Marketing Science

Market Roll-Out and Retailer Adoption for New Brands

Bart J. Bronnenberg, Carl F. Mela,

Market Roll-Out and Retailer Adoption for New Brands

Bart J. Bronnenberg

University of California, 110 Westwood Plaza, Suite B4.18, Los Angeles, California 90095, bbronnen@anderson.ucla.edu

Carl F. Mela

Fuqua School of Business, Duke University, Box 90120, Durham, North Carolina 27708, mela@duke.edu

This paper proposes a descriptive model of the spatial and temporal evolution of retail distribution for new packaged goods. The distribution model postulates separate processes for local market entry by manufacturers, and adoption by retailers given entry. Of special interest is whether retail adoption occurs along a competitive network with retailers as nodes and overlapping trade areas of these retailers as links. The model is calibrated on data covering the introduction of two very successful new brands in the frozen pizza category. For these brands, manufacturers sequentially enter markets based on spatial proximity to markets already entered (spatial evolution), and on whether chains in these markets adopted previously elsewhere (market selection). A retail chain adopts new brands based on the adoption timing of competing chains within its trade territory (competitive contagion) and on the fraction of its trade area in which the new brand is available (trade area coverage). The effects of market selection and of trade area coverage create dependencies between market entry and retail adoption. Because of these dependencies the attraction of a particular market as a lead market depends on its location in the geographic structure of the U.S. retail trade.

Key words: spatial diffusion; network diffusion; retail distribution; new product research
History: This paper was received September 3, 2002, and was with the authors 6 months for 4 revisions; processed by Scott Neslin.

1. Introduction

New product programs are an important driver of long-term profitability for manufacturers. It is critical to the success of these programs new products obtain broad retail distribution. Distribution is often obtained via a roll-out strategy, i.e., via a sequence of regional introductions to new brands. Such a strategy may be contrasted with a national launch, wherein a new brand is introduced in all regions concurrently. National launches are costly and imply substantial losses should the innovation fail. For this reason, phased roll-outs are a less-risky alternative to national launches, and they are the norm with entirely new brands or product lines (as opposed to simple line extensions) of repeat purchase goods. Despite their obvious importance in new product management, little academic research exists on regional roll-outs for new brands.

The objective of the present study is to fill this gap by providing a descriptive model of how new brand distribution evolves across regional markets, retail chains, and time periods. We focus on explaining the timing of two key events in this process: (1) regional market entry by a manufacturer (e.g., the New York market, the Los Angeles market, and so on), and (2) first-time adoption by retail chains whose

trade areas include entered markets (e.g., Pathmark or Albertsons, respectively). On one hand, manufacturers consider regional markets to be the relevant spatial unit for launch because many launch costs are made at the market level. Retailers, on the other hand, often approve a new brand for the retailer's entire trade area. These two events may be interrelated: Regional entry can be influenced by past chain adoptions, and chain adoptions can be influenced by past regional market entry.

The contribution of this paper is intended to be twofold. First, the data and model in the paper identify and quantify several feedback mechanisms in the evolution of new brand distribution. These mechanisms include (1) a spatial proximity effect of past market entry on current market entry, (2) a market selection effect of past retailer adoptions on current market entry, (3) a contagion effect of past retailer adoption on current adoption along a competitive retailer network, and (4) an effect of trade area coverage (past market entry) on retailer adoption. Second, these effects imply that new brand distribution evolves over two linked units: regional markets and retailer trade areas. This has consequences for product roll-out because decisions about regional market entry (including, but not limited to, lead market selection)

depend on the connectedness of retailers within that region to retailers outside it. A simulation is used to reveal some of the implications of this dependence.

We estimate our model of market entry and chain adoption using multimarket store-level data from the frozen pizza category. We focus on the introduction of two major new brands into the frozen pizza category and find the following:

1. Local market entry is subject to proximity effects, i.e., manufacturers fan out from selected lead markets and gradually move from one area of the United States to another. In addition, local market entry is subject to a selection effect, i.e., manufacturers enter markets in which many chains operate that previously have adopted elsewhere. Manufacturers also first enter markets in which their extant brands have high category share.

2. Adoption by a given retail chain is subject to contagion effects, i.e., past adoption by other chains in one's own territory increases the likelihood of adopting. In contrast, there is no contagion effect from the national total of adopting retailers. Adoption is positively impacted by trade area coverage, i.e., a retailer adopts more quickly if the new product is available in a large part of its trade area. It is also positively associated with manufacturer share in the chain, and with retailer size.

3. Markets that are serviced by large chains whose territories do not overlap much lead to the shortest diffusion times. These markets can be viewed as good locations for new product launch, all else being equal. In addition, such markets need not be geographically central.

Focusing on distribution abstracts from other important components of new product growth. To better position our study in the context of other work in this domain, we decompose—in Figure 1—new brand sales for repeat purchase goods into four underlying components. As can be seen from this decomposition, other foci on new product growth exist, including product assortment, product trial, and penetration depth. In this study, we focus on distribution of new brands for several reasons. First, demand and profits for new products are conditional on distribution. Indeed, for many brand managers of consumer goods, obtaining retailer distribution is the primary objective during the early stages of a product's life cycle. Second, distribution decisions are interesting in the context of product strategy in repeat-purchase categories because the decision by a retail chain to distribute a nondurable product is often a durable commitment. Third, extant empirical research in packaged goods focuses on product, promotion, and price, but rarely on place, notable exceptions notwithstanding (e.g., McLaughlin and Rao 1991, Montgomery 1975, Reibstein and Farris 1995).

The remainder of this paper is organized as follows. Section 2 summarizes relevant academic research on diffusion, distribution, and retailer decisions. Section 3 gives an overview of the frozen pizza industry. Section 4 states the models of market entry and retailer adoption. Section 5 contains the data analysis. Section 6 uses the empirical results to make recommendations for lead market selection. Section 7 contains a discussion of the results, and concludes.

2. Academic Research and Background

Our work draws from several research streams in marketing and sociology, including retailer adoption of new products, diffusion of innovations, including theories of social and spatial contagion, and market entry. The nature of the problem we study leads us to integrate these disparate streams because as it has aspects of each.

Figure 1   Fit of the Present Study in New Product Research
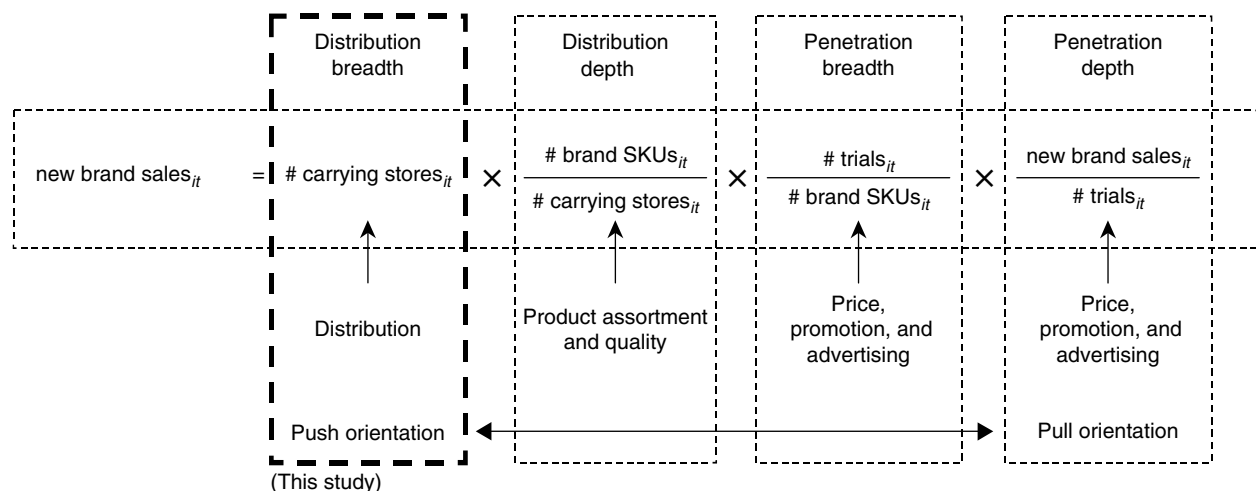
2.1. Cross-Sectional Models of New Product Adoption by Retailers

McLaughlin and Rao (1991) study retailer adoption of new brands. They find that retailer acceptance of new products is related to a variety of variables ranging from marketing spending by vendors to product and vendor status. Montgomery (1975) finds that the percentage of competition carrying the new brand is important in the product adoption decision. These analyses are cross-sectional.

2.2. Models of New Product Diffusion

New product diffusion research has been of considerable and persistent academic interest to marketing researchers since Bass (1969). Early studies of new product diffusion often sought to explain the category sales of durable goods at an aggregate level (e.g., the domestic United States) across time. Under almost all circumstances, this aggregate loses information about the cross-sectional processes that govern contagion.[1] Because we seek to model the evolution of product distribution across markets and retailers, it is important to consider these cross-sectional processes, as well. Hence, a feature that distinguishes this paper from research on diffusion at an aggregate level is that the contagion process across geographic space and retailer networks is explicitly modeled.

The literature on spatial diffusion represents the strength of contagion between two adopting agents as a function of how geographically close they are. This contagion concept has been applied to research questions in the atmospheric sciences (Niu and Tiao 1995), epidemiology (Cliff et al. 1981), sociology (Hedström 1994), spatial statistics (Stoffer 1986), and other fields. Some marketing researchers have also considered diffusion across markets (Dekimpe et al. 2000a, Putsis et al. 1997). Dekimpe et al. (2000a) make within-country adoption of technologies dependent on the cross-country diffusion of such technologies. They allow cross-country adoption to be influenced by the cumulative number of adopting countries, not by geographic proximity of the two countries. Putsis et al. (1997) also allow adoption in one country to depend directly on adoption in all countries, but estimate the cross effects explicitly as a mixing model. Our treatment of spatial effects considers pair-wise proximity and differential effects across pairs of regions. In a recent study, Garber et al. (2004) propose that spatial diffusion patterns in sales data can be used to make early predictions of new product success.

The literature on social networks formalizes the communication links between potential adopters and traces contagion in adoption along these links (e.g., Coleman et al. 1966, Greve 1996, Strang and Tuma 1993, Valente 1995). In our study, this literature is relevant to the definition of a retailer network along which new brands are proposed to diffuse.

2.3. Market Entry

While market entry in the presence of spatial and competitive network effects is a nascent research domain within marketing, it is more widely considered in sociology (Greve 2000, Haveman 1993, Haveman and Nonnemaker 2000, Korn and Baum 1999). Our analysis considers a different context from this extant work, namely the evolution of new brand distribution across markets and retailers.

An adoption model estimated in absence of market entry is likely to be biased for several reasons. If one omits market entry timing, then observed adoption timing is the sum of market entry timing and timing of adoption given entry. Inferences on this observed adoption timing are subject to an omitted variables problem, where the omitted variable (market entry timing) correlates with the observed timing of adoption by construction. As Van den Bulte and Lilien (2001a) show, inferences about what constitutes social contagion can be influenced by omitted variables problems, especially if these variables correlate with the social contagion construct. In the same vein, Van den Bulte and Lilien (2001b) show, using a model of awareness and adoption, that estimates for contagion are affected by whether or not awareness is modeled explicitly.

3. The Industry

To facilitate our subsequent model exposition, we describe the industry from which we have data (frozen pizza), discuss how distribution decisions are made for the main new brands in this category, and illustrate how retail distribution evolves across markets and time.

3.1. General Description

Consumers. The frozen pizza industry accounted for roughly $2.2 billion of sales in the year 1997 in the United States. The category has the highest penetration of all frozen prepared foods: 57% of all American households buy frozen pizza. The market for frozen pizza was forecasted to grow at a compounded annual rate of 8.9% per year between 1997 and 2002. Frozen pizza consumption tends to be higher in the Midwest than elsewhere in the United States. Supermarket sales account for 90% of frozen pizza sales in the United States (Holcomb 2000).

---

[1] An exception occurs when the nonlinearities in the individual level behavior aid in identification at the aggregate level (see, e.g., Zenor and Srivastava 1993).

Products. Before 1996, most sales occurred in the so-called regular frozen pizzas. The two leading brands in this market were Tombstone and Tony's, which were marketed by Kraft and Tony's Pizza Service, respectively. The latter manufacturer also produces the Red Baron brand. Each of these two leading brands offered a variety of recipes and crusts. Prior to 1996 Kraft's share of the industry was 33.7%, whereas Tony's Pizza Service's share was 23.5% (Holcomb 2000).

