The Dynamic Effect of Innovation on Market Structure

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Abstract

New product innovation is endemic among consumer packaged goods firms, and it is an integral component of their marketing strategy. As these innovations may considerably change the markets they enter, there is a pressing need to develop market response models that adapt well to such changes in the marketing environment. We propose a Dynamic Linear Model (DLM) that naturally copes with the challenges these dynamic environments entail: nonstationary time series, varying parameters, missing data, and the presence of disaggregate data. We use the DLM to model sales response in the frozen pizza category, in which the introduction of rising crust pizza brands represented a major innovation.

As we hypothesize, the innovation i) makes the existing brands appear more similar, as indicated by increasing cross-brand price elasticities, ii) decreases purchase accelerations as indicated by a reduction in own-brand price elasticities and iii) increases the variance-covariance matrix of the sales response equations temporarily around the time of the introduction of the innovation, indicating increased uncertainty in sales response. The adjustment of the market to the innovations takes about four months, as indicated by relatively high lag parameters in the autoregressive structure we assume for the model parameters. The predictive validation shows that the DLM specification outperforms a number of benchmark specifications based on log Bayes factors.

We conclude by discussing the managerial implications by i) presenting maps of how clout, vulnerability and brand similarity evolve over time, ii) assessing the effect of new brands on cannibalization and iii) considering the strategic implications of introducing a flanker innovation to facilitate the ability of an extant brand to attack an extant incumbent leader.

Keywords: Innovation, Brand Entry, Market Structure, Frozen Pizza, Time Series Methods, Dynamic Linear Models, Bayesian Methods, Gibbs Sampler, Long-term Effects
Introduction

New product innovation is endemic among consumer packaged goods firms, and is an integral component of their marketing strategy. Over 16,000 new products appear annually in groceries and drugstores (Kotler 2000). Thus, there is a pressing need to develop market models that adapt well to these changes in the marketing environment. Accordingly, we develop an approach for this context, although it can readily be applied to other nonstationary environments including changes in firms’ promotional strategy over recent years (Mela, Gupta, and Lehmann 1997), changes in the marketing environment, changes in consumer tastes, changes in the composition of firms in the market, changes in regulatory and economic factors as well as other environmental changes.

New products not only benefit firms, but also benefit consumers as product variety increases. Accordingly, product innovation plays a major role in firms' marketing strategy. One key to assessing the efficacy of these innovations is an understanding of the effects these innovations have on existing markets, and this is the focus of this paper. Pan and Lehmann (1993, p. 83) provide laboratory evidence that the introduction of a new brand into a market increases the perceived similarity of brands already operating within a market, and indicate that, “perhaps the most serious issue for future research is to see how pervasive these effects would be in a more realistic setting.”

In spite of the importance surrounding the effect of product innovation, econometric analyses of the effects of innovations on market structure remain sparse in comparison to extant econometric work regarding the effect of advertising and promotions on market structure and brand differentiation (Boulding, Lee and Staelin 1994; Kaul and Wittink 1995). As a consequence, there has been some recent interest in modeling the effects of product entry within markets (Chintagunta, Bonfrer, and Song 2001; Kadiyali, Vilcassim, and Chintagunta 1999; Pauwels and Srinivasan 2002). We extend this work in at least three respects. First, we consider the dynamics of product entry. We do not assume that market response to these innovations is

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1 Market structure is defined as the representation of brand positions within an attribute space (Elrod and Keane 1995). Often, the structure of markets is inferred via the substitution patterns evidenced by own and cross price elasticities. Products with higher cross price elasticities are more substitutable, and thus more similar (Kamakura and Russell 1989; Manchanda, Ansari and Gupta 1999; Mela, Gupta and Jedidi 1998; Bucklin, Russell and Srinivasan 1998).
instantaneous. Innovations’ effects are not immediate as it takes time for innovations to diffuse into the market place (Rogers 1995; Mahajan, Muller and Bass 1995). An understanding of the dynamics of market response to the pioneer’s introduction is particularly useful to managers of extant brands and potential future entrants. Second, we consider the introduction of substantially different brand forms, as opposed the minor line extensions or store brand introductions. Highly disparate brands induce range and categorization effects, which can make extant brands appear more similar to consumers (Pan and Lehmann 1993). Thus, market structure effects are amplified in such environments. Finally, we explicitly accommodate the possibility that the innovation may increase the uncertainty in the marketplace around the time of the launch.

From a methodological perspective, we develop and implement a flexible and adaptive modeling approach that is tailored to the characteristics of data typically arising in dynamic marketing environments. Specifically, our method embeds the Dynamic Linear Model (West and Harrison 1997) into a Gibbs sampler. Some advantages of our modeling approach include allowing for nonstationarity, estimating of varying parameter paths and accommodation of missing data. We also show that these advantages improve model fit and prediction significantly in our application.

We study the effects of innovative product entry using data from the frozen pizza category. This category has experienced a major shift in demand patterns as a result of a substantial technological innovation that resulted in the launch of rising crust pizzas.² These introductions sparked a 12% growth in the hitherto no growth frozen pizza market, with Kraft’s DiGiorno brand capturing 13% share (to become the number three brand) two years after its launch (Holcomb 2000). We use weekly store level data from this category over a five-year period. These data are particularly suited to study of potentially nonstationary markets. In addition, the five year span of the data is a long enough to allow for us to detect changes in the market, if any, and the resulting dynamics.

Our results indicate that the introduction of the new brand form led to significant changes in the structure of the market. Our main finding, as predicted by previous theoretical work, is that the introduction

² In rising crust pizzas, yeast is included in the pizza crust. This causes the crust to rise during the baking process, resulting in a superior tasting end product.
of a disparate new brand results in the old brands becoming closer substitutes. We also find that, as predicted, the own price sensitivity of the existing brands decreases. In terms of the speed and timing of adjustment, we find that on average, the response parameters adapt to the new values in about four months (fifteen weeks). Interestingly, the cross-price parameters adapt the fastest – about two months after the launch. Our results also indicate that the variance of the sales equation(s) is highest just after the introduction of the new brand. Our approach also yields a dynamic map of brand positions in the market place, and this map indicates that the advantageous positioning of the extant high quality brand(s) is most adversely compromised by the introduction of a new product form.

The rest of the paper is organized as follows. We first provide a brief literature review on the effects of innovation on market structure, and we formulate our hypotheses. We next discuss why modeling market response in dynamic environments (such as ones characterized by innovations) leads to a number of challenges. We then introduce our model in general terms and show why it represents a flexible approach to cope with these challenges. The data from the pizza category are discussed next, after which we present the detailed model specification. We present the results in the subsequent section, and then conclude by summarizing the paper and offering potential extensions.

**Literature Review and Hypotheses**


The consumer behavior literature on brand introductions offers insights into the consequences arising for the cross-price response of existing brands. In particular, Pan and Lehmann (1993) suggest that range and categorization effects make extant brands appear more similar when a new, distinctive brand is introduced. The range effect (Niedrich, Sharma and Wedell 2001) implies that the difference between two stimuli on a perceptual dimension decreases when the range (i.e., the difference between the two extremes on that dimension) increases. Thus, two brands will appear more similar when a brand is positioned away from
them. *Categorization* effects may also occur, whereby the introduction of a radically dissimilar alternative leads to a categorization of the old and new alternatives. As members of the same category are perceived to be more similar (Sujan and Bettman 1989), it is reasonable to presuppose that the categorization process resulting from the introduction of an innovation leads to greater perceived similarity across the set of existing brands.

It should be noted that our emphasis is on the introduction of a new brand form instead of a line extension or the addition of another brand of the same form (e.g., a store brand). This is an important distinction as a new brand form as is close to being a “new” product in the same category as possible. As such, the new brand form represents a true innovation, and by virtue of its distinctive qualities one might expect a manifestation of range and categorization effects upon the innovation’s introduction. Likewise, one would not expect such effects from subsequent “me-too” entrants, as they neither increase the perceptual range of goods in the category nor lead to new categorizations (a supposition that is confirmed in our empirical analysis).

In sum, the introduction of a new innovation leads to existing brands being perceived as more similar due to range and categorization effects. Consequently we expect to find that these brands become more sensitive to changes in each another’s prices. Thus:

*H1: All else equal, the introduction of innovative brand(s) should increase the magnitude of the existing brands' cross-price elasticities.*

In addition, we consider the effect of new brand introductions on own price response. The own price response can be decomposed into secondary demand effects (brand switching) and primary demand effects (category expansion). As argued in hypothesis 1, secondary demand effects are hypothesized to increase. This would argue for increased own price response. On the other hand, primary demand effects are in part due to stockpiling. To the extent the number of brands in the marketplace increases, consumers have greater choice. Thus, there will be less need to accelerate purchases compared to a case where fewer brands exist, because a price cut for any given alternative may be imminent. In other words, when a fewer number of brands exist, the need to accelerate purchase is greater. Thus, we expect that stockpiling effects will decrease when more brands are added to the choice set (Jedidi, Mela and Gupta 1999). This would argue for
decreased own price response. In addition, the other components of primary demand effects (store switching, category switching, increased consumption, deal-to-deal purchasing) are also less likely to occur for the existing brands when the superior-quality new brand is available, further suggesting decreased price response. Hence, total primary demand effects decrease after the new brand introduction. The net effect of the increase in secondary demand effects and the decrease of primary demand effects can go either way.

