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Product innovation is endemic among consumer packaged goods firms and is an integral component of their marketing strategy. As innovations affect markets, there is a pressing need to develop market response models that can adapt to such changes. The authors' model copes with the challenges that dynamic environments entail: nonstationarity, changes in parameters over time, missing data, and cross-sectional heterogeneity. They use this approach to model sales response in the frozen pizza category, in which the introduction of rising-crust pizza brands represents a major innovation. The model is directly applicable to other domains in which market structure might be nonstationary, such as changes in promotion strategy, shifts in the retail environment, and movements in macroeconomic factors. The authors find that innovation (1) makes the existing brands appear more similar, as indicated by increasing cross-brand price elasticities; (2) decreases brand differentiation for the existing brands, as indicated by an increase in the magnitude of own-brand price elasticities; and (3) increases the variance of the sales response equations temporarily around the time of the introduction of the innovation, indicating increased uncertainty in sales response. The authors discuss the managerial implications by presenting maps of how clout and vulnerability evolve over time, assessing the effect of new brands on cannibalization, and considering the strategic implications of the introduction of a flanker innovation to facilitate an extant brand's ability to attack an incumbent leader.

The Dynamic Effect of Innovation on Market Structure

Product innovation is endemic among consumer packaged goods firms and is an integral component of their marketing strategy. More than 16,000 new products appear annually in groceries and drugstores (Kotler 2000). Thus, it is imperative to develop marketing models that adapt well to these changes in the marketing environment. Accordingly, we offer an approach to deal with such nonstationary market environments, though our approach can readily be applied to other nonstationary environments. These include changes in firms' promotional strategy, in the marketing environment, in consumer tastes, in the composition of firms in the market, in regulatory and economic factors, and in the environment.

Despite the importance of the effect of product innovation, econometric analyses of the effects of innovations on market structure remain sparse compared with 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).[1]

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[1]*Market structure* is defined as the representation of brand positions in an attribute space (Elrod and Keane 1995). Often, the structure of markets is inferred from the substitution patterns evidenced by own- and cross-price elasticities. Products with higher cross-price elasticities are more substitutable and thus more similar (Bucklin, Russell, and Srinivasan 1998; Kamakura and Russell 1989; Manchanda, Ansari, and Gupta 1999; Mela, Gupta, and Jedidi 1998). Bucklin, Russell, and Srinivasan (1998) show how switching matrices and elasticities correspond; we use the latter to infer structure.

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As a consequence, there has been some interest in modeling the effects of product entry in markets. 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 innovations is instantaneous. Innovations' effects are not immediate; it takes time for innovations to diffuse into the marketplace (Mahajan, Muller, and Bass 1995; Rogers 1995). Second, we consider the introduction of substantially different brand forms rather than minor line extensions or store-brand introductions.[2] Highly disparate brands induce range and categorization effects, which can make consumers perceive extant brands as more similar (Pan and Lehmann 1993). Indeed, Pan and Lehmann (1993, p. 83) indicate that "perhaps the most serious issue for future research is to see how pervasive these effects would be in a more realistic setting." Likewise, such effects would not be expected from subsequent "me-too" entrants, because they neither increase the perceptual range of goods in the category nor lead to new categorizations (a supposition that our empirical analysis confirms). Third, we explicitly accommodate the possibility that the innovation increases uncertainty in the marketplace around the time of the launch.

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 led to the launch of rising-crust pizzas.[3] This major innovation sparked 12% growth in the hitherto no-growth frozen pizza market, and Kraft's DiGiorno brand captured 13% share (to become the number three brand) two years after its launch (Holcomb 2000). Our results indicate that the introduction of the new brand form led to significant changes in the market structure. Our main finding, as predicted by previous theoretical work, is that the introduction of a disparate new brand results in the old brands' becoming closer substitutes as measured by cross-price elasticities (Allenby 1989; Bucklin, Russell, and Srinivasan 1998; Kamakura and Russell 1989; Mela, Gupta, and Jedidi 1998). We also find that this adjustment occurs over a period of time (i.e., it does not occur instantaneously after launch).

The rest of the article is organized as follows: We discuss why the modeling of market response in dynamic environments (e.g., ones characterized by innovations) leads to several challenges. We then introduce our model in general terms and show why it represents a flexible approach to cope with these challenges. We discuss the data from the pizza category, after which we present the detailed model specification. We present the results in the subsequent section, offer some managerial implications, and conclude by summarizing the article and offering potential extensions.

MODELING MARKET RESPONSE IN DYNAMIC ENVIRONMENTS

Modeling of market response in dynamic environments (e.g., markets with brand introductions) leads to several key challenges: nonstationarity, changes in parameters over time, missing data, and cross-sectional heterogeneity. We subsequently discuss these challenges.

First, nonstationarity is an important issue.[4] The usual approach to addressing nonstationarity is to filter the data in the hope of making the series mean stationary and covariance stationary. However, means for filtering series, such as taking first differences, can induce distortion in the spectrum, thus affecting inferences about the dynamics of the system (Hamilton 1994). Furthermore, West and Harrison (1997, p. 300) indicate that the process of filtering to make series stationary can (1) hinder model interpretability, (2) confound model components, (3) emphasize noise at the expense of signal, and/or (4) 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 model of how one parameter (e.g., price sensitivity) can change in response to exogenous factors (e.g., brand introductions). Moreover, although differencing controls for some sources of stationarity (e.g., a random walk in a series), it does not control for others (e.g., a shift in the scale of the error variance over time, interventions, structural breaks).

Second, market response parameters are likely to change over time, especially in dynamic environments. There have been several articles in marketing and economics that have sought to assess how market response parameters vary over time in response to promotion. In general, the models fall into three classes: (1) those that provide parameter paths, (2) those that provide only the expected values of the parameters conditioned on observed covariates, and (3) those that perform 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 windows yield unreliable estimates, and long windows lead to coarse estimates and may induce autocorrelations when none exist.

The expectations-based approach typically presumes that the varying parameter is 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, it is typically assumed that the effects of the covariates on the parameter, as well as the covariance of the errors in the parameter process functions, are stationary. This may not be the case in dynamic markets. The before-and-after model (Kadiyali, Vilcassim, and Chintagunta 1999; Pauwels and Srinivasan 2004) estimates different models before and after an event occurs. The after model is estimated on data

[2]Moreau, Lehmann, and Markman (2001) conclude that continuity of the innovation affects the ease with which consumers can use existing category knowledge structures to evaluate and to categorize new brands. This implies that more discontinuous innovations are likely to lead to greater differences in categorization. Goldenberg, Mazursky, and Solomon (1999) define *innovation* as a change in product attributes. As such, we expect that minor innovations, such as a store-brand extension that offers no change in attributes, differ from innovations in which a major feature is changed or multiple features are mutated. As the degree of discontinuity increases, we expect that the categorization effects become more pronounced.

[3]In rising-crust pizzas, yeast is an ingredient in the pizza crust. This causes the crust to rise during the baking process and results in a superior end product. *Consumer Reports* (1997) indicates that the quality of the innovation was substantially higher than all other previously existing brands of frozen pizza and comparable to delivery pizzas.

[4]A 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.

starting from some time after the event, and it is assumed that the data represent the new, stabilized market situation. A drawback of this approach is that there exists a loss in statistical efficiency from ignoring the effects observed in a given part of the data. Another consideration pertains to the nature of the underlying adjustment: It is presumed to occur instantaneously. In practice, it may take some time for the market to adjustment to reach a new equilibrium. Finally, the models assume nonvarying parameters before and after the structural break (Perron 1994). Our approach relaxes these stringent assumptions.

Third, missing data are endemic in dynamic environments. Product entries and exits change the dimension of the data, thus 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 with classical 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 previously). The approach we employ adjusts the size of the regression matrix to the number of brands each period. As a result, the response parameters for the brands with all periods of data benefit from use of data before and after the brand introduction.[5]

Fourth, there is often a hierarchical nature to price sensitivity and other model parameters that results from (1) cross-sectional differences in price response across stores and households and/or (2) commonalities in response across classes of brands (e.g., new versus old). Time-series approaches are often difficult to implement with the use of hierarchical models (Horváth and Wieringa 2002; Pesaran and Smith 1995). Thus, time-series approaches commonly aggregate data across cross-sections. However, aggregation across cross-sections (e.g., stores) leads to aggregation biases in parameter estimates (Christen et al. 1997; Pesaran and Smith 1995).[6] Therefore, it is preferable to retain the cross-sectional and longitudinal nature of the data.[7] The dynamic linear model (DLM) we employ accommodates cross-sectional heterogeneity (e.g., differences in intercepts and sales response parameters across stores) because it readily integrates with a hierarchical Bayesian approach.

Notably, the issues of longitudinal heterogeneity (e.g., changing parameters across time) and cross-sectional heterogeneity (e.g., changing parameters across stores) are related. In each case, the researcher attempts to allow for variation across strata (time in one case, cross-sections in the other). In both cases, shrinkage approaches can be used to allow for differences in means across strata to increase forecasting validity and model efficiency. In this sense, our DLM approach of modeling parameter variation over time can be considered a longitudinal generalization of the cross-sectional models of heterogeneity in marketing (Rossi and Allenby 2003).

Together, all these factors (covariance nonstationarity, dynamic parameter paths, missing information, and cross-sectional heterogeneity) suggest that dynamic market environments present a unique challenge to the measurement and modeling of market response. Such environments may be the rule rather than the exception, especially for long data series. Therefore, it is our objective to develop an approach that enables us to address all four factors that pertain to the modeling of dynamic marketing response. Specifically, we embed the DLM into a Gibbs sampler and estimate the model on data from the frozen pizza category.

MODELING APPROACH

Our overall approach to modeling sales response in nonstationary environments proceeds in three steps. First, we specify a model of sales as a function of marketing variables. Second, we allow the marketing response parameters and covariance structure in the model to change over time. Third, we model cross-sectional differences in model parameters.

General Approach

We begin by presenting the model in its most general form, and we then adapt it to our application and data. We stack log sales of brand k (k = 1, …, K) in store i (i = 1, …, I) in vector y_t at time t (t = 1, …, T): $y_t = (y_{11t}, y_{12t}, ..., y_{1Kt}, y_{21t}, ..., y_{2Kt}, ..., y_{I1t}, ..., y_{IKt})'$. We model this as follows:

$$(1) \qquad \underset{IK \times 1}{y_t} = \underset{IK \times MIK}{\mathbf{F}_t'} \; \underset{MIK \times 1}{\beta_t} + \underset{IK \times 1}{v_t},$$

where $\mathbf{F}_t'$ is a matrix of M regressors (e.g., price, promotion) posited to affect y_t. We denote Equation 1 as the observation equation. We assume that $v_t \sim N(0, \mathbf{V}_t)$, where $\mathbf{V}_t$ is an IK × IK covariance matrix of error correlations across stores and brands. We let the scale of $\mathbf{V}_t$ change over time to accommodate nonstationarity in the covariance structure; that is, $\mathbf{V}_t = \zeta_t\mathbf{V}$.[8]

The system in Equation 1 can adapt to changes in the environment (e.g., economic factors, regulatory factors, technological changes), in the firm (e.g., entries and exits, changes in management), and among consumers (e.g., changing populations and tastes). Thus, we allow the model parameters to vary over time as follows:

$$(2) \qquad \underset{MIK \times 1}{\beta_t} = \underset{MIK \times MIK}{\mathbf{G}} \; \underset{MIK \times 1}{\beta_{t-1}} + \underset{MIK \times MPIK}{\mathbf{Z}_t'} \; \underset{MNIK \times 1}{\delta} + \underset{MIK \times 1}{\omega_t},$$

where $\omega_t \sim N(0,W)$, $\mathbf{Z}_t'$ is a vector of P regressors that can include an intercept,[9] and $\mathbf{G}$ is a matrix that can denote a general lag structure (e.g., its elements need not be constrained to less than one; i.e., a random walk is nested in Equation 2). The $\mathbf{G}$ matrix enables us to assess whether the

[5]Missing data are of two types: structural and empirical. The former arises when the data do not exist (i.e., sales data before a brand's introduction); the latter arises when the data exist but are not available to the analyst. Our discussion and application apply to the former, though our approach can also handle the latter (West and Harrison 1997, p. 351). An alternative approach to the latter is to use data-imputation techniques (Efron 1994).

