+ \begin{bmatrix} Z_{1t}^{1} & \cdots & Z_{1t}^{m} & 0 & \cdots & \cdots & 0 \\ Z_{2t}^{1} & \cdots & Z_{2t}^{m} & 0 & & & 0 \\ Z_{2t}^{1} & \cdots & Z_{3t}^{m} & 0 & \cdots & 0 & 0 \\ 0 & \cdots & 0 & Z_{1t}^{1} & \cdots & Z_{1t}^{m} & 0 \\ \vdots & & 0 & Z_{2t}^{1} & \cdots & Z_{2t}^{m} & 0 \\ \vdots & & 0 & Z_{2t}^{1} & \cdots & Z_{3t}^{m} & 0 \\ \vdots & & 0 & 0 & \cdots & 0 & \ln SALES_{1t-1} \\ \vdots & & & & & 0 & \ln SALES_{2t-1} \\ 0 & \cdots & \cdots & \cdots & \cdots & 0 & \ln SALES_{3t-1} \end{bmatrix} \begin{bmatrix} \gamma_1^{\alpha} \\ \vdots \\ \gamma_m^{\alpha} \\ \gamma_1^{\beta} \\ \vdots \\ \gamma_m^{\beta} \\ \gamma^{\mu} \end{bmatrix} + \begin{bmatrix} \omega_{1t}^{\alpha} \\ \omega_{2t}^{\alpha} \\ \omega_{3t}^{\alpha} \\ \omega_{1t}^{\beta} \\ \omega_{2t}^{\beta} \\ \omega_{3t}^{\beta} \\ \omega_{1t}^{\mu} \\ \omega_{2t}^{\mu} \\ \omega_{3t}^{\mu} \end{bmatrix},$$

where *J* is the total number of brands, *S* is the total number of chains.

(A2.10) $\ln \overline{\overline{SALES}}_{jst} \equiv \ln \overline{SALES}_{jst} - \phi_j \overline{FND}_{jst} - \sum_{\substack{j'=1 \\ j' \neq j}}^{J} \rho_{j'j} \ln \overline{CPR}_{j'st} - \sum_{i=1}^{I} \tau_i^s SD_{it}$

is log sales net of sales attributed to the variables with non-time varying parameters, and

(A2.11) $$\ln \overline{\overline{ACTPR}}_{jst} \equiv \ln \overline{ACTPR}_{jst} - \sum_{i=1}^{I} \tau_i^p SD_{it}$$

is log actual price net off seasonality variables.

The system evolution matrix G, shown in Equation (A2.9), is modified in order to incorporate competitor interaction parameters (ϑs), which are the off-diagonal elements in the lower right block. The first and the third components in Equation (A2.9) make up the term h_t in our previous notation, and $\mathrm{h}_\mathrm{t} = \delta + \mathrm{Z}'_\mathrm{t}\gamma$.

Define $\mathrm{Y}_\mathrm{t} = [\mathrm{Y}'_{1\mathrm{t}} \;\; \mathrm{Y}'_{2\mathrm{t}}]'$, where Y_{1t} includes sales and prices net of the non-time varying block (Equation A2.10 and A2.11), Y_{2t} includes the marketing mix instruments, and Y_{1t} and Y_{2t} are jointly normally distributed. Also define $\mathrm{F}_{3\mathrm{t}} = \mathrm{I}_5 \otimes [1_\mathrm{j} \quad \mathrm{S}_{\mathrm{jkt}-1} \quad \mathrm{S}_{\mathrm{j'kt}-1}]$, and a vector, say π, of non-time varying parameters from the marketing mix equations. Given that,