Until recently, secondary demand effects of price promotions were believed to be bigger than primary demand effects (Gupta 1988, Bell, Chiang, and Padmanabhan 1999). That is, the short-term brand choice elasticity is about three quarters of the total elasticity. On the other hand, recent work shows the reverse both for short-term effects in terms of unit sales (Van Heerde, Gupta, Wittink 2002; Van Heerde, Leeflang, and Wittink 2002) and for long-term effects in terms of both sales and elasticities (Jedidi, Mela, and Gupta 1999, Pauwels, Hanssens, and Siddarth 2002). These four studies suggest that primary demand effects are bigger than secondary demand effects when one accounts for dynamics, unit sales and store switching. Therefore, we expect the decrease in primary demand effects also to dominate the increase in secondary demand effect. This leads to a net decrease in the own-brand price response. Hence we hypothesize:

\[ H2: \text{All else equal, the entry of new brands should decrease the magnitude of the existing brands' own price elasticities.} \]

Finally, we consider the ability of a sales model to capture the variability in sales at and about the time of the new brand introduction. Given that consumers will undergo a period of trial of new brands and updating preferences for those brands, it is reasonable to expect that preferences might become highly volatile before settling back to some stable level (Lipstein 1968). Thus, we expect that the error variance of the sales model might be greater during this period. Accordingly, we hypothesize:

\[ H3: \text{Error variance in sales increases during the period surrounding a brand introduction.} \]

In the next section we explain why modeling the effects of innovations on market structure may entail some challenges.
Modeling market response in dynamic environments

Modeling market response in dynamic environments (such as markets with brand introductions) leads to four key challenges: nonstationarity, changes in the parameters, missing data, and capturing dynamics in panel settings. We discuss these below.

First, nonstationarity is an important issue.³ The usual approach to dealing with this is to filter the data in the hope of making the series mean- and covariance stationary. However, means for filtering series such as taking first differences can induce distortion in the spectrum, thus affecting inference regarding the dynamics of the system (Hamilton 1994). Further, West and Harrison (1997 p. 300) indicate that the process of filtering to make series stationary can (i) hinder model interpretability, (ii) confound model components, (iii) highlight noise at the expense of signal, and/or (iv) fail to capture sources of nonstationarity that deviate from processes implied by the filter. In particular, working with differences in lieu of levels makes it difficult to develop and estimate a structural model of how one parameter (such as price sensitivity) can change in response to exogenous factors such as brand introductions. Moreover, differencing, while controlling for some sources of stationarity, such as a random walk in a series, does not control for others (such as a shift in the scale of the error variance over time or interventions and structural breaks).

Second, market response parameters are likely to change over time, especially in dynamic environments. There have been a number of papers in marketing and economics that have sought to assess how market response parameters vary in response to promotion. Generally these models fall into three classes: those that provide parameter paths, those that provide only the expected values of the parameters conditioned on observed covariates, and those that do a before-and-after analysis. Models that yield parameter paths (Bronnenberg, Mahajan, and Vanhonacker 2000; Mela, Gupta and Lehmann 1997) typically rely on moving windows to compute changing parameter values, which can lead to inefficient estimates (only a subset of the data is analyzed each time). This approach also presents a dilemma inasmuch as short

³A series is strictly stationary when its distribution is independent of time. A series is weakly stationary when its expectation and variance are independent of time.
windows yield unreliable estimates, and long windows lead to very coarse estimates, and may even induce
autocorrelations when none exist.

The assumption of abrupt changes in parameter values from one window to the next is also
problematic. The expectations based approach typically presumes the varying parameter to be a function of
some covariates and an error (Jedidi, Mela and Gupta 1999). Only the variance of the parameter estimate is
computed. Thus, it is not possible to reconstruct the parameter paths over time. Moreover, the effects of the
covariates on the parameter, as well as the covariance of the errors in the parameter process functions are
also typically assumed to be stationary. This may not be the case in dynamic markets. The before-and-after
type model (Kadiyali, Vlccassim and Chintagunta 1999; Pauwels and Srinivasan 2002) estimates different
models before and after an event occurs. The after-model is estimated on data starting from some time after
the event, and these data are assumed to represent the new, stabilized market situation. One drawback of this
approach is that there exists a loss in statistical efficiency by ignoring the effects observed in a given half of
the data. A second consideration regards the nature of the underlying adjustment: it is presumed to occur at a
fixed time instantaneously. In practice, it may take some time for the market to adjustment to reach a new
equilibrium. Finally, these models assume non-varying parameters before and after the structural break
(Perron 1994) – we relax these stringent assumptions.

Third, missing data are endemic in dynamic environments. Product entries and exits change the
dimension of the data, making estimation of such models difficult. For example, it is not clear how to
include the cross-price effect of later entrants when modeling the sales of existing brands when using
classical regression or VAR approaches. Solutions to this problem are listwise deletion (which is not
efficient inasmuch as it removes information), imputation (which can induce biases), and pre-post analyses
of the data (which suffer from the limitations described above).

Fourth, market structure is often inferred from panel data, i.e., data that are a combination of a cross-
section (e.g., stores, households) and time (e.g., weeks). Examples of panel data are store-level- and
household-level scanner data sets. Time series approaches are often difficult to generalize to panel level data
(Pesaran and Smith 1995). Perhaps because of this as well as a paucity of software for VAR models for
panel data, most VAR applications in marketing aggregate across the cross-sections and use market-level data. However, aggregation has been shown to lead to aggregation biases in parameter estimates (Christen et al. 1997, Pesaran and Smith 1995), and therefore it is preferable to keep the disaggregate nature of panel data.⁴

Together, all of these factors (covariance nonstationarity, dynamic parameter paths, missing information, and panel data structure) suggest that dynamic market environments present a unique challenge to measuring and modeling market response. Such environments may be the rule rather than the exception, especially for very long data series. It is therefore our objective to develop an approach that enables us to address all four factors pertaining to modeling dynamic marketing response. In this paper, we use a flexible and adaptive modeling approach that enables us to accommodate the abovementioned aspects of the data. Specifically, we embed the Dynamic Linear Model (West and Harrison 1997) into a Gibbs sampler and estimate the model on data from the frozen pizza category. We describe the modeling approach below and indicate how it copes with the issues detailed above.

**Modeling Approach**

In this section, we outline our modeling approach. Our overall approach to modeling sales response in nonstationary environments proceeds in three steps. First, we specify a model of sales. Second, we allow the response parameters and covariance structure in this model to change over time. Finally, we specify the process that governs how the parameter paths evolve over time.

**General Approach**

We begin by presenting the model in its most general form, and then adapt it to our application and data. We stack log sales of brand $k$, ($k = 1, ..., K$), in a store $i$, ($i = 1, ..., I$) in a vector $y_i$ at time $t$, ($t = 1, ..., T$):

$$y_i = (y_{1i}, y_{12}, ..., y_{1K}, y_{2i}, ..., y_{2K}, ..., y_{11}, ..., y_{IK})'$$

and model it as:

$$y_i = F_{ik} \beta_i + \epsilon_i$$

Note that Nijs et al. (2001) show that the aggregation bias is small in their application.⁴
where $F'$ is a matrix of $M$ regressors (e.g., price and promotion) posited to affect $y_t$. Equation (1) is denoted the observation equation. We assume that $v_t \sim N(0, V_t)$, where $V_t$ is an $IK \times IK$ covariance matrix of error correlations across stores and brands. We let the scale of $V_t$ change over time to accommodate nonstationarity in the covariance structure. That is, $V_t = \zeta_t V$.\(^5\)

The system of equations in (1) can adapt in the face of environmental (e.g., economic factors, regulatory factors, technological changes), firm (e.g., entries and exits, changes in management), and consumer changes (e.g., changing populations and tastes). Thus, we enable the model parameters to vary over time as follows:

$$
(2) \quad \beta_{t+1}^{MIK*} = G_{MIK*MIK}^{MIK*} \beta_{t+1}^{MIK*} + Z_{t+1}^{MIK*} V_{t+1}^{MIK*} + \omega_t^{MIK*},
$$

where $\omega_t \sim N(0, W_{MIK*MIK})$ and $Z_t^{MIK*}$ is a vector of $N$ regressors which can include an intercept.\(^6\) $G$ is a matrix that can denote a general lag structure (e.g., it need not be constrained to less than one – that is, a random walk is nested in (2)). For parsimony, we assume that the error term $\omega_t$ of $\beta_t$ is correlated across brands and stores, but is independent across time (note, however, that the $\beta_t$ follow an autoregressive process). Equation (2) is denoted the system equation.

The system of equations in (1) and (2) is known as a Dynamic Linear Model or DLM (Chib and Greenberg 1995; West and Harrison 1997).\(^7\) Conditioned on $V_t$, $W$, and $G$, the $\beta$ can obtained through a series of updating steps. However, in contrast to the other approaches in marketing that use the DLM (e.g.,

\(^5\) Note that the product, $\zeta_t V$, is not uniquely identified. We therefore set $\zeta_1$ to 1. This does not affect our interpretation since we are interested in the relative magnitude of $V$ in each time period.

\(^6\) When $W=0$, the posterior estimates for $\beta$ reduce to the standard normal regression posteriors (DeGroot 1971).

\(^7\) Some readers will recognize the similarity of the DLM to the Kalman filter (Hamilton 1994, Xie et al 1997, Naik, Mantrala, and Sawyer 1998, Naik and Tsai 2000). West, Harrison and Migon (1985, p. 97) contrast the DLM with the Kalman filter, noting that the Kalman filter "was originally applied to a restricted problem—that of estimating a mean vector evolving in time according to a linear, dynamic model with the variance structure completely known (...). The normal updating equations in a DLM coincide with the Kalman-filter forms. The general Bayesian learning procedure goes far beyond this limited case (...), coping with unequally spaced observations, and unknown, even time varying, observational variances." Thus, it appears that the DLM is a more appropriate model for our context.
Neelamegham and Chintagunta 2002), our approach has the following unique characteristics. First, we do not fix the covariance matrices of the observation and state equations. In other words, we estimate, rather than specify, the matrices $V_t$ and $W$. This improves our estimates of $\beta$ and the forecasting ability of the model. Second, we not only estimate the covariance matrix of the observation equation, we allow it to vary in each time-period, as we expect this variance to be affected in the period around the introduction of a new brand. Finally, we do not specify the $G$ but estimate it. The $G$ matrix allows us to assess whether the marketing effects are transient or enduring (cf. Dekimpe and Hanssens 1995). We specify proper priors for $V_t, W$, and $G$ and derive the full conditional distributions given the likelihood. Details on the DLM updation, the prior and full conditional distributions and the Gibbs sampler are provided in the appendix.

