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Estimating Cannibalization Rates for Pioneering Innovations

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To evaluate the success of a new product, managers need to determine how much of its new demand is due to cannibalizing the firm's other products, rather than drawing from competition or generating primary demand. We introduce a time-varying vector error-correction model to decompose the base sales of a new product into its constituent sources. The model allows managers to estimate cannibalization effects and calculate the new product's net demand, which may be considerably less than its total demand. We apply our methodology to the introduction of the Lexus RX300 using detailed car transaction data. This case is especially interesting because the Lexus RX300 was the first crossover sport utility vehicle (SUV), implying that its demand could come from both the luxury SUV and the luxury sedan categories. Because Lexus was active in both categories, there was a double cannibalization potential. We show how the contribution of the different demand sources varies over time and discuss the managerial implications for both the focal brand and its competitors.

Key words: new product; cannibalization; aggregate response models; time-series models; missing data; Bayesian methods; dynamic linear models

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1. Introduction

Innovation, the process of bringing new products and services to market, is one of the most important issues for firms and researchers alike (Hauser et al. 2006). To evaluate the success of a new product, managers need a method to gauge not only how much new demand it generates but also to what extent this demand comes at the expense of (cannibalizes) their other products (Carpenter and Hanssens 1994). When ignored, the success of the new product will be overestimated (Reddy et al. 1994, Srinivasan et al. 2005). Although managers practicing category management are typically aware of the cannibalization phenomenon (Basuroy et al. 2001, Zenor 1994), they typically are less clear on to how to quantify the size of the cannibalization risk.

The problem is exacerbated when manufacturers operate in multiple categories and when introducing radical, pioneering innovations. Manufacturers are often active in more than one category. Unilever's portfolio, for example, includes many food products, as well as several household and personal-care items. Hewlett-Packard is active in the notebook, desktop,

printer, and scanner markets, and many car manufacturers sell cars in both the luxury sport utility vehicle (SUV) and the luxury sedan categories. Even when managers are aware that the new product may cannibalize their other products in the *same* category, they may overlook a similar cannibalization potential in *other* categories. This is especially an issue in the case of radical, pioneering innovations. These products add a new dimension to the consumers' decision process (Cooper 2000), making it less obvious which categories will be affected (Moreau et al. 2001). For example, Apple's iPhone crossed the boundaries of two categories (portable media players and mobile phones), with a clear cannibalization potential for the pioneering firm (LeClaire 2007). Similarly, Febreze, manufactured by Procter & Gamble (P&G), may draw from the air freshener category because it eliminates odors, but it also may draw from the laundry detergent category because it works directly on fabric (Gielens and Steenkamp 2007). Given P&G's presence in both categories, there are again two potential sources of cannibalization. Also, Purell combines features from multiple categories (Parasumaran

et al. 2004, pp. 95–96): liquid soap, skin care, and sanitizers. Interestingly, Nielsen/IRI placed Purell with the liquid soaps, whereas many retailers considered it part of the skin-care category. The placement of the product in a certain category not only affects the brand's market-share calculations (Day et al. 1979), but it may also limit the manager's "radar screen" for the cannibalization threat to the focal category only. The obvious danger is that cannibalization from other categories is overlooked.

Therefore, it is crucial to measure *within*-category as well as *between*-category cannibalization effects. Both cannibalization sources are unattractive to the firm, as neither implies that the net number of products sold increases (although profit may increase, depending on the respective margins). Within- and between-category *brand switching*, in contrast, comes at the expense of other brands and is therefore much more attractive from the introducing firm's perspective. Finally, part of a new product's demand can be really new (i.e., representing a *primary demand* effect) and can come at the expense of the outside good (Albuquerque and Bronnenberg 2009).

Even though the marketing literature has offered a plethora of methods and approaches to capture the total demand patterns of new products (see, e.g., Mahajan et al. 2000 for an overview), little attention has been given to how to estimate the relative contributions of cannibalization effects, both within the focal category and across categories (Hauser et al. 2006).¹ Still, such an assessment of the extent of cannibalization is crucial for understanding whether the introduction can be considered a success for the firm as a whole.