[6]Note that Nijs and colleagues (2001) show that the aggregation bias is small in their application.

[7]Although we use store-level scanner data, our Bayesian approach is readily extendable for obtaining household-level parameters using household panel data in a limited dependent-variables framework. Thus, the problems of missing data and nonstationarity in means and covariances can also be redressed for household panel data (moreover, our approach can be readily integrated with recent advances in modeling household heterogeneity).

[8]Note that the product, $\zeta_t\mathbf{V}$, is not uniquely identified; thus, we set ζ_1 equal to 1. This does not affect our interpretation because we are interested in the relative magnitude of $\mathbf{V}$ in each time period.

[9]When $\mathbf{W} = 0$, the posterior estimates for β reduce to the standard normal regression posteriors (DeGroot 1971).

marketing effects are transient or enduring (Dekimpe and Hanssens 1995). For parsimony, we assume that the error term ω_t of β_t is independent across time (however, note that the β_t can follow an autoregressive process). We denote Equation 2 as the system or state equation.

The system represented by Equations 1 and 2 is known as a DLM (Chib and Greenberg 1995; West and Harrison 1997).[10] Conditioned on $\mathbf{V}_t$, $\mathbf{W}$, and $\mathbf{G}$, the β can be obtained through a series of updating steps. We specify proper priors for $\mathbf{V}_t$, $\mathbf{W}$, and $\mathbf{G}$ and derive the full conditional distributions given the likelihood. Details on the DLM updating, 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 naturally with the four challenges that pertain to the modeling of market response in dynamic environments: nonstationarity, dynamic parameter paths, missing information, and cross-sectional heterogeneity. We next indicate how the DLM does this.

First, the DLM parameters can be nonstationary. For example, the DLM allows for a random walk (or random walk with trend) in the parameters, which is obtained when $\mathbf{G}$ is the identity matrix and $\delta = 0$: $\beta_t = \beta_{t-1} + \omega_t$.[11] This implies that if our estimate for an element on the diagonal of $\mathbf{G}$ is one, any short-term shock in the corresponding parameter is enduring (Dekimpe and Hanssens 1995). Using Equation 1, we can also model a random-walk process for y_t by modeling time-varying intercepts only: $\mathbf{F}'_t$ and $\mathbf{G}$ are the identity matrices, $v_t = 0$, and $\beta_t = \beta_{t-1} + \omega_t$ (for a more general discussion of how to write any time-series model in the form of an observation equation and a system equation, see Hamilton 1994, p. 375). Because random walks are embedded in the DLM, it is not necessary to test for unit roots in our approach.[12] Thus, we specify the model in levels rather than differences, even when the series are nonstationary, thereby enhancing model interpretation. Other forms of nonstationarity are also embedded in our model. We capture increased uncertainty by a shift in scale of the $\mathbf{V}_t$ matrix at or near the time of product introduction. In addition, we can model shifts in series means or stochastic trends directly in the system equations.

Second, use of the DLM within the Gibbs sampler enables us to obtain dynamic parameter paths. We allow the parameters to evolve over time in a general manner as a function of lags and covariates (e.g., 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 after introduction. Thus, we relax the assumption of pre–post models that changes in parameters are instantaneous; indeed, the DLM nests such models.

Third, dynamic environments often entail missing data. Product entries (and exits) change the dimension of the data, which makes estimation of such models difficult. The Bayesian estimation approach for the DLM allows for selective updating of the parameters only for which information is available, making the accommodation of missing or unevenly spaced data straightforward. For example, the parameter for the effect of price changes of a later entrant on an existing brand's sales begins to be updated when the later entrant becomes available. This property enables us to exploit all the available information, thereby increasing the efficiency of the model estimation. Furthermore, in standard time-series models, data on the pricing and sales of the new product do not exist before introduction, which leads to difficulties in the estimation of a system of equations with missing data. In contrast, the DLM allows the dimensions of $\mathbf{F}_t$, y_t, and $\mathbf{V}_t$ to vary by period; these dimensions expand as the number of brands increases. A detailed description of how we handle missing data is provided in the Appendix.

Finally, our approach handles cross-sectional heterogeneity in a straightforward way. The parameter vector β_t in Equation 1 is dimensioned MIK by 1, which implies that there is a separate set of response parameters for each store. We shrink the store-level parameters to common means across stores, which we explain in more detail in the "Model Specification" section.

In summary, our new-brand context induces us to integrate (1) cross-sectional heterogeneity, (2) longitudinal heterogeneity, (3) shrinkage of cross-price effects, (4) product introduction dynamics, (5) missing data, and (6) nonstationarity in observational variances. Other articles in the marketing and statistics literature have one or more of these features, and some have used Gibbs sampling techniques to estimate state space models (see, e.g., Carter and Kohn 1994; Gamerman 1998; Neelamegham and Chintagunta 2001; West and Harrison 1997). However, to our knowledge, no article combines all these features, yet together these elements are critical to the assessment of dynamics in market structure.

DATA

As we mentioned previously, our data, provided by Information Resources Inc. (IRI), are from the frozen pizza category and span the almost-five-year period (247 weeks) from April 1995 to December 1999. The frozen pizza category is one of the most important categories in frozen food, constituting 19% of all frozen-food sales. During the period 1993–95, the category exhibited low growth ($1.6 billion in 1993 to $1.7 billion in 1995). However, the introduction of rising-crust pizzas resulted in an average growth in annual dollar volume of approximately 12% in this category (Holcomb 2000). Market researchers estimated that this growth was likely to be maintained at approximately 8.9% annually through 2002 (Find/SVP 1998). Frozen pizza has the high-

[10]Some readers will recognize the similarity of the DLM to the Kalman filter (Akçura, Gönül, and Petrova 2004; Hamilton 1994; Naik, Mantrala, and Sawyer 1998; Naik and Tsai 2000; Xie et al. 1997). 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." In addition, the DLM readily handles heterogeneity and shrinkage. Thus, it appears that the DLM is a more appropriate model for our context.

[11]We estimated another model of this form and found that it predicts worse than a model that does not restrict the **G** matrix to have ones on the diagonal.

[12]Given that power considerations affect unit root tests, models that difference to control for unit roots can be sensitive to those tests. Our approach obviates this consideration, because we can model directly in levels even in the presence of a random walk.

Table 1
THE FROZEN PIZZA MARKET: SALES AND MARKET SHARE

Brand	Manufacturer	*Pre-Innovator* Mean Weekly Sales (lb.)	*Post-Innovator* Mean Weekly Sales (lb.)
DiGiorno	Kraft	0	145
Freschetta	Schwan's	0	61
Red Baron	Schwan's	166	176
Stouffer's	Nestlé	49	31
Tombstone	Kraft	591	574
Tony's	Schwan's	108	126
Totino's	Pillsbury	48	40
Total		961	1153
		Mean Share (%)	
DiGiorno	Kraft	0	13
Freschetta	Schwan's	0	5
Red Baron	Schwan's	17	15
Stouffer's	Nestlé	5	3
Tombstone	Kraft	61	50
Tony's	Schwan's	11	11
Totino's	Pillsbury	5	3

Notes: The pre-innovator period is from Week 14 of 1995 to Week 40 of 1996; the post-innovator period is from Week 41 of 1996 to Week 52 of 1999. The means reported are across the 22 stores and the relevant time period.

est penetration among frozen prepared foods: In 1996, 58% of U.S. households purchased a frozen pizza during a typical 30-day period (this is more than the number of households that purchased takeout pizza during the same period) (IRI 1996). Demographically speaking, frozen pizza consumption is highest among people 18–44 years of age, in households with children, and in the Midwest (Holcomb 2000).

Our data are from the Chicago market area. The resultant sample includes the 22 supermarkets from the IRI sample that had five years of weekly data. We included the top seven national brands from this category in our analysis, which together account for 55% of all volume sales in the market.[13] The seven brands are DiGiorno, Freschetta, Red Baron, Stouffer's, Tombstone, Tony's, and Totino's. The brands are produced by the four major manufacturers in this market: Kraft, Nestlé, Schwan's, and Pillsbury. 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 mid-1996 and Freschetta in mid-1997.

In our data, rising-crust pizza was introduced in some stores as early 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). The five-year span of the data is sufficient to enable us to detect changes in the market, if any, and the resultant dynamics.

Table 1 provides the mean quantities sold and market share for each brand before and after the introduction of the rising-crust innovation into the market (i.e., the DiGiorno introduction). As Table 1 shows, there is an increase in category volume sales after DiGiorno was introduced. We also regressed category sales on time and on the proportion of stores carrying the new brands. The results show that there is no discernible overall time trend and that there is an increase in total category volume sales after the DiGiorno launch but not after the Freschetta launch. As is shown in Table 1, Kraft's Tombstone is the dominant player in the category; however, it lost significant share after the launch of DiGiorno. Indeed, except for Tony's, all the old brands lost share after entry.

In terms of marketing activity, the mean weekly price in dollars per pound (including the effect of temporary price reductions) of each brand is provided in Table 2. As is shown in Table 2, the two new brands are more expensive than the existing brands (with the exception of Stouffer's). We used an indicator variable that we set equal to 1 whenever we observed a feature, display, or feature and display. We then averaged this indicator across stockkeeping units to arrive at the brand–store promotion variable. The mean weekly promotional intensity (percentage of store-weeks on promotion) for each brand is given in Table 2.

To rule out systematic changes in before-and-after marketing variables, we also estimated ordinary least squares (OLS) models of prices and promotions as a function of time and the proportion of stores carrying the new brands. The results show that there is hardly any significant change in the variables across time or after the introduction of either DiGiorno or Freschetta.

Table 2
THE FROZEN PIZZA MARKET: PRICE AND PROMOTION

Brand	Mean Price ($ per lb.)	Mean Promotion
DiGiorno	3.18	.12
Freschetta	3.37	.22
Red Baron	3.06	.22
Stouffer's	4.11	.08
Tombstone	3.01	.30
Tony's	2.96	.24
Totino's	2.39	.06

Notes: The means reported are across the 22 stores for the time period when each brand was available.

[13]These are the major brands in the category (Holcomb 2000).