Coping with the challenges of dynamic environments

The DLM copes in a natural way with the four challenges pertaining to modeling market response in dynamic environments: nonstationarity, dynamic parameter paths, missing information, and panel data structure. We next indicate how the DLM does this.

First, the parameters modeled by the DLM are allowed to be nonstationary. For example, the DLM allows for a random walk (or random walk with trend) in the parameters, which is obtained when $G$ is the identity matrix and $\delta = 0$: $\beta_t = \beta_{t-1} + \omega_t$. This implies that if our estimate for an element on the diagonal of $G$ is one, any short-term shock in the corresponding parameter is enduring (Dekimpe and Hanssens 1995). With equation (1) we can also model a random walk process for $y_t$ by modeling time varying intercepts only: $F_t'$ and $G$ are the identity matrices, $\nu_t = 0$ and $\beta_t = \beta_{t-1} + \omega_t$ (see Hamilton 1994, p. 375 for a more general discussion of how any time series model can be written in the form of an observation equation and a system equation). As random walks are embedded in the DLM, there is no need to test for

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8 We show later, using Bayes factors, that our model outperforms a model with fixed $V$ and $W$ as well as a model that constrains $V_t$ to $V$.

9 We estimated an alternative model of this form and found it predicts worse than a model that does not restrict the $G$ matrix to have ones on the diagonal.
unit roots in our approach.\textsuperscript{10} Thus, the model is specified in levels instead of differences even when the series are nonstationary, thereby enhancing model interpretation. Other forms of nonstationarity are also embedded in our model. Increased uncertainty manifested as “shopping around” can be captured by a shift in scale of the $V_t$ matrix at or about the time of product introduction. In addition, shifts in series means or stochastic trends can be modeled directly in the system equations.

Second, the use of the Dynamic Linear Model within the Gibbs sampler allows us to obtain dynamic parameter paths. We allow the parameters to evolve over time in a very general manner as a function of lags and exogenous covariates (such as a new brand introduction). Our approach makes no assumptions about the speed and timing of market response to events such as new brand introductions, and it estimates how long it takes for changes in the market structure to settle down. Thus, our paper relaxes the assumption of pre-post models that changes in parameters are instantaneous.

Third, we had noted that data from dynamic environments can have lots of missing data. Product entries (and exits) change the dimension of the data, making estimation of such models difficult. The Bayesian estimation approach for the DLM allows to selectively update only those parameters for which information is available, making the accommodation of missing or unevenly spaced data straightforward (see the appendix for more detail). For example, the parameter for the effect of price changes of a later entrant on an existing brand’s sales starts being updated when the later entrant becomes available. This property lets us exploit all of the information available, thereby increasing the efficiency of the model estimation. Further, in standard time series models, data regarding the pricing and sales of the new product do not exist prior to introduction, leading to difficulties in estimating a system of equations with missing data.

Finally, our approach handles panel data structures in a very straightforward way. The vector $y_t$ in (1) can contain observations from multiple cross-sections (stores in our application). This allows us to keep the disaggregate nature of the data, which minimizes the possibility of aggregation biases.

\textsuperscript{10}Given that unit root tests can suffer from power considerations, and that the error assumptions of the difference models would be violated should the test fail not to reject a unit root, models that difference to control for unit roots can be sensitive to the test for unit roots. Our approach obviates this consideration as we can model directly in levels even in the presence of a random walk. Indeed, we find some lags on the order of 0.99, suggesting that it might be difficult to discriminate from 1.00.
Data

As mentioned earlier, our data, provided by Information Resources, Inc., come from the frozen pizza category and span the five year period (247 weeks) from January 1995 to December 1999.\textsuperscript{11} The frozen pizza category is one of the most important categories in frozen food comprising 19\% of all frozen food sales. During the period 1993-1995, this category exhibited very low growth ($1.6 billion in 1993 to $1.7 billion in 1995). However, the introduction of rising crust pizzas resulted in an average annual dollar volume growth of about 12\% in this category (Holcomb 2000). Market researchers estimated that this growth was likely to be maintained at about 8.9\% annually through 2002 (Find/SVP 1998). Frozen pizza has highest penetration amongst frozen prepared foods – in 1996, 58\% of U.S. households purchased a frozen pizza during a typical 30-day period (this is higher than the number of households purchasing take-out pizza during the same period) (IRI 1996). Demographically, speaking, frozen pizza consumption is the highest among people 18-44 years of age, households with children and in the Midwest (Holcomb 2000).

To increase the representativeness of our sample, we selected data from two markets instead of one. We selected markets from a small and medium city in two different geographic regions. We sought to minimize differences arising from the timing of introduction and rate of store adoption. This led us to select the Raleigh-Durham (North Carolina) and Chicago (Illinois) market areas, where the penetration rates (defined as percent of stores adopting over time) are highly correlated (0.992 for DiGiorno, and 0.963 for Freschetta). The resulting sample comprises twenty-five supermarkets. We included the top seven national brands from this category in our analysis.\textsuperscript{12} These seven brands are DiGiorno, Freschetta, Red Baron, Stouffers, Tombstone, Tony’s and Totinos. They are produced by the four major manufacturers in this market - Kraft, Nestle, Schwan’s and Pillsbury. The first two brands – DiGiorno and Freschetta (the innovator and the follower brand respectively) – are rising crust pizza brands that were introduced during the span of our data. Specifically, DiGiorno was introduced in early 1996 and Freschetta in late 1996.

In our data, across the two markets, rising crust pizza started being available in some stores as early

\textsuperscript{11}Our definition includes all types of frozen pizzas except novelty items such as bite-size snacks and breakfast pizzas.

\textsuperscript{12}These are the major brands in the category (Holcomb 2000).
as week 21 of 1996 and was available in all stores by week 49 of 1996 (the major jump in availability occurred in weeks 37-40 of 1996). Figure 1 shows the availability pattern (store penetration) of the innovation across the twenty-five stores over the duration of our data.\footnote{As the availability pattern across the two markets is essentially identical (correlated 0.992 over time for DiGiorno and 0.963 for Freschetta, we use a single availability measure.}

The total category sales across the five years are given in Figure 2. As can be seen from the figure, there is a small but perceptible increase in category volume sales after DiGiorno was introduced while no change can be discerned after Freschetta was introduced. We also ran simple OLS models of category sales as a function of time and the proportion of stores carrying the new brands. The results show that there is no discernible overall time trend and that there is a small increase in total category volume sales after the DiGiorno launch but there isn’t any after the Freschetta launch. Table 1 provides the mean quantities sold for each brand prior to, and after the introduction of the rising crust innovation into the market (i.e., the introduction of DiGiorno).

The mean market shares of the five “old” brands pre- and post-innovation are given in Table 1. As can be seen from the table, Tombstone from Kraft is the dominant player in the category. However, it loses significant share after the innovation has been launched (as discussed above, the category expansion effect post entry is small). In fact, except for Tony’s all the old brands lose share post entry.

In terms of the marketing activity, the mean weekly price in $/lb. (including the effect of temporary price reductions) of each of the seven brands is given in Table 2. As can be seen from the table, the two new brands are more expensive than the existing brands (with the exception of Stouffers). We use an indicator variable that is set to one whenever we observe a feature, display or feature and display. We then average this indicator across SKUs to arrive at the brand-store deal variable. The mean weekly deal intensity for each brand is given in Table 2.
Model Specification

The modeling approach laid out earlier is quite general. This generality implies that the number of parameters within the model can quickly "explode" unless some structure is imposed on the model. For example, with 10 brands, 5 explanatory variables, 20 stores and 5 moderating variables for each parameter, there would be 5000 parameters to estimate and interpret (a formidable task).\(^\text{14}\) Accordingly, we turn to the prior literature and theory to inform our model specification and to provide some structure to our system of equations. Recall that our goal is to assess the effect of innovation on market structure. This suggests that the moderating effects we wish to specify should include covariates that represent innovation. Also, recall that our primary interest is the effect of innovation on cross-price response (as opposed to non-price promotion). We therefore first model the effect of own and cross marketing activity on sales prior to the innovation, and second, we assess how innovation moderates these effects.

We use a constant elasticity sales model similar to Kopalle, Mela and Marsh (1999) i.e.,

\[
\ln S_{ikt} = \sum_{k=1}^{K} \beta_{0kt} B_k + \beta_{1kt} (\ln \text{Price})_{ikt} + \beta_{2kt} \ln \text{Price}_{ikt} \\
+ \beta_{3kt} \ln \text{Price}_{ikt} + \beta_{4kt} \text{Prom}_{ikt} + \nu_{ikt}
\]

where \(S_{ikt}\) represents sales of brand \(k\) in store \(i\) in week \(t\), price represents the price index, Prom indicates whether there was a feature or display, and \(B_k\) represents an indicator variables for brand \(k\), and \(\nu\) is an error term.\(^\text{15}\) We assume the error is distributed normal, and independent across time, but not necessarily stores and brands (again, note that this assumption does not preclude the \(\beta\) including the brand intercepts, from being autoregressive). A single bar over a variable denotes a share-weighted average of the log price indices for the original set of competing brands in the category. A double bar over a variable denotes the share-weighted average across the innovators in the category. Kopalle, Mela and Marsh (1999) show that the share weighted geometric average is equivalent to an assumption that larger competing brands tend to have greater

\(^{14}\) Recall that the dimension of \(\hat{\beta}\) is \(\text{MIK}\) (and the covariance matrix of \(\Theta\) with no structure has dimension \(\text{MIK} \times \text{MIK}\)).