New Product Distribution Process. We interviewed several managers who were involved in the introduction of the new brands in this category to learn how these products were distributed. The process begins with manufacturers deciding which markets to enter. Subsequently, manufacturers offer the product along with incentives to retailers in the markets that they enter. Manufacturers do not launch the brand trade area–wide to a single retailer because many launch costs (e.g., advertising and transportation) will not depend on how many retailers adopt in a given market. Hence, it would be inefficient to target a single retailer in all of its markets. Next, a retail chain to whom the product has been offered decides whether to approve the brand for distribution on its entire trade area. If the brand is approved, individual stores from this chain can carry the brand once it becomes locally available. When the product is approved at the chain level, it is generally the case, according to retail managers, that the brand is quickly adopted at the store level (provided the manufacturer makes it available in the store's region). Thus there is very little variation in store-level adoption within chain, and we therefore model adoption at the chain level. Chain-level adoption is especially immediate when there exists a direct sales force, and the product is a major innovation from a leading manufacturer. In sum, this process implies that we model market entry by a manufacturer and first-time adoption by a chain.

Positive influences on early market entry mentioned by category managers include transportation cost, a low local share of the manufacturer's existing brands, local popularity of the category, a low degree of cannibalization, and multiple retailers in the market. One manager noted that the DiGiorno product sought to expand the frozen pizza category by competing with take-out pizza, which may or may not have played a role in the selection of lead markets.

3.2. The Introduction of DiGiorno and Freschetta

Timing. Both Kraft and Tony's Pizza Service developed and launched a premium frozen pizza with rising crust. First, in 1995 Kraft introduced the DiGiorno brand, followed in late 1996 by Tony's Pizza Service

Figure 2 Spatio-Temporal Development in Retail Distribution for DiGiorno Pizza

(a) September 1995

(b) May 1996

(c) August 1996

(d) April 1998

● 25% ACV ◎ 50% ACV ⬤ 75% ACV ⬤ 100% ACV
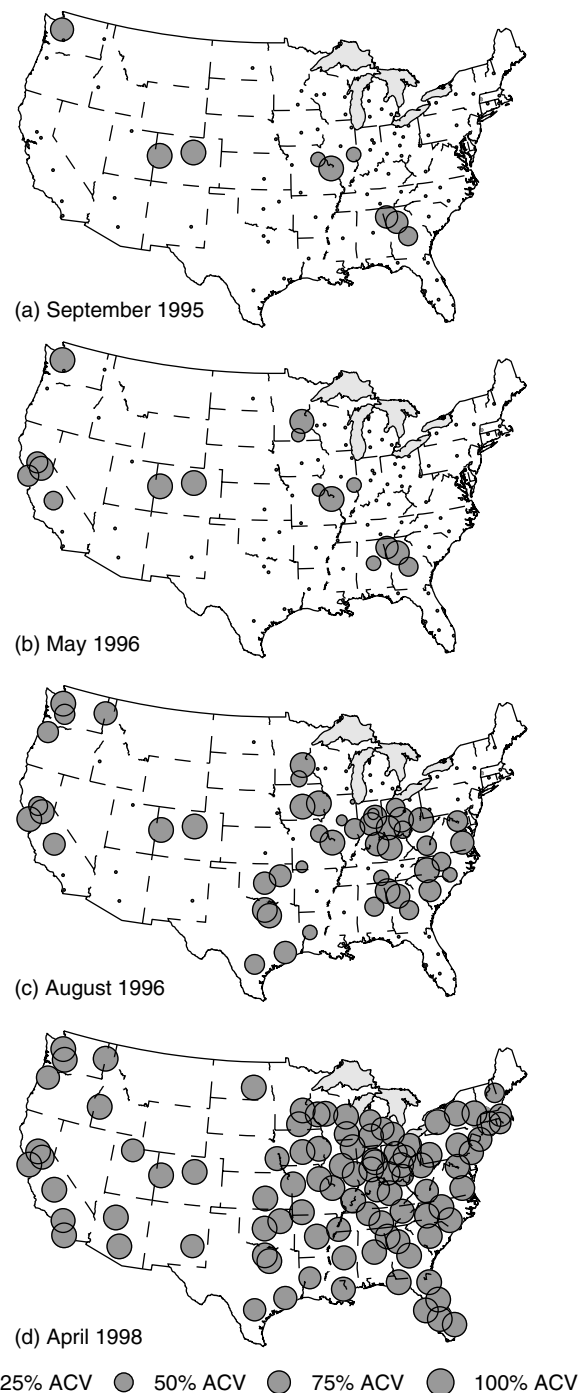
Note. ACV = all-commodity volume.

with the introduction of the Freschetta line. These two introductions are the main focus of our empirical study. Figures 2 and 3 illustrate the diffusion of supermarket distribution for these two brands in the continental United States.

Diffusion Patterns. In both instances, brands are launched in a select number of lead markets and a considerable amount of time (15–30 months) passes

Figure 3 Spatio-Temporal Development in Retail Distribution for Freschetta Pizza

(a) January 1997

(b) April 1997

(c) October 1997

(d) July 1998

○ 25% ACV ● 50% ACV ● 75% ACV ● 100% ACV
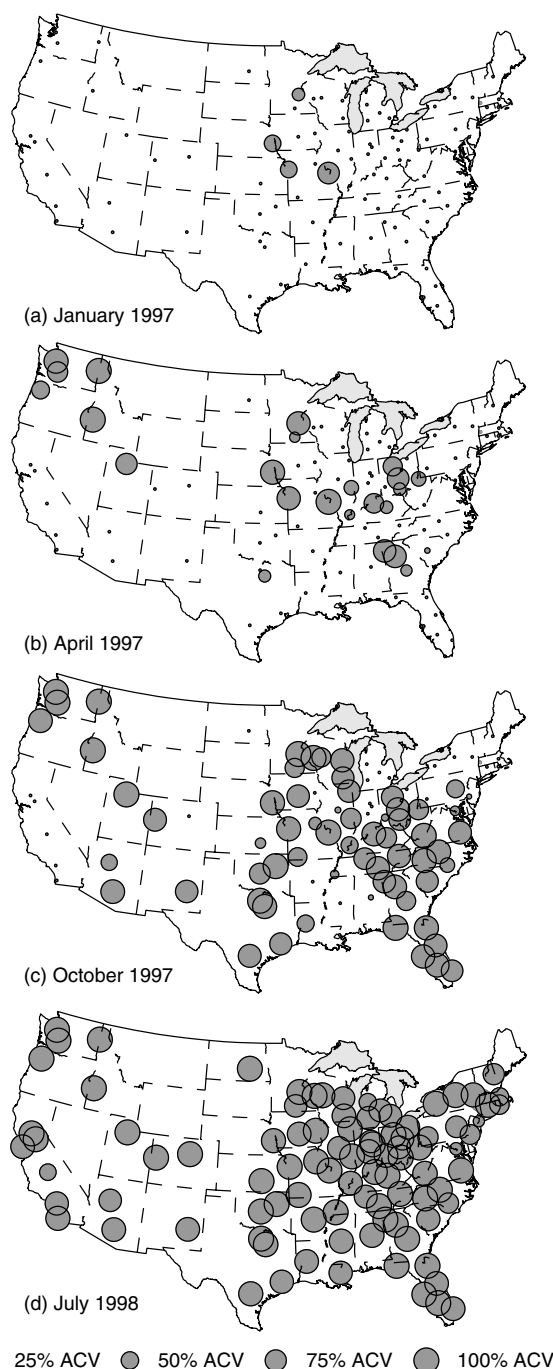
Note. ACV = all-commodity volume.

before the brands have national distribution. In the case of DiGiorno, the brand is launched in Denver, St. Louis, Seattle, and Atlanta. The first two of these belong to the top-10 metropolitan areas in frozen pizza consumption per capita (Holcomb 2000). In the case of Freschetta, the brand is launched in Omaha, St. Louis, Minneapolis, and Kansas City. The first three of these markets belong to the same top-10 metro areas. The launch of Freschetta seems more

local than that of DiGiorno in the sense that DiGiorno initially spans a large area of the United States with a select number of lead markets and fills in the empty space between these cities through subsequent introductions. An alternative to this policy is to first create a dense concentration of lead markets and expand— radially—from this base. There appears to be some indication that initially Freschetta uses such a policy, expanding from north to south. In both cases there appears to be a strong local component to sequential market entry. For instance, in Figure 2 we see that DiGiorno expands from the Seattle market to three neighboring markets in the period May–August 1996. Likewise, in Figure 3 it can be seen that Freschetta seeks to move south from Atlanta into the Florida markets between April and October of 1997. Ample other examples like these exist in Figures 2 and 3.

Success of the Launches. Both launches were commercially successful. Both brands obtained national distribution, with Freschetta starting later but rolling out faster than DiGiorno.

4. Model
Based on the discussion above, the empirical model of the evolution of retailer distribution focuses on the manufacturer's timing of local market entry and— conditional on this event—on the retailer's timing of carrying the brand. Our modeling strategy consists of representing these events as discrete-time hazards. Figure 4 visualizes the reduced-form model of these events. The model contains local contagion and spatial effects that are introduced by allowing entry and adoption to be (cross)dependent on past entry and adoption. For instance, the adoption of a new brand by a given retailer is allowed to depend on the past adoption decisions of direct competitors (arrow (i) in Figure 4). Along the same lines, market entry is possibly influenced by past entry in neighboring markets (arrow (ii)). Furthermore, retailers may adopt a new

Figure 4 The Main Features of the Model
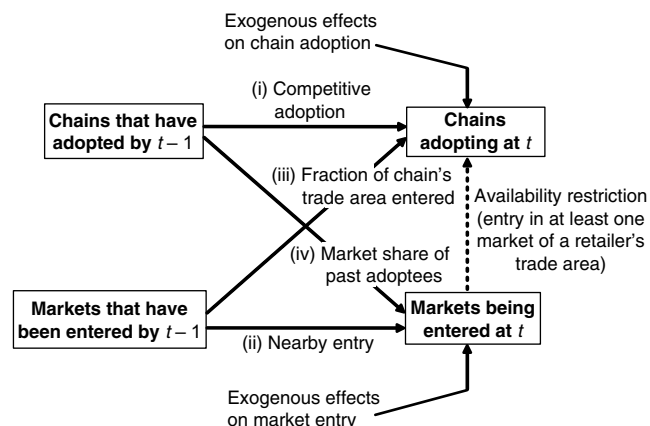
brand because many of the markets on which they operate have been entered (arrow (iii)), and market entry can be affected by which retailers adopted in the past (arrow (iv)).

Below, the models for market entry and retailer adoption are operationalized and the definitions of the effects (i–iv) are made explicit. Because the spatial unit of evolution is different for entry (markets) than for retailer adoptions (multimarket trade areas), their respective definitions of neighborhood effects are also different.

4.1. Market Entry

Denote the presence of a brand in a market by y_{imt}, where $i = 1, \ldots, I$ indexes brands, $m = 1, \ldots, M$ indexes markets, and $t = 1, \ldots, T$ indexes time. The variable y_{imt} is discrete and assumes the value 1 if brand i is present in market m at time t, and 0 else. The event $y_{imt} = 1$ is treated as absorbing because we are modeling market entry, not exit.

Entry into market m by manufacturer i in week t is formalized using a probit model to represent the hazard of entry.

$$\Pr(y_{imt} = 1) = \begin{cases} \Phi(U_{imt}) & \text{if } y_{imt-1} = 0 \\ 1 & \text{if } y_{imt-1} = 1. \end{cases} \quad (1)$$

In this model U_{imt} is the entry attractiveness of market m in week t to manufacturer i, and Φ is the CDF of the standard normal distribution $\mathcal{N}(0, 1)$. The above formulation implies that, for inference, only observations until and including the moment of entry are relevant.

The attractiveness function U_{imt} is formalized using a random-effects model that includes brand, market, and time variables. Specifically, let

$$U_{imt} = \mathbf{X}_{imt}^y \cdot \boldsymbol{\theta} + \beta_m, \quad (2)$$

so that in addition to fixed effects $\mathbf{X}_{imt}^y \cdot \boldsymbol{\theta}$ we allow for random components at the market level β_m. The random-effects structure in the model was chosen to accommodate unobserved heterogeneity in entry rates across markets.

Fixed Effects. To allow for flexible temporal patterns in U_{imt}, we estimate a piecewise constant baseline hazard function for each brand i and period τ (i.e., we use a semiparametric model).[2] The period τ is measured in an appropriate unit of time given the temporal density of market entry of brand i (months, quarters, and so on). The baseline hazards are incorporated in the model as the effect to dummy variables $D_{i\tau}^y$, which in turn are defined as

$$D_{i\tau}^y = \begin{cases} 1 & \text{if brand } i \text{ and } t \in \tau \\ 0 & \text{otherwise,} \end{cases} \quad (3)$$

---

[2] An alternative to this procedure is to specify a random temporal effect with an autoregressive structure. Results with such a model are substantively identical to the semiparametric approach.

where $t \in \tau$ denotes that week t belongs to, e.g., quarter τ. Depending on the responses to these variables, the semiparametric model allows for increasing, decreasing, or nonmonotone baseline hazard rates for each brand.