MODEL SPECIFICATION

The modeling approach we described previously is quite general. We subsequently indicate our particular instantiation. We begin by relating marketing activity to sales in the observation equation. Next, we detail how parameters evolve over time in the state equation (including the effect of innovation), and we conclude by outlining our treatment of cross-sectional heterogeneity.

Observation Equation

We use a log–log sales model similar to those of Montgomery (1997) and Van Heerde, Leeflang, and Wittink (2000):

$$\text{(3)} \qquad \ln S_{ikt} = \beta_{0ikt} + \sum_{k'=1}^{K} \beta_{k'ikt} \ln \text{Price}_{ik't} + \beta_{K+1ikt}\text{Prom}_{ikt} + \nu_{ikt},$$

where S_{ikt} represents sales of brand k in store i in week t, Price represents the price index,[14] Prom indicates whether there was a feature and/or display,[15] and v is an error term.[16] We assume that the error is distributed normal and independent across time, but we allow for correlation between brands, separately for each store (i.e., we have a storewise block diagonal V). Note that this assumption does not preclude β (including the brand intercepts), and thus ln S, from being autoregressive. In addition, we allow the covariance matrix for ν_t to be nonstationary with covariance $\zeta_t V$. We place an inverse Wishart prior on V and an inverse gamma prior on ζ_t.

State Equation

We expect that the innovation effects occur gradually as the innovation diffuses through the population. A parsimonious model to capture the dynamic effects is given by $\beta_t = \lambda\beta_{t-1} + Z_t'\delta + \omega_t$ (Clarke 1976). When $\lambda = 0$, an innovation's effect occurs immediately after it is introduced. As λ approaches 1, the effect of innovation on market structure is far more dilatory. 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 with the data.

We capture the dynamic effects of brand introductions on market structure with the following sets of equations for intercepts, own-price elasticities, cross-price elasticities, and promotion effects, respectively:

$$\text{(4a)} \qquad \beta_{0ikt} = \delta_{00ik} + \lambda_{0k}\beta_{0ikt-1} + \delta_{01ik}\text{NEW1}_{it} + \delta_{02ik}\text{NEW2}_{it} + \omega_{0ikt},$$

$$\text{(4b)} \qquad \beta_{kikt} = \delta_{10ik} + \lambda_{kk}\beta_{kikt-1} + \delta_{11ik}\text{NEW1}_{it} + \omega_{1ikt},$$

$$\text{(4c)} \qquad \beta_{k'ikt} = \bar{\delta}_{k'0ik} + \bar{\lambda}_{1k}\beta_{k'ikt-1} + \bar{\delta}_{k'1ik}\text{NEW1}_{it} + \omega_{2ikt} \quad (\text{where } k' = \text{old brand}, k' \neq k),$$

$$\beta_{k'ikt} = \bar{\delta}_{k'0ik} + \bar{\lambda}_{2k}\beta_{k'ikt-1} + \bar{\delta}_{k'1ik}\text{NEW1}_{it} + \omega_{2ikt} \quad (\text{where } k' = \text{new brand}, k' \neq k),$$

and

$$\text{(4d)} \qquad \beta_{(K+1)ikt} = \delta_{(K+1)0ik} + \lambda_{(K+1)k}\beta_{(K+1)ikt-1} + \omega_{3ikt},$$

where NEW1_{it} is a dummy variable that represents whether store i has adopted the innovator brand at time t, and NEW2_{it} is a dummy variable that represents whether store i has adopted the follower brand at time t. We assume that the ωs are independently distributed and are brand and store specific. However, this error assumption does not imply that the posteriors for the βs are independent. For a brand-sales equation in a given store, the response parameters are dependent because they are from the same equation and because of the block diagonal structure of V. We place an inverse gamma prior on the elements of ω and a normal prior on λ. We subsequently indicate our priors for δ.

In Equation 4, we assume that only the introduction of the innovator has effects on the own-price elasticities β_{kikt} and the cross-price elasticities $\beta_{k'ikt}$ because this introduction represents a major shock to the market. The inclusion of the NEW1_{it} and NEW2_{it} variables in Equation 4 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; the speed of adjustment is given by λ. The range and categorization effects to which we alluded previously suggest that the introduction of the follower brand does 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 we consider only the later entrants' effect on intercepts to capture substitution effects.[17] The system in Equation 4 enables us to assess the effects of innovation on price sensitivity and model intercepts (the effect of innovation on the intercept can also be interpreted as its main effect). Thus, we are able to ascertain the effect of pioneering entry on existing brands' cross-price effects ($\delta_{k'1ik}$), on the existing brands' own-price effect δ_{11ik}, and on the intercepts δ_{01ik}. We also allow the promotion effects to change over time (Equation 4d).[18]

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[14]We define Price as actual (net) price divided by regular price (Van Heerde, Leeflang, and Wittink 2000).

[15]We combine feature and display into one variable for reasons similar to those outlined by Bucklin, Gupta, and Siddarth (1998) and Drèze and Bell (2003); namely, it is more parsimonious, and the information contained in these variables is somewhat redundant.

[16]Although the log–log model in Equation 3 is appropriate for descriptive analyses and has the advantage that the parameters can be interpreted directly as elasticities, it has limitations when used normatively (Vilcassim and Chintagunta 1995; Zenor 1994). To redress this consideration, a different function or a constraint on prices (e.g., the average of the optimized prices = the average of the observed prices) can be used. We thank the guest editor and an anonymous reviewer for this insight.

[17]Note that we also estimate an extended model that does include the additional effects of NEW2 in Equations 4b and 4c, and we find that the restricted model outperforms the extended model based on the Bayes factor (we discuss this "benchmark model e" in a subsequent section).

[18]Our objective pertains to changes in price elasticities as a measure of market structure. Thus, we do not specify introduction effects on the nonprice promotion coefficient. To assess whether our conclusions are affected by this specification, we estimate such a model (inclusion of NEW1 effects on promotions in Equation 4d). We find no material difference in the substantive results, though the number of parameters to be estimated increases (with an attendant decrease in the reliability of our parameter estimates). Moreover, the improvement in predictive validity is negligible (.3%), and in only one case (out of five) did NEW1 affect promotion elasticities.

The system in Equation 4 requires some identifying restrictions. For the pioneering brand, δ_{01ik}, δ_{11ik}, and δ_{21ik} are zero, because 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, because the later entrant appears after the pioneer. Moreover, the effects of the introduction of the follower brand on its own intercept, own-price effect, and cross-price effects are not observable.

Heterogeneity

Across stores. The panel nature of our data (i.e., time-series observations for each store) implies that we can accommodate heterogeneity in response across stores. Because the δs in Equation 4 are store-specific, we shrink these across stores (Montgomery 1997; Montgomery and Rossi 1999). The variable m denotes the state equation for a specific β (e.g., m = 1 for intercept, m = 2 for own effect, m = 3 for cross-price effect, m = 4 for promotion). The variable p denotes a modifier in the state equation for a parameter in the observation equation (e.g., p = 0 for the main effect, p = 1 for the effect of NEW1 [DiGiorno], p = 2 for the effect of NEW2 [Freschetta]). Then, each δ in Equation 4 can be denoted as $\delta_{mik} = (\delta_{0mik}, \delta_{1mik}, \delta_{2mik})'$, and we can specify the following:

$$(5) \qquad \delta_{mik} = \mu_{mk} + \varepsilon_{\delta mik},$$

where $\mu_{mk} = (\mu_{0mk}, \mu_{1mk}, \mu_{2mk})'$, and $\varepsilon_{\delta mik} \sim N(0, \Sigma_{\delta_{mk}})$. Thus, we can consider μ_{pmk} an average effect of a moderating variable across stores. For example, μ_{13k} is the mean effect of the product introduction of DiGiorno on cross-price sensitivity for brand k. Thus, this parameter is of central importance as a summary test for the effects of new product introduction on consumer response. We place an inverse gamma prior on the diagonals of $\Sigma_{\delta_{mk}}$. For the μ that pertains to the effect of NEW1 and NEW2 on the intercept, own-price effects, and own-promotion parameters, we choose proper but diffuse priors. In essence, this enables the data to determine the mean intercept, own-price response, and own-promotion response in the sales model.

Across cross-price elasticities. We shrink each brand's cross-price parameters to a common mean (Wedel and Zhang 2003): one mean for its old competitors and another for its new competitors.[19] This implies that competing brands (old or new) exert some mean level of effect on a brand's sales. For stronger cross-brands, this effect should be greater. We then allow for variation around this mean. Thus, for m = 3, we use $\mu_{pmk} \sim N(\bar{\mu}_{cpk}, \sigma^2_{\bar{\mu}cpk})$, where $\bar{\mu}_{cpk}$ represents the average effect of competing brands' prices on a brand's sales across the two new competing brands (c = 1) and old competing brands (c = 2). Placement of a normal diffuse prior on $\bar{\mu}_{cpk}$ and an inverse gamma prior on $\sigma^2_{\bar{\mu}cpk}$ completes our model specification.

We summarize our model as a directed acyclic graph in Figure 1. The complete sampling scheme for the model is detailed in the Appendix.

[19]We thank an anonymous reviewer for this suggestion. Note that we use within-equation shrinkage of cross-effects instead of between-equation shrinkage of parameters (Boatwright, McCulloch, and Rossi 1999).

RESULTS

We estimate Equations 3–5 using the Gibbs sampling steps, which we outline in the Appendix. To obtain cumulative effects for the parameters in the observation (or sales) equation, we divide μ_{mk} in Equation 5 by $1 - \lambda_{mk}$, the corresponding lag parameter.[20] We report the means and the lower and upper bound of the 95% highest posterior density region in Table 3, and we indicate the sign we expect for each parameter.

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 2000). More specifically, the estimates for the intercept should be near zero because we used data that were mean-centered by store (both dependent and independent variables), and Table 3 shows that this is the case for all seven brands. The estimates for the price elasticities range from –1.54 (Red Baron) to –4.79 (Freschetta), which is consistent with findings from other price-promotion studies (Nijs et al. 2001; Tellis 1988). Notably, the two new brands (DiGiorno and Freschetta) have the highest magnitude (strongest) price elasticities (most negative), which suggests that their price promotions are the most effective. This may be because the innovative and (relatively) expensive brands are especially attractive for consumers to stockpile when they are discounted. Such an effect may also arise from increased trial resulting from dealing. The estimates for the log-deal multipliers are significant and positive for all seven brands, as we expected. When taking the anti-log transformation of the log-deal multipliers, we obtain the deal multipliers. These are the multiplication factors for brand sales when an item has a nonprice promotion. The deal multipliers range from 1.84 (Totino's) to 4.73 (Tony's), which are comparable to SCAN*PRO results (Wittink et al. 1988).

Almost all the estimates for the cross-price elasticities are less (in magnitude) than one. This is consistent with Sethuraman, Srinivasan, and Kim's (1999, p. 30) meta-analysis results on cross-price elasticities. Cross-price effects on the newer brands all are not significant, indicating that they are somewhat distinctive and thus not affected by the other brands' price promotions. Across the 20 cross-price elasticities for the five old brands, 10 are significant and positive (before the introduction of DiGiorno) and the rest are not significant.

Our model indicates that parameters indeed change over time. To illustrate this, we display an example of changes in own- and cross-brand price elasticities in Figure 2. The graphs show spikes around the introduction of DiGiorno (in the second half of 1996). In addition, note that the changes are not instantaneous.