(A2.12) $$\begin{bmatrix} \mathrm{Y}_{1\mathrm{t}} \\ \mathrm{Y}_{2\mathrm{t}} \end{bmatrix} \sim \begin{bmatrix} \mathrm{F}_\mathrm{t}\Theta_\mathrm{t} \\ \mathrm{F}_{3\mathrm{t}}\pi \end{bmatrix}, \begin{pmatrix} \mathrm{V}_{11} & \mathrm{V}_{12} \\ \mathrm{V}_{21} & \mathrm{V}_{22} \end{pmatrix} \Bigg],$$

we can construct the conditional covariance matrix by $\widetilde{\mathrm{V}} = \mathrm{V}_{11} - \mathrm{V}_{12}\mathrm{V}_{22}^{-1}\mathrm{V}_{21}$, and the conditional mean vector by $\widetilde{\mathrm{Y}}_{1\mathrm{t}} = \mathrm{Y}_{1\mathrm{t}} - \mathrm{V}_{12}\mathrm{V}_{22}^{-1}(\mathrm{Y}_{2\mathrm{t}} - \mathrm{F}_{3\mathrm{t}}\pi)$.

Assuming that the DLM is closed to external information at times $t \geq 1$ -i.e., given initial information D_0 at $t = 0$, at any future time *t* the available information set is simply $\mathrm{D}_\mathrm{t} = \{\widetilde{\mathrm{Y}}_{1\mathrm{t}}, \mathrm{D}_{\mathrm{t}-1}\}$, and D_0 includes all values of $\mathrm{h}_\mathrm{t}, \mathrm{G}, \widetilde{\mathrm{V}}, \mathrm{W}$ and $\Theta_0 \mid D_0 \sim N(\mathrm{m}_0, \mathrm{C}_0)$. Conditional on these parameters the solution is given by West and Harrison (1997).

- Prior at time *t* is $\Theta_\mathrm{t} \mid \mathrm{D}_{\mathrm{t}-1} \sim N(\mathrm{a}_\mathrm{t}, \mathrm{R}_\mathrm{t})$, where the mean and the covariance matrix are $\mathrm{a}_\mathrm{t} = \mathrm{Gm}_{\mathrm{t}-1} + \mathrm{h}_\mathrm{t}$ and $\mathrm{R}_\mathrm{t} = \mathrm{GC}_{\mathrm{t}-1}\mathrm{G}' + \mathrm{W}$.

- One-step ahead forecast at time *t* is $\widetilde{Y}_{1t} \mid D_{t-1} \sim N(f_t, Q_t)$, where $f_t = F_t a_t$ and $Q_t = F_t R_t F_t' + \widetilde{V}$.
- The posterior distribution at time *t* is $\Theta_t \mid D_t \sim N(m_t, C_t)$, where $m_t = a_t + R_t F_t' Q_t^{-1}(\widetilde{Y}_{1t} - f_t)$, and $C_t = R_t - R_t F_t' Q_t^{-1} F_t R_t$.

The DLM recursions derived above are conditional on $\Phi = \{V, W, \lambda, \gamma, \delta, \vartheta\}$. In reality these parameters are unknown, thus they have to be inferred. In order to carry out the inference for these unknown parameters we have to derive the posterior distribution. However sampling from such a posterior distribution is not tractable. Therefore, we use a Gibbs sampler, which allows us to simulate iteratively from the full conditional posteriors. We run the sampling chain for 120,000 iterations; 60,000 for burn-in and 60,000 for sampling, with a thinning of 60. The long-burn in is necessary as the model takes a considerable number of iterations to converge. Next, we derive these full conditional posterior distributions.

Step 1: $p(\Theta \mid \Phi)$

In order to sample from the conditional distribution of Θ we adopt the forward filtering, backward sampling algorithm proposed by Carter and Kohn (1994) and Frühwirth-Schnatter (1994). The sampling of system parameters starts with the standard DLM updating.

- For $t = 1,\ldots,T$ we apply forward filtering to obtain the moments, m_t and C_t.
- At $t = T$ we sample a vector of system parameters from the distribution $N(m_t, C_t)$.
- Then we sequence backwards for $t = T-1,\ldots,1$ sampling from $p(\Theta_t \mid \Theta_{t+1}, \Phi) \sim N(q_t^*, Q_t^*)$, 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 $B_t = C_t G' R_{t+1}^{-1}$.