\(^{15}\) Defined as actual (net) price divided by regular price (Van Heerde, Leeflang, and Wittink 2001).
draw on sales than smaller competing brands, and find the weighted average specification leads to more stable estimates of competitive effects, and superior adjusted $R^2$ than models that include all cross effects separately. Note that we mean-center the dependent and independent variables by store to account for fixed store effects.

We expect the innovation effects to occur gradually as the innovation diffuses through the population. A parsimonious model to capture these dynamic effects is given by $\beta_t = \lambda \beta_{t-1} + Z_t \delta + \omega_t$ (Clarke 1976). When $\lambda = 0$, an innovations' effect occurs immediately after it is introduced. As $\lambda$ approaches 1, the effect of innovations on market structure is far more dilatory. A number of other functional forms are possible (e.g., time varying lags or multiple lags), but for reasons of parsimony, we adopt the geometric lag structure. Moreover, the geometric specification does not mandate that the decay be geometric; given the random component of the parameter process function, many potential parameter paths may be realized given the data.

In sum, we capture the dynamic effects of brand introductions on market structure by the following sets of equations

$$\begin{align*}
\beta_{0kt} &= \delta_{00k} + \lambda_{0k} \beta_{0kt-1} + \delta_{01k} I_{Npt} + \delta_{02k} I_{Nft} + \omega_{0kt} \\
\beta_{1kt} &= \delta_{10k} + \lambda_{1k} \beta_{1kt-1} + \delta_{11k} I_{Npt} + \omega_{1kt} \\
\beta_{2kt} &= \delta_{20k} + \lambda_{2k} \beta_{2kt-1} + \delta_{21k} I_{Npt} + \omega_{2kt}
\end{align*}$$

(4)

where $I_{Npt}$ is a variable representing the fraction of stores that have adopted the innovator brand at time $t$, and $I_{Nft}$ represents the fraction of stores that have adopted the follower brand at time $t$. In (4) we assume that only the introduction of the innovator has effects on the own-price elasticities $\beta_{1kt}$ and cross-price elasticities $\beta_{2kt}$, since this introduction represents a major shock to the market. The inclusion of the $I_N$ variables is analogous to the inclusion of a structural break in time series data (Perron 1994). It differs inasmuch as the break can manifest slowly or quickly, with the speed of adjustment given by $\lambda$. Our theory suggests that the introduction of the follower brand will not induce additional effects on market structure because it is not a technical innovation to the market. Therefore we do not model its effects on price.
elasticities, and consider only the later entrants effect on intercepts to capture substitution effects.\textsuperscript{16} The system of equations in (4) enables us to assess the effects of innovation on price sensitivity and model intercepts (the effect of innovation on the intercept can alternatively be interpreted as its main effect). Thus, we are able to ascertain the effect of pioneering entry on existing brands' cross price effects ($\delta_{21k}$), on the existing brands’ own price effect, $\delta_{11k}$, and on the intercepts, $\delta_{01k}$. We use a step dummy specification for these effects (more precisely, $I_{N_{pr}}$ and $I_{N_{f}}$ can take any value between zero and one). Hence the model allows for long-term (as in enduring) effects even in the case if $\beta$ is a stationary series (Hansens, Parsons, and Schultz, 2001, p. 293-296). In addition, we can further explore changes in price sensitivity and brand intercepts over time.

The system of equations in (4) requires some identifying restrictions. For the pioneering brand, $\delta_{01}, \delta_{11}, \text{ and } \delta_{21}$ are zero, as the effect of the pioneer's introduction on its own intercept, price sensitivity, and cross-price sensitivity is not observable. Similarly, these three effects of the pioneers' introduction on the later entrant are not identified, as the later entrant appears after the pioneer. Moreover, the effects of the introduction of follower brand on its own intercept, own price effect, and cross price effects are not observable.

For the non-price promotion parameters, we specify

\begin{equation}
\beta_{3\text{t}} = \delta_{30\text{t}} + \lambda_{3\text{t}} \beta_{3\text{t}-1} + \omega_{3\text{t}}.
\end{equation}

This enables the promotion effects to change over time. We do not specify introduction effects on the non-price promotion coefficient as these are merely control variables, and the inclusion of such effects would substantially increase the number of parameters to be estimated with an attendant decrease in the reliability of our other parameter estimates of central concern. It should be noted that these promotion parameters are indeed free to change over time, including after an introduction.

\textsuperscript{16} Note that we also estimate an extended model that does include these additional effects in equation (4), and find that the restricted model outperforms the extended model based on the Bayes Factor (we discuss this in detail later).
Results

We estimate equations (3)-(5) using the Gibbs sampling steps as outlined in the appendix. We focus on the cumulative effects for the observation model parameters (as opposed to current effects), as these can be directly interpreted as intercepts, price elasticities, and promotion effects. This transformation makes the parameters easier to interpret and easier to compare to parameter estimates from static models (note that the substantive results are identical for the transformed and untransformed parameter – we use the transformation solely to enhance interpretability). To obtain long-run estimates for the parameters in the observation (or sales) equation, we divide the $\delta_{mn}$ in equations (4) and (5) by one minus the corresponding lag parameter, $\lambda_{mk}$. This gives the long-run values of the parameters. We report the means and the lower and upper bound of the 95% highest posterior density region in Table 3, and also indicate whether or not hypotheses 1 and 2 are supported.

[Insert Table 3 Here]

Observation Equation (Sales Function) Parameter Estimates

The parameter estimates are comparable to those obtained in other store-level data studies using (variants) of the SCAN*PRO model (Christen et al. 1997, Foekens, Leeflang, and Wittink 1999, Nijs et al., 2001, Van Heerde, Leeflang, and Wittink 2002). More specifically, the estimates for intercept should be near zero since we use mean-centered data, and Table 3 shows that this is the case for all seven brands. The estimates for the price elasticities are in the range $-1.28$ (Stouffers) to $-3.16$ (DiGiorno), which is consistent with findings from other price promotion studies (Tellis 1988, Nijs et al. 2001). Interestingly, the two new brands, DiGiorno and Freschetta have the strongest price elasticities (most negative), suggesting that their price promotions are the most effective. This may be because these innovative and (relatively) expensive brands are especially attractive to stockpile when they are discounted. Such an effect may also arise from increased trial incentivized by dealing. As we shall demonstrate forthwith, the strong deal effects belie the relatively effect other brands have on DiGiorno and Freschetta.

The estimates for the cross price elasticities are all smaller (in magnitude) than one. Seven of the fourteen are significantly positive, and three of fourteen are significantly negative. These results are
consistent in magnitude and sign with the meta-analysis results on cross-price elasticities by Sethuraman, Srinivasan, and Kim (1999, p. 30). The estimates for the log deal multipliers are, as expected, significantly positive for all seven brands. When take the antilog transformation of the log deal multipliers, we obtain the deal multipliers. These are the multiplication factors for brand sales when an item has a non-price promotion. These deal multipliers are in the range 1.79 (DiGiorno) to 2.69 (Tony’s), which are comparable to SCAN*PRO results (Wittink et al 1987, Van Heerde, Leeflang, and Wittink 2002).

Our model indicates that parameters do, in fact, change over time. To illustrate this, we display these changes in seven different cross- and own-brand elasticities in Figure 3 and 4. The graphs show clear jumps in the cross-and own-brand price elasticities around the introduction of DiGiorno (in the second half of 1996).

[Insert Figures 3 and 4 Here]

Next, we assess whether support exists for the hypotheses that the cross-price elasticity for the old brands increases in magnitude (H1) and that the own-price elasticity decreases (become closer to zero) (H2) after the introduction of the innovator brand. The system equations afford a test of these hypotheses.

System Equation Parameter Estimates

The results in Table 3 suggest that for four of the five existing brands (Red Baron, Stouffers, Tombstone and Tony’s), the cross-price elasticity significantly increases after the introduction of DiGiorno. This supports hypothesis 1. These four cases are displayed in Figure 3. Hypothesis 2 is confirmed for three of the five existing brands (Red Baron, Stouffers and Totinos), which means that for these brands, the own-brand price elasticity decrease in magnitude. These three cases are shown in Figure 4.

Our model also includes the impact of the introduction of DiGiorno and Freschetta on the brand intercepts (see Table 3). This allows us to judge to what extent these new brands cannibalize sales from brands of the same company. The introduction of the innovator brand DiGiorno (Kraft) has a significantly negative impact on the intercepts of Tombstone (also by Kraft) and Stouffers (Nestle). Thus, there is significant cannibalization across Kraft’s product line. The introduction of the follower brand Freschetta (Schwans) on the other hand, only significantly decreases the intercepts of competing brands: Stouffers
(Nestle) and Totinos (Pillsbury). Figure 5 shows the over-time patterns in the intercepts of Stouffers, Tombstone, and Totinos. There are two marked decreases in the Stouffers intercept, occurring after the introduction of DiGiorno (around week 38 of 1996) and Freschetta (around week 27 of 1997). Tombstone suffers only from the introduction of DiGiorno, whereas Totinos suffers only from the introduction of Freschetta.

[Insert Figure 5 Here]

**Autoregressive Parameters**

The autoregressive parameters $\lambda$ represent the amount of carry-over effects in the $\beta$ series (or, alternatively, the speed of adjustment to a new equilibrium after the introduction of a new brand). There is a unique $\lambda$ for each of the thirty-five parameters in the sales equations (seven brands times five independent variables), and we report these in Table 4.

[Insert Table 4 Here]

The average $\lambda$ equals 0.86, and the 95% highest posterior density interval does not include one for 34 of the 35 parameters (not shown). Thus, the parameters are mean reverting (consistent with no unit roots) for the vast majority of the cases. The only exception is the own-price elasticity for Tombstone, for which we cannot rule out a stochastic decreasing trend over time (as $\lambda = 1$ is in the 95% interval about the mean).