[20]We focus on the cumulative effects for the observation model parameters (rather than current effects), because we can directly interpret these intercepts, price elasticities, and promotion effects. This transformation makes the parameters easier to compare with parameter estimates from static models (note that the substantive results are identical for the transformed and untransformed parameter).

Figure 1
DIRECTED ACYCLIC GRAPH FOR THE ESTIMATION STEPS

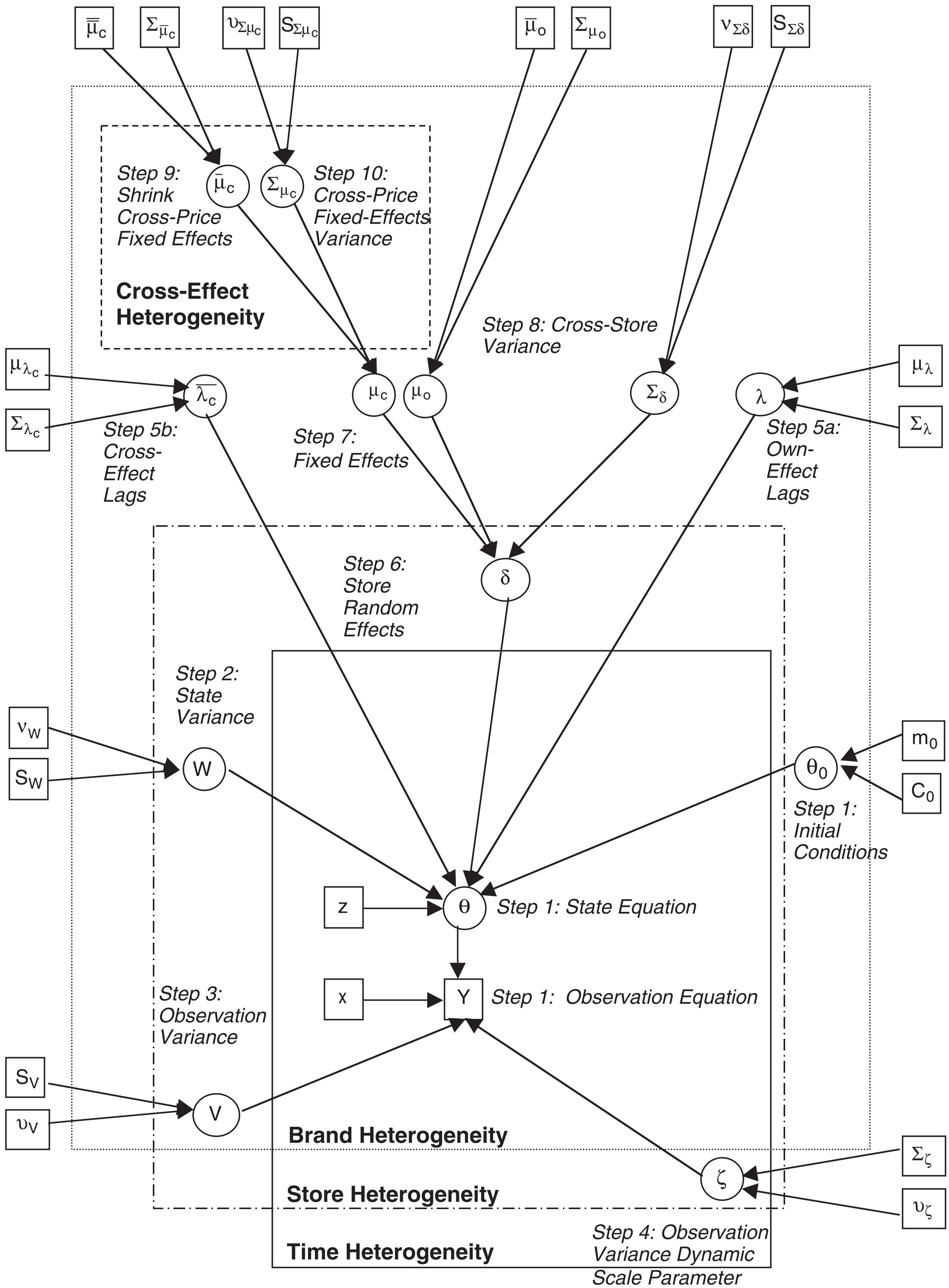


Table 3
LONG-TERM POSTERIOR PARAMETER ESTIMATES

Brand and Effect	*Mean*	*2.5th Percentile*	*97.5th Percentile*	*Standard Deviation*	*Expected Sign*
Red Baron					
Intercept	–.03	–.14	.09	.06	0
Introduction DiGiorno on intercept	–.05	–.27	.14	.10	–
Introduction Freschetta on intercept	.17	–.02	.34	.09	–
Price elasticity	–1.54	–2.58	–.36*	.67	–
Introduction DiGiorno on price elasticity	–2.11	–3.41	–1.01*	.69	–
Elasticity to Stouffer's price	.05	–.16	.26	.13	+
Introduction DiGiorno on elasticity to Stouffer's price	.19	.12	.26*	.03	+
Elasticity to Tombstone's price	.25	.13	.41*	.07	+
Introduction DiGiorno on elasticity to Tombstone's price	.19	.13	.26*	.03	+
Elasticity to Tony's price	.15	–.01	.27	.07	+
Introduction DiGiorno on elasticity to Tony's price	.19	.12	.26*	.03	+
Elasticity to Totino's price	.25	.13	.38*	.07	+
Introduction DiGiorno on elasticity to Totino's price	.19	.12	.26*	.03	+
Elasticity to DiGiorno's price	.17	–.11	.36	.13	+
Elasticity to Freschetta's price	.28	.02	.56*	.14	+
Deal-log multiplier	1.20	1.08	1.33*	.06	+
Stouffer's					
Intercept	.08	.00	.17*	.04	0
Introduction DiGiorno on intercept	.05	–.08	.17	.06	–
Introduction Freschetta on intercept	–.29	–.46	–.14*	.08	–
Price elasticity	–2.81	–3.69	–2.16*	.37	–
Introduction DiGiorno on price elasticity	.30	–.32	1.13	.37	–
Elasticity to Red Baron's price	.07	–.01	.20	.05	+
Introduction DiGiorno on elasticity to Red Baron's price	.22	.15	.30*	.04	+
Elasticity to Tombstone's price	.06	–.02	.15	.04	+
Introduction DiGiorno on elasticity to Tombstone's price	.22	.15	.30*	.04	+
Elasticity to Tony's price	.06	–.02	.14	.04	+
Introduction DiGiorno on elasticity to Tony's price	.21	.10	.29*	.05	+
Elasticity to Totino's price	.05	–.03	.14	.04	+
Introduction DiGiorno on elasticity to Totino's price	.24	.16	.35*	.05	+
Elasticity to DiGiorno's price	–.17	–.54	.24	.26	+
Elasticity to Freschetta's price	–.21	–.49	.17	.18	+
Deal-log multiplier	1.03	.93	1.14*	.05	+
Tombstone					
Intercept	.02	–.04	.08	.03	0
Introduction DiGiorno on intercept	–.02	–.12	.09	.05	–
Introduction Freschetta on intercept	–.05	–.18	.08	.07	–
Price elasticity	–1.65	–2.16	–1.07*	.29	–
Introduction DiGiorno on price elasticity	–.57	–1.12	–.13*	.26	–
Elasticity to Red Baron's price	.00	–.05	.05	.02	+
Introduction DiGiorno on elasticity to Red Baron's price	.20	.09	.32*	.06	+
Elasticity to Stouffer's price	.00	–.04	.05	.02	+
Introduction DiGiorno on elasticity to Stouffer's price	.01	–.19	.19	.12	+
Elasticity to Tony's price	.00	–.04	.05	.02	+
Introduction DiGiorno on elasticity to Tony's price	.14	.05	.24*	.05	+
Elasticity to Totino's price	.00	–.05	.05	.02	+
Introduction DiGiorno on elasticity to Totino's price	.14	.05	.23	.04	+
Elasticity to DiGiorno's price	1.02	.89	1.19*	.08	+
Elasticity to Freschetta's price	.69	.54	.92*	.09	+
Deal-log multiplier	.88	.74	1.04*	.08	+
Tony's					
Intercept	.10	–.07	.26	.08	0
Introduction DiGiorno on intercept	–.23	–.40	–.05*	.09	–
Introduction Freschetta on intercept	.18	–.14	.49	.16	–
Price elasticity	–2.89	–3.18	–2.62*	.14	–
Introduction DiGiorno on price elasticity	–.77	–1.10	–.46*	.17	–
Elasticity to Red Baron's price	.32	.14	.59*	.11	+
Introduction DiGiorno on elasticity to Red Baron's price	.75	.61	1.01*	.09	+
Elasticity to Stouffer's price	.27	.18	.37*	.05	+
Introduction DiGiorno on elasticity to Stouffer's price	.53	.37	.74*	.09	+
Elasticity to Tombstone's price	.25	.12	.39*	.08	+
Introduction DiGiorno on elasticity to Tombstone's price	.34	.13	.51*	.10	+
Elasticity to Totino's price	.25	.15	.38*	.06	+
Introduction DiGiorno on elasticity to Totino's price	–.52	–.67	–.40*	.07	+
Elasticity to DiGiorno's price	.30	–.04	.59	.20	+
Elasticity to Freschetta's price	.15	–.18	.52	.21	+
Deal-log multiplier	1.55	1.37	1.74	.09	+

Table 3

CONTINUED

Brand and Effect	*Mean*	*2.5th Percentile*	*97.5th Percentile*	*Standard Deviation*	*Expected Sign*
Totino's					
Intercept	.08	.00	.15	.04	0
Introduction DiGiorno on intercept	.11	–.02	.24	.07	–
Introduction Freschetta on intercept	–.35	–.50	–.22*	.07	–
Price elasticity	–1.89	–2.19	–1.61*	.14	–
Introduction DiGiorno on price elasticity	–.02	–.29	.22	.12	–
Elasticity to Red Baron's price	.10	.04	.16*	.03	+
Introduction DiGiorno on elasticity to Red Baron's price	.13	.06	.22*	.04	+
Elasticity to Stouffer's price	.11	.05	.16*	.03	+
Introduction DiGiorno on elasticity to Stouffer's price	.13	.06	.21*	.04	+
Elasticity to Tombstone's price	.10	.05	.16*	.03	+
Introduction DiGiorno on elasticity to Tombstone's price	.12	.06	.19*	.04	+
Elasticity to Tony's price	.11	.05	.17*	.03	+
Introduction DiGiorno on elasticity to Tony's price	.11	.02	.19*	.04	+
Elasticity to DiGiorno's price	.00	–.21	.23	.11	+
Elasticity to Freschetta's price	–.06	–.34	.23	.14	+
Deal-log multiplier	.61	.49	.71*	.06	+
DiGiorno (Innovator)					
Intercept	.12	.05	.20*	.04	0
Introduction Freschetta on intercept	–.14	–.24	–.05*	.05	–
Price elasticity	–4.06	–4.28	–3.89*	.12	–
Elasticity to Red Baron's price	.09	–.01	.19	.05	+
Elasticity to Stouffer's price	.07	–.08	.20	.07	+
Elasticity to Tombstone's price	.02	–.08	.14	.06	+
Elasticity to Tony's price	–.01	–.09	.07	.04	+
Elasticity to Totino's price	.08	–.06	.22	.07	+
Elasticity to Freschetta's price	.17	–.14	.43	.15	+
Deal-log multiplier	.79	.68	.90*	.05	+
Freschetta (Follower)					
Intercept	.03	–.04	.09	.03	0
Price elasticity	–4.79	–5.87	–3.72*	.56	–
Elasticity to Red Baron's price	.03	–.10	.18	.07	+
Elasticity to Stouffer's price	–.09	–.33	.16	.12	+
Elasticity to Tombstone's price	.01	–.14	.15	.08	+
Elasticity to Tony's price	.00	–.17	.16	.08	+
Elasticity to Totino's price	–.03	–.28	.15	.11	+
Elasticity to DiGiorno's price	.06	–.36	.62	.32	+
Deal-log multiplier	.96	.86	1.05*	.05	+

*Indicates that the 95% posterior probability interval excludes zero.