For the starting values of time varying parameters, we use non-time varying OLS results in the mean vector m_0, and set the initial variance C_0 to $0.01 I_{NJ}$.

Step 2: $p(W \mid \Theta, \Phi_{(-W)})$

We assume that the system equation error covariance matrix is diagonal, and 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

(A2.13) $$n_{W1} = n_{W0} + T - 1,$$

(A2.14) $$S_{W1} = S_{W0} + \sum_{t=1}^{T} (\Theta_{2t} - G\Theta_{2t-1} - h_t)^2 .$$

We use a diffuse prior with n_{W0}= 3 and S_{W0}=0.001.

Step 3: $p(V \mid \Theta, \Phi_{(-V)})$

We assume that the observation equation error covariance matrix has a block diagonal structure, and allow for correlation between the error terms for sales, prices and marketing mix instruments of a brand. We place an Inverse Wishart on the blocks of observation equation error covariance matrix. The full conditional posterior distribution is given by

(A2.15) $$p(V \mid \Theta, \Phi_{(-V)}) \propto p(V) p(Y \mid \Theta, \Phi_{(-V)}) .$$

Take prior degrees of freedom n_{V0} and a $(2S+N)\times(2S+N)$ positive definite matrix S_{V0}, then the full conditional posterior distribution has

(A2.16) $$n_{V1} = n_{V0} + T ,$$

(A2.17) $$S_{V1} = S_{V0} + \sum_{t=1}^{T} (Y_{rt} - F_{rt}\Theta_{rt})(Y_{rt} - F_{rt}\Theta_{rt})',$$

where r stands for a brand. We use a diffuse prior for V that has a prior mean-diagonal element that is close to the residual variances we obtained using OLS separately for each brand. We set the degrees of freedom to $2S+N+2$.

Step 4: $p(\lambda, \vartheta \mid \Theta, \Phi_{(-\lambda,-\vartheta)})$

In this step we derive the full conditional posteriors of the category specific decay parameters and competitive responses. Let

(A2.18) $$G^{\alpha} = \lambda^{\alpha} I_j ,$$

(A2.19) $$G^{\beta} = \lambda^{\beta} I_j ,$$

(A2.20) $$G^{\mu} = (\lambda^{\mu}, \vartheta_{12}, \vartheta_{13}, \vartheta_{21}, \vartheta_{23}, \vartheta_{31}, \vartheta_{32})' .$$

We place a Normal prior on all parameters, $G^i \sim N(\underline{\mu}_{Gi}, \underline{\Sigma}_{Gi})$, where $i = \{\alpha, \beta, \mu\}$. We first stack the observations $\alpha_{jt}, \beta_{jt}, \mu_{jt}$ across time and brands in vectors i_T and i_{T-1}, running from $t = 2,...,T$ and $t = 1,...,T-1$ respectively. We also stack the corresponding components of h_t in h_T^i. Then for each time varying parameter group *i* we define

(A2.21) $$y_{\alpha T} \equiv \alpha_T - \delta_{0jk}^{\alpha} - h_T^{\alpha} = \lambda_k^{\alpha} \alpha_{T-1} + e_T^{\alpha},$$

(A2.22) $$y_{\beta T} \equiv \beta_T - \delta_{0jk}^{\beta} - h_T^{\beta} = \lambda_k^{\beta} \beta_{T-1} + e_T^{\beta},$$

(A2.23) $$y_{\mu T} \equiv \mu_T - \delta_{0jk}^{\mu} - h_T^{\mu} = \tilde{\mu}_{T-1} G^{\mu} + e_T^{\mu}.$$