In addition, we allow entry to be influenced by the category development index, CDI_{mt}^y. This index is operationalized by the weekly category dollar sales as a percentage of total weekly dollar sales scanned in a market. In the same vein, market entry may be affected by the manufacturer development index, MDI_{imt}^y. This index is defined as manufacturer i's dollar share of the category in market m and week t. To the extent that transportation costs play a role in the entry of markets, we use distance to manufacturing site, DSM_{im}^y (in 1,000 miles).

Next, the arrows (ii) and (iv) in Figure 4 are operationalized by two variables that capture past entry by manufacturers: SPT_{imt}^y, and past adoption by retailers, PRV_{imt}^y, respectively. The spatial variable, SPT_{imt}^y, captures market entry in neighboring markets. The adjacency of two markets can be coded in an $M \times M$ matrix $\mathbf{W}_s$, whose rows add to one and whose entries $[m, m']$ are positive if m and m' are neighbors and 0 if they are not. Such a matrix is called a spatial lag operator (see, e.g., Anselin 1988) and is defined subsequently. Arraying the market entry variables at $t-1$ across markets into the $M \times 1$ vector $\mathbf{y}_{it-1}$, SPT_{imt}^y is defined as the mth element of

$$\mathbf{SPT}_{it}^y \underset{(M \times 1)}{=} \mathbf{W}_s \cdot \mathbf{y}_{it-1}. \quad (4)$$

In practical terms, SPT_{imt}^y is the weighted average of past entry in neighboring markets. We expect the spatial effects of SPT_{imt}^y on entry to be positive, i.e., past entry in contiguous markets is expected to have positive effects on market entry.

The previous adoption variable, PRV_{imt}^y, represents the combined local share of all those chains in market m that have adopted brand i prior to t in another market $m' \neq m$. This variable corresponds to the arrow (iv) in Figure 4. To compute this variable, define an M by K matrix $\mathbf{H}$ containing the all-commodity volume (ACV) of chain k in market m. If retailer k does not operate on market m, the corresponding element of $\mathbf{H}$ is 0. $\mathbf{H}$ can be interpreted as a representation of the geographical structure of U.S. retailers. Denote the mth row of $\mathbf{H}$ by $\mathbf{H}_m$ (of size $1 \times K$). The total ACV of market m is $\mathbf{H}_m \mathbf{1}_K$, where $\mathbf{1}_K$ is a column vector of 1's. Denote the distribution status of brand i by $z_{ikt-1} = 1$ if chain k adopted before or in week $t-1$ and $z_{ikt-1} = 0$ if the chain did not adopt at or before $t - 1$. Array the adoption variables across chains to obtain a $K \times 1$ vector $\mathbf{z}_{it-1}$. Then the scalar PRV_{imt}^y is defined as

$$\text{PRV}_{imt}^y = \frac{\mathbf{H}_m \mathbf{z}_{it-1}}{\mathbf{H}_m \mathbf{1}_K}. \quad (5)$$

PRV_{imt}^y can be interpreted as a weighted average of past adoption among retailers that are in market m. This measure is between 0 (none of the chains in market m has adopted the brand in the past anywhere else) and 1 (all chains on market m have already adopted the brand previously in some other market $m' \neq m$).

Random Effects. Equation (2) contains a market-level component β_m to allow for heterogeneity in market entry. This component is populated with market-level covariates in a hierarchical regression model. The inclusion of the market-level covariates in the hierarchical model is done for reasons of statistical efficiency (see also Ainslie and Rossi 1998). Three market-level covariates are used in the hierarchical model. First, market size, ACV_m^y, is measured as the average weekly volume sold on a given market in millions of dollars. Second, market level concentration of the retailers, HRF_m^y, is equal to the Herfindahl index computed from the ACV-based shares of the retailers in market m. The final variable, SNI_m^y, is the local combined share of retail chains, as opposed to that of independent stores.[3] This variable is a proxy for how connected a market is in the network of retailers. That is, the larger the market share of independent stores is in a given market, the fewer ties will exist across markets because such independent stores do not have multimarket presence.[4]

To summarize the discussion above, the complete specification of the market entry model used in this study is as follows:

$$U_{imt} = \theta_{i\tau}D_{i\tau}^y + \theta_1 CDI_{mt}^y + \theta_2 MDI_{imt}^y + \theta_3 DSM_{im}^y$$
$$+ \theta_4 SPT_{imt}^y + \theta_5 PRV_{imt}^y + \beta_m, \quad t \in \tau, \quad (6)$$

with

$$\beta_m \sim \mathcal{N}(\phi_1 ACV_m^y + \phi_2 HRF_m^y + \phi_3 SNI_m^y, \sigma_\beta^2). \quad (7)$$

4.2. Chain Adoption

Similar to the model of market entry, a probit model is used to represent the probability that a retail chain adopts the brand. For each chain k, brand i, and week t, let $z_{ikt} = 1$ if the brand is adopted at or before week t and $z_{ikt} = 0$ if the brand is not adopted. Adoption can occur only if the brand is made available by the manufacturer in at least one market in chain k's trade area. Formally, let C_k be the set of markets in which chain k operates, and let y_{iC_kt} be an indicator

[3] SNI stands for shares of non-independent chains.

[4] Alternative measures of market connectedness in the network of retailers were defined based on the number of retailers that two markets have in common. However, the SNI_m^y variable had the strongest effect and was ultimately chosen to represent this aspect of connectedness in the model.

variable that assumes the value 1 if brand i is available at week t on at least one market $m \in C_k$, and 0 in all other cases, then adoption by retailer k of manufacturer i's brand in week t is modeled as

$$\Pr(z_{ikt} = 1)$$
$$= \begin{cases} 0 & \text{if } y_{iC_kt} = 0 \\ \Phi(V_{ikt}) & \text{if } y_{iC_kt} = 1, \text{ and } z_{ikt-1} = 0 \quad (8) \\ 1 & \text{if } y_{iC_kt} = 1, \text{ and } z_{ikt-1} = 1. \end{cases}$$

Thus the relevant observations for inference on V_{ikt} fall between—and include—the time of manufacturer entry in the retailer's trade area and the time of adoption by the chain somewhere in its trade area.

Analogous to the market entry model above, we specify that V_{ikt} contains fixed and random effects:

$$V_{ikt} = \mathbf{X}_{ikt}^z \boldsymbol{\mu} + b_k. \quad (9)$$

Fixed Effects. As with the model for U_{imt}, a semi-parametric model for V_{ikt} is used to account for a piecewise constant baseline hazard function. A separate effect is estimated for each brand i and period ξ where ξ is expressed in an appropriate unit of time given the temporal density of retail adoption (e.g., monthly, quarterly, and so on). The units of ξ may be equal to those of τ used in the market entry model, but this is not necessary. Different baseline hazards for each brand i and period ξ are estimated as the effect of dummy variables $D_{i\xi}^z$, which are defined as

$$D_{i\xi}^z = \begin{cases} 1 & \text{if brand } i \text{ and } t \in \xi \\ 0 & \text{otherwise,} \end{cases} \quad (10)$$

where the notation $t \in \xi$ means that week t belongs to, e.g., quarter ξ.

We allow for the following other variables to influence adoption timing. First, we specify an effect of the retailer category development index, CDI_{kt}^z. This variable is defined as the weekly category sales for a retailer as a percentage of that retailer's total ACV. We expect retailers with higher CDI_{kt}^z to adopt earlier. Second, we include the manufacturer development index, MDI_{ikt}^z, at the retailer level, defined as manufacturer i's dollar share in the category with retailer k. We expect retailers with a higher share of i's existing brands to adopt i's new brand earlier than retailers with a lower share of i's existing brands. Next, adoption is allowed to decelerate or accelerate in the time that elapsed since brand i became available in the trade area of retailer k, TSA_{ikt}^z. We have no a priori expectation of the effect of time since the product became available in a chain's territory on the chain's likelihood of adoption.

Central to this study, we introduce a variable, DIF_{ikt}^z, that allows the adoptions by chains to be related to past adoptions by direct competitors. This

variable corresponds to the arrow (i) in Figure 4. Direct competitors are defined as retailers with overlapping retail trade areas. Pairs of direct competitors can be represented with a $K \times K$ matrix $\mathbf{W}_n$ (to be defined) whose rows add to one, and whose entries $[k, k']$ are positive if k and k' are direct competitors and 0 if they are not. Array the K distribution variables z_{ikt-1} at $t-1$ across markets into the $K \times 1$ vector $\mathbf{z}_{it-1}$. Next, DIF_{ikt}^z is the kth element of

$$\mathbf{DIF}_{it}^z \underset{(K \times 1)}{=} \mathbf{W}_n \mathbf{z}_{it-1}. \qquad (11)$$

This variable is equal to the fraction of competing chains that already carry brand i in its assortment. Consistent with the central hypothesis in social contagion research, the expectation is that the effect of DIF_{ikt}^z on the adoption is positive.[5]

Next a variable is defined that captures manufacturer i's coverage of the trade area of retailer k.[6] The effect of this variable corresponds to arrow (iii) in Figure 4. The variable, denoted FAE_{ikt}^z for fraction of area entered, is operationalized as the ACV fraction of the trade area of retailer k that has been entered by manufacturer i prior to week t. Recall that the $M \times K$ matrix $\mathbf{H}$ contains the ACV volume of retailer k in market m. Denote the kth column of $\mathbf{H}$ by $\mathbf{H}_k$ (of size $M \times 1$). The total ACV size of retailer k is $\mathbf{H}_k' \mathbf{1}_M$ with $\mathbf{1}_M$ denoting a column vector of ones. The entry status of brand i at time $t-1$ across all M markets is collected in the $M \times 1$ vector $\mathbf{y}_{it-1}$. Manufacturer i's coverage of the trade area of chain k, FAE_{ikt}^z, is defined as

$$\mathrm{FAE}_{ikt}^z = \frac{\mathbf{H}_k' \mathbf{y}_{it-1}}{\mathbf{H}_k' \mathbf{1}_M}. \qquad (12)$$

This variable measures the ACV fraction of a trade area that has been entered by the manufacturer. Its value lies between 0 (i.e., in the preceding period brand i was available in none of retailer k's markets) and 1 (i.e., in the preceding period brand i was available in all of retailer k's markets).

Furthermore, we define a variable, TVR_{it}^z, that is equal to the total volume of the retailers (measured in ACV) that have adopted brand i prior to week t. This variable is similar to the contagion variable in traditional diffusion models. If contagion in adoption behavior is local, rather than global, one may expect that this variable does not affect adoption behavior. Finally, we also construct a dummy variable, IND_{ikt}^z, which captures whether independent stores have adopted brand i prior to t in the trade area of chain k.

Random Effects. The components b_k contain the retailer-level effects on adoption timing. These components help account for the influence of unobserved retailer-specific variables, such as chain-specific incentives (inasmuch as these incentives are constant until the chain adopts). Two variables are included in the hierarchical model of b_k. First, ACV_k^z is the total size of the retail chain in \$MM aggregated across all markets in k's trade area and averaged over weeks. The effect of chain size on adoption is expected to be positive because larger chains have more specialized freezer space to experiment with new products. Second, the variable HRF_k^z measures the degree of spatial concentration of a retailer's sales volume over the markets on which it operates. It is measured as the Herfindahl index of total retailer volume across markets. For example, Dominick's is a retailer whose volume is very concentrated in Chicago and is an example of a retailer with a high HRF_k^z. Retailers with a spatially concentrated trade area face competing retailers in fewer markets than retailers with a spatially dispersed trade area. Accordingly, the effect of HRF_k^z on adoption might be expected to be negative.

To summarize our retailer adoption model, we use a probit model (8), of which the complete specification is

$$V_{ikt} = \mu_{i\xi} D_{i\xi}^z + \mu_1 \mathrm{CDI}_{kt}^z + \mu_2 \mathrm{MDI}_{ikt}^z + \mu_3 \mathrm{TSA}_{ikt}^z + \mu_4 \mathrm{DIF}_{ikt}^z$$
$$+ \mu_5 \mathrm{FAE}_{ikt}^z + \mu_6 \mathrm{TVR}_{it}^z + \mu_7 \mathrm{IND}_{ikt}^z + b_k, \quad t \in \xi \quad (13)$$

with

$$b_k \sim \mathcal{N}(\psi_1 \mathrm{ACV}_k^z + \psi_2 \mathrm{HRF}_k^z, \sigma_b^2). \qquad (14)$$

Obviously, from a diffusion perspective, special interest is with the contagion parameters μ_4 and μ_5. On the one hand, if μ_4 is positive, retailers tend to be influenced by past adoptions of retailers that are direct competitors. On the other hand, such local contagion effects are less important if the effect of TVR_{it}^z dominates that of DIF_{ikt}^z.