State-Equation Parameter Estimates

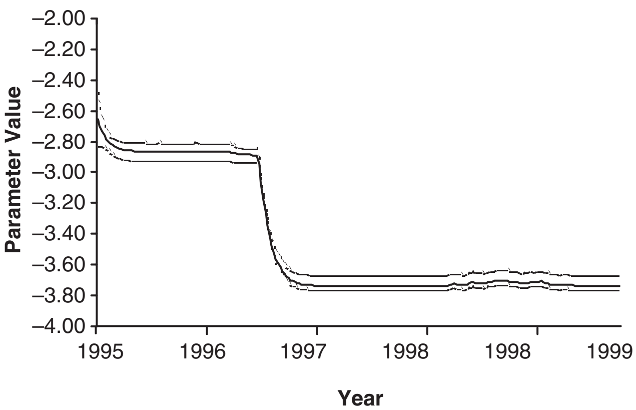
The results in Table 3 imply that 18 of the 20 cross-price elasticities significantly increase after the introduction of DiGiorno, 1 decreases significantly, and 1 is insignificant. The consumer behavior literature on brand introductions offers insight into this result. In particular, Pan and Lehmann (1993) suggest that *range* and *categorization* effects make extant brands appear to be 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 appear to be more similar when a third brand is positioned away from them. *Categorization* effects may also occur, whereby the introduction of a radically dissimilar alternative leads to categorization of the old and new alternatives. Because consumers perceive members of the same category as more similar (Sujan and Bettman 1989), it is reasonable to suppose that the categorization process that results from the introduction of an innovation leads to greater perceived similarity across the set of existing brands. Greater similarity should lead to larger cross-price elasticities (Allenby 1989; Bucklin, Russell, and Srinivasan 1998; Kamakura and Russell 1989; Mela, Gupta, and Jedidi 1998), which is what we find quite convincingly.[21]

In addition, we consider the effect of new-brand introductions on own-price response. For three of the five existing brands (Red Baron, Tombstone, and Tony's), the own-brand price elasticity increases in magnitude (becomes more negative). The own-brand price elasticity is a measure of brand differentiation (Boulding, Lee, and Staelin 1994). Firms with a less price-elastic demand function (i.e., a lower absolute own-price elasticity) are more differentiated. Consistent with range and categorization effects, we find evidence of decreased differentiation. Fischer (1995) provides a related explanation, suggesting that a decrease in variation on an attribute increases the salience of the

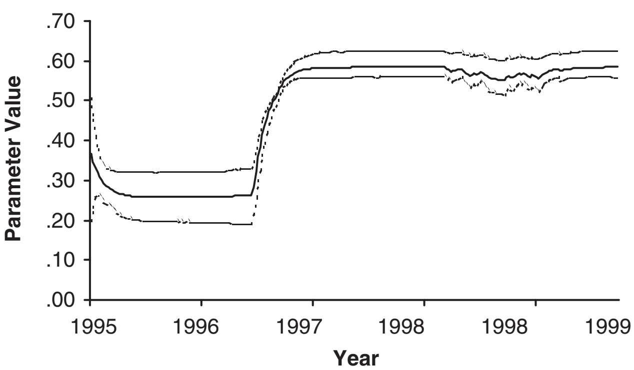
[21]We can rule out another explanation (related to changes in base levels of sales after the introduction) because we used a multiplicative model ($y = a \times x^b$). In such a model, the elasticity b is independent of the marketing effort x and base level of sales a. Thus, a diminution in a brand's consumer base after the innovation's introduction need not lead to a change in elasticities.

Figure 2
EXAMPLES OF ELASTICITY PATTERNS

Own-Price Elasticity for Tony's



Elasticity of Tony's Sales to Tombstone's Price



Notes: Solid line indicates posterior mean; dotted lines indicate a 95% posterior probability interval.

remaining attributes in decision making. To the extent that consumers perceive brands as more similar in perceptual (attribute) space, price becomes increasingly important. It is noteworthy that only the brands at the extreme ends (high-quality, high-priced Stouffer's and low-quality, low-priced Totino's) were unaffected in terms of own-price effects.[22]

Our model also includes the impact of the introduction of DiGiorno and Freschetta on the brand intercepts (see Table 3). This enables us to judge the extent to which the new brands cannibalize sales from brands of the same company. The introduction of the innovator brand, DiGiorno (Kraft), has a significant (negative) impact on only one brand (Tony's). This is consistent with the notion that the introduction of DiGiorno has led to category growth. In other words, this suggests that the innovation increased the potential size of the primary market for frozen pizza. In contrast, the introduction of the follower brand, Freschetta (Schwan's), seems to have appropriated sales from existing brands as the intercept terms of DiGiorno, Stouffer's, and Totino's decrease significantly.

Autoregressive Parameters

The autoregressive parameter λ (see Table 4) represents the amount of carryover effects in the β series (or the speed of adjustment to a new equilibrium after the introduction of a new brand). The average λ equals .70, and the 95% highest-posterior-density interval does not include one for any λ (not shown). Thus, the parameters are mean-reverting (consistent with no unit roots) for all cases. Table 4 also portrays the mean λ for each independent variable, for both the existing brands and the new brands. In addition, we compute 90% duration intervals. This interval shows the number of weeks 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 7 weeks before system parameters adjust. Notably, the cross-brand price elasticity for existing brands adjusts most quickly, taking only 3 weeks. This implies that the increase in this cross-brand elasticity after the introduction of the innovator happens rather quickly. The duration interval for the own-brand sales elasticity for the existing brands is much longer (11 weeks).

[22]The higher elasticities for DiGiorno and Freschetta mitigate the likelihood that higher elasticities for existing brands arise as a result of the low price sensitivity of consumers migrating to the higher-quality innnovations. This would imply that the elasticities would be lower for the new brands than for the existing brands.

Table 4
RESULTS FOR λ PARAMETERS

		Average	*Minimum*	*Maximum*	*90% Duration Interval (Weeks)*
All brands	All λ	.70	.24	.95	7
Existing brands	All λ	.62	.24	.95	5
	λ for intercept	.67	.24	.95	6
	λ for price elasticity to existing brands	.81	.74	.88	11
	λ for elasticity to existing brands' prices	.41	.26	.90	3
	λ for elasticity to new brands' prices	.94	.94	.94	38
	λ for deal-log multiplier	.54	.39	.67	4
New brands	All λ	.93	.78	.95	30
	λ for intercept	.95	.94	.95	41
	λ for price elasticity to new brands	.93	.93	.93	34
	λ for elasticity to existing brands' prices	.94	.94	.94	40
	λ for elasticity to new brands' prices	.94	.94	.94	36
	λ for deal-log multiplier	.80	.78	.81	10

Notes: Existing brands are Red Baron, Stouffer's, Tombstone, Tony's and Totino's. New brands are DiGiorno and Freschetta.

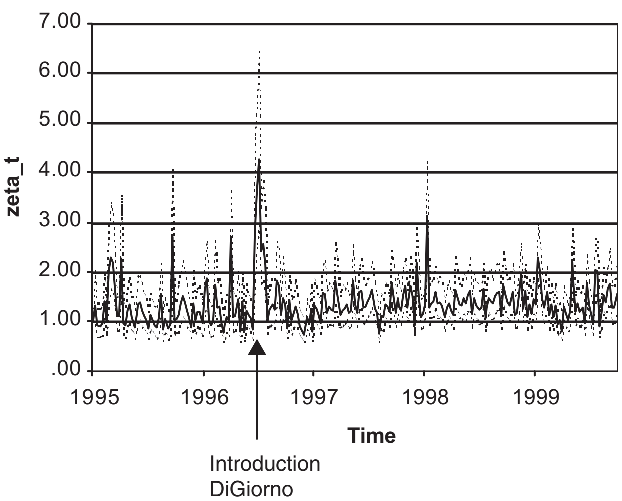
Changes in Covariance

As we mentioned previously, our model includes a time-varying covariance matrix for the observation equation ($\mathbf{V}_t = \zeta_t\mathbf{V}$). In Figure 3, we show the mean, lower (2.5%), and upper (97.5%) bounds for the ζ_t parameter, averaged across stores.

There is an increase in the ζ_t parameter near the time of the DiGiorno introduction (Weeks 21–49 of 1996; see Figure 1). In this interval, ζ_t averages 1.58, whereas its overall average across all periods is 1.36. The strongest increase in ζ_t occurs in Weeks 38–40 of 1996 (which coincides with the strongest increase in DiGiorno availability), with an average ζ_t of 3.58. In all three weeks, the highest-posterior-density interval for ζ_t excludes one. An explanation for this result is that ζ_t captures the effect of unobserved factors near the time of introduction, thus leading to greater error variance. An example of such a factor stems from the theory developed by Lipstein (1968), who suggests that consumers undergo a period of trial of new brands and updating preferences for those brands and that it is thus reasonable to expect that preferences become highly volatile before they settle back to a stable level. In contrast, 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 ζ_t is 1.34, which is below the overall average of 1.36. Thus, we find no support for an increased error variance for the introduction of Freschetta.[23] Coupled with the subsequent finding 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 increased uncertainty.

Figure 3

TIME-VARYING FACTOR ς FOR VARIANCE–COVARIANCE MATRIX FOR THE OBSERVATION EQUATION



Notes: Solid line indicates posterior mean; dotted lines indicate a 95% posterior probability interval.

Model Comparison

In this section, we compare our model with five plausible specifications:

1. All the λ parameters are set to zero. Thus, this specification assumes that the adaptation of the system parameters to shocks is immediate, as in pre–post models.
2. All the moderator effects are zero. This specification assumes that state parameters do not change in the long run as a result of the introduction of the new brands (i.e., the moderator effects of NEW1 and NEW2 in Equation 4 are zero). Thus, we assume that innovations have no effect on market structure.
3. The variance of the observation equation (for log sales) is stationary; that is, there is little increase in uncertainty near the time of introduction of the brand. Thus, $\zeta_t = 1$, so $\mathbf{V}_t = \mathbf{V}$ for all t.
4. The covariance matrices **V** and **W** are constant and fixed (instead of being estimated). This specification is a common instantiation of the DLM.
5. A specification that includes the effects of the introduction of the follower brand, Freschetta (NEW2), on own- and cross-price elasticities in addition to the effects of the DiGiorno introduction (NEW1) on the own- and cross-brand price elasticities in Equations 4b and 4c. Because 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, it might be expected that Freschetta's introduction would have no effect on the model parameters.