We develop a methodology to estimate the extent of cannibalization (within and between categories), brand switching (within and between categories), and primary demand that is generated when a pioneering product is introduced. By looking at all these sources simultaneously, we can derive not only the *absolute* extent of cannibalization but also its *relative* importance. We believe there is a need for a new methodology as a result of three required features not addressed by extant methods. First, the model needs to accommodate cannibalization and brand-switching effects coming from *multiple* brands within and between categories, because it is unlikely that just one brand is affected. Second, the cannibalization and brand-switching effects need to be *time varying*.

Demand changes are unlikely to fully materialize instantaneously nor are they likely to appear in a completely deterministic fashion. As such, we have to allow for a gradual evolution in the cannibalization rates and for stochastic variations in those rates. Finally, the method should cope with *missing data*, as these characterize markets with frequent product introductions and deletions.

To meet these challenges, we propose a time-varying vector error-correction (VEC) model, estimated with Bayesian techniques. It allows management to gauge the cannibalization and brand-switching rates at an early stage of the innovation's life cycle, offering the possibility to quickly detect any need for corrective actions. We apply our methodology to the introduction of the Lexus RX300 using six years of weekly automobile transaction data. The case of the Lexus RX300 is interesting because it was the first crossover SUV, implying that it could draw customers from two categories: the luxury SUV and the luxury sedan categories. Lexus had a significant presence in both, making the cannibalization potential quite prominent.

The remainder of this paper is structured as follows. Section 2 positions our work in the literature by elaborating on the aforementioned model requirements and on how our proposed time-varying VEC model deals with them. After that, we present the model in §3, discuss the empirical application in §4, and present results in §5, and conclusions in §6.

2. Modeling Challenges and Extant Literature

Our modeling approach estimates five constituent sources of demand for the pioneering innovation: (i) cannibalization within the category, (ii) cannibalization between categories, (iii) brand switching within the category, (iv) brand switching between categories, and (v) primary demand. In doing so, we identify three required model features:

- Allowing for *multivariate* cannibalization and brand-switching effects;
- Capturing *time-varying* cannibalization and brand-switching effects, and
- Being able to *handle missing data*.

We elaborate on these features below and discuss to what extent existing methods address them. Table 1 summarizes points of difference and parity between the different approaches.

2.1. Multivariate Cannibalization and Brand-Switching Effects

The pioneering innovation may induce cannibalization and brand-switching effects coming from *multiple* brands within and across categories. To account

¹ Recently, the rise of the Internet has stimulated research on channel cannibalization. Deleersnyder et al. (2002), for example, quantifies the impact of a free Internet version on the revenues of traditional newspapers, and Bialogorsky and Naik (2003) checks whether Tower Records' Internet sales division cannibalized its retail sales. In both instances, little evidence of such channel cannibalization was found.

Table 1 Comparison of Proposed Model Specification vs. Extant Approaches

Modeling approach	Illustrative examples	Multivariate cannibalization and brand-switching effects	Time-varying cannibalization and brand-switching effects		Handling of missing data
			Gradual adjustment	Stochastic effects	
1. Aggregate logit models	Albuquerque and Bronnenberg (2009)	✓	—	✓	—
2. Univariate structural break models	Deleersnyder et al. (2002), Kornelis et al. (2008)	—	✓	—	—
3. Vector time-series models					
Conventional vector autoregressive models with independent variables (VARX)	Nijs et al. (2001)	✓	✓	—	—
Recursive VARX	Pauwels and Hanssens (2007)	✓	✓	✓	—
Pre- and post-VARX	Pauwels and Srinivasan (2004)	✓	✓	—	✓
Conventional VEC models	Fok et al. (2006)	✓	✓	—	—
4. DLMS					
Conventional DLMS	Neelamegham and Chintagunta (2004), van Heerde et al. (2004b)	✓	✓	—	✓
Time-varying VEC model	van Heerde et al. (2007)	✓	✓	—	✓
Time-varying VEC model with stochastic effects of introduction	Present paper	✓	✓	✓	✓

for this, the model should have a multivariate specification, modeling cross effects or correlated error structures, or both, across all relevant brands simultaneously. This requirement rules out univariate time-series models that have been developed to measure cannibalization effects (e.g., Deleersnyder et al. 2002 and Kornelis et al. 2008), but this requirement is met by multivariate time-series models (vector autoregressive (VAR) and VEC models), dynamic linear models (DLMS), and/or aggregate logit models.