4.3. The Representation of Geographic Proximity
The spatial variable SPT_{imt} uses a weight matrix $\mathbf{W}_s$ which identifies spatial adjacency based on a simple concept called Voronoi polygons (Okabe et al. 2000). These polygons divide geographic space (e.g., the United States) exhaustively into mutually exclusive areas around centers (e.g., local markets such as New York, Los Angeles, and so on) whose interior points are closest to these centers. We define as neighbors two local markets whose Voronoi polygons are adjacent, i.e., have a common edge. A market cannot be a neighbor of itself. For an illustration of the use of Voronoi polygons to define local U.S. markets, see Bronnenberg and Mahajan (2001). For other

---

[5] Additionally, a contagion variable representing competitive sales was considered. However, in estimation this variable was too collinear with DIF_{ikt}^z to estimate the effect jointly and did not explain adoption as well as DIF_{ikt}^z in isolation.

[6] We thank an anonymous reviewer for suggesting this variable.

illustrations of the use of geographic neighbors in marketing models, see e.g., Ter Hofstede et al. (2002).

To define the weights in $\mathbf{W}_s$ denote the neighbor set of market m by $\{B_m\}$ and the average dollar-sales volume per week in market m by ACV_m. Then,

$$w_s(m, m') = \begin{cases} \dfrac{\text{ACV}_{m'}}{\sum_{m'' \in \{B_m\}} \text{ACV}_{m''}} & \text{if } m' \in \{B_m\} \\ 0 & \text{else.} \end{cases} \quad (15)$$

The weight matrix $\mathbf{W}_s$ is populated by the $w_s(m, m')$.[7]

4.4. The Representation of the Retailer Network and Network Effects
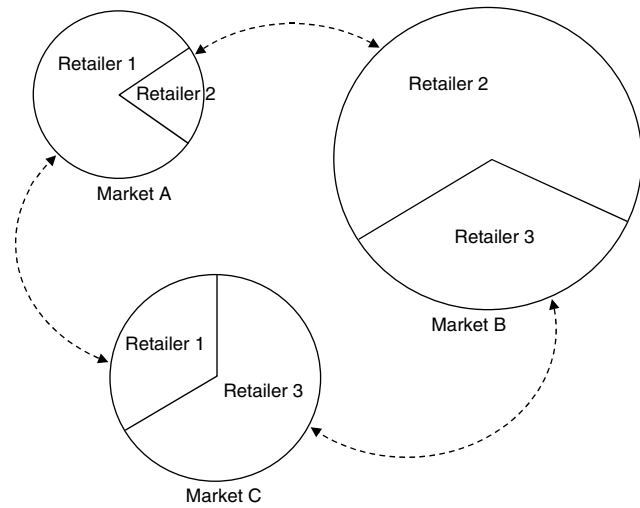
Because we wish to measure the role of retailer connectedness in the evolution of retail distribution for new products, a definition of connectedness is needed. We propose a definition that is based on trade-area overlap of pairs of retailers. Let retailer k operate in a set of markets $m \in C_k$, with C_k being its retail trade area. Denote the average dollar-sales volume per week by retailer k in market m by ACV_{km}. Then, the relative influence of retailer k' on retailer k is defined by the former's share of ACV in the latter's trade area (see Bronnenberg and Sismeiro 2002), i.e.,

$$w_n(k, k') = \frac{\sum_{m \in C_r} \text{ACV}_{k'm}}{\sum_{k'' \neq k} \sum_{m \in C_k} \text{ACV}_{k''m}} \quad \text{and}$$
$$w_n(k, k) = 0, \ \forall k = 1, \ldots, K. \quad (16)$$

This measure is between 0 and 1 and adds to 1 over all competitors k' of a given retail chain k. The direct influence $w_n(k, k')$ is 0 for all pairs of retail chains whose trade areas do not overlap, and it becomes larger with the degree to which the trade areas of two retailers coincide. This definition also expresses that, for any given retail chain, large direct competitors have more influence than small direct competitors.[8] Our definition further implies asymmetric influences, i.e., that $w_n(k, k')$ is in general not equal to $w_n(k', k)$.

Figure 5 helps to explain this definition. This figure represents a hypothetical situation with three markets and three retail chains. Retailer 1 operates in markets A and C, and faces competition from Retailer 2 in market A and from Retailer 3 in Market C. The above

---

[7] An alternative definition of these weights as $1/N_m$ was explored, where N_m is the number of markets in the neighbor set $\{B_m\}$. Within the confines of our empirical example, this operationalization is equivalent in terms of model fit to the operationalization in the text. We present the results with the weighting by market size.

[8] Another definition of the influence of Retailer k' on k was explored that is based on the interaction of k' and k's local size. This measure expresses that greater weight is accorded to competing chains that operate within a chain's core (i.e., large share) markets. Model fit favored the definition in the text.

Figure 5   Overlapping Retail Territories and Market Links

definition of w_n states that the relative influence on Chain 1 can be expressed as

$$w_{n, acv}(1, 1) = 0, \qquad w_{n, acv}(1, 2) = \frac{\text{ACV}_{2A}}{\text{ACV}_{2A} + \text{ACV}_{3C}}$$

and

$$w_{n, acv}(1, 3) = \frac{\text{ACV}_{3C}}{\text{ACV}_{2A} + \text{ACV}_{3C}}. \quad (17)$$

Taking the size of the circles proportional to market size, Retailer 3 is a larger retailer than Retailer 2 in Retailer 1's trade area. Our definition of w_n in Equation (16) then implies that Retailer 3 has more influence on Retailer 1's adoption than does Retailer 2.

The combination of all possible pairs of retailers spans a $K \times K$ matrix $\mathbf{W}_n$, as follows:

$$\mathbf{W}_n = \begin{bmatrix} 0 & w_n(1, 2) & \cdots & w_n(1, K) \\ w_n(2, 1) & 0 & \cdots & w_n(2, K) \\ \vdots & \vdots & \ddots & \vdots \\ w_n(K, 1) & w_n(K, 2) & \cdots & 0 \end{bmatrix}.$$

This sparse matrix, i.e., which contains many $w_n(k, k') = 0$, represents the network of retailers as a sociomatrix with asymmetric links (see, e.g., Wasserman and Faust 1994, ch. 4).

4.5. Discussion

The model introduced above presents a testable account of the spatial and temporal patterns with which new brands are rolled out to markets and adopted by retailers. It can be classified as a reduced-form model, in which the market entry and retailer adoption equations are assumed to be independent after controlling for lagged effects. This assumption is acceptable for a number of reasons. First, the

equations contain as covariates the variables that were enumerated to be strategically relevant by manufacturers and retailers. Second, the sample rate of the data is high (weekly) compared with the time scale associated with market entry and retailer adoption decisions. Therefore, controlling for lagged effects makes residual contemporaneous dependence between the equations unlikely. For example, given the time needed to plan a local launch, the fact that a retailer k adopts in week t cannot cause the manufacturer to enter other markets on which k operates in the same week. Obviously, this would not be true if time were measured in years. Third, the conjecture of independence can explicitly be checked by testing for covariation between market entry and chain adoption. This can be done by incorporating the (market-level ACV weighted average of) random retailer effects b_k as a covariate in the market-entry model. The associated effect of unobserved retailer characteristics on market entry (including unobserved tendencies to adopt quickly) is not different from zero. Thus, the statistical independence of the equations appears acceptable.

We asked managers directly what they take into account in making timing decisions about market entry and retailer adoption. For this reason our model represents what decision makers say they do, not necessarily what they should do in a normative sense. A normative model of roll-outs originates from a maximization of long-term profits with respect to the timing of local entry, accounting for the attitude toward risk of commercial failure. This requires an optimization over time, markets, retailers, and several unobservables. In addition, the optimization should take into account risk tolerance from managers and feedback effects from the outcomes of earlier decisions. Given the complexity of this problem, our representation of the strategic behavior of managers as a set of heuristics is likely an acceptable representation of what firms do in practice.

The variables in the market entry models are related to launch cost and other strategic considerations. Indeed, it may be cheaper for manufacturers to enter markets that are concentrated (fewer retailers), that are located close to markets that were entered before, or on which many retailers operate who adopted previously. If contagion among retailers is important, we would also expect manufacturers to enter markets with large shares of multimarket retail chains early, i.e., we expect a positive effect of the local market share by multimarket retailers, SNI_m^k.

The random effects at the market level and retailer level are included to account for market- and retailer-level variables that are not in the model (to the extent that these variables are not correlated with the regressors). Examples of such omitted variables are market demographics or retailer incentives, respectively.

Finally, the model is simple and easy to estimate in its current form through a variety of methods. The hierarchical form and specific estimation methods employed in this paper accommodate feasible estimation of additional features to the ones represented in Equations (6) and (13), including random effects along the temporal dimension and dependence of these effects within and across equations.

5. Empirical Analysis

5.1. Data
The data used in this study consist of store-level sales data from the frozen pizza category for a national sample of approximately 1,900 supermarket stores drawn from many retail chains and local markets. Information Resources, Inc. defines a market as either a metropolitan area (e.g., New York) or a region (e.g., New Mexico/West Texas). We retain in the analysis 95 markets that have at least three stores in the IRI sample.

The data span 5 years of weekly store-level sales data. As stated in the introduction, two major new brands—DiGiorno and Freschetta—were launched during the timeframe of the data. Both brands obtained national retail distribution coverage.

We confine our modeling efforts and interpretations to the evolution of distribution among retail chains. For each store, a store name and an IRI market number are observed. A retail chain is defined from these data as the recurrence of the same store name across at least two different stores. This definition is inclusive and identifies more than 150 retailers in our data. We do not analyze the adoption behavior of independent stores. First, their joint ACV is only 10% of the U.S. volume of the grocery trade. Second, both manufacturers and retailers interviewed for this study indicated that their role in new product launch was negligible. Third, independent stores are usually not targeted individually by manufacturers but rather as a (to us unobserved) group of stores served by food brokers.

Some retailers join the IRI sample after the brand is available to them for adoption. Such retailers have missing data on several covariates, and inasmuch as adoption has taken place prior to entering the sample, generally add little information about adoption timing. These left-censored cases are rare in our data and they were not used in the analysis; for additional support see Greve et al. (2001).

Market entry and retailer adoption are, in principle, unobserved to the analyst. Nonetheless, the available IRI data allow for high-quality proxies for the timing of these two decisions. The moment of market entry is defined as the week of first sales in a given market. Similarly, the moment of chain adoption is taken as

the first week in which sales of the brand are observed for a retailer anywhere in its trade area.

There are three aspects of these definitions that warrant discussion. First, a potential problem with these definitions arises if diverting, i.e., the practice by retailers to redistribute products to other markets or channels, occurs frequently. For the data used in this study, there are several reasons why diverting is not a concern. First, manufacturers prohibit diverting. Second, there is no advertising or trade support in unentered markets for diverted brands. Third, several extant brands in the category are stocked in stores directly by the manufacturers, making potential diverting of new brands by retailers easy to detect. Finally, scanner data identify diverting by a retailer as a pattern of early sales for only one or few retailers prior to broader adoption in a market. Such patterns are not observed.[9]

A second potential issue with these two operationalizations is that, in selected cases, entry and adoption are inferred from the same observation of store sales. To rule out the potential simultaneity that this could create, we estimate the model using only those adoptions that do not coincide with our proxies for market entry.[10]

Third, while there may be small deviations between the first time that sales are observed and the actual decision timing by manufacturers and retailers, the variation in the timing measures is clearly beyond any reasonable measure of observation error. For example, for DiGiorno the difference between national launch date and having entered 50% of the markets is 59 weeks, whereas the last market is entered 135 weeks after national launch. For Freschetta, these numbers are 27 weeks and 69 weeks, respectively. Hence, the observed variation in entry timing is very large compared with the potential timing differences between the decision to enter a given market and the implementation of that decision. As a consequence, we take the observed timing of entry to be informative about the actual entry decisions by manufacturers. Along the same lines, the deviation across retailers in their timing of adoption measured from the moment of availability is 17 weeks for DiGiorno and 19 weeks for Freschetta.[11] We therefore believe

that these observed adoption times are informative about retailer adoption timing, because it is unlikely that a delay in adoption of 3 months or more is a measurement error.