Table 4 also portrays the mean $\lambda$ for each independent variable, both for the existing and new brands. In addition, we impute 90% duration intervals. This interval shows the number of weeks it takes before 90% of the long-term effect of a short-term shock has been realized (Leone, 1995, equation (7)). The introduction of a new brand represents such a shock. On average, it takes fifteen weeks before the system parameters have adjusted. Interestingly, the cross-brand price elasticity for the existing brands adjusts the fastest, in seven weeks. This implies that the increase in this cross-brand elasticity after the introduction of the innovator (H1) happens rather quickly. Thus, it does not take long before the existing brands become more similar in the eyes of consumers. The duration interval for the own-brand sales elasticity for the existing brands is much longer, 34 weeks. Increases in this elasticity due to the introduction of the innovator (H2) are the net result of changes in secondary demand (cross-brand) effects and primary demand effects.
Apparently, it takes longer for this net effect to settle than it does for one component (cross-brand effect) to settle.

**Changes in Covariance**

Hypothesis three stated that the error variance increases during the period surrounding a new brand introduction. As mentioned earlier, our model includes a time varying covariance matrix for the observation equation \( \mathbf{V}_t = \zeta_t \mathbf{V} \), which allows us to test this hypothesis. We show in Figure 6 the mean, lower (2.5%) and upper (97.5%) bound for the \( \zeta_t \) parameter.

[Insert Figure 5 Here]

We see an increase in the \( \zeta_t \) parameter around the time of the introduction of DiGiorno (weeks 21-49 of 1996, see Figure 1). In this interval, \( \zeta_t \) averaged 1.13, whereas its overall average across all periods is 0.99. The strongest increase in \( \zeta_t \) occurs in weeks 38-40 of 1996 (coinciding with the strongest increase in the availability of DiGiorno), with an average zeta of 1.71. In all three weeks, the highest posterior density interval for \( \zeta_t \) excludes one, which confirms Hypothesis 3 for the introduction of DiGiorno. On the other hand, the introduction of the follower brand Freschetta does not have a similar impact on the error variance. In the period of its introduction (weeks 24-31 of 1997) the average \( \zeta_t \) is 0.98, and it is not significantly different from one in any week in this period. Thus, we find no support for H3 for the introduction of Freschetta. Coupled with the finding below that Freschetta has no effect on the parameter paths, this result suggests that it is the introduction of the new form, rather than the new brand, that leads to the increased uncertainty.

**Forecasts**

The Dynamic Linear model sequentially updates the system parameters. They key elements in updating are the one-step ahead forecasts. Based on the available information at time \( t-1 \) represented in \( D_{t-1} \), the predictive distribution of the vector of dependent variables is (see the appendix for more detail on nomenclature):
Define $y_{ikt} = \ln S_{ikt}$ as the log sales for brand $k$ in store $i$ in week $t$, $f_{ikt}$ as its forecasted mean value, and $Q_{ikt}$ as its forecasted variance, obtained from the diagonal of $Q_t$. We display in Figure 7 the forecasts $f_{ikt}$ and the 95% reliability interval $[f_{ikt} - 1.96Q_{ikt}, f_{ikt} + 1.96Q_{ikt}]$, as well as the realizations for $y_{ikt}$. Choosing a store at random, we depict the forecasted sales in the period around the introduction of the innovation (week 38 of 1996). Note that, as mentioned earlier, log sales has been mean-centered, therefore they vary around zero.

The graph for DiGiorno illustrates the temporal “learning” capability of our version of the DLM. Prior to week 38 of 1996, the brand is unavailable. From the introduction through week 40 of 1996, there are large shocks in log sales, which the DLM tries to capture with a relatively big reliability interval, but it does not succeed completely. Then follows a period (weeks 40-50 of 1996) in which almost all the realizations do fall in the prediction interval, but the predictions are not too close to actual log sales. From about week 50 of 1996 the model starts to predict log sales quite adequately, as the DLM has learned what the parameters for this brand should be. The graphs for the five existing brand shows that the model predicts log sales very well. In addition, almost all realizations are within the 95% reliability interval. For Stouffers, Tony’s and Totinos, the reliability interval becomes wider around week 38 of 1996. Thus, the model adapts to the increased uncertainty that is due to the shock represented by the introduction of DiGiorno.

Model Comparison

As discussed above (and illustrated in Figure 7), our specification of the DLM predicts quite well out of sample. However, innumerable alternate specifications are possible. In this section, we compare our model to five plausible alternate specifications. These include:

(a) A specification in which all the $\lambda$ parameters are set to zero. Thus, this model has system equations (see equation 4) that include intercepts and moderator effects and error terms, but that exclude lagged parameter effects. Similarly, for this model, equation (5) only has intercepts and error terms. Hence,
this specification assumes that the adaptation of the system parameters to shocks is immediate, as in pre-
post models. In contrast, the full model allows for an adjustment period by having nonzero
\( \lambda \) parameters (see Table 4).

(b) A specification that sets all the moderator effects to zero. This specification assumes system parameters
do not change in the long run due to the introduction of the two new brands, i.e., the moderator effects of
\( I_{Npt} \) and \( I_{Nft} \) in equation (4) are zero. Thus, any short-term effect the introduction of the new brands
might have on the parameters (via the error term) is assumed to mean revert in the long run, and
innovation is assumed to have little effect on market structure.

(c) A specification that assumes the variance of the observation equation (for log sales) is constant over
time, that is, there is little increase in uncertainty around the time of introduction of the brand. Thus, we
assume that \( \zeta \), equals one for all \( t \), so that \( V_t = V \) for all \( t \). Note that we still estimate \( V \) and \( W \) in this
specification.

(d) A specification that assumes a constant and fixed \( V \) and \( W \) (as opposed to estimating them). As
mentioned earlier, this is the default assumption in the marketing literature.

(e) A specification that includes the effects of the introduction of the follower brand Freschetta on own and
cross-price elasticities in addition to the effects of the introduction of DiGiorno (\( I_{Npt} \)) on the own- and
cross-brand price elasticities in equation 4. Given that the range and categorization effects manifest for
new, disparate alternatives, the addition of a second similar alternative after the pioneering innovation
should not induce any such effects. As such, one might expect that the Freschetta’s introduction would
have no effect on the model parameters.

Note that the first four specifications, (a)-(d), are restricted versions of the current specification
model, while the fifth specification, (e), extends the current specification. All other model parametrizations,
priors and initial values are identical across the current specification and the five alternate specifications.

We compare the predictive validity of each alternate specification with the current specification via
the log Bayes factor. As indicated before, for each model, the one-period ahead predictive distribution for
the observation equation is \( (y_t \mid D_{r-1}) \sim N(f_t, Q_t) \) (see appendix for notational detail. We write the predictive distribution of the current specification as \( p_0(y_t \mid D_{r-1}) \), and the predictive distribution of the alternate specification as \( p_1(y_t \mid D_{r-1}) \). Since the error terms of the predictive distribution of \( (y_t \mid D_{r-1}) \) and \( (y_{t+1} \mid D_{r}) \) are independent, the log Bayes factor for the comparison of the two models is equal to (West and Harrison, p. 394):

\[
B = \log \left[ \frac{\prod_{t=1}^{T} p_0(y_t \mid D_{r-1})}{\prod_{t=1}^{T} p_1(y_t \mid D_{r-1})} \right]
\]

A log Bayes factor larger than two presents strong evidence in favor of the null model (West and Harrison 1997, p. 394). We show in Table 5 the log Bayes factors for the comparison between current specification and the alternate specifications. The current specification model clearly outperforms all five alternate specifications since the log Bayes factors are far greater than two.

The results of our out of sample tests of predictive validity indicate several contributions. First, pre-post analysis overstates the pace with which brand introductions affect market response, so it is important to capture the dynamics of innovations. Second, we show that innovations do indeed affect market structure. Third, we find that there is indeed increased uncertainty at the time of introduction of the brand. Fourth, it is the innovation, as opposed to any given me-too introduction (e.g., a store brand), leading to changes in market structure. Fifth, estimation of the covariation structure merits the additional complexity required to do so.

**Managerial Implications**

The estimated parameter paths enable one to depict a graphical representation of the evolution of market structure over the course of the new product introduction. Such a description can be informative for product line managers, who are concerned with the relative positioning of their brands within the marketplace. We
consider the impact of the new introduction from two perspectives: the asymmetric relationship between brands (which brands dominate others), and the substitutability of brands.

First, we describe the changes in asymmetry in the market using two well-known metrics that summarize a brand’s competitive position – clout and vulnerability (Kamakura and Russell 1989). The clout at time $t$ for brand $j$ is the total impact of brand $j$ on other brands, and it is defined as, $\text{clout}_j = \sum_{k=1}^{K} \beta_{jk_t}$, where $\beta_{jk_t}$ is the elasticity of brand $k$’s sales to brand $j$’s price at time $t$. The vulnerability at $t$ of brand $k$ is the total impact the other brands have on this brand, $\text{vulnerability}_k = \sum_{j=1, j \neq k}^{K} \beta_{jk_t}$. We obtain the cross-brand elasticities from equation (3). For example, the cross-price term for the five existing brands ($j=1,...,5$) in that equation is defined as: $\beta_{2kr} \ln \text{Price}_{jk_t} = \beta_{2kr} \left( \sum_{j=1}^{5} m_j \ln \text{Price}_{jj_t} \right)$, where $m_j$ is the market share of brand $j$ at time $t$. Thus, we have $\hat{\beta}_{jk_t} = m_j \hat{\beta}_{2kr}$. We obtain the cross-price elasticities for the two new brands in a similar manner.

[Insert Figure 8 Here]

In Figure 8 we show the clout and vulnerability metrics for each brand over time (the series are smoothed in Figure 8 to obtain a more interpretable depiction of the general movement of brands over time). There are five interesting findings implied by the figure.