Let the right hand side variables be arranged in regressor matrices, x_T^i, and choose W^i such that it includes the corresponding elements of W. Finally we define $\mathrm{W}_T^i = \mathrm{W}^i \otimes I_{T-1}$. Given the normal priors, and the likelihoods, the full conditional posterior distributions are $N(\overline{\mu}_{Gi}, \overline{\Sigma}_{Gi})$, where

(A2.24) $$\overline{\mu}_{Gi} = \overline{\Sigma}_{Gi} \{\underline{\Sigma}_{Gi}^{-1} \underline{\mu}_{Gi} + [x_T^i{}' \mathrm{W}_T^{-1} y_T^i]\},$$

(A2.25) $$\overline{\Sigma}_{Gi} = \{\underline{\Sigma}_{Gi}^{-1} + [x_T^i{}' \mathrm{W}_T^{-1} x_T^i]\}^{-1}.$$

We use a diffuse prior $\underline{\mu}_{Gi} = 0$ and $\underline{\Sigma}_{Gi} = 100$.

<u>Step 5:</u> $p(\delta \mid \Theta, \Phi_{(-\delta)})$

The conditional posterior distribution of the system equation intercepts, $\delta = (\delta_j^{\alpha}, \delta_j^{\beta}, \delta_j^{\mu})'$, is straightforward, given the previous derivation. First define

(A2.26) $$y_{\alpha T}^{\delta} \equiv \alpha_T - \lambda_k^{\alpha} \alpha_{T-1} - h_T^{\alpha} = \delta_{0jk}^{\alpha} + e_T^{\alpha},$$

(A2.27) $$y_{\beta T}^{\delta} \equiv \beta_T - \lambda_k^{\beta} \beta_{T-1} - h_T^{\beta} = \delta_{0jk}^{\beta} + e_T^{\beta},$$

(A2.28) $$y_{\mu T}^{\delta} \equiv \mu_T - \tilde{\mu}_{T-1} G^{\mu} - h_T^{\mu} = \delta_{0jk}^{\mu} + e_T^{\mu}.$$

Next, stack left hand side variables in y_T^{δ}, and right hand side variables in x_T^{δ}. We choose W such that it includes the corresponding elements of W, and define $\mathrm{W}_T = \mathrm{W} \otimes I_{T-1}$. Given the normal prior, $\delta \sim N(\underline{\mu}_{\delta}, \underline{\Sigma}_{\delta})$, and the likelihood, the full conditional posterior distribution is $N(\overline{\mu}_{\delta}, \overline{\Sigma}_{\delta})$, where

(A2.29) $$\overline{\mu}_{\delta} = \overline{\Sigma}_{\delta} \{\underline{\Sigma}_{\delta}^{-1} \underline{\mu}_{\delta} + [x_T^{\delta}{}' \mathrm{W}_T^{-1} y_T^{\delta}]\},$$

(A2.30) $$\overline{\Sigma}_{\delta} = \{\underline{\Sigma}_{\delta}^{-1} + [x_T^{\delta}{}' \mathrm{W}_T^{-1} x_T^{\delta}]\}^{-1}.$$

We use a diffuse prior $\underline{\mu}_{\delta} = 0$ and $\underline{\Sigma}_{\delta} = 100$.

Step 6: $p(\gamma \mid \Theta, \Phi_{(-\gamma)})$

In order to obtain the conditional posterior distribution of the marketing mix penetration coefficients and the performance feedback coefficients in the pricing equations, $\gamma = (\gamma_1^\alpha, ..., \gamma_m^\alpha, \gamma_1^\beta, ..., \gamma_m^\beta, \gamma^\mu)'$, we define

(A2.31) $$y_{\alpha T}^\gamma \equiv \alpha_T - \lambda_k^\alpha \alpha_{T-1} - \delta_{0jk}^\alpha = h_T^\alpha + e_T^\alpha ,$$

(A2.32) $$y_{\beta T}^\gamma \equiv \beta_T - \lambda_k^\beta \beta_{T-1} - \delta_{0jk}^\beta = h_T^\beta + e_T^\beta ,$$