We compare the predictive validity of each alternative specification with the current specification using the log Bayes factor (West and Harrison 1997, p. 394). A log Bayes factor that is greater than two presents strong evidence in favor of the null model. In Table 5, we show the log Bayes

[23]If the increase in error variance was caused by missing variables, we would also expect it to occur for the introduction of Freschetta.

Table 5

COMPARISON OF CURRENT SPECIFICATION WITH ALTERNATIVE SPECIFICATIONS

Alternative Specification	*Substantive Meaning*	*Log Bayes Factor*
All lambdas in Equation 4 are equal to zero.	Immediate adjustment of model parameters to shocks	870.9
Moderating effects of NEW1 and NEW2 in Equation 4 are zero.	No long-term effects of the introduction of DiGiorno on model parameters	4833.5
V is constant.	Variance–covariance matrix for the observation equation constant over time	984.0
Fix **V** and **W**.	Variance–covariance matrices for observation equation and system equations are fixed rather than estimated	651.7
Includes moderator effects of NEW2 in Equation 4.	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	5.1

factors for the comparison between the current specification and the alternative specifications. The current specification model outperforms all five other specifications because the log Bayes factors are greater than two.

The results of our out-of-sample tests of predictive validity indicate several contributions. First, pre–post analysis overstates the pace at which brand introductions affect market response, so it is important to capture the dynamics of innovations. Second, we show that innovations affect market structure. Third, we find increased uncertainty at the time of brand introduction, which implies the value of capturing this form of nonstationarity. Fourth, estimation of the covariation structure merits the additional complexity that is required to do so. Finally, it is the innovation, not a me-too introduction, that leads to changes in market structure.

MANAGERIAL IMPLICATIONS

The estimated parameter paths enable us to depict 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 in the marketplace. We describe the changes in market asymmetry 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 follows:

$$\text{clout}_{jt} = \sum_{\substack{k=1 \\ k \neq j}}^{K} \beta_{jkt}, \quad (6)$$

where β_{jkt} is the elasticity of brand k's sales to brand j's price at time t. The vulnerability at time t of brand k is the total impact that the other brands have on brand K and is defined as follows:

$$\text{vulnerability}_{jt} = \sum_{\substack{k=1 \\ k \neq j}}^{k} \beta_{kjt}. \quad (7)$$

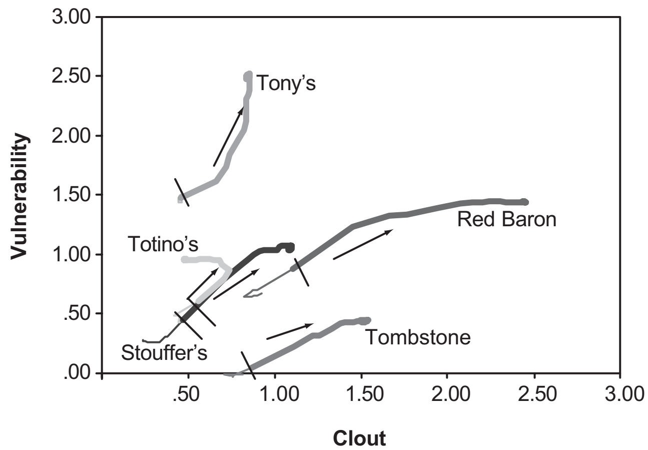
In Figure 4, we show the clout and vulnerability metrics for each of the five old brands over time. There are four notable findings implied in Figure 4:

1. The large change in the metrics for the old brands occurs after the introduction of DiGiorno. Thus, there is a change in structure.
2. The clout and vulnerability for most of the old brands increase over time, indicating that consumers perceive these brands as more similar.
3. The competitive positions have changed. Kraft's launch of DiGiorno made its lead brand, Tombstone, vulnerable to other brands, whereas its prelaunch vulnerability was zero. This may be an undesirable consequence even though its clout has increased.
4. The preintroduction premium brand, Stouffer's (by Nestlé), used to have a competitive slot that was highly desirable: low vulnerability and well differentiated. After the introduction of DiGiorno, Stouffer's left this slot and is now much more vulnerable and less differentiated. This should be worrisome news for Nestlé.

Managers can use our findings on the impact of new-brand forms to affect the perceptions of existing brands in the marketplace. For example, to increase the effect of a medium-quality brand on a high-quality brand, a firm might introduce an extremely high-quality innovation. The range and categorization effects imply that the former high-end brand becomes more similar to the medium-quality brand (similar to what we observed for Stouffer's). Similarly, firms need to consider the effects of new-form introductions when ascertaining the impact of any technological innovation on their existing portfolio of brands. It is interesting to speculate that range and categorization effects might also predict that the introduction of a low-quality product increases the perceived similarity of the existing brands.

Figure 4

CLOUT AND VULNERABILITY OVER TIME



Notes: A thin line indicates before the introduction of DiGiorno; a thick line indicates after the introduction. The thin perpendicular line indicates the moment of introduction.

Of additional interest is the overall impact of the innovation on Kraft's product line. DiGiorno increased the primary market for frozen pizza, and Kraft gained a reasonable share of the increased market (the total Kraft share increased from 61% to 63% after introduction). In addition, the cannibalization of its lead brand, Tombstone, was modest (sales of Tombstone fell only 2.9%, but sales of Kraft overall increased by 21.7%). However, the introduction made Tombstone less distinctive and more susceptible to price competition from the existing brands. We conjecture that this is an unanticipated consequence of product launch that might lead to overstating of the overall impact of the innovation on firm profits.

SUMMARY AND CONCLUSIONS

Innovation is key to firms' future. The entry of innovative products (and the exit of older products) creates dynamic markets. In this article, using a general and flexible model, we examine the dynamics of market structure that result from an innovative product entry into a stagnant product category. 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 do not occur instantaneously but over a period of time. Notably, the fastest adjustment is made in terms of the substitutability of the existing brands. Our results also pinpoint the temporary increase in 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 of the brands in the market over the period of the data. We illustrate how these findings have implications for product-line policy.

From a methodological point of view, our instantiation of the DLM allows for a general and flexible model structure that easily accommodates data from dynamic environments. This is important because the modeling of data from such environments presents considerable challenges. First, the time series of sales or marketing-mix instruments may be nonstationary, thus reducing the applicability of models that rely on stationary time series. Second, 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, there is often a hierarchical nature to price sensitivity and other model parameters that results from cross-sectional differences in price response. Our formulation of the DLM copes naturally with each of these challenges, as our application to the frozen pizza category shows. A result of this approach is a dynamic map of market structure, which should be useful to managers who try to ascertain the long-term effects of their marketing policy.

There are several notable future research directions. First, it would be of interest to study the impact of innovations on market structure for many categories to enhance the generalizability of our findings. Second, our approach can easily be extended to other nonstationary environments that are characterized by frequent product entry and exit, such as high-technology and fashion markets. Another domain in which our model would be particularly appropriate is emerging markets, in which the regulatory and consumer environment may be changing rapidly. Finally, the insights we have uncovered are informative for normative research on product location. For example, Ansari, Economides, and Ghosh (1994) consider the optimal entry location for a new product under the assumption that existing firms' positions in perceptual space are invariant to entry. Our analysis indicates otherwise, and it suggests that normative analyses can benefit from addressing this possibility.

As with any research, our study has some limitations. First, we use store-level data. This makes it difficult to understand precisely the change in the preference structure of individual customers. Toward that end, it would be desirable to extend our model to consumer-level data. Second, the DLM is general, and consequently the dimensionality of the model can easily become large. This problem is probably more severe than it is in most time-series techniques. However, the Bayesian nature of our estimation approach is amenable to shrinkage techniques, as we have shown, or even to the application of a factor approach. Third, we use natural experiments to study the effects of innovations on market structure. Unlike controlled lab experiments on innovation (e.g., Pan and Lehmann 1993), real-world introductions involve unobserved marketing activities that are concurrent with launch (e.g., advertising, slotting fees, coupons). Because we do not have data on these marketing activities, we cannot isolate their effects, even though they may explain a portion of our results. Thus, the NEW1 and NEW2 variables represent the total effect of the entire new product introduction strategy in a real-world setting. If there were enough variation in the marketing activities across many introductions, it should be possible to tease out the factors that contribute to the total effect of introductions on market structure (though the finding that increased similarity is caused by DiGiorno, not Freschetta, hints that it is innovation rather than launch that leads to such effects). Fourth, 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, Mela, and Marsh (1999) and Naik and Winer (2003) find no evidence of these effects in the SCAN*PRO model. It would be a challenge to model interdependent supply-side decisions and demand-side responses dynamically in a nonstationary environment. In our application, the challenge would be to solve a dynamic optimization problem for the market-level decision to introduce not only the new brand and the follower brand but also, 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 avenue for further research. In this spirit, we hope that the research outlined herein will motivate further research into marketing dynamics.

APPENDIX: MODEL ESTIMATION

The General Model

Our estimation approach employs a multiplicative model of sales with time-varying parameters. When k = {1, …, K} denotes brand and i = {1, …, I} denotes store, we can model the log of sales as

$$\ln S_t = \mathbf{X}_t'\beta_t + v_t, \quad \text{(A1)}$$

where $\ln S_t$ is an IK × 1 vector of log sales at time t; $\mathbf{X}_t'$ is an IK × MIK matrix of regressors, where M is the number of variables in the sales model; β_t, which is dimensioned MIK × 1, is the parameter capturing the relationships between $\mathbf{X}_t'$ and $\ln S_t$; and v_t is an IK × 1 vector of errors. These errors capture potential within-store dependencies on sales across brands and are distributed $N(0, \mathbf{V}_t)$.

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

$$\beta_t = \mathbf{G}\beta_{t-1} + \mathbf{Z}_t'\delta + \omega_t, \quad \text{(A2)}$$

where **G** is a diagonal MIK × MIK matrix that captures the duration of the long-term effects; $\mathbf{Z}_t'$ are the variables we expect to affect the response parameters in Equation A1 and is dimensioned MIK × MPIK (where P is the number of regressors in Equation A2); δ is an MPIK × 1 vector of parameters that captures the magnitude of the effect of $\mathbf{Z}$ on the parameters in Equation A1 (e.g., the effect of innovation on price sensitivity); and ω_t is an MIK × 1 vector of error terms that we assume to be distributed normally as $\omega_t \sim N(0, \mathbf{W})$.

Estimation

We can write the system of expressions in Equations A1 and A2 as follows:

$$\text{(A3)} \quad y_t = \mathbf{F}_t'\theta_t + \nu_t \qquad \nu_t \sim N(0, \mathbf{V}_t)$$
$$\theta_t = h_t + \mathbf{G}\theta_{t-1} + \omega_t \qquad \omega_t \sim N(0, \mathbf{W})$$
$$\theta_0|D_0 \sim N(m_0, \mathbf{C}_0),$$

where $y_t = \ln S_t$, $\mathbf{F}_t' = \mathbf{X}_t'$, $\mathbf{V}_t = \zeta_t\mathbf{V}$, $\theta_t = \beta_t$, $h_t = \mathbf{Z}_t'\delta$, $\mathbf{G} = \lambda$, D_t is the information available at time t, and m_0 and $\mathbf{C}_0$ reflect the prior belief about the mean and variance for θ at time 0. Note that the prior is not informative when $\mathbf{C}_0$ is chosen to be large.