- First, consistent with our earlier findings (see Figure 3), the figure shows that the big change in these metrics for the old brands occurs after the introduction of DiGiorno (in the second year of our data).
- Second, we find that the clout and vulnerability for most of the old brands increases over time indicating that these brands are seen as more similar.
- Third, except for Totino’s, the change in vulnerability over time is larger than the change in clout for the old brands. This suggests the brands have been weakened by the new product introduction.
• Fourth, from a product line perspective, the launch of DiGiorno by Kraft has resulted in a much weaker competitive position for its leader brand, Tombstone. Schwans’ brands are not as affected by the launch of Freschetta, indicating perhaps a better positioning from the perspective of intra-firm cannibalization of sales. That said, Schwans has also been affected by the launch of Kraft’s DiGiorno (resulting in much weaker positions for Schwans’ brands – Tony’s and Red Baron).

• Finally, DiGiorno now occupies a competitive slot (low vulnerability, well differentiated) that was previously occupied by the pre-introduction premium brand, Stouffers (by Nestle). This slot, with positive clout and negative vulnerability, is highly desirable since a brand in this slot benefits from other brands’ price cuts (e.g., by category expansion effects). This should be worrisome news for Nestle.

These findings are useful to managers in managing product lines to position their brands.

Another metric affords insights into the similarity of brands over time. By partialing the asymmetric effects out of the elasticity matrix, it is possible to obtain a residual similarity matrix to uncover the underlying similarity between brands. It is important to distinguish between these asymmetric effects and similarity effects. In other words, a brand can increase its asymmetric dominance over brands (its draw from other brands as defined by the elasticity matrix) without impacting its similarity to other brands – in this event, a brand is good at drawing share from others but immune to attacks. Like Blattberg and Wisniewski (1989), we view changes in asymmetry to be distinct from one wherein brands become more substitutable, i.e., their cross price effects on one another both increase. To partial these similarity effects from asymmetric effects, we propose to decompose the cross-price elasticity \( \beta_{jkt} \) into a similarity part \( s_{jk} \), a “residual clout” part \( c_i \), a “residual vulnerability” part \( v_j \), and an error term \( e_{jkt} \):

\[
\beta_{jkt} = s_{jk} + c_i + v_j + e_{jkt},
\]

where \( e_{jkt} \sim N(0, \sigma^2) \). Equation (8) allows for asymmetric cross elasticities via the terms \( c_i \) and \( v_j \).

Note that “residual clout” and “residual vulnerability” though related to the “clout” and “vulnerability” discussed earlier, differ somewhat in their interpretation. Residual clout and residual vulnerability capture only the asymmetric portion of the elasticity matrix, whereas clout and vulnerability combine both the symmetric and asymmetric effects.
We model similarity as the inverse Euclidean distance between two brands $j$ and $k$ in a two-dimensional MDS plot: 

$$s_{jk} = 1/\sqrt{(x_j - x_k)^2 + (y_j - y_k)^2},$$

where $(x_j, y_j)$ and $(x_k, y_k)$ are the coordinates for brands $j$ and $k$, respectively (a likelihood ratio test indicates a two dimensional solution fits the data best). We estimate equation (7) using Maximum Likelihood, while we impose some identifying restrictions.\(^{18}\) We analyze the data from 1995 (week $t = 1,\ldots,39$) and from 1999 (week $t = 196,\ldots,247$) in our data (it is possible to present a map showing movement across each week – though the insights are the same, the presentation is obfuscated). Likelihood ratio tests indicate that the two-dimensional Euclidean map indeed fits the best. This solution is presented in Figure 9.

[Insert Figure 9 Here]

From the figure it is clear that the similarity of the old brands has increased - except for Totinos, all the other brands have moved towards Red Baron (which is fixed by construction at the origin). Interestingly, Stouffers remains the most distinct brand in both time periods. Given that industry reports suggest that Stouffer’s is perceived to be a higher-quality (and premium priced) brand while Totino’s is perceived as a lower quality brand (Consumer Reports, January 2002, pp. 39-41) we conjecture that the horizontal axis represents quality (we are unable to interpret the vertical axis). Therefore it seems that the high quality positioning of Stouffer’s has suffered significantly post the DiGiorno launch. Interestingly for both Kraft and Schwan’s, the quality perception of their brands has not been significantly affected.

Note that the finding that the innovation’s effect on Stouffer’s is most pronounced is consistent with range effects. The introduction of a high-quality form (rising crust) must have stretched the range of the quality attribute. According to the range effect theory, the difference between two existing two stimuli on a perceptual dimension decreases in this case. Thus, extant brands appear to become more similar due to the

\(^{18}\)To estimate equation (7), we impose the following identifying restrictions. We fix one brand at the origin to solve location ambiguities. One other brand is fixed at the position $(x_j,0)$ to solve rotation ambiguities. We also impose the restriction that the average residual clout and vulnerabilities should be zero, and that the residual clout of each brand equals the average residual vulnerability of its cross brands. These restrictions also ensure that a concurrent increase in cross-elasticities for a brand pair will manifest in increased similarity in lieu of a concurrent increase in residual clout and similarity.
introduction of a new brand with an outstanding attribute. As Stouffer’s used to have the highest quality positioning, the range effect is the strongest for this brand.

Managers could use our findings regarding the impact of new brand forms to affect the perceptions of existing brands in the marketplace. To increase the effect of a medium quality brand on a high-end brand, for example, a firm could introduce a very high quality innovation. The range and categorization effects would imply that former high-end brand is now more similar to the medium quality brand (similar to what we observe with Stouffer’s). Similarly, the effects of new form introductions need to be considered when ascertaining the impact of any technological innovation on a firms’ existing portfolio of brands. It is interesting to speculate that range and categorization effects would also predict that the introduction of a very low quality might also increases the perceived similarity of the existing brands.

**Summary and Conclusions**

Innovation is a key to a firm’s future. The entry of innovative products (and the exit of older products) creates markets that are dynamic. In this paper, we examine the dynamics of market structure as a result of an innovative product entry into a stagnant product category through the use of a general and flexible model. In our application, we find that the launch of an innovative brand makes the existing brands appear to be closer substitutes, as indicated by cross-price elasticities that increase in magnitude. This finding is consistent with range and categorization effects reported in the consumer behavior literature (Pan and Lehmann 1993). We also find that the own-price elasticities of existing brands increase in magnitude. We find strong evidence that these changes occur do not occur instantaneously but over a period of time. Interestingly, the fastest adjustment is made in terms of the substitutability of the existing brands. Our results also pinpoint the temporary increase in the uncertainty as a function of introduction in the model of sales response, consistent with Lipstein’s (1968) conjecture. From a managerial perspective, we use the estimated parameters to describe the changes in competitive position and the similarity of the brands in the market over the time period of the data. We illustrate how these findings have implications for product line policy.
From a methodological point of view, we embed the DLM in a Gibbs sampler. This allows for a
general and flexible model structure that accommodates data from dynamic environments easily. This is
important, as modeling data from such environments presents considerable challenge. The time series of
sales or marketing mix instruments may be nonstationary, reducing the applicability of models that rely on
stationary time series. In addition, the market structure in terms of cross- and own-brand price elasticities
may adapt gradually to the new situation. Third, the introduction of a new brand leads to changing
dimensions of the model and to missing data for some parameters. Fourth, such changes typically exist in
the context of panel data. Our formulation of the DLM copes naturally with each of these challenges as our
application to the frozen pizza category shows.

There exist a number of interesting future research directions. First, our approach can easily be
extended to other nonstationary environments characterized by frequent product entry and exit such as high
technology markets and fashion markets. Another domain where our model would be particularly
appropriate is emerging markets where the regulatory and consumer environment may be changing rapidly.
Finally, the insights uncovered herein are informative for normative research on product location. For
example, Ansari, Economides and Ghose (1994) consider the optimal entry location for new product under
the assumption that existing firms’ positions in perceptual space are invariant to entry. Our analysis
indicates otherwise, and suggests that normative analyses could benefit from addressing this possibility.

As with any research, our study has some limitations. First, we use store-level data. This makes it
very hard to precisely understand the change in the preference structure of individual customers. Second, the
Dynamic Linear Model is very general and, as a consequence, the dimensionality of the model can easily
become very big. This problem is probably more severe than in most time series techniques. Third, we do
not account for the possibility that the firms set prices as a function of demand. That said, weekly discounts,
which we model, are arguably not subject to such effects because price calendars are set well in advance of
any knowledge of demand shocks. Kopalle et al. (1999) find no evidence these effects in the SCAN*PRO
model. Fourth, we assume that the decision to launch the innovation is independent of the prevailing
demand conditions. It would be a huge challenge to dynamically model interdependent supply-side decisions
and demand-side responses in a nonstationary environment. In our application, the challenge would be to solve a dynamic optimization model in a nonstationary setting not only for the market-level decision to introduce the new brand and the follower brand but also for each store, for each brand and for each week the values of the price index variables and the promotional dummies for all the stores and the entire set of manufacturers. This formidable dynamic optimization task presents a potential fruitful avenue for future research. In this spirit, we hope that the research outlined herein will instantiate further research into marketing dynamics.
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Appendix: Model Estimation

The General Model

Our approach employs constant elasticity model of sales. Letting \( k = \{1, \ldots K\} \) denote brand, and \( i = \{1, \ldots I\} \) denote store, the log of sales can be modeled as

\[
\ln S_t = X'_t \beta_i + \nu_t,
\]

where \( \ln S_t \) is an \( IK \times 1 \) vector of log sales at time \( t \); \( X'_t \) is a \( IK \times IK \) matrix of regressors (we pool the parameters across stores), where \( M \) are the number of variables in the sales model; \( \beta_i \), dimensioned \( MK \times 1 \), are the parameters capturing the relationships between the \( X'_t \) and \( \ln S_t \); and \( \nu_t \) is an \( IK \times 1 \) vector of errors. These errors capture potential dependencies in sales across brands and stores, and are distributed \( N(0, V_i) \).