(A2.33) $$y_{\mu T}^\gamma \equiv \mu_T - \tilde{\mu}_{T-1} G^\mu - \delta_{0jk}^\mu = h_T^\mu + e_T^\mu .$$

Next we stack these dependent variables into y_T^γ, and the right hand side variables into z_T. We again place a Normal prior on the parameters, $\gamma \sim N(\underline{\mu}_\gamma, \underline{\Sigma}_\gamma)$. The full conditional posterior directly follows, $\gamma \sim N(\overline{\mu}_\gamma \overline{\Sigma}_\gamma)$, where

(A2.34) $$\overline{\mu}_\gamma = \overline{\Sigma}_\gamma \{\underline{\Sigma}_\gamma^{-1} \underline{\mu}_\gamma + [z_T \mathrm{W}_T^{-1} y_T^\gamma]\} ,$$

(A2.35) $$\overline{\Sigma}_\gamma = \{\underline{\Sigma}_\gamma^{-1} + [z_T \mathrm{W}_T^{-1} z_T' \ ]\}^{-1} .$$

$\mathrm{W}_T = \mathrm{W} \otimes I_{T-1}$, where W is the corresponding block of the system equation error covariance matrix. We use a diffuse prior $\underline{\mu}_\gamma = 0$ and $\underline{\Sigma}_\gamma = 100$.

Step 7: $p(\phi, \rho, \tau^s, \tau^p, \pi \mid \Theta, \Phi)$

In order to obtain the conditional posterior distribution of the non-time varying observation equation parameters $\Pi = \left(\phi, \rho, \tau^s, \tau^p, \pi\right)'$, we define $\overline{\overline{\mathrm{Y}}}_{\mathrm{t}}$ that stacks sales and prices net of the time varying part, and the marketing mix instruments. We also define

(A2.36) $$\overline{\overline{\mathrm{F}}}_{\mathrm{t}} = diag(\mathrm{F}_{2\mathrm{t}}, \mathrm{F}_{3\mathrm{t}}) ,$$

(A2.37) $$\mathrm{F}_{2\mathrm{t}} = diag([\overline{FND}_{jskt} \quad \ln \overline{CPR}_{j'skt} \quad SD_{it}],[SD_{it}]) ,$$

(A2.38) $$\mathrm{F}_{3\mathrm{t}} = \mathrm{I}_5 \otimes [1_{\mathrm{j}} \quad \mathrm{S}_{\mathrm{jkt-1}} \quad \mathrm{S}_{\mathrm{j'kt-1}}] ,$$

We place a Normal prior on the parameters, $\Pi \sim N(\underline{\mu}_\pi, \underline{\Sigma}_\pi)$. Then the full conditional posterior is $\Pi \sim N(\overline{\mu}_\pi \overline{\Sigma}_\pi)$ where

(A2.39) $$\overline{\mu}_\pi = \overline{\Sigma}_\pi \{\underline{\Sigma}_\pi^{-1} \underline{\mu}_\pi + [\overline{\overline{\mathrm{F}}}_{\mathrm{t}} \mathrm{V}_T^{-1} \overline{\overline{\mathrm{Y}}}_{\mathrm{t}}]\} ,$$

(A2.40) $$\overline{\Sigma}_\pi = \{\underline{\Sigma}_\pi^{-1} + [\overline{\overline{\mathrm{F}}}_{\mathrm{t}} \mathrm{V}_T^{-1} \overline{\overline{\mathrm{F}}}'_{\mathrm{t}} \ ]\}^{-1} ,$$

and $\mathrm{V}_T = \mathrm{V} \otimes I_T$. We use a diffuse prior.