A pioneering innovation is not only disruptive (Cooper 2000, Deleersnyder et al. 2002), but it also tends to stay for a prolonged period of time. To capture this enduring impact, we model the impact of the innovation as a change in base sales of incumbent brands, i.e., after short-run fluctuations have settled. With *base sales* we mean the expected sales level when (i) all marketing instruments are at their mean levels and (ii) when all short-run fluctuations have settled (see Ataman et al. 2010, p. 8 for a similar definition).² Within the multivariate specifications, the VEC model is specifically suited to separate short-term fluctuations from base sales fluctuations (Fok et al. 2006). That is why we adopt a VEC specification as the backbone of our model.

2.2. Time-Varying Cannibalization and Brand-Switching Effects

A pioneering innovation may induce cannibalization and brand-switching effects that may vary over time for two reasons. First, when the pioneering innovation has been introduced, not all potential customers may react immediately, as documented by Rogers (2003). Because of this heterogeneity in adoption timing, the adjustments to the new base sales levels (for the focal introduction as well as for the incumbent brands) will not be completed immediately but will be spread out over time (see also Deleersnyder et al. 2002, Perron 1994). Our model should be able to accommodate for such a gradual adjustment.

Second, many factors can cause temporary disturbances in a brand's base sales, making it unlikely for base sales to follow a fully deterministic pattern. This idea is also reflected in Tellis and Crawford's (1981) evolutionary approach to product growth (which extends the more traditional deterministic product life cycle). In line with Gatignon's (1993) plea for allowing for stochastic variation in parameter process functions, we will add error terms in the cannibalization and brand-switching rates.

Whereas extant univariate and multivariate time-series (conventional VAR and VEC) models and DLMS allow for gradual adjustments, they do not accommodate stochastic variation in cannibalization and brand-switching effects. The recursive VAR model of Pauwels and Hanssens (2007) can derive flexible time paths for these effects; however, each

² *Baseline sales*, in contrast, are typically defined as the sales in the absence of marketing support (Ataman et al. 2010, footnote 2), e.g., in the absence of a promotion (Abraham and Lodish 1987).

point in these paths is (by definition) estimated on only a subset of the data, which reduces the statistical efficiency. Moreover, the choice of estimation window is subjective and may affect the inferences.

2.3. Partially Missing Data

The model needs to estimate the extent of cannibalization, brand switching, and primary demand generation while (i) controlling for the own- and cross-brand impact of the new entrant's marketing instruments and (ii) using both pre- and postintroduction data for inferences about changes in base sales of the incumbent brands. This reduces potential omitted-variable problems and maximally uses the available information for more reliable parameter estimation. However, the combination of conditions (i) and (ii) may lead to missing-data problems in markets with product introductions and deletions (Zanutto and Bradlow 2006). By the very nature of a market with a pioneering innovation, data are (at the very least) missing on the marketing variables of the new product prior to its introduction. Hence, traditional estimation procedures such as VARX models only allow us to use postintroduction data (Lemieux and McAlister 2005). That is, if a cross-brand instrument has some missing data (e.g., the brand is only introduced later in time) while the focal sales series is observed all the time, classical models have to omit the entire observation (i.e., all data prior to the introduction). Alternatively, data-imputation methods may lead to biases in regression estimates (e.g., Cooper et al. 1991).

Yet another solution is to estimate separate pre- and post-VARX models (Pauwels and Srinivasan 2004), but that approach assumes that all parameters change, which is statistically inefficient, and it does not allow for a gradual adjustment. In addition, if there are n new product introductions, this approach would have to distinguish $n + 1$ regimes. In contrast, DLMS are very much suited to handle partial missing data resulting from brand entries (e.g., van Heerde et al. 2004b) or exits (e.g., van Heerde et al. 2007). Our model capitalizes on this property of DLMS.

2.4. Our Model

None of the extant approaches ticks the boxes for all required features in Table 1. We therefore develop a new model that accounts for all three requirements. The model is a time-varying VEC model framed as a DLM, and it explicitly allows for *multivariate dependencies* across the different brands and categories through direct cross effects or correlated error structures, or both. The changes in incumbents' base sales stemming from the pioneering innovation are captured through time-varying long-run intercepts. We allow for two types of time variation in these intercepts: both a *gradual adjustment* to the new base sales levels

and *stochastic variation* around these levels. By adding the base sales of the pioneering brand to our system, we derive the primary demand effect as the difference between (i) the total impact on that series and (ii) the sum of the impacts across all competitor brands.