Equation (A1) captures the short-term (or instantaneous) effect of the \( X \) on sales. Following Mela, Gupta and Lehmann (1997), Papatla and Krishnamurthi (1996) and others we specify a Koyck-like model to capture these dynamic effects

\[
\beta_i = G \beta_{i-1} + Z'_i \delta + \omega_i
\]

where \( G \) is a diagonal \( MK \times MK \) matrix that captures the duration of these long-term effects; \( Z'_i \) are the variables expected to affect the response parameters in (A1) and is dimensioned \( MK \times MNK \) (where \( N \) are the number of regressors in (A2)); \( \delta \) is an \( MNK \times 1 \) vector of parameters that capture the magnitude of the effect of the \( Z \) on the parameters in (A1), e.g., the effect of innovation on price sensitivity; and \( \omega_i \) is an \( MK \times 1 \) vector of error terms and is assumed to be distributed normally, \( \omega_i \sim N(0, W) \).

Estimation

The system of equations given by (A1), (A2), and (A3) can be written

\[
\begin{align*}
\theta_t &= F \theta_t + \nu_t, \quad \nu_t \sim N(0, V_t) \\
\theta_0 | D_0 &\sim N(m_0, C_0)
\end{align*}
\]

(A4)
where $y_t = \ln S_t$, $F'_t = X'_t$, $V_t = \zeta_t V$, $\theta_t = \beta_t$, $h_t = Z_t \delta$, $G = \lambda$, $D_t$ is the information available at time $t$, and $m_0$ and $C_0$ reflect the prior belief regarding the mean and variance for $\theta$ at time 0.

Note that this prior is not informative when $C_0$ is chosen to be big.

The equation in (A4) falls under a class of models known as Dynamic Linear Model, or DLM (West and Harrison 1997). Assuming $h_t$, $G$, $V_t$ and $W$ are known (an assumption we shall relax shortly) the solution to the system in (A4) is given by (West and Harrison 1997, p. 103)

1. Posterior at $t - 1$

$$\theta_{t-1} | D_{t-1} \sim N(m_{t-1}, C_{t-1})$$

2. Prior at $t$

$$\theta_t | D_{t-1} \sim N(a_t, R_t) \text{ where } a_t = h_t + G m_{t-1} \text{ and } R_t = G C_{t-1} G' + W$$

3. One-step forecast

$$y_t | D_{t-1} \sim N(f_t, Q_t) \text{ where } f_t = F'_t a_t \text{ and } Q_t = F'_t R_t F_t + V_t$$

4. Posterior at $t$

$$\theta_t | D_t \sim N(m_t, C_t) \text{ where } m_t = a_t + A_t (Y_t - f_t), C_t = R_t - A_t Q'_t A_t' \text{ and } A_t = R_t F_t Q_t^{-1}$$

For the priors, we set $m_0$ close to the results from an OLS model. We set $C_0$ to 0.01 (where $U$ is the identity matrix). Note that this is much larger than the mean prior for $W$ (discussed below). This allows the posterior distribution of the parameters to be dominated by the likelihood quickly.

Obtaining $\lambda$, $\delta$, $V_t$ and $W$

As noted above, the process assumes that $\lambda$, $\delta$, $V_t$ ($=\zeta_t V$) and $W$ are known, that is, $p(\theta | D, \lambda, \delta, \zeta, V, W)$. By using Gibbs sampling techniques (Gelman et al. 1995), we can sample from each of these distributions. We estimate the model using MCMC techniques as described below. As is usual, we monitored the time-series of the draws to assess convergence. Although the parameter distributions converge after about 100 MCMC steps, we use 2000 iterations for burn-in, and use
the next 500 iterations for inference. The sampling chain consists of draws from the full conditional distributions of the unknowns: i) \( p(\theta \mid D, \lambda, \delta, \zeta, V, W) \), ii) \( p(V \mid D, \theta, \lambda, \delta, \zeta, W) \), iii) \( p(\zeta, D, \theta, \lambda, \delta, V, W) \), \( t=1,...,T \), iv) \( p(W \mid D, \theta, \lambda, \delta, \zeta, V, W) \), and vi) \( p(\delta \mid D, \theta, \lambda, \zeta, V, W) \). These are detailed below.

i) \( p(\theta \mid D, \lambda, \delta, \zeta, V, W) \). We use backward sampling as described by West and Harrison (1997, p. 570).\(^{20}\) We simulate the individual state vectors \( \theta_T, \theta_{T-1}, \ldots, \theta_1 \) as follows:

1. Sample \( \theta_T \) from \( (\theta_T \mid D_T) \sim N(m_T, C_T) \), then
2. for each \( t = T-1, T-2, \ldots, 1 \), sample \( \theta_t \) from \( p(\theta_t \mid \theta_{t-1}, D_t) \), where the conditioning value of \( \theta_{t+1} \) is the value just sampled. The required conditional distributions are:

\[
(\theta_t \mid \theta_{t+1}, D_t) \sim N(h_t, H_t), \text{ where } h_t = m_t + B_t(\theta_{t+1} - a_{t+1}) \text{ and } H_t = C_t - B_tR_{t+1}B_t',
\]

where

\[
B_t = C_tG_{t+1}R_{t+1}.
\]

ii) \( p(V \mid D, \theta, \lambda, \delta, \zeta, W) \). We assume that the prior on the covariance matrix \( V \) is Inverse Wishart \( \sim \text{InvWishart}(V_n, V_S) \). Then the full conditional distribution for \( V \) is Inverse Wishart \( \sim \text{InvWishart}(v_V + T, S_V + \sum_{i=1}^{T} (Y_i - F_i\theta_i)(Y_i - F_i\theta_i)'). \)

The choice of priors for the two variance components of the DLM, \( V \) (observation equation and \( W \) (state equation) is somewhat complicated. Using very diffuse and uninformative priors yields parameter paths that are highly unstable leading to interpretation problems. At the other extreme, the use of a fixed \( V \) and \( W \) leads to poor model performance. Our preliminary analyses showed that it was possible to improve model performance by using the data to inform the posterior distribution of \( V \) and \( W \) (see the earlier discussion on alternative specifications along with Table 5 for an example of model comparison of fixed \( V \) and \( W \) versus estimated \( V \) and \( W \)). We therefore chose somewhat informative priors – the prior mean for \( V

\[ \text{Note that we use } U \text{ to denote the Identity matrix in this appendix.} \]

\[ \text{See also Carter and Kohn (1994).} \]
had diagonal elements that are close to the residual variances obtained via OLS (cf. Montgomery 1997).

Specifically, we set $v_\nu = IK + 1 = 176$ and $S_\nu = 0.35U$.

iii) $p(\zeta_t | D, \theta, \lambda, \delta, V, W, t=1,\ldots,T)$. We assume that the prior on the time varying scale factor for $V, \zeta_t$, is Inverse Gamma $(v_\zeta / 2, S_\zeta / 2)$ (West and Harrison 1997, p. 642). Then the full conditional for $\zeta_t$ is Inverse Gamma

$\sim \left( \frac{v_\zeta + IK}{2}, \frac{(S_\zeta + (Y_t^i - f_t^i)'V^{-1}(Y_t^i - f_t^i))/2}{2} \right), \ t = 1,\ldots,T.$

Recall that, for $\zeta_t$, we are interested in the relative magnitude of this parameter over time. We therefore chose a prior distribution such that the marginal posterior is has a mean close to one. Specifically, we set $v_\zeta = 1, S_\zeta = 60$. As mentioned earlier, $\zeta_t$ is set to one for identification purposes.

iv) $p(W | D, \theta, \lambda, \delta, \zeta, V)$. We assume that the prior on the covariance matrix $W$ is Inverse Wishart $(v_w, S_w)$. Then the full conditional distribution for $W$ is Inverse Wishart

$\sim \left( v_w + T, S_w + \sum_{t=1}^{T} (\theta_t - (h_t + G\theta_{t-1})(\theta_t - (h_t + Г_{t-1})))' \right).$ As discussed above, the chosen prior for $W$ is somewhat informative. Our objective in choosing this prior was that it should allow the parameters to evolve smoothly while accommodating random shocks on a week-to-week basis. We therefore use $v_w = MK + 1 = 36$ and $S_w = 0.0001U$.

v) $p(\lambda | D, \theta, \delta, \zeta, V , W)$. We assume the same prior for each element of lambda. Specifically, for brand $k$, independent variable $m$ we assume: $\lambda_{mk} \sim N(\mu_k, \Sigma_k)$. The likelihood may be derived as follows. Note that, by rearranging the second line in (4) and stacking the observations for parameter $\beta_{mk}$ across time in $\beta'_{mkT} = (\beta_{mk2},\ldots,\beta_{mkT})$ and in $\beta'_{mkT-1} = (\beta_{mk1},\ldots,\beta_{mkT-1})$, we obtain

$$
(\hat{\beta}_{mkT} - Z_{mk}^{\delta_{mkT}}) = \hat{\beta}_{mkT-1} - \lambda_{mk} + \omega_{mkT} \quad \text{where} \quad \omega_{mkT} \sim N(0, W_{mk}).
$$

$\lambda_{mk}$ is a scalar and $W_{mk}$ is the diagonal element from $W$ corresponding to $\beta_{mk}$. This is the standard form for a multivariate regression and therefore the likelihood for
Given that the prior and likelihood are normal, the full conditional distribution is given by
\[ p(\lambda_{mk} | D, \Theta, \delta, \zeta, V, W) \sim N((\Sigma_\lambda^{-1} + S_{\delta mk}^{-1})^{-1}(\Sigma_\lambda^{-1} \mu_\lambda + S_{\delta mk}^{-1} l_{\delta mk}), (\Sigma_\lambda^{-1} + S_{\delta mk}^{-1})^{-1}) \]. For \( \lambda \) we use \( \mu_\lambda = 0.90 \) and \( \Sigma_\lambda = 0.01 \). This represents our belief that the mean carry-over effect is strong and that the 95% prior probability interval for individual carry-over effects is [0.70, 1.10].

vi) \( p(\delta | D, \Theta, \lambda, \zeta, V, W) \). We assume the same prior for each element of \( \delta \). Specifically, for brand \( k \), independent variable \( m \) we assume \( \delta_{mk} \sim N(\mu_\delta, \Sigma_\delta) \). We construct the likelihood as follows.