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Nederlandse Samenvatting

Inleiding

Merken zijn cruciaal voor fabrikanten. Ze worden ontwikkeld, onderhouden, en – wanneer het zover is – uit de markt gehaald door dezelfde fabrikant die ze creëerden. Het onderhouden van een merk is een uitdaging, die een doordachte planning en implementatie van lange termijn marketingstrategieën vereist. De uitdaging voor de fabrikant is voornamelijk het simultaan, zowel over tijd als in verschillende geografische gebieden, managen van tastbare en niet tastbare merkprestatie componenten met dezelfde instrumenten, de marketingmix.

Omdat productcategorieën groeien en verzadigen, markten uitbreiden en concurrentie toeneemt, hebben merken toenemende marketingondersteuning, en dus financiële middelen nodig om hun posities te verkrijgen en te behouden. Het effect van deze uitgaven is van centraal belang voor veel bedrijven. Onderzoek in marketing heeft laten zien wat de rol van marketing is op het sturen van de vraag. Echter, het merendeel van onze kennis bestaat uit wat de onmiddellijke effecten zijn van de marketingmix instrumenten op de vraag. Hoewel de er recent een toenemende nadruk wordt gelegd op de lange termijn effecten van marketingstrategieën op merken, zijn er geen studies die (1) een vergelijking maken van de relatieve lange termijn effecten van de totale marketingmix (prijs, promotie, product en plaats), (2) de lange termijn effecten vergelijken van marketinguitgaven op *nieuwe en gevestigde merken*, (3) inzicht vergaren van *longitudinale en ruimtelijke* analyses op merkprestaties, en (4) deze effecten vergelijken over een grote verzameling categorieën om bevindingen te kunnen generaliseren.

Dus, belangrijke vragen zijn nog steeds onbeantwoord: “Hoe worden grote merken ontwikkeld?”, en “Welke elementen van de marketingmix zijn het belangrijkst in het verkrijgen van brand equity?". Deze vragen bestaan al decennia lang, omdat het beantwoorden ervan grote datasets en geavanceerde modellen vergt, die pas onlangs beschikbaar kwamen voor onderzoekers. De drie essays in dit proefschrift proberen een meer complete kennis te geven hoe merken gemanaged dienen te worden op de lange termijn.

Beschrijving van de hoofdstukken

Gegeven de centrale rol die nieuwe producten spelen op de winst van ondernemingen, richt hoofdstuk 2, "Strategieën voor het ontwikkelen van nieuwe merken", op de antecedenten van de prestatie van nieuwe merken. Het onderzoek bepaalt welke marketingintroductie strategieën het grootste effect hebben op het succes van nieuwe merken door de groeiprestatie van nieuwe levensmiddelenmerken toe te schrijven aan de marketingkeuzen van ondernemingen. De prestatie van nieuwe producten wordt uitgesplitst naar het marktpotentieel en de snelheid waarmee het merk dit potentieel benadert. Wij stellen dat een onderneming die het product aanbiedt, het marktpotentieel van haar merk kan vergroten en/of groei kan genereren door de marketingmix te managen. Daartoe onderzoeken we hoe adverteren, promoties, distributie, en productactiviteiten groei en marktpotentieel beïnvloeden. Om dit te bereiken ontwikkelen we een dynamisch lineair diffusiemodel waarin groei en marktpotentieel direct gekoppeld worden aan de lange termijn advertentie-, promotie-, distributie- en productstrategieën van nieuwe merken.

In hoofdstuk 3, "De Lange termijn Effecten van Marketingstrategieën op Merkprestaties", richten we ons op gevestigde merken. Alhoewel recent onderzoek onze kennis over de lange termijn effecten van prijspromoties en adverteren op gevestigde merken heeft vergroot, bestaat er veel minder onderzoek naar de lange termijn effecten van product- en distributiestrategieën. Bovendien bestaat er geen onderzoek die de invloed van de totale marketingmix op gevestigde merken generaliseert over langere periodes, door de effecten over vele jaren en categorieën te bestuderen. In dit hoofdstuk proberen we een compleet inzicht te krijgen wat de factoren zijn die de prestatie van gevestigde merken beïnvloeden. We doen dit door de effecten van alle vier de elementen van de marketingmix simultaan te bestuderen. Gebruikmakend van de brand equity literatuur, meten we merkprestatie met quantity premium (basis omzet) en margin premium (inverse van de prijselasticiteit), en modelleren hoe de quantity en margin premium van een merk zich ontwikkelen over de tijd als functie van marketingactiviteiten.