Table 1 lists the descriptive statistics of the variables used in this study. The descriptive statistics report on averages and standard deviations over all relevant observations of market entry y_{imt} and retailer adoption z_{ikt}.

5.2. Estimation

We estimate the heterogeneous hazard model in Equations (6) and (13) using a Markov chain Monte Carlo (MCMC) approach. To implement this estimation approach, we specify the full-conditional distributions of all model parameters and their prior distributions. Appendix A contains the full conditionals, and Appendix B contains the MCMC algorithm. The prior distributions used in this study are of two types and are chosen to be uninformative. For all model parameters other than variance terms, we use independently and identically distributor (IID) $\mathcal{N}(0, 10,000)$ distributions. The variance terms of the model have an $IG(1, 1)$ prior distribution.

Several considerations regarding implementation of the MCMC chain are worth noting. Poor mixing, i.e., the phenomenon that the parameters meander slowly, occurs with models of the type contained in Equations (6) and (13) (see e.g., Gilks et al. 1996, Vines et al. 1996). Methods to ensure more efficient mixing are available (see e.g., Chib and Carlin 1999, Gelfand et al. 1995, Vines et al. 1996). In our application, and without any loss in generality, we enhance the mixing properties of the chain by demeaning the covariates of the random components in the model (i.e., by sweeping the effect of the mean into the intercepts of the model). This does not affect the parameter estimates except for a shift in the intercept to compensate the sweep of the mean. The convergence with sweeping is markedly quicker than without.

We executed the MCMC chain for 500,000 draws, used the first 50,000 draws for burn-in, and then sampled every 50th draw from the MCMC chain for further analysis. Thus a total of 9,000 draws are used in the computation of the parameter estimates.

A number of variations on the models in Equations (6) and (13) that were estimated deserve mention. As an alternative for semiparametric baseline hazards, several flexible specifications were estimated with random temporal effects at the brand level. These models were alternatively operationalized with and without time trend and autocorrelation in the random effects. Alternative specifications

---

[9] Two exceptions are noted where a single independent store sold one of the brands much earlier than retail chains. The timing of market entry in these cases was inferred excluding the early sales in the independent stores.

[10] We thank an anonymous reviewer for suggesting this approach.

[11] The large variation in the data also helps to dispel the possibility that the differences in adoption across retailers are manufacturer controlled. This would, for instance, happen if manufacturers initially make their brand selectively available to a subset of retailers in a given market. From a cost perspective, it makes little sense to hold back new brands selectively (for as long as multiple quarters)

---

from some retailers, given that many launch costs (e.g., advertising or transportation) are forcibly made at the market level.

Table 1   Sample Description of the Variables

Model	Variable	Abbreviation	Units	Mean	Std
Market entry	Category development index	CDI_{mt}^{y}	%cat.sales$_{mt}$/ACV$_{mt}$	0.78	0.50
	Manufacturer development index	MDI_{imt}^{y}	mfr. sales$_{imt}$/cat.sales$_{mt}$	0.25	0.14
	Distance to manufacturing site	DSM_{im}^{y}	10^3 Miles	0.70	0.46
	Spatial proximity	SPT_{imt}^{y}	[ ]	0.15	0.24
	Share of previous adopters	PRV_{imt}^{y}	% market ACV	0.32	0.31
	Market size	ACV_{m}^{y}	MM$/week	4.99	3.67
	Market concentration	HRF_{m}^{y}	[ ]	0.29	0.13
	Share of retail chains	SNI_{m}^{y}	% market ACV	0.91	0.10
Retailer adoption	Category development index	CDI_{kt}^{z}	%cat.sales$_{kt}$/ACV$_{kt}$	0.64	0.40
	Manufacturer development index	MDI_{ikt}^{z}	mfr. sales$_{ikt}$/cat.sales$_{kt}$	0.17	0.16
	Time since availability	TSA_{ikt}^{z}	weeks	31.41	36.35
	Competitive retailer adoption	DIF_{ikt}^{z}	[ ]	0.68	0.27
	Manufacturer presence	FAE_{ik}^{z}	[ ]	0.78	0.36
	Total volume of adopting retailers	TVR_{it}^{z}	[ ]	276.78	82.35
	Local adoption by independents	IND_{ikt}^{z}	MM$/week	0.53	0.50
	Retailer size	ACV_{k}^{z}	[ ]	2.13	4.06
	Retailer concentration	HRF_{k}^{z}	[ ]	0.73	0.31

were also estimated with brand-level versus pooled effects for the four feedback variables. The results of these models are substantively identical to the model presented here.

Finally, alternative versions of the contagion variables can be computed from either including or not including the ACV of independents in the matrices **H**, $\mathbf{W}_n$, and $\mathbf{W}_s$. We report on the case where the ACV of independents is included. Empirically, this distinction does not matter for the effects of the associated variables.

5.3.   Results

5.3.1.   Adoption Conditional on Market Entry.

5.3.1.1.   *Market Entry Model*. Estimation results for the full model are in Table 2. Because market entry is a relatively low-probability event, and because there are relatively few markets, the data lack the density to estimate piecewise constant baseline hazards at the quarterly level. Therefore these were estimated for periods of 6 months. This resulted in the estimation of a total of seven piecewise constant hazards. The baseline hazards increase in time for both brands. Combined with the increasing variables SPT_{imt}^{y} and PRV_{imt}^{y}, U_{imt} therefore increases with time, i.e., firms accelerate roll-outs. Possible explanations for this behavior are that the risk of entering new markets decreases, or that the commercial success in early markets makes the capital available to enter more markets.

The effect θ_1 of the category development index, CDI_{mt}^{y}, on market entry y_{imt} is not different from 0. In other words, the two manufacturers do not seem to enter markets in increasing or decreasing order of category importance.

In contrast, the effect θ_2 of the manufacturer development index, MDI_{imt}^{y}, is significant and positive. Manufacturers have a tendency to enter early markets

on which they have a large existing share. While this may be logical, prima facie, it seems conservative of a manufacturer to launch a new brand first where it already has high shares with extant brands. On one hand, the potential for cannibalization is highest in such markets (see e.g., Kotler 2003, Schultz et al. 1984). On the other hand, if the new brand is targeted to a new market segment that is not currently served,[12] there are potential reputation benefits with retailers in markets with high MDI_{imt}^{y}. This is, in turn, a plausible reason for early entry of markets with a high MDI_{imt}^{y}.

The distance to the manufacturing site, DSM_{im}^{y}, has no impact on the timing of entry or the order in which markets are entered (θ_3 is not different from 0). This suggests that transportation cost does not impact market entry, which may be reasonable if such costs are carried forward to the consumer through local market prices (Anderson and de Palma 1988).

The values of θ_4 and θ_5 represent the spatial and selection effects on market entry. The value of θ_4 is positive, i.e., manufacturers tend to launch brands close to markets that have already been entered. A possible explanation for this entry pattern is more efficient use of multimarket resources in the distribution channel such as distribution centers, transportation carriers, and so on. Note that the possible existence of such efficiencies does not need to mediate a possible impact of transportation costs on prices.

The effect θ_5 of PRV_{imt}^{y} is also positive. This means that markets are more likely to be entered if retailers

---

[12] There is some support for this condition. According to a Kraft manager, DiGiorno was developed and marketed to compete with take-out pizza and not with frozen pizza brands that were already on the market. The DiGiorno slogan "It's not delivery, it's DiGiorno!" reflects this positioning.

Table 2   Estimation Results of the Full Model[a]

Symbol	Variable	Abbreviation	Percentile 2.5%	50%	97.5%
			Market entry		
θ_1	Category development index	CDI^y_{mt}	−0.368	−0.095	0.173
θ_2	Manufacturer development index	MDI^y_{imt}	0.373	1.006	1.672
θ_3	Distance manufacturing site	DSM^y_{im}	−0.343	−0.051	0.223
θ_4	Spatial proximity	SPT^y_{imt}	1.172	1.530	1.904
θ_5	Share of previous adopters	PRV^y_{imt}	0.363	0.742	1.135
ϕ_1	Market size	ACV^y_m	−0.052	−0.010	0.033
ϕ_2	Market concentration[b]	HRF^y_m	−2.250	−1.033	0.134
ϕ_3	Share of retail chains[b]	SNI^y_m	−0.107	1.308	2.796
σ^2_β	Variance market component		0.146	0.261	0.450
Symbol	Variable		Chain adoption		
μ_1	Category development index	CDI^z_{kt}	−0.113	0.132	0.364
μ_2	Manufacturer development index	MDI^z_{ikt}	0.469	1.021	1.578
μ_3	Time since availability	TSA^z_{ikt}	−0.014	−0.008	−0.001
μ_4	Competitive retailer adoption	DIF^z_{ikt}	0.376	0.838	1.330
μ_5	Manufacturer presence	FAE^z_{ikt}	0.926	1.301	1.710
μ_6	Total volume of adopting retailers	TVR^z_{it}	−0.006	−0.002	0.003
μ_7	Local adoption by independents	IND^z_{ikt}	0.172	0.362	0.561
ψ_1	Retailer size	ACV^z_k	0.020	0.062	0.105
ψ_2	Retailer concentration	HRF^z_k	−1.639	−1.032	−0.487
σ^2_b	Variance retailer component		0.216	0.365	0.586

[a] The semiannual dummy effects $\theta_{i\tau}$ and quarterly dummy effects $\mu_{i\xi}$ are not reported to avoid cluttering.
[b] The 90% credibility interval does not cover zero.

that operate in them have previously adopted in other markets. This effect creates a feedback from retailer adoption to market entry.

A potential empirical concern with these two effects is their proper separation or discriminant validity. Such a concern would be especially valid if many retailers are common to two neighboring markets and, conversely, if two markets that have retailers in common are also located close to each other. If this were the case, the effects of PRV^y_{imt} and SPT^y_{imt} would be confounded. However, whereas neighboring markets do share retailers in the United States, markets with common retailers do not necessarily have to be spatially close. For example, Safeway is large in San Francisco and in Washington, D.C. (see Figure 6) but these markets are separated by a large distance. As a result, the variables SPT^y_{imt} and PRV^y_{imt} are only moderately (0.21) correlated. Hence, the spatial effects θ_4 and market-selection effects θ_5 are properly separated.

Of the covariates of the market-level random effect β_m the parameter ϕ_1 is not different from 0, and hence market size ACV^y_m does not impact β_m, and by extension does not impact the timing of market entry. Second, $\phi_2 < 0$ at the 90% credibility level. Concentration of the retail industry in a given market, HRF^y_m, thus has a negative significant impact on market entry: Markets with multiple important retailers tend to be entered earlier than markets that have one dominant retailer. It therefore seems that during early launch

manufacturers avoid reliance on only one or few retailers. The latter inference echoes a statement made by a Kraft manager that lead markets were chosen to avoid being dependent on the early success of the brand with a single, dominant, retail chain.

The effect of the share of retail chains, SNI^y_m, is positive, that is, $\phi_3 > 0$ at the 90% credibility level. This effect implies that manufacturers initially seek to enter where multimarket retailers have a large share. Conversely, markets with many, or larger, independent retailers are entered relatively late.

5.3.1.2. *Chain Adoption Model.* Because of the relatively higher density of adoption data, these data

Figure 6   Markets with High Contagion Potential and Trade Areas in the United States
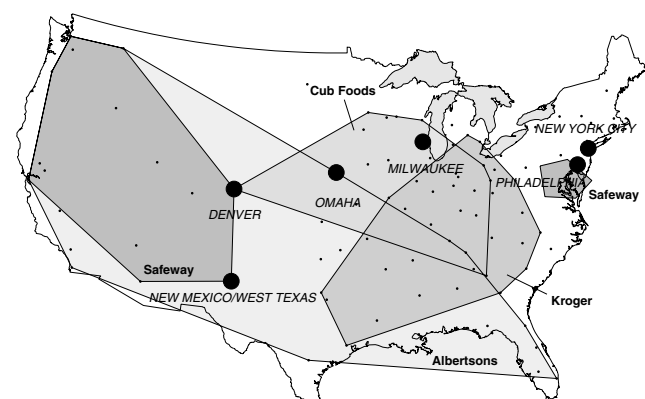
allow for estimation of piecewise constant baseline hazards at the quarterly level. A total of 19 piecewise constant baseline hazards were estimated, allowing for flexible patterns in time. Baseline adoption rates for DiGiorno are not higher than those of Freschetta. Interestingly, this suggests that first-mover effects commonly observed in the consumer adoption of new brands (Kalyanaram and Urban 1992, Kalyanaram et al. 1995) do not manifest as readily in retail adoption of new brands. The baseline hazards are nonmonotone, albeit overall somewhat increasing, and all negative (i.e., adoption is a relatively rare event at the weekly level).