The expressions in Equation A3 fall under a class of models known as DLMs (West and Harrison 1997). Under the assumption that h_t, $\mathbf{G}$, $\mathbf{V}_t$, and $\mathbf{W}$ are known (an assumption we relax shortly), we can solve the system in Equation A3 (West and Harrison 1997, p. 103).

First, the posterior is at t – 1:

$$\text{(A4)} \quad \theta_{t-1}|D_{t-1} \sim N(m_{t-1}, \mathbf{C}_{t-1}).$$

Second, the prior is at t:

$$\text{(A5)} \quad \theta_t|D_{t-1} \sim N(a_t, \mathbf{R}_t),$$

where $a_t = h_t + \mathbf{G}m_{t-1}$, and $\mathbf{R}_t = \mathbf{G}\mathbf{C}_{t-1}\mathbf{G}' + \mathbf{W}$. Third is the one-step forecast:

$$\text{(A6)} \quad y_t|D_{t-1} \sim N(f_t, \mathbf{Q}_t),$$

where $f_t = \mathbf{F}_t'a_t$, and $\mathbf{Q}_t = \mathbf{F}_t'\mathbf{R}_t\mathbf{F}_t + \mathbf{V}_t$. Finally, the posterior is at t:

$$\text{(A7)} \quad \theta_t|D_t \sim N(m_t, \mathbf{C}_t),$$

where $m_t = a_t + \mathbf{A}_t(Y_t - f_t)$, Y_t is the realization of y_t, $\mathbf{C}_t = \mathbf{R}_t - \mathbf{A}_t\mathbf{Q}_t\mathbf{A}_t'$, and $\mathbf{A}_t = \mathbf{R}_t\mathbf{F}_t\mathbf{Q}_t^{-1}$. For the priors, we set m_0 close to the results from an OLS model. We set $\mathbf{C}_0$ to .01I (where $\mathbf{I}$ is the identity matrix). Note that this is much larger than the mean prior for $\mathbf{W}$ (which we discuss subsequently). This enables the likelihood to dominate the posterior distribution of the parameters quickly.

Obtaining the Parameters

As we noted previously, the process assumes that λ, δ, $\mathbf{V}_t$ (= $\zeta_t\mathbf{V}$), and $\mathbf{W}$ are known; that is, p(θ|D, λ, δ, μ, ζ, $\mathbf{V}$, $\mathbf{W}$), where $\zeta' = (\zeta_1, ..., \zeta_T)$. By using Gibbs sampling techniques (Gelman et al. 1995), we can sample from each distribution. We estimate the model using Markov chain Monte Carlo techniques, which we subsequently describe. We applied Raftery and Lewis's (1995) criterion to determine the number of burn-in draws and final draws for inferences. This led to 8500 draws for inferences, which we thinned by taking every tenth draw (after a burn-in of 1500 draws). The effective sample size is 850. The sampling chain consists of draws from the full conditional distributions of the unknowns: θ, $\mathbf{V}$, ζ_t(t = 1, ..., T), λ, δ, μ, Σ_δ, $\bar{\mu}$, and Σ_μ. We detail these subsequently and summarize these steps in Figure 1.

Step 1: p(θ|D, $\mathbf{W}$, $\mathbf{V}$, ζ, λ, δ, μ, Σ_δ, $\bar{\mu}$, Σ_μ). To obtain the parameters, θ, in the observation equation, we use backward sampling, as West and Harrison (1997, p. 570) describe (see also Carter and Kohn 1994). We simulate the individual state vectors, θ_T, θ_{T-1}, ..., θ_1, as follows: First, we sample θ_T from $(\theta_T|D_T) \sim N(m_T, \mathbf{C}_T)$. Second, for each t = T – 1, T – 2, ..., 1, we sample θ_t from $p(\theta_t|\theta_{t-1}, D_t)$, where the conditioning value of θ_{t+1} is the value just sampled. The required conditional distributions are $(\theta_t|\theta_{t+1}, D_t) \sim N(g_t, H_t)$, where $g_t = m_t + B_t(\theta_{t+1} - a_{t+1})$, and $\mathbf{H}_t = \mathbf{C}_t - \mathbf{B}_t\mathbf{R}_{t+1}\mathbf{B}_t'$, where $B_t = C_tG'R_{t+1}^{-1}$.

Step 2: p($\mathbf{W}$|D, θ, $\mathbf{V}$, ζ, λ, δ, μ, Σ_δ, $\bar{\mu}$, Σ_μ*).* We assume that there is a time-constant, diagonal state-equation covariance matrix $\mathbf{W}_{mik} = \text{diag}(\{W_{mik}\}; m = 1, ..., M; k = 1, ..., K; i = 1, ..., I)$. The diagonality assumption is not too restrictive because it does not imply that θ_{it} is independent. Rather, the assumption of diagonal W implies only conditional independence; thus, W captures longitudinal rather than cross-sectional variance. The prior on diagonal element W_{mik} is inverse gamma ($v_W/2$, $S_W/2$). The full conditional distribution for W_{mik} is inverse gamma ~ $\{(v_W + T)/2, S_W/2 + \Sigma_{t=1}^T[\theta_{mikt} - (h_{mikt} + \lambda_{mk}\theta_{mikt-1})]^2/2\}$. We choose a diffuse prior for W: $v_W = 3$ and $S_W = .001$.

Step 3: p($\mathbf{V}$|D, θ, $\mathbf{W}$, ζ, λ, δ, μ, Σ_δ, $\bar{\mu}$, Σ_μ). We assume that the variance in the observation equation $\mathbf{V}$ is block diagonal, which allows for nonzero covariances between the errors of the brand log-sales equations within stores but assumes that there are zero covariances between errors between stores: $\mathbf{V} = \text{diag}(\mathbf{V}_i)_{i=1}^I$. Given that cross-store effects have been shown to be modest, we believe that this is a reasonable assumption (Bucklin and Lattin 1992; Slade 1995). We specify that the prior on the covariance matrix $\mathbf{V}_i$ is inverse Wishart (v_v, $\mathbf{S}_v$). The full conditional distribution for $\mathbf{V}_i$ is inverse Wishart ~ $[v_v + T, \mathbf{S}_v + \Sigma_{t=1}^T(y_{it} - \mathbf{F}_{it}'\theta_{it})(y_{it} - \mathbf{F}_{it}'\theta_{it})']$, where $y_{it} = (y_{i1t}, y_{i2t}, ..., y_{iKt})'$, and $\mathbf{F}_{it}'$ is defined analogously. 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 (Montgomery 1997). Specifically, we set $v_v = K + 2 = 9$, and $\mathbf{S}_v = .60 \times \mathbf{I}$.

Step 4: p(ζ_t|D, θ, $\mathbf{W}$, $\mathbf{V}$, λ, δ, μ, Σ_δ, $\bar{\mu}$, Σ_μ), t = 1, ..., T. In this step, we estimate the scale effect for the observation equation (this captures covariance nonstationarity). We assume that the prior on the time-varying scale factor for $\mathbf{V}$, ζ_t, is inverse gamma ($v_\zeta/2$, $S_\zeta/2$) (West and Harrison 1997, p. 642). The full conditional for ζ_t is inverse gamma ~ $[(v_\zeta + IK)/2, S_\zeta/2 + (Y_t - f_t)'\mathbf{V}^{-1}(Y_t - f_t)/2]$, t = 1, ..., T. For ζ_t, we are interested in the relative magnitude of this parameter over time. Therefore, we set ζ_1 equal to 1 for identification purposes, and we use the diffuse prior parameters $v_\zeta = 3$, $S_\zeta = 2$, with a prior mean of 1 (= 2/[3 – 1]).

Step 5: p(λ|D, θ, $\mathbf{W}$, $\mathbf{V}$, ζ, δ, μ, Σ_δ, $\bar{\mu}$, Σ_μ). We categorize λ into two types: (Step 5a) decay parameters specific to brand k's own effects (λ_{mk}) and (Step 5b) decay parameters for cross-price effects of other brands, $\bar{\lambda}_{ck}$, where c = 1 for the effects of new brand prices on old brands, and c = 2 for the effects of old brand prices. That is, we assume that the decay parameters for all old brand cross-price effects are the same and that the decay parameters for all new brand cross-price effects are the same. However, we assume that that new and old brand decay parameters can differ. We make these assumption because we can find no theoretical rationale in the literature to induce us to believe that the introduction of a new alternative would differentially affect the rate at which cross-effects of competing brands adapt to a postintroduction equilibrium (though we do allow the magnitude of cross-effects to vary across brands).

For brand k–specific decay parameters (Step 5a), we use the same prior specification for each element of λ corresponding to own effects (e.g., intercept, price, promotion). Specifically, for brand k's independent variable m, we assume that $\lambda_{mk} \sim N(\mu_\lambda, \Sigma_\lambda)$. By rearranging the second line in Equation A2 and stacking the observations for parameter β_{mikt} across time in $\beta'_{mikT} = \beta_{mik2}, ..., \beta_{mikT})$ and in $\beta'_{mikT-1} = (\beta_{mik1}, ..., \beta_{mikT-1})$, we obtain the following:

(A8) $$\beta_{mikT} - \mathbf{Z}'_{mikT}\delta_{mik} = \lambda_{mk}\beta_{mikT-1} + \omega_{mikt},$$

where $\omega_{mikt} \sim N(0, W_{mik})$, λ_{mk} is a scalar, and W_{mik} is the diagonal element from $\mathbf{W}$ that corresponds to β_{mikt}. Furthermore, we stack the β_{mikT-1} across stores to obtain β_{mkT-1}, and we stack the $\beta_{mikT} - Z'_{mikT}\delta_{mik}$ across stores to obtain $y_{\lambda mk}$. This yields an $I(T-1) \times 1$ vector of observations for each β_{mkT-1} and $y_{\lambda mk}$. In turn, this yields the standard form for a regression, for which the likelihood is expressed as follows:

(A9) $$\lambda_{mk} \sim N\Big[\big(\beta'_{mkT-1}\mathbf{W}_{mk}^{-1}\beta_{mkT-1}\big)^{-1}\big(\beta'_{mkT-1}\mathbf{W}_{mk}^{-1}y_{\lambda mk}\big), \big(\beta'_{mkT-1}\mathbf{W}_{mk}^{-1}\beta_{mkT-1}\big)^{-1}\Big] \equiv N(l_{\lambda_{mk}}, S_{\lambda_{mk}}),$$

where $\mathbf{W}_{mk} = \mathrm{diag}(\{W_{mik}\}; i = 1, ..., I) \otimes \mathbf{I}_{T-1}$. Because the prior and likelihood are normal, the full conditional distribution is $p(\lambda_{mk}|D, \theta, \delta, \mu, \zeta, \mathbf{V}, \mathbf{W}) \sim N[(\Sigma_\lambda^{-1} + S_{\lambda_{mk}}^{-1})^{-1}(\Sigma_\lambda^{-1}\mu_\lambda + S_{\lambda_{mk}}^{-1} l_{\lambda_{mk}}), (\Sigma_\lambda^{-1} + S_{\lambda_{mk}}^{-1})^{-1}]$. For λ, we use the diffuse prior $\mu_\lambda = .90$ and $\Sigma_\lambda = 10$.