In hoofdstuk 4, “Levensmiddelen in Frankrijk: Nationale Merken, Regionale Ketens, Locale Merkstrategieën”, bestuderen we de grootte en robuustheid van de variatie in de prestatie van gevestigde merken over markten. Bronnenberg, Dhar en Dubé (2007) observeren dat geografische variatie een overheersende bron is van variatie in nationale marktaandelen van merken. Wij breiden dit verrassende en voorgaand ongedocumenteerd resultaat uit op verschillende aspecten.

Uitkomsten

In deze drie onderzoeken hebben we systematisch de prestatie van 295 merken in 25 verschillende productcategorieën, gebruikmakend van wekelijkse data over maximaal 5 jaar met een bijna uitputtende collectie marketingmix instrumenten, geanalyseerd. We hebben het volgende gevonden:

- Kortingen helpen nieuwe merken sneller te laten groeien, maar ze kunnen eventueel leiden tot een lager marktpotentieel van deze merken. Het netto effect op de lange termijn prestatie is klein maar negatief. Bovendien verlagen kortingen de quantity premium en de margin premium van gevestigde merken. Deze bevindingen geven aan dat kortingen negatieve lange termijn gevolgen hebben voor merken ongeacht de positie in de merklevenscyclus.
- Adverteren vergroot het marktpotentieel van een nieuw merk en vergemakkelijkt snellere groei. Wanneer een merk de status bereikt van een gevestigd merk, helpt adverteren het quantity premium te vergroten, maar is het effect op de margin premium verwaarloosbaar.
- Folderaanbiedingen (of features), promotiemateriaal op de winkelvloer (of displays) en andere communicatie in de winkel kunnen niet alleen de verkopen vergroten op korte termijn maar ook het marktpotentieel vergroten voor nieuwe merken door de unieke eigenschappen van een merk te adverteren. De lange termijn effecten op de twee componenten van de prestatie van gevestigde merken (quantity premium en margin premium) moeten nog onderzocht worden.
- Twee onderbelichte factoren van merkprestatie, de lengte van een productlijn en de samenstelling, blijken van cruciaal belang te zijn. Nieuwe merken met een langere productlijn verkrijgen hogere verkopen in de evenwichtssituatie en bereiken deze situatie sneller dan merken die minder alternatieven bieden. De samenstelling van een productlijn, of de variëteit binnen de productlijn die merken helpt te differen-

tiëren van andere merken, verhoogt zowel de quantity als de margin premium van gevestigde merken.

- De breedte (het aantal winkels waar product verkocht wordt) en diepte (het aandeel van een product in een winkel) van de distributie, ook onderbelichte determinanten van merkprestatie, zijn cruciaal voor zowel nieuwe als gevestigde merken. Het effect van de breedte van het distributiekanaal overtreft het gecombineerde effect van alle andere marketing effecten die het marktpotentieel van nieuwe merken beïnvloeden. Het is ook het belangrijkste marketingmix instrument dat de groeisnelheid bepaalt. Bovendien vergroot een brede aanwezigheid van het merk de efficiëntie van de andere marketingmix instrumenten. Echter, de breedte van het distributiekanaal heeft weinig lange termijn effecten op de quantity premium van een groot nationaal merk, omdat deze merken toch al breed gedistribueerd zijn en additionele verspreiding waarschijnlijk via kleine winkels gebeurt waar de omzet laag is. Aan de andere kant heeft de breedte van het distributiekanaal het grootste (positieve) lange termijn effect op de margin premium. Tenslotte spelen distributiekanalen een centrale rol in het verklaren van de verschillen in verkopen tussen geografische regio's in Frankrijk.