The effect of CDI_{kt}^z, μ_1, is not different from 0. Hence, empirically, retailers with a larger category share for frozen pizza (as a percentage of retailer ACV) do not adopt a new brand earlier than retailers with a smaller revenue share of this category.

Retailers adopt a brand faster if the manufacturer has a large revenue share of the category with the retailer, i.e., μ_2, the effect of manufacturer i's development index with retailer k, MDI_{ikt}^z, is positive. Perhaps retailer k takes a high MDI_{ikt}^z as an indication that products from manufacturer i are preferred by consumers, which in turn would lead to early adoption. Alternatively, a high MDI_{ikt}^z may be indicative of a strong sales force relation, which would facilitate early adoption.

All else being equal, retailer adoption decelerates with the elapsed time since the brand became available in its trade area, TSA_{ikt}^z, i.e., $\mu_3 < 0$. This implies that the longer it takes for a retailer to adopt, the less likely it is that it ever will.

Importantly, the competitive contagion effect among retailers, μ_4, is positive. Retailers have an increased tendency to adopt the brand if other retailers in their trade area have previously done so.

Retailer adoption is also positively affected by the coverage of manufacturer i's new brand in retailer k's trade area, FAE_{ikt}^z. The effect μ_5 is positive. The two variables FAE_{ikt}^z and DIF_{ikt}^z have discriminant validity. The variables correlate 0.59 and their corresponding effects μ_4 and μ_5 correlate only -0.21. Hence, empirically the two effects do not substitute for each other.[13] This effect creates a feedback from entry $\mathbf{y}_{it-1}$ to adoption $\mathbf{z}_{it}$.

The effect of the total volume of previously adopting retailers, μ_6, is nonsignificant, suggesting that adoption by individual retailers is not positively impacted by the cumulative volume of retailers that have adopted in the past. Taken together with the previous effect, retailer adoption seems to be influenced locally but not globally, which supports our formalization of retailer adoption. Finally, the effect μ_7 of local adoption of independent retailers on adoption by a chain is positive but smaller than that of competing chains.

Next we discuss the random effects b_k. These random effects have two covariates. Because $\psi_1 > 0$, we infer that retailer size (measured by ACV_k^z) increases the probability of early adoption. Rogers (1983) notes, supportive of this effect, that early adoption of industrial goods is related to the size of the adopter. The effect ψ_2 of concentration of retailers across markets, HRF_k^z, is negative. This suggests that retailers whose business is geographically concentrated will not adopt as fast as retailers whose business is spread more evenly over multiple markets. We attribute this effect to the relative isolation of retailers who are active in only a few markets.

Adoption Confounded with Availability. The results discussed above are obtained from the two-stage model where retailer adoption timing is conditioned on availability. Most diffusion models, even individual level models (e.g., Lattin and Roberts 2000), do not take this condition into account. In our specific case, the omission of the availability condition leads to different inferences for the adoption behavior of retailers. Table 3 shows the estimation results of a model which ignores availability as a necessary condition for adoption. In such a model, the attribution is made that manufacturer delays in market entry are in fact retailer delays in adoption.

A contrast between the full model of Table 2 and the single-stage model suggests that the most important difference between these models is that the influence of the feedback variables—i.e., competitive contagion (μ_4) and manufacturer presence (μ_5)—is substantially higher in the single-stage model than in the full model (30% and 70%, respectively). This is most likely because the spatial contiguity of retail trade areas substitutes in part for the spatial roll-out patterns of manufacturer entry. In sum, by ignoring the marketing actions (launch strategy) of manufacturers, the effect of local competitive contagion is substantially overstated.

Interestingly, and in a different context, Van den Bulte and Lilien (2001a) also find that taking the marketing actions of manufacturers into account tends to weaken estimates of the external or social contagion. For other examples, see Van den Bulte and Lilien (2001b) and Dekimpe et al. (2000b). However, Bass et al. (1994) present examples suggesting that the inclusion of marketing mix variables does not always has this effect.

---

[13] Indeed, while the two variables may be correlated, DIF_{ikt}^z and FAE_{ikt}^z represent different information. For instance, when DIF_{ikt}^z is close to 0, it may still be that the brand is available in the entire trade area retailer k. Indeed, FAE_{ikt}^z can (and does) range from close to 0 to almost 1. Alternatively, when $DIF_{ikt}^z = 1$, FAE_{ikt}^z can (and does) range from close to 0 to 1. Additionally, when both variables are interior on $[0, \ldots, 1]$, there is no ordering between them.

Table 3   **Estimation Results Ignoring market Entry[a]**

		Percentile	2.5%	50%	97.5%
Symbol	Variable	Abbreviation		Chain adoption	
μ_1	Category development index	CDI_{kt}^z	−0.114	0.131	0.377
μ_2	Manufacturer development index	MDI_{ikt}^z	0.387	0.935	1.497
μ_3	Time since availability	TSA_{ikt}^z	−0.024	−0.013	−0.003
μ_4	Competitive retailer adoption	DIF_{ikt}^z	0.643	1.089	1.592
μ_5	Manufacturer presence	FAE_{ik}^z	1.837	2.180	2.580
μ_6	Total volume of adopting retailers	TVR_{it}^z	−0.003	0.001	0.005
μ_7	Local adoption by independents	IND_{ikt}^z	0.241	0.440	0.649
ψ_1	Retailer size	ACV_k^z	0.050	0.094	0.139
ψ_2	Retailer concentration	HRF_k^z	−2.107	−1.484	−0.923
σ_b^2	Variance retailer component		0.325	0.511	0.782

[a] The quarterly dummy effects $\mu_{i\xi}$ are not reported to avoid cluttering.

6. Lead Markets and Contagion Potential

With every new product roll-out, managers need to decide where to launch first, i.e., select lead markets. One impetus for such selections is that not all markets are equally strong in generating contagion or spillover effects. To analyze the spillover potential for a given market, the models (6) and (13) were used in a numerical experiment that focuses on the combination of the spatial and selection effects (SPT_{imt}^y and PRV_{imt}^y) on entry, and the competitive and trade area coverage effects (DIF_{ikt}^z and FAE_{ikt}^z) on adoption. The purpose of this analysis is thus to summarize the implication of the feedback effects in our model for the contagion potential of geographical markets.

The experiment is set up as follows. We initiate a product roll-out in each of the M markets at $t = t_0$ by making the new brand available in that market. In subsequent periods other markets m are entered, and chains k adopt, probabilistically guided by the models (6) and (13). At the same time, the four variables above, SPT_{imt}^y, PRV_{imt}^y, DIF_{ikt}^z, and FAE_{ikt}^z, are recursively updated based on which markets are entered and which retailers adopt. To isolate the effects of the U.S. geography and the geographical retail structure, we set the parameters for all variables to 0, except for those of the variables above. The values for these parameters are set at the parameter values for SPT_{imt}^y, PRV_{imt}^y, DIF_{ikt}^z, and FAE_{ikt}^z from Table 2.

Given the probabilistic representation of the process of market entry and retailer adoption, not all sample paths of diffusion of the brand from a given lead market m are identical. Indeed, the number of possible diffusion paths across all retailers and geographical markets presents a formidable combinatorial problem. Therefore, we approximate the variability of sample paths by running for each candidate lead market $m = 1, \ldots, M$, 500 replications, $\ell = 1, \ldots, 500$. For each combination of m and ℓ, the number of weeks, $T_{m\ell}$, is retained at which all markets are entered and

enough retailers adopt to account for minimally 50% of total sales volume.[14]

To report on the findings of the experiment, we order the markets $m = 1, \ldots, M$ on the mean (of a left quantile to be chosen)[15] of $T_{m\ell}$ for each m. For instance, below we report the mean of the best 10% of the completion times $T_{m\ell}$ for each market. Figure 6 depicts the location of the markets which perform best on this criterion. To facilitate interpretation, these lead markets are placed relative to the location of four of the main retailers in the United States.

From both a geographical and a retailer network standpoint, Denver is an attractive lead market. This is not because of its central location in the United States—many such central markets fare poorly—although its location does contribute to its attractiveness. Rather, Denver is in the trade area of three major retailers and is on the edge of two of them, opening up a large set of markets in the United States (through the market selection effect of PRV_{imt}^y).

Three of the best markets from a spatial or contagion perspective are on the spatial edge of the United States. The West Texas market is in the trade area of both Safeway and Albertsons. Together, these two retailers cover the majority of the U.S. markets. New York and Philadelphia are attractive markets because they are large and because these markets are good locations for contagion to both the East and the West coasts (through Safeway which also has a small presence in Indianapolis, Indiana). So, whereas Philadelphia is an edge market in Euclidean space, from a retailer perspective it is a more central market.

The results for the average of other quantiles of $T_{m\ell}$ are reasonably robust. For instance, the average

---

[14] We also considered the percentage of national distribution obtained as an objective function. The results are similar and are available from a previous version of the paper.

[15] We use a left quantile because, in the spirit of lead market selection, interest is with the best diffusion paths and not with the average path.

completion time based on the 10th percentile correlates 0.95 with the average based on the 25th percentile. The results of the simulations are also robust to moderate changes in the parameter values. The what-if scenario presented above makes, therefore, few assumptions. While the exact ordering of markets on average completion time may change somewhat, markets tend to perform consistently well or consistently poorly. For example, the unique location of the Denver market, central both from a geographic as well as a retailer-network viewpoint, makes Denver consistently a very strong lead market.

7. Discussion and Conclusions

Despite its importance for the study and practice of new product innovation, the distribution of brands remains the least-studied aspect of marketing strategy. In this context, the present study focuses on the evolution of retail distribution for new brands across markets, retailers, and time. The model developed in this paper represents this process as an interdependent sequence of manufacturers entering local markets and retailers adopting the brand for distribution. The key events in this process, i.e., phased roll-outs across many geographic locations and retailers' local distribution (adoption) decisions, are relevant to the practice of introducing of new brands of consumer packaged goods in the United States. With some license, the same processes can be applied to the introduction of new consumer goods in an international context. For example, not unlike the local roll-outs considered in this paper, in Europe manufacturers launch new brands of consumer goods sequentially in different countries. Also, not unlike the multimarket presence of retailers in the United States, many European retail chains such as Ahold or Carrefour operate in multiple markets (in this case, multiple countries).

We find that for new brands of consumer goods, local market entry by manufacturers often occurs in phases and takes place in our data over a period of up to 30 months. Markets are more likely entered if they are in the vicinity of markets previously entered and if retailers in such markets have adopted in the past elsewhere. The sequential entry pattern is consistent with what Kalish et al. (1995) call a waterfall strategy. They note that such strategies outperform the strategy of entering everywhere at once (a so-called sprinkler strategy) when there are unfavorable conditions in markets not previously entered, or when the competition in nonentered markets is weak. Somewhat consistent with the latter prediction, DiGiorno (being the first mover and therefore having no competition) rolled out at a much slower pace than did Freschetta (who faced local competition from DiGiorno).

Results further suggest that adoption by retail chains is positively influenced by the manufacturer push into the trade area of a retailer, as measured by the fraction of the retailer's trade area on which the brand is present. Adoption is also subject to positive contagion effects among retailers. Specifically, we find that a chain's adoption of a new brand is positively affected by the adoption of the competitors with whom it has trade-area overlap. This contagion effect is amplified when the size of the competing retailer is large. Seen through the lens of social contagion research, this form of contagion operates along direct relations rather than among structurally equivalent retailers (Strang and Tuma 1993, p. 624). The direct relations concept is consistent with our definition of direct competitors, i.e., pairs of chains with overlapping trade areas. In contrast, structural equivalence means that retail chains have identical ties to and from all other actors in the network (Wasserman and Faust 1994, p. 356). Because U.S. retailers have unique geographical trade areas, most of them face their own unique set of competitors. Therefore, not many retailers can be labeled structurally equivalent in our context. Another aspect of the nature of contagion is that it is local, i.e., retailer adoption is not affected by the national (as opposed to local) volume of adopting retailers.

Given the effects in the model, a market's appeal for early entry is impacted by the location and shape of retail trade areas on that market. To explore this issue, we used a simulation to determine which lead markets accelerate national diffusion and why. While other sensible criteria exist, we find that markets located on a common trade-area border of large retailers make good lead markets, all other factors held constant. Such markets are not necessarily central in geographic space. Putsis et al. (1997) also make recommendations for lead market selection based on estimates of the local strength of contagion within and across countries. Our context, model, and mechanism for lead market selection are different. First, we do not consider adoption by a chain per se, but rather adoption behavior conditioned on the timing of manufacturers making the product available in the chain's territory. In our application this distinction matters. Second, our model offers an explanation for the differences in contagion strength across retailers based on trade-area overlap. Third, because the units of contagion (retailers) are not the units of entry (markets), the desirability of markets for early entry is a consequence not only of local contagion strength of retailers, but also of the location and the extent of their trade areas.