For decay parameters for cross-price effects (Step 5b), the likelihood for λs that are pooled across cross-effects ($\bar{\lambda}_{ck}$) is similar to the likelihood for brand k–specific decay parameters (Step 5a), except that the observations are pooled over cross-effects and stores. This implies stacking each C cross-effect parameter for a brand (separately for the cross-price effects from the old brands and the new brands), β_{mkT-1} and $y_{\lambda mk}$, into β_{CkT-1} and $y_{\lambda Ck}$, which are each dimensioned as $CI(T-1) \times 1$. Creation of a diagonal matrix $\mathbf{W}_{Ck}$ of dimension $CI(T-1) \times CI(T-1)$, whose diagonal element is the $\mathbf{W}_{mik}$ that corresponds to the cross-effects for brand k, enables us to write the likelihood as follows:

(A10) $$\lambda_{ck} \sim N\big[(\beta'_{CkT-1}\mathbf{W}_{Ck}^{-1}\beta_{CkT-1})^{-1}(\beta'_{CkT-1}\mathbf{W}_{Ck}^{-1}y_{Ck}), (\beta'_{CkT-1}\mathbf{W}_{Ck}^{-1}\beta_{CkT-1})^{-1}\big] \equiv N(d_{\bar{\lambda}_{ck}}, S_{\bar{\lambda}_{ck}}).$$

Thus, the posterior for $\bar{\lambda}_{ck}$ is given by the following:

(A11) $$p(\bar{\lambda}_{ck}|D, \theta, \delta, \mu, \zeta, \mathbf{V}, \mathbf{W}, \Sigma_\delta) \sim N[(\Sigma_\lambda^{-1} + S_{\bar{\lambda}_{ck}}^{-1})^{-1}(\Sigma_\lambda^{-1}\mu_\lambda + S_{\bar{\lambda}_{ck}}^{-1} d_{\bar{\lambda}_{ck}}), (\Sigma_\lambda^{-1} + S_{\bar{\lambda}_{ck}}^{-1})^{-1}].$$

For $\bar{\lambda}$, we also use the diffuse prior $\mu_\lambda = .90$ and $\Sigma_\lambda = 10$.

Step 6: $p(\delta|D, \theta, \mathbf{W}, \mathbf{V}, \zeta, \lambda, \mu, \Sigma_\delta, \bar{\mu}, \Sigma_\mu)$. In this step, we shrink the estimates for δ across stores. For brand k, independent variable m, store i, we assume the normal prior $\delta_{mik} \sim N(\mu_{mk}, \Sigma_{\delta_{mk}})$. We construct the likelihood as follows: We rearrange Equation A8 to yield $(\beta_{mikT} - \lambda_{mk}\beta_{mikT-1}) = \mathbf{Z}'_{mikT}\delta_{mik} + \omega_{mikt}$, where $\omega_{mikt} \sim N(0, W_{mik})$. This is a standard regression equation. Thus, the likelihood is $\delta_{mik} \sim N\{(\mathbf{Z}'_{mikT}\mathbf{Z}_{mikT})^{-1}[\mathbf{Z}'_{mikT}(\beta_{mikT} - \lambda_{mk}\beta_{mikT-1})], (\mathbf{Z}'_{mikT}\mathbf{Z}_{mikT})^{-1}W_{mik}\} \equiv N(d_{\delta_{mik}}, S_{\delta_{mik}})$. When combined with the normal prior, the full conditional distribution is the following:

(A12) $$N[(\Sigma_{\delta_{mk}}^{-1} + S_{\delta_{mik}}^{-1})^{-1}(\Sigma_{\delta_{mk}}^{-1}\mu_{mk} + S_{\delta_{mik}}^{-1}d_{\delta_{mik}}), (\Sigma_{\delta_{mk}}^{-1} + S_{\delta_{mik}}^{-1})^{-1}] \equiv N(\tilde{d}_{\delta_{mik}}, \tilde{S}_{\delta_{mik}}).$$

Step 7: $p(\mu|D, \theta, \mathbf{W}, \mathbf{V}, \zeta, \lambda, \delta, \Sigma_\delta, \bar{\mu}, \Sigma_\mu)$. In this step, we estimate the priors for the own effects (price, promotion, and intercept) and shrink cross-effects to a common mean. The prior for $\delta_{pmik} \sim N(\mu_{pmk}, \Sigma_{\delta pmk})$, or $\delta_{pmik} = \mu_{pmk} + \varepsilon_{pmik}$; $\varepsilon_{pmik} \sim N(0, \Sigma_{\delta pmk})$. By stacking across stores, we can write this as $\delta_{pmk} = 1_I\mu_{pmk} + \varepsilon_{pmk}$, where 1_I is a $I \times 1$ vector of ones, μ_{pmk} is a scalar, and $\varepsilon_{pmk} \sim N(0, \Sigma_{\delta_{pmk}}\mathbf{I}_I)$, where $\mathbf{I}$ is the identity matrix. Because the prior for μ is $\mu_{pmk} \sim N(\bar{\mu}_{cmk}, \Sigma_{\mu cmk})$, the posterior for μ is the following:

(A13) $$\mu_{pmk} \sim N\left(\left[\Sigma_{\mu_{mpk}}^{-1} + 1_I'\left(\Sigma_{\delta_{pmk}}^{-1}\mathbf{I}_I\right)1_I\right]^{-1}\left\{\Sigma_{\mu_{cmk}}^{-1}\bar{\mu}_{cmkI} + \left[1_I'\left(\Sigma_{\delta_{pmk}}^{-1}\mathbf{I}_I\right)\delta_{pmk}\right]\right\}\left[\Sigma_{\mu_{cmk}}^{-1} + 1_I'\left(\Sigma_{\delta_{pmk}}^{-1}\mathbf{I}_I\right)1_I\right]^{-1}\right).$$

We use the diffuse priors $\bar{\mu} = 0$ and $\Sigma_\mu = 10$ for all own effects (e.g., price, promotion, intercept). We further shrink the δs associated with cross-effects across brands to increase their efficiency. Given that our focus is cross-effects, it is important to estimate these reliably. We outline our approach for this in Steps 9 and 10.

Step 8: $p(\Sigma_\delta|D, \theta, \mathbf{W}, \mathbf{V}, \zeta, \lambda, \delta, \mu, \bar{\mu}, \Sigma_\mu)$. In this step, we estimate the variance of δ across stores. The prior for $\Sigma_{\delta pmk}$ is inverse gamma $(\nu_{\Sigma_\delta}/2, S_{\Sigma_\delta}/2)$. The full conditional for $\Sigma_{\delta pmk}$ is inverse gamma $\sim [(\nu_{\Sigma_\delta} + I)/2, S_{\Sigma_\delta}/2 + \Sigma_{i=1}^{I}(\delta_{pmik} - \mu_{pmk})^2/2]$. We use the diffuse prior $\nu_{\Sigma_\delta} = 3$, $S_{\Sigma_\delta} = .0001$.

Step 9: $p(\bar{\mu}|D, \theta, \mathbf{W}, \mathbf{V}, \zeta, \lambda, \delta, \mu, \Sigma_\delta, \Sigma_\mu)$. In this step, we estimate the common prior for the cross-effects of other brands' prices on brand k. The prior for μ, $\mu_{pmk} \sim N(\bar{\mu}_{cpk}, \Sigma_{\mu cpk})$, or $\mu_{pmk} = \bar{\mu}_{cpk} + \varepsilon_{pmk}$; $\varepsilon_{pmk} \sim N(0, \Sigma_{\mu_{cpk}})$. By stacking across the C cross-effects, we obtain $\mu_{pCk} = 1_C\bar{\mu}_{cpk} + \varepsilon_{pk}$; $\varepsilon_{pk} \sim N(0, \Sigma_{\mu cpk}\mathbf{I}_C)$, where 1_C is a $C \times 1$ vector of ones (the number of cross-effects), μ_{pCk} is $C \times 1$, and $\mathbf{I}_C$ is a C-dimensional identity matrix. The prior for mu-bar is $\bar{\mu}_{cpk} \sim N(\bar{\bar{\mu}}, \Sigma_{\bar{\mu}})$. We use the diffuse prior $\bar{\bar{\mu}} = 0$; $\Sigma_{\bar{\mu}} = 10$. Therefore, the posterior for mu-bar is the following:

(A14) $$\bar{\mu}_{cpk} \sim N\left(\left\{\Sigma_{\bar{\mu}}^{-1} + \left[1_C'\left(\Sigma_{\mu_{cpk}}^{-1}\mathbf{I}_C\right)1_C\right]\right\}^{-1}\left[1_C'\left(\Sigma_{\mu_{cpk}}^{-1}\mathbf{I}_C\right)\mu_{pCk}\right], \left\{\Sigma_{\bar{\mu}}^{-1} + \left[1_C'\left(\Sigma_{\mu_{cpk}}^{-1}\mathbf{I}_C\right)1_C\right]\right\}^{-1}\right).$$

Step 10: $p(\Sigma_\mu|D, \theta, \mathbf{W}, \mathbf{V}, \zeta, \lambda, \delta, \mu, \Sigma_\delta, \bar{\mu})$. This step determines the variance in the cross-effects (how tightly the cross-effects shrink to a common mean). The prior for $\Sigma_{\mu cpk}$ is inverse gamma $(\nu_{\Sigma_\mu}/2, S_{\Sigma_\mu}/2)$. The full conditional for $\Sigma_{\mu cpk}$ is inverse gamma $\sim [(\nu_{\Sigma_\mu} + C)/2, S_{\Sigma_\mu}/2 + \Sigma_{c=1}^{C}(\mu_{mpk} - \bar{\mu}_{cpk})^2/2]$. We use the diffuse prior $\nu_{\Sigma_\mu} = 3$, $S_{\Sigma_\mu} = .0001$.

The Gibbs sampler proceeds to sequence through Steps 1–10 until 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. Combined with the normal likelihood, these priors result in full conditional distributions that are normal, inverse Wishart and inverse gamma. This makes it easy to implement the sampler. We coded the DLM in Gauss.

Missing Data

The DLM copes naturally with missing data. Because two brands are introduced during the data period, we cannot estimate the sales models for the new brands for all the periods. Therefore, we begin to estimate the models only when the brand is introduced. This implies that the vector y and the matrix F have a varying number of rows and that the matrix **V** has a varying number of rows and columns (= number of rows). In the beginning of the data, there are five (old) brands in the 22 stores; thus, the number of rows is 110. When DiGiorno has been introduced in a specific store, the dimension increases by 1, until DiGiorno is introduced in all stores. The introduction of Freschetta into a store also increases the dimension by 1, until the moment that all brands are available in all stores, at which point the dimensionality becomes 154 (= 22 × 7). The sizes of the parameter vector β and lags (**G**) remain constant at maximum size. Before the introduction of a new brand, we cannot update its corresponding parameters in β and **G** in the DLM recursions. This implies that the posterior for the parameter is the same as the (diffuse) prior and thus does not update if no data are available.

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