Partially missing data may arise from not observing sales or marketing mix values *initially* (e.g., a brand is absent in the beginning of the data), *temporarily* (e.g., a brand is temporarily absent in the middle of the data set), or *finally* (e.g., a brand is absent at the end of the data set). To handle missing data, we estimate our time-varying VEC model by Bayesian methods. In the estimation, we keep a single model that at any moment includes all available brands. We selectively update all cross-effect parameters for which the pair of products is available. Our estimation method ensures that all available information is used on all variables, even if observations are partially missing.

3. Modeling Approach

3.1. Model Specification

This section outlines our time-varying VEC model. Because a mathematically consistent unit-sales decomposition is derived from decomposing sales linearly (van Heerde et al. 2003),³ we need to model sales rather than any transformation (e.g., log).

3.1.1. A Simple Example to Set the Stage. To facilitate model exhibition, we start with a small example with two brands, 1 and 2, each selling one variety in a single category, c . A variety corresponds to a stock-keeping unit in grocery retailing or a model in the car industry. The sales and a (mean-centered) marketing mix instrument for variety j in period t are denoted by S_{jt} and X_{jt} , respectively. Variable D_t represents a seasonality variable, e.g., a dummy for Christmas. The time-varying vector error-correction model is stacked across the two varieties:

$$\begin{pmatrix} \Delta S_{1t} \\ \Delta S_{2t} \end{pmatrix} = \begin{bmatrix} \Delta X_{1t} & \Delta X_{2t} & 0 & 0 \\ 0 & 0 & \Delta X_{1t} & \Delta X_{2t} \end{bmatrix} \begin{pmatrix} \theta_{1t}^{sr} \\ \theta_{2t}^{sr} \\ \theta_{3t}^{sr} \\ \theta_{4t}^{sr} \end{pmatrix} + \begin{bmatrix} \Pi_1 & 0 \\ 0 & \Pi_2 \end{bmatrix} \cdot \left[\begin{pmatrix} S_{1t-1} \\ S_{2t-1} \end{pmatrix} - \begin{pmatrix} \theta_{01t-1}^{lr} \\ \theta_{02t-1}^{lr} \end{pmatrix} - \begin{bmatrix} X_{1t-1} & X_{2t-1} & 0 & 0 \\ 0 & 0 & X_{1t-1} & X_{2t-1} \end{bmatrix} \begin{pmatrix} \theta_{1t-1}^{lr} \\ \theta_{2t-1}^{lr} \\ \theta_{3t-1}^{lr} \\ \theta_{4t-1}^{lr} \end{pmatrix} \right]$$

³ Whereas Albuquerque and Bronnenberg (2009) unravel the responses underlying the sources of demand in the tradition of the elasticity decomposition (Gupta 1988), we focus on sources of demand in unit sales (van Heerde et al. 2003).

$$+ \begin{bmatrix} D_t & 0 \\ 0 & D_t \end{bmatrix} \begin{pmatrix} \delta_1 \\ \delta_2 \end{pmatrix} + \begin{pmatrix} \nu_{1t} \\ \nu_{2t} \end{pmatrix};$$

$$\begin{pmatrix} \nu_{1t} \\ \nu_{2t} \end{pmatrix} \sim N(0, \mathbf{V}). \quad (1a)$$

In model (1a), Δ is the first difference operator: $\Delta X_t = X_t - X_{t-1}$. The parameters θ_{kt}^{sr} , $k = 1, \dots, 4$, capture the short-term own-sales (θ_{1t}^{sr} and θ_{4t}^{sr}) and cross-sales (θ_{2t}^{sr} and θ_{3t}^{sr}) effects of the marketing instruments, with the θ_{kt}^{lr} parameters ($k = 1, \dots, 4$) as their long-run counterparts. The Π_j ($j = 1, 2$) parameters determine the speed of adjustment to an expected long-run sales level, given by

$$\begin{pmatrix} ES_{1t} \\ ES_{2t} \end{pmatrix} = \begin{pmatrix} \theta_{01t}^{lr} \\ \theta_{02t}^{lr} \end{pmatrix} + \begin{bmatrix} X_{1t} & X_{2t} & 0 & 0 \\ 0 & 0 & X_{1t} & X_{2t} \end{bmatrix} \begin{pmatrix} \theta_{1t}^{lr} \\ \theta_{2t}^{lr} \\ \theta_{3t}^{lr} \\ \theta_{4t}^{lr} \end{pmatrix}, \quad (1b)$$

with θ_{01t}^{lr} and θ_{02t}^{lr} as the long-run intercepts.⁴ As shown in Equation (1b), the expected long-run sales levels are conditional on the values of the various marketing mix variables. Moreover, short-run fluctuations in sales (i.e., ΔS_{1t} and ΔS_{2t}) are driven by short-run fluctuations in the marketing-support variables (i.e., ΔX_{1t} and ΔX_{2t}), as well as by a correction (hence the term error correction) for the previous period's difference between the actually observed sales level and the performance level expected given the support levels in that period. The higher the Π parameters, the more weight is attached to this correction.