Samengevat, onze resultaten suggereren – in tegenstelling tot de aandacht die adverteren en kortingen krijgen in de literatuur – dat product en distributie de belangrijkste factoren van het lange termijn succes van merken zijn. Deze bevindingen hebben de volgende implicaties voor marketeers.

Een Breed Distributiekanaal is Vitaal voor Merken: Toegang krijgen tot distributiekanalen – verbreden van het distributiekanaal – is de belangrijkste determinant van de lange termijn prestatie van merken en behoort daarom bovenaan de checklist van een merkmanager te staan. Op het moment dat de opbrengsten van het toevoegen van verkooppunten daalt, is een fabrikant aangewezen op andere instrumenten uit de marketingmix, zoals adverteren en uitbreidingen van de productlijn om groei te garanderen. Echter, het is cruciaal om de breedte van het distributiekanaal op peil te houden.

Merken Hebben Productlijn Uitbreidingen Nodig die de Variëteit Vergroten: Een onderneming kan de positie van een merk in de markt vergroten door de productlijn uit te breiden, omdat het toevoegen van producten (of SKUs) aan de productlijn de kans vergroot dat het merk door de consument geselecteerd wordt en omdat een uitbreiding de aanwezigheid op het schap vergroot door een vergroting van de diepte in het distributiekanaal. Deze effecten gelden zowel voor nieuwe als gevestigde merken. Echter, de samenstelling van een productlijn is ook cruciaal. De variëteit dat een merk aanbiedt daalt wanneer gelijkende (of 'me-too') producten toegevoegd worden aan de productlijn. Fabrikanten moeten deze tegenwerkende factoren dus in acht nemen wanneer ze hun productlijn samenstellen.

Harmoniseer de Agenda's van het Merk en die van de Merkmanager: Tactische zetten – vooral het aanbieden van grote en regelmatige kortingen – die merkmanagers aanbieden om de prestatie van hun merk te vergroten op korte termijn en om zichzelf te bewijzen voor een promotie naar een hogere functie, verlagen de prestatie van het merk op de lange termijn. Merkmanagers kunnen ervoor kiezen om marketingmix instrumenten die positieve lange termijn effecten hebben te negeren, omdat er weinig prikkels zijn om te investeren in de lange termijn – lange termijn effecten zijn pas zichtbaar voor hun opvolgers. Aan de ander kant, fabrikanten zoeken naar merken die sterke, langdurige posities in de markt hebben. Een oplossing voor dit fabrikant-brandmanager doelstellingsprobleem is om brandmanagers te beoordelen op de mate waarin ze hun lange termijn doelen behalen naast de korte termijn doelstellingen.

Maak Gebruik van Nieuwe Verkoop Modellen: Merkmanagers kunnen ook afzien van lange termijn investeringen omdat er weinig bewijs is over de effecten (het kan maanden of jaren duren voordat deze zichtbaar zijn), en daarom benadrukken ze de korte termijn met kortingen omdat deze effecten groot en eenvoudig te meten zijn. Het ontwikkelen en/of gebruiken van een merkgezondheid waarderingssysteem, dat korte termijn analyses aanvult met lange termijn analyses, kan de benodigde motivatie opleveren om in lange termijn merkontwikkeling instrumenten te investeren. Een noodzakelijke voorwaarde om zo'n systeem te kunnen gebruiken is het opslaan van verkoop- en marketingmix data over meerdere jaren, hetgeen al aanwezig is in de databases van onderzoeksbureaus. Wanneer een bedrijf over deze data beschikt kan het management de modellen schatten die ontwikkeld zijn in dit proefschrift, en hun voorspellingen bijwerken wanneer nieuwe data beschikbaar komen (of wanneer een nieuwe waardering nodig blijkt te zijn), gebruikmakend van de Bayesiaanse aard van onze modellen.