Several contextual factors related to our empirical setting warrant discussion. DiGiorno enters all but one market before Freschetta and is available

in more than 90% of markets before Freschetta is even introduced. As a result, it is not possible to explicitly model effects of local order-of-entry or of the interaction of entry by the two manufacturers. Another situational factor is that diverting by retailers is not suspected in our data. This condition is required to measure the timing of market entry and chain adoption.

Our study has the following limitations. First, no data are available about retailer incentives from the manufacturer during the introduction of the brands. To some extent, our random retailer effects account for these missing variables, but only to the extent that manufacturers offer similar trade deals to the same retailer (and that these incentives are independent of observed factors). Second, as discussed and argued above, we have focused on the adoption timing by retail chains, not by independent stores.

There are several potentially fruitful avenues for further study. First, the spatial and temporal evolution of other key performance variables in new product launch awaits further study. Candidates for such other variables are the three remaining ratios in Figure 1, i.e., assortment breadth, consumer trial, and consumer repeat purchase for new brands of repeat purchase goods. Second, in new product diffusion of consumer durables, sales growth is often attributed to the adoption timing by consumers, not to entry timing by manufacturers or adoption timing by retailers. An implication of our finding that there are long delays in local entry and retailer adoption in our data is that manufacturer roll-out strategies and retailer adoption decisions for nondurables account for a substantial dynamic component of new-product growth. Neither roll-out decisions nor chain distribution decisions should be interpreted as adoption timing by consumers. A good research question in the context of research on new product strategy therefore is, "Which fraction of the observed sales growth of new national brands is related to the timing decisions by manufacturers, by retailers, and by consumers?" A third worthwhile extension of the paper is to study whether the order in which markets are entered is based on entry by competitors (Manufacturer B enters because Manufacturer A did), or simply based on local market characteristics that are the same to all entrants (Manufacturer B enters after observing the same favorable market characteristics as Manufacturer A).

To close, this paper is the first to operationalize and apply a model of the spatial and temporal evolution of retail distribution for new brands of consumer goods. This process can be appreciated fully only when it formally accounts for the local timing of manufacturer entry and of retailer adoption. We believe that this paper makes a contribution by modeling these key decisions in the new product launch process and by offering empirical results on how they affect the buildup of retail distribution for new brands.

Appendix A. Full Conditional Distributions

A.1. The Market-Entry Model

- $[\tilde{y}_{imt} \mid y_{imt}, \text{rest}]$

The variables $\tilde{y}_{imt}$ conditional on the outcomes y_{imt} have truncated Normal distributions. Specifically, for all weeks that fall between the moment of global launch of the brand and entry in m, i.e., for $T_{\text{global launch of } i} \leq t \leq T_{i \text{ enters in } m}$,

$$[\tilde{y}_{imt} \mid y_{imt}, \text{rest}]$$

$$\sim \mathcal{N}(\mathbf{X}^y_{imt} \cdot \boldsymbol{\theta} + \beta_m, 1) \begin{cases} \text{left-truncated at 0 if } y_{imt} = 1 \\ \text{right-truncated at 0 if } y_{imt} = 0. \end{cases} \quad (A.1)$$

- $[\boldsymbol{\theta} \mid \text{rest}]$

Define $y^\theta_{imt} = \tilde{y}_{imt} - \beta_m$. Construct the array $N_y \times 1$ array $\mathbf{y}^\theta$ and the $N_y \times P_y$ matrix $\mathbf{X}^y$ by stacking over brands, markets, and time. The full conditional for $\boldsymbol{\theta}$ is proportional to

$$[\boldsymbol{\theta} \mid \text{rest}] \propto [\boldsymbol{\theta} \mid \mathbf{y}^\theta, \mathbf{X}^y][\boldsymbol{\theta}_0],$$

with $[\boldsymbol{\theta} \mid \mathbf{y}^\theta, \mathbf{X}^y] \sim \mathcal{N}((\mathbf{X}^{y\prime}\mathbf{X}^y)^{-1}\mathbf{X}^{y\prime}\mathbf{y}^\theta, (\mathbf{X}^{y\prime}\mathbf{X}^y)^{-1})$ and prior $[\boldsymbol{\theta}_0] \sim \mathcal{N}(\mathbf{0}, \mathbf{V}_{\theta 0})$. This leads to the following full conditional

$$[\boldsymbol{\theta} \mid \text{rest}] = \mathcal{N}(\mathbf{m}_\theta, \mathbf{v}_\theta)$$

$$\mathbf{m}_\theta = \mathbf{v}_\theta \mathbf{X}^{y\prime}\mathbf{y}^\theta$$

$$\mathbf{v}_\theta = (\mathbf{V}_{\theta 0}^{-1} + \mathbf{X}^{y\prime}\mathbf{X}^y)^{-1}. \quad (A.2)$$

- $[\boldsymbol{\beta} \mid \text{rest}]$

Define $y^\beta_{imt} = \tilde{y}_{imt} - \mathbf{X}^y_{imt} \cdot \boldsymbol{\theta}$. Array all covariates of the hierarchical model for β_m in a $1 \times P_\beta$ row vector $\mathbf{X}_{\beta m}$ (in the operationalization below Equation (6) $\mathbf{X}_{\beta m} = [\text{ACV}^y_m \ \text{HRF}^y_m \ \text{SNI}^y_m]$). Array these covariates further into the $M \times P_\beta$ matrix $\mathbf{X}_\beta = [\mathbf{X}'_{\beta 1} \cdots \mathbf{X}'_{\beta m} \cdots \mathbf{X}'_{\beta M}]'$. Also form the $N_y \times 1$ vector $\mathbf{y}^\beta$ by stacking over brands, markets, and time. Finally, define an index matrix $\mathscr{I}_m$ of size $N_y \times M$ which maps each observation y_{imt} into m and write an M dimensional identity matrix as $\mathbf{I}_M$. Then, the vector $\boldsymbol{\beta}$ of random factors β_m has the following full conditional distribution

$$[\boldsymbol{\beta} \mid \text{rest}] = \mathcal{N}(\mathbf{m}_\beta, \mathbf{v}_\beta)$$

$$\mathbf{m}_\beta = \mathbf{v}_\beta \left(\mathscr{I}'_m \mathbf{y}^\beta + \frac{1}{\sigma^2_\beta} \mathbf{X}_\beta \boldsymbol{\phi} \right)$$

$$\mathbf{v}_\beta = \left(\mathscr{I}'_m \mathscr{I}_m + \frac{1}{\sigma^2_\beta} \mathbf{I}_M \right)^{-1}. \quad (A.3)$$

- $[\phi \mid \text{rest}]$. The full conditional for ϕ is proportional to

$$[\phi \mid \text{rest}] \propto [\phi \mid \boldsymbol{\beta}, \mathbf{X}_\beta][\phi_0],$$

with $[\phi \mid \boldsymbol{\beta}, \mathbf{X}_\beta] \sim \mathcal{N}((\mathbf{X}_\beta' \mathbf{X}_\beta)^{-1} \mathbf{X}_\beta' \boldsymbol{\beta}, \sigma_\beta^2 (\mathbf{X}_\beta' \mathbf{X}_\beta)^{-1})$ and prior $[\phi_0] \sim \mathcal{N}(\mathbf{0}, \mathbf{V}_{\phi 0})$. This leads to the following full conditional

$$[\phi \mid \text{rest}] = \mathcal{N}(\mathbf{m}_\phi, \mathbf{v}_\phi)$$

$$\mathbf{m}_\phi = \frac{\mathbf{v}_\phi}{\sigma_\beta^2} \mathbf{X}_\beta' \boldsymbol{\beta}$$

$$\mathbf{v}_\phi = \left(\mathbf{V}_{\phi 0}^{-1} + \frac{1}{\sigma_\beta^2} \mathbf{X}_\beta' \mathbf{X}_\beta \right)^{-1} \tag{A.4}$$

- $[\sigma_\beta^2 \mid \text{rest}]$

The full conditional distribution for the variance σ_β^2 is proportional to the product of the distribution $[\boldsymbol{\beta}] = \mathcal{N}_M(\mathbf{X}_\beta \phi, \sigma_\beta^2 \mathbf{I}_M)$ and the prior $[\sigma_\beta^2] = IG(q_\beta, r_\beta)$, i.e.,

$$p(\sigma_\beta^2) \propto \frac{r_\beta^{q_\beta}}{\Gamma(q_\beta)} (\sigma_\beta^2)^{-(q_\beta + 1)} e^{-r_\beta / \sigma_\beta^2}.$$

This distribution and the multivariate Normal distribution combines into

$$[\sigma_\beta^2 \mid \text{rest}] = IG \left(q_\beta + \frac{M}{2}, r_\beta + \frac{1}{2} (\boldsymbol{\beta} - \mathbf{X}_\beta \phi)'(\boldsymbol{\beta} - \mathbf{X}_\beta \phi) \right). \tag{A.5}$$

A.2. The Chain-Adoption Model

- $[\tilde{z}_{ikt} \mid z_{ikt}, \text{rest}]$

As above, we specify the distribution of the latent probit variables $\tilde{z}_{ikt}$ such that $\tilde{z}_{ikt} > 0$ if and only if $z_{ikt} = 1$ and $\tilde{z}_{ikt} \le 0$ if and only if $z_{ikt} = 0$. The variables $\tilde{z}_{ikt} \mid z_{ikt}$ are distributed truncated Normal. Specifically, for all weeks that fall between the moment of trade area availability and adoption of the brand by retailer k, i.e., for $T_{\text{avail}, k} \le t \le T_{\text{adopt}, k}$,

$$[\tilde{z}_{ikt} \mid z_{ikt}, \text{rest}]$$

$$\sim \mathcal{N}(\mathbf{X}_{ikt}^z \cdot \boldsymbol{\mu} + b_k, 1) \begin{cases} \text{left truncated at 0 if } z_{ikt} = 1 \\ \text{right truncated at 0 if } z_{ikt} = 0. \end{cases} \tag{A.6}$$

- $[\boldsymbol{\mu} \mid \text{rest}]$

Define z_{ikt}^μ by $\tilde{z}_{ikt} - b_k$. Construct the $N_z \times 1$ array $\mathbf{z}^\mu$ and the $N_z \times P_z$ matrix $\mathbf{X}^z$ by stacking over brands, retailers, and time. The full conditional for $\boldsymbol{\mu}$ is proportional to

$$[\boldsymbol{\mu} \mid \text{rest}] \propto [\boldsymbol{\mu} \mid \mathbf{z}^\mu, \mathbf{X}^z][\boldsymbol{\mu}_0],$$

with $[\boldsymbol{\mu} \mid \mathbf{z}^\mu, \mathbf{X}^z] \sim \mathcal{N}((\mathbf{X}^{z'} \mathbf{X}^z)^{-1} \mathbf{X}^{z'} \mathbf{z}^\mu, (\mathbf{X}^{z'} \mathbf{X}^z)^{-1})$ and prior $[\boldsymbol{\mu}_0] \sim \mathcal{N}(\mathbf{0}, \mathbf{V}_{u0})$. This conjugate pair leads to the following full conditional

$$[\boldsymbol{\mu} \mid \text{rest}] = \mathcal{N}(\mathbf{m}_\mu, \mathbf{v}_\mu)$$

$$\mathbf{m}_\mu = \mathbf{v}_\mu \mathbf{X}^{z'} \mathbf{z}^\mu$$

$$\mathbf{v}_\mu = (\mathbf{V}_{\mu 0}^{-1} + \mathbf{X}^{z'} \mathbf{X}^z)^{-1}. \tag{A.7}$$

- $[\mathbf{b} \mid \text{rest}]$

Define $z_{ikt}^b = \tilde{z}_{ikt} - \mathbf{X}_{ikt}^z \cdot \boldsymbol{\mu}$. Array all covariates of the hierarchical model for b_k in a $1 \times P_b$ row vector $\mathbf{X}_{bk}$ (in the operationalization below Equation (13) $\mathbf{X}_{bk} = [\text{ACV}_k^z \ \text{HRF}_k^z]$). Array these covariates further into the $K \times P_b$ matrix