Rearranging equation (A9) yields
\[ (\hat{\beta}_{mkT} - \hat{\beta}_{mkT-1} \hat{\lambda}_{mk}) = Z_i \delta_{mk} + \omega_{mk} \] where \( \omega_{mk} \sim N(0, W_{mk}) \). This is a standard regression equation. Thus the likelihood for \( \delta_{mk} \sim N((Z_i'Z_i)^{-1}(Z_i' (\hat{\beta}_{mkT} - \hat{\beta}_{mkT-1} \hat{\lambda}), (Z_i'Z_i)^{-1}W_{mk}) \equiv N(d_{\delta mk}, S_{\delta mk}) \).

When combined with the normal prior, the full conditional distribution is given as
\[ N((\Sigma_\delta^{-1} + S_{\delta mk}^{-1})^{-1}(\Sigma_\delta^{-1} \mu_\delta + S_{\delta mk}^{-1} d_{\delta mk}), (\Sigma_\delta^{-1} + S_{\delta mk}^{-1})^{-1}) \]. For \( \delta \) we use a proper but diffuse prior, \( \mu_\delta = 0 \) and \( \Sigma_\delta = U \).

The Gibbs sampler proceed to sequence through steps i) to vi) until the we arrive at the marginal posterior distribution of the unknowns. An attractive feature of our approach is that we use normal, inverse Wishart and inverse Gamma priors. These priors, combined with the normal likelihood, result in full conditional distributions that are normal, inverse Wishart and inverse Gamma. This makes it easy to implement the sampler.
### Table 1: The Frozen Pizza Market – Sales and Market Share

<table>
<thead>
<tr>
<th>Brand</th>
<th>Manufacturer</th>
<th>Pre-Innovator*</th>
<th>Post-Innovator</th>
<th>Pre-Innovator Mean Sales (lb.)**</th>
<th>Post-Innovator Mean Sales (lb.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DiGiorno</td>
<td>Kraft</td>
<td>0</td>
<td>3632</td>
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<td></td>
</tr>
<tr>
<td>Freschetta</td>
<td>Schwan's</td>
<td>0</td>
<td>1380</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Red Baron</td>
<td>Schwan's</td>
<td>3851</td>
<td>4052</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stouffers</td>
<td>Nestle</td>
<td>1151</td>
<td>742</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tombstone</td>
<td>Kraft</td>
<td>13342</td>
<td>12813</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tony's</td>
<td>Schwan's</td>
<td>2480</td>
<td>2844</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Totinos</td>
<td>Pilsbury</td>
<td>1144</td>
<td>964</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td>21968</td>
<td>26157</td>
<td></td>
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</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Mean Share (%)</th>
<th>Mean Share (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DiGiorno</td>
<td>Kraft</td>
</tr>
<tr>
<td>Freschetta</td>
<td>Schwan's</td>
</tr>
<tr>
<td>Red Baron</td>
<td>Schwan's</td>
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<tr>
<td>Stouffers</td>
<td>Nestle</td>
</tr>
<tr>
<td>Tombstone</td>
<td>Kraft</td>
</tr>
<tr>
<td>Tony's</td>
<td>Schwan's</td>
</tr>
<tr>
<td>Totinos</td>
<td>Pilsbury</td>
</tr>
</tbody>
</table>

* The Pre-Innovator is the period from week 14 of 1995 to week 40 of 1996 while the Post-Innovator period is from week 41 of 1996 to week 52 of 1999. ** The means reported are across the 25 stores and the relevant time period.

### Table 2: The Frozen Pizza Market – Price and Promotion

<table>
<thead>
<tr>
<th>Brand</th>
<th>Mean Price ($/lb.) *</th>
<th>Mean Deal *</th>
</tr>
</thead>
<tbody>
<tr>
<td>DiGiorno</td>
<td>3.11</td>
<td>0.115</td>
</tr>
<tr>
<td>Freschetta</td>
<td>3.36</td>
<td>0.206</td>
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<td>Red Baron</td>
<td>3.04</td>
<td>0.254</td>
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<tr>
<td>Stouffers</td>
<td>3.98</td>
<td>0.099</td>
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<tr>
<td>Tombstone</td>
<td>2.92</td>
<td>0.360</td>
</tr>
<tr>
<td>Tony's</td>
<td>2.94</td>
<td>0.246</td>
</tr>
<tr>
<td>Totinos</td>
<td>2.33</td>
<td>0.069</td>
</tr>
</tbody>
</table>

* The means reported are across the 25 stores for the time period during when each brand was available.

### Table 3: Long-run parameter estimates
<table>
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<tr>
<th>Brand</th>
<th>Effect</th>
<th>Mean</th>
<th>2.5th percentile</th>
<th>97.5th percentile</th>
<th>Hypothesis</th>
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<td>Red Baron</td>
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<td>0.56</td>
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<td>Introduction DiGiorno ? intercept</td>
<td>-0.02</td>
<td>-0.71</td>
<td>0.28</td>
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<td></td>
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<td>-0.25</td>
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<td>0.03</td>
<td>0.33*</td>
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<td>0.15</td>
<td>0.56*</td>
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<td>-0.18</td>
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<td>-2.66*</td>
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<td>0.53</td>
<td>0.65*</td>
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<td>Freschetta (Follower)</td>
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<tr>
<td>Intercept</td>
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<td>−0.25</td>
<td>−0.03*</td>
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<td>Deal log multiplier</td>
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<td>0.75</td>
<td>0.90*</td>
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* A * indicates that the 95% highest posterior density excludes zero.
Table 4: Results for λ parameters

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<th>average</th>
<th>min</th>
<th>max</th>
<th>90% duration interval (weeks)</th>
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<td><strong>All brands</strong></td>
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<td>All λ</td>
<td>0.86</td>
<td>0.70</td>
<td>0.99</td>
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<td><strong>Existing brands</strong></td>
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<td>All λ</td>
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<tr>
<td>λ for intercept</td>
<td>0.82</td>
<td>0.79</td>
<td>0.85</td>
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<tr>
<td>λ for price elasticity existing brands</td>
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<td>0.86</td>
<td>0.99</td>
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<td>λ for elasticity to existing brands’ prices</td>
<td>0.77</td>
<td>0.73</td>
<td>0.84</td>
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<td>λ for elasticity to new brands’ prices</td>
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<td>0.78</td>
<td>0.95</td>
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<td>λ for deal log multiplier</td>
<td>0.82</td>
<td>0.74</td>
<td>0.89</td>
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<tr>
<td><strong>New brands</strong></td>
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<tr>
<td>All λ</td>
<td>0.87</td>
<td>0.70</td>
<td>0.97</td>
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<td>λ for elasticity to existing brands’ prices</td>
<td>0.77</td>
<td>0.70</td>
<td>0.84</td>
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<tr>
<td>λ for elasticity to new brands’ prices</td>
<td>0.79</td>
<td>0.75</td>
<td>0.84</td>
<td>10</td>
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<td>λ for deal log multiplier</td>
<td>0.89</td>
<td>0.89</td>
<td>0.90</td>
<td>20</td>
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<td>Alternate Specification</td>
<td>Substantive meaning</td>
<td>Log Bayes Factor</td>
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<tr>
<td>(a) All lambdas in (4) and (5) equal to zero</td>
<td>Immediate adjustment of model parameters to shocks</td>
<td>62.9</td>
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<td>(b) Moderating effects of $I_{Npt}$ in (4) are zero</td>
<td>No long-term effects of the introduction of DiGiorno on model parameters</td>
<td>342.6</td>
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<td>(c) $\mathbf{V}$ constant</td>
<td>Variance-covariance matrix for the observation equation constant over time</td>
<td>17.6</td>
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<tr>
<td>(d) Fix $\mathbf{V}$ and $\mathbf{W}$</td>
<td>Variance-covariance matrices for observation equation and system equations are fixed rather than estimated</td>
<td>8907.6</td>
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<td>(e) Also includes moderator effects of $I_{Npt}$ in (4)</td>
<td>Includes effects of the introduction of Freschetta on all own- and cross-price elasticities in addition to the effects of DiGiorno’s introduction on these parameters</td>
<td>63.5</td>
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</table>
Figure 1: Distribution index of the innovator (DiGiorno) brand

Figure 2: Weekly Category Volume
Figure 3: Patterns in cross-brand elasticities for the existing brands

Cross-price elasticity for Red Baron

Cross-price elasticity for Stouffers

Cross-price elasticity for Tombstone

Cross-price elasticity for Tony’s

Solid line: posterior mean, dotted lines: 95% highest posterior density.
Figure 4: Patterns in own-brand elasticities for the existing brands

Own-price elasticity for Red Baron

Own-price elasticity for Stouffers

Own-price elasticity for Totinos
Figure 5: Intercept patterns for three existing brands

Intercept Stouffer

Intercept Tombstone

Intercept Totinos

Solid line: posterior mean, dotted lines: 95% highest posterior density.
Figure 6: Time varying factor $\zeta$ for variance-covariance matrix for the observation equation

Solid line: posterior mean, dotted lines: 95% highest posterior density.
Figure 7: One-step ahead forecasts of the DLM around the introduction of DiGiorno

DiGiorno

Red Baron

Solid line: actual log sales, dashed line: model forecasts, dotted lines: 95% reliability interval.
Solid line: actual log sales, dashed line: model forecasts, dotted lines: 95% reliability interval.
Solid line: actual log sales, dashed line: model forecasts, dotted lines: 95% reliability interval.
Figure 8: Clout and Vulnerability over time

Figure 9: MDS positions in first and last year