Of key interest to us are the intercepts θ_{01t}^{lr} and θ_{02t}^{lr} . They give the brands' base sales levels, corresponding to the brands' expected long-run performance (i) under average marketing support (remember that the marketing instruments are mean centered) and (ii) after taking into account (controlling for) all relevant short-term fluctuations, reflecting the two criteria listed in §2.1. The essence of our approach is to measure the impact of the focal innovation on these time-varying intercepts to estimate cannibalization effects (impact on same-brand varieties) or brand-switching effects (impact on other brands). Whereas the starting point of the change in base sales is at a known point

in time (when the focal innovation is introduced), the adjustment to the new base sales level may be gradual. Note that we not only add a time subscript to these intercepts but also to the effectiveness parameters to reflect their time-varying nature. Finally, the ν_{jt} ($j = 1, 2$) are error terms with full covariance matrix \mathbf{V} to capture any unmodeled cross effect, and the δ_j ($j = 1, 2$) are the seasonality parameters.

3.1.2. Generalization. In practice, more than two varieties need to be considered. Indeed, brands can offer multiple varieties (e.g., the Lexus RX300 and the Lexus 450) and can be active in multiple categories (e.g., luxury SUV category and luxury sedan category). As such, we need to stack sales series across varieties $j = 1, \dots, J_{cb}$, brands $b = 1, \dots, B_c$, and categories $c = 1, \dots, C$, to generalize (1a) to

$$\Delta S_t = \Delta \mathbf{X}_t' \boldsymbol{\theta}_t^{sr} + \Pi(\mathbf{S}_{t-1} - \boldsymbol{\theta}_{0t-1} - \mathbf{X}_{t-1}' \boldsymbol{\theta}_{t-1}^{lr}) + \mathbf{D}_t' \boldsymbol{\delta} + \boldsymbol{\nu}_t, \quad \boldsymbol{\nu}_t \text{ i.i.d.} \sim N(\mathbf{0}, \mathbf{V}), \quad (2)$$

where

\mathbf{S}_t = vector ($B \times 1$), where B is the total number of products ($B = \sum_{c=1}^C \sum_{b=1}^{B_c} J_{cb}$), with sales (in units) of brands $b = 1, \dots, B_c$, varieties $j = 1, \dots, J_{cb}$, in categories c , $c = 1, \dots, C$, in week t .

\mathbf{X}_t = matrix ($B \times K$) with mean-centered marketing mix variables. For each variety, we use price and advertising both (i) for all varieties in the category and (ii) for the same-brand varieties in other categories.

\mathbf{D}_t = matrix ($B \times L$) of seasonality and other control variables. Let \mathbf{d}_t' be a vector of seasonality and other control variables. We allow for idiosyncratic effects for each variety by specifying $\mathbf{D}_t' = \mathbf{I}_B \otimes \mathbf{d}_t'$, where \otimes is a Kronecker product.

$\boldsymbol{\theta}_{0t}$ = vector ($B \times 1$) with intercepts of brands $b = 1, \dots, B_c$, varieties $j = 1, \dots, J_{cb}$, in categories c , $c = 1, \dots, C$.

$\boldsymbol{\theta}_t^{sr}$ = vector ($K \times 1$) with short-run effects.

$\boldsymbol{\theta}_t^{lr}$ = vector ($K \times 1$) with long-run effects.

Π = diagonal matrix ($B \times B$) with adjustment effects.

$\boldsymbol{\delta}$ = vector ($L \times 1$) with seasonality effects.

$\boldsymbol{\nu}_t$ = vector ($B \times 1$) of error terms of brands $b = 1, \dots, B_c$, varieties $j = 1, \dots, J_{cb}$, in categories c , $c = 1, \dots, C$ in week t .

\mathbf{V} = full covariance matrix ($B \times B$) of the error term $\boldsymbol{\nu}_t$.

Because all marketing mix instruments in (2) are mean centered, we can again interpret the long-run intercept as the respective brands' base sales. Within-category own-brand and cross-brand effects, as well as cross-category within-brand effects, are captured

⁴ The error-correction specification is quite general (Hendry 1995). In a conventional specification, it requires the variables to be stationary or cointegrated (Fok et al. 2006). Framed in a DLM setting, these requirements do not apply because DLMs handle both stationary and nonstationary variables (West and Harrison 1999, pp. 299–300).

through elements of θ_t^{sr} and θ_t^{lr} .⁵ We allow for correlated errors across all varieties and all categories through the covariance matrix \mathbf{V} to capture any additional within- and between-category effects.

3.2. Time-Varying Intercepts

To capture the effects of the focal introduction on the base sales of the different brands, we need a flexible time-varying specification for the long-run intercepts. As argued in §2.2, it should allow for two types of time variation in cannibalization and brand-switching rates: (i) gradual adjustment and (ii) stochastic variation. Therefore, we specify base sales (the time-varying intercept) for each brand b and variety j in each category c as

$$\theta_{0cbjt} = \psi_{0cbj} + \lambda_{cbj}\theta_{0cbjt-1} + \psi_{cbjt}INTRO_t + \omega_{cbjt}^{\theta 0}, \quad (3)$$

$$\psi_{cbjt} = \psi_{1cbj} + \omega_{cbjt}^{\psi}. \quad (4)$$

Equation (3) specifies the base sales as a function of an intercept ψ_{0cbj} , the effect of past base sales ($\lambda_{cbj}\theta_{0cbjt-1}$), a step dummy $INTRO_t$ representing the focal introduction (zero before, one after) and its impact on the long-run intercept (ψ_{cbjt}), and an error term $\omega_{cbjt}^{\theta 0}$. The autoregressive nature of Equation (3) captures inherent inertia in the system and allows for a *gradual adjustment* of the long-run intercept following the introduction (Deleersnyder et al. 2002, Perron 1994). Equation (3) accommodates both stationary base sales ($0 \leq \lambda_{cbj} < 1$) and nonstationary base sales ($\lambda_{cbj} \geq 1$).

Equation (4) allows for a time-varying effect ψ_{cbjt} , where ω_{cbjt}^{ψ} captures the required *stochastic variation* in the cannibalization and brand-switching effects. Equations (3) and (4) allow for more flexibility in base sales than the random-walk specification (i.e., $\theta_{0cbjt} = \theta_{0cbjt-1} + \omega_{cbjt}^{\theta 0}$) used in Neelamegham and Chintagunta (2004), van Everdingen et al. (2005), or Winer (1979). It is also more flexible than previous DLM applications in marketing (e.g., Ataman et al. 2008, Lachaab et al. 2006, van Heerde et al. 2007) that used *nonstochastic* effects; i.e., $\psi_{cbjt} = \psi_{1cbj}$. In §5 we compare our model with (i) a benchmark model with time-invariant (rather than time-varying) effects and (ii) a benchmark model with instantaneous (rather than gradual) adjustment.

The extra time-varying layer in the model (Equation 4) causes the evolution error variance to be heteroscedastic, which we accommodate by following West and Harrison (1999, p. 287). For details on the distributional properties of the error terms, we refer

to the electronic companion to this paper, available as part of the online version that can be found at <http://mktsci.pubs.informs.org/>.

3.3. Marketing Mix Effects

While estimating the time-varying intercepts, we need to control for the own and cross effects of the marketing instruments. For the effects for which we have no missing data on either the independent variable (marketing instrument) or the dependent variable (first difference in sales), we use a fixed-mean specification:

$$\theta_{cbjkt}^{sr} = \theta_{cbjk}^{sr} \quad \forall t \quad (5a)$$

for the short-run effect of independent variable k on the dependent variable for brand b , variety j , in category c , and

$$\theta_{cbjkt}^{lr} = \theta_{cbjk}^{lr} \quad \forall t \quad (5b)$$

for the corresponding long-run effect.

However, model estimation is complicated as a result of product entries (in particular the focal innovation) and exits. We consequently do not always observe a full series of the independent variable or dependent variable. To overcome this problem, we specify for the parameters that involve missing data a model with stochastic variation around a fixed mean:

$$\theta_{cbjkt}^{