$\mathbf{X}_b = [\mathbf{X}_{b1}' \cdots \mathbf{X}_{bk}' \cdots \mathbf{X}_{bK}']'$. Finally, form the $N_z \times 1$ vector z^b by stacking z_{ikt}^b over brands, retailers, and time, and define an index matrix $\mathscr{I}_k$ of size $N_z \times K$ which maps each observation z_{ikt} into k and a $P_b \times 1$ vector $\boldsymbol{\Psi}$. Then, the vector $\mathbf{b}$ of random factors b_k has the following full conditional distribution

$$[\mathbf{b} \mid \text{rest}] = \mathcal{N}(\mathbf{m}_b, \mathbf{v}_b)$$

$$\mathbf{m}_b = \mathbf{v}_b \left(\mathscr{I}_k' z^b + \frac{1}{\sigma_b^2} \mathbf{X}_b \boldsymbol{\psi} \right)$$

$$\mathbf{v}_b = \left(\mathscr{I}_k' \mathscr{I}_k + \frac{1}{\sigma_b^2} \mathbf{I}_K \right)^{-1}. \tag{A.8}$$

- $[\boldsymbol{\psi} \mid \text{rest}]$. The full conditional for $\boldsymbol{\psi}$ is proportional to

$$[\boldsymbol{\psi} \mid \text{rest}] \propto [\boldsymbol{\psi} \mid \mathbf{b}, \mathbf{X}_b][\boldsymbol{\psi}_0],$$

with $[\boldsymbol{\psi} \mid \mathbf{b}, \mathbf{X}_b] \sim \mathcal{N}((\mathbf{X}_b' \mathbf{X}_b)^{-1} \mathbf{X}_b' \mathbf{b}, \sigma_b^2 (\mathbf{X}_b' \mathbf{X}_b)^{-1})$ and prior $[\boldsymbol{\psi}_0] \sim \mathcal{N}(\mathbf{0}, \mathbf{V}_{\psi 0})$. This leads to the following full conditional

$$[\boldsymbol{\psi} \mid \text{rest}] = \mathcal{N}(\mathbf{m}_\psi, \mathbf{v}_\psi)$$

$$\mathbf{m}_\psi = \frac{\mathbf{v}_\psi}{\sigma_b^2} \mathbf{X}_b' \mathbf{b}$$

$$\mathbf{v}_\psi = \left(\mathbf{V}_{\psi 0}^{-1} + \frac{1}{\sigma_b^2} \mathbf{X}_b' \mathbf{X}_b \right)^{-1}. \tag{A.9}$$

- $[\sigma_b^2 \mid \text{rest}]$

The full conditional distribution for the variance σ_b^2 is proportional to the product of the distribution $[\mathbf{b}] = \mathcal{N}_M(\mathbf{X}_b \boldsymbol{\psi}, \sigma_b^2 \mathbf{I}_K)$ and the prior $[\sigma_b^2] = IG(q_b, r_b)$. The full conditional distribution makes use of this conjugate pair and results in

$$[\sigma_b^2 \mid \text{rest}] = IG \left(q_b + \frac{K}{2}, r_b + \frac{1}{2} (\mathbf{b} - \mathbf{X}_b \boldsymbol{\psi})'(\mathbf{b} - \mathbf{X}_b \boldsymbol{\psi}) \right). \tag{A.10}$$

Appendix B. The MCMC Algorithm

The full conditional distributions are all closed form. Hence, the algorithm uniquely consists of Gibbs steps. Draws from the joint posterior distribution of the parameters are obtained by passing through the following conditional distributions while updating the parameters on which these depend by the most recent posterior draws.

1. Market-entry model
   (a) draw from $[\tilde{y}_{imt} \mid y_{imt}, \text{rest}]$; see Equation (A.1).
   (b) set $y_{imt}^\theta = \tilde{y}_{imt} - \beta_m$, draw from $[\boldsymbol{\theta} \mid \text{rest}]$; see Equation (A.2).
   (c) set $y_{imt}^\beta = \tilde{y}_{imt} - \mathbf{X}_{imt}^y \cdot \boldsymbol{\theta}$, draw from $[\boldsymbol{\beta} \mid \text{rest}]$; see Equation (A.3).
   (d) draw from $[\phi \mid \text{rest}]$; see Equation (A.4).
   (e) draw from $[\sigma_\beta^2 \mid \text{rest}]$; see Equation (A.5).
2. Retailer-adoption model
   (a) draw from $[\tilde{z}_{ikt} \mid z_{ikt}, \text{rest}]$; see Equation (A.6).
   (b) set $z_{ikt}^\mu = \tilde{z}_{ikt} - b_k$, draw from $[\boldsymbol{\mu} \mid \text{rest}]$; see Equation (A.7).
   (c) $z_{ikt}^b = \tilde{z}_{ikt} - \mathbf{X}_{ikt}^z \cdot \boldsymbol{\mu}$, draw from $[\mathbf{b} \mid \text{rest}]$; see Equation (A.8).
   (d) draw from $[\boldsymbol{\psi} \mid \text{rest}]$; see Equation (A.9).
   (e) draw from $[\sigma_b^2 \mid \text{rest}]$; see Equation (A.10).

References

Ainslie, Andrew, Peter E. Rossi. 1998. Similarities in choice behavior across multiple categories. *Marketing Sci.* **17**(2) 91–106.

Anderson, Simon P., André de Palma. 1988. Spatial price discrimination with heterogeneous products. *Rev. Econom. Stud.* **55** 573–592.

Anselin, Luc. 1988. *Spatial Econometrics: Methods and Models.* Kluwer Academic Publishers, New York.

Bass, Frank M. 1969. A new product growth model for consumer durables. *Management Sci.* **15**(5) 215–227.

Bass, Frank M., Trichy Krishnan, Dipak Jain. 1994. Why the Bass model fits without decision variables. *Marketing Sci.* **13**(3) 203–223.

Bronnenberg, Bart J., Vijay Mahajan. 2001. Unobserved retailer behavior in multimarket data: Joint spatial dependence in market shares and promotion variables. *Marketing Sci.* **20**(3) 284–299.

Bronnenberg, Bart J., Catarina Sismeiro. 2002. Using multimarket data to predict brand performance in markets for which no or poor data exist. *J. Marketing Res.* **39**(1) 1–17.

Chib, Siddhartha, Bradley P. Carlin. 1999. On MCMC sampling in hierarchical longitudinal models. *Statist. Comput.* **9** 17–26.

Cliff, A. D., P. Haggett, J. K. Ord, G. R. Versey. 1981. *Spatial Diffusion: An Historical Geography of Epidemics in an Island Community.* Cambridge University Press, Cambridge, U.K.

Coleman, James S., Elihu Katz, Herbert Menzel. 1966. *Medical Innovation: A Diffusion Study.* Bobbs-Merrill, New York.

Cressie, Noel. 1993. *Statistics for Spatial Data.* Wiley and Sons, New York.

Dekimpe, Marnik G., Philip M. Parker, Miklos Sarvary. 2000a. Global diffusion of technological innovations: A coupled hazard approach. *J. Marketing Res.* **37**(1) 47–59.

Dekimpe, Marnik G., Philip M. Parker, Miklos Sarvary. 2000b. Globalization: Modeling technology adoption timing across countries. *Tech. Forecasting Soc. Change* **63** 25–42.

Garber, Tal, Jacob Goldenberg, Barak Libai, Eitan Muller. 2004. From density to destiny: Using spatial dimension of sales data for early prediction of new product success. *Marketing Sci.* **23**(3) 419–428.

Gelfand, A. E., S. K. Sahu, B. P. Carlin. 1995. Efficient parameterization for normal linear mixture models. *Biometrika* **82**(3) 479–488.

Gilks, W. R., S. Richardson, D. J. Spiegelhalter. 1996. *Markov Chain Monte Carlo in Practice.* Chapman & Hall, New York.

Greve, Henrich R. 1996. Patterns of competition: The diffusion of a market position in radio broadcasting. *Admin. Sci. Quart.* **41**(1) 29–60.

Greve, Henrich R. 2000. Market niche entry decisions: Competition, learning and strategy in Tokyo banking, 1894–1936. *Acad. Management J.* **43**(5) 816–836.

Greve, Henrich R., Nancy Brandon Tuma, David Strang. 2001. Estimation of diffusion processes from incomplete data: A simulation study. *Sociological Methodology Res.* **29**(4) 435–467.

Haveman, Heather A. 1993. Organizational size and change: Diversification in the savings and loan industry after deregulation. *Admin. Sci. Quart.* **38**(1) 20–50.

Haveman, Heather A., Lynn Nonnemaker. 2000. Competition in multiple geographic markets: The impact on growth and market entry. *Admin. Sci. Quart.* **45**(2) 232–267.

Hedström, Peter. 1994. Contagious collectivities: On the spatial diffusion of Swedish trade unions. *Amer. J. Soc.* **99**(5) 1157–1179.

Holcomb, Rodney B. 2000. *Food Industry Overview: Frozen Pizza.* Oklahoma State University Food Technology Facts, FAPC-103, Food and Agricultural Product Center, Oklahoma State University, Stillwater, OK.

Kalish, Shlomo, Vijay Mahajan, Eitan Muller. 1995. Waterfall and sprinkler new product strategies in competitive global markets. *Internat. J. Res. Marketing* **12**(2) 105–121.

Kalyanaram, Gurumurthy, Glen L. Urban. 1992. Dynamic effects of the order of entry on market share, trial, penetration, and repeat purchases for frequently purchased consumer goods. *Marketing Sci.* **11**(3) 235–250.

Kalyanaram, Gurumurthy, William T. Robinson, Glen L. Urban. 1995. Order of market entry: Established empirical generalizations, emerging empirical generalizations, and future research. *Marketing Sci.* **14**(3) G212–G221.

Korn, Helaine, Joel A. C. Baum. 1999. Chance imitative and strategic antecedents to multimarket contact. *Acad. Management J.* **42**(2) 171–193.

Kotler, Philip. 2003. *Marketing Management,* 11th ed. Prentice Hall, Upper Saddle River, NJ.

Lattin, James M., John H. Roberts. 2000. The application of an individual level diffusion model prior to launch. Working paper, Stanford University Graduate School of Business, Palo Alto, CA.

McLaughlin, Robert, Vithala Rao. 1991. *Decision Criteria for New Product Acceptance and Success.* Quorum Books, New York.

Montgomery, David B. 1975. New–product distribution: An analysis of supermarket buyer decisions. *J. Marketing Res.* **12**(3) 255–264.

Niu, X. F., George C. Tiao. 1995. Modeling satellite ozone data. *J. Amer. Statist. Assoc.* **90**(431) 969–983.

Okabe, Atsuyuki, Barry Boots, Kokichi Sugihara, Sung Nok Chiu. 2000. *Spatial Tessellations: Concepts and Applications of Voronoi Diagrams*, 2nd ed. Wiley and Sons, New York.

Parker, Philip, Hubert Gatignon. 1994. Specifying competitive effects in diffusion models: An empirical analysis. *Internat. J. Res. Marketing* **11**(1) 17–39.

Putsis, William P. Jr., Sridhar Balasubramanian, Edward H. Kaplan, Subrata K. Sen. 1997. Mixing behavior in cross-country diffusion. *Marketing Sci.* **16**(4) 354–369.

Reibstein, David, Paul Farris. 1995. Market share and distribution: A generalization, a speculation, and some implications. *Marketing Sci.* **14**(3, Part 2) G130–G202.

Rogers, Everett M. 1983. *Diffusion of Innovations*, 3rd ed. Free Press, New York.

Schultz, Don E., Dennis Martin, William P. Brown. 1984. *Strategic Advertising Campaigns.* Crain Books, Chicago, IL.

Stoffer, D. S. 1986. Estimation and identification of space-time ARMAX models in the presence of missing data. *J. Amer. Statist. Assoc.* **81** 762–772.

Strang, David, Nancy Brandon Tuma. 1993. Spatial and temporal heterogeneity in diffusion. *Amer. J. Sociology* **99**(3) 614–639.

Ter Hofstede, Frenkel, Michel Wedel, Jan-Benedict E. M. Steenkamp. 2002. Identifying spatial segments in international markets. *Marketing Sci.* **21**(2) 160–177.

Valente, Thomas W. 1995. *Network Models of the Diffusion of Innovations.* Hampton Press, Cresskill, NJ.

Van den Bulte, Christophe, Gary L. Lilien. 2001a. Medical innovation revisited: Social contagion vs. marketing effort. *Amer. J. Sociology* **106**(5) 1409–1435.

Van den Bulte, Christophe, Gary L. Lilien. 2001b. Two-stage partial observability models of innovation adoption. Working paper, Wharton School, University of Pennsylvania, Philadelphia, PA.

Vines, S. K., W. R. Gilks, P. Wild. 1996. Fitting Bayesian multiple effects models. *Statist. Comput.* **6** 337–346.

Wasserman, Stanley, Katherine Faust. 1994. *Social Network Analysis: Methods and Applications.* Cambridge University Press, New York.

Zenor, Michael J., Rajendra K. Srivastava. 1993. Inferring market structure with aggregate data: A latent segment logit approach. *J. Marketing Res.* **30**(3) 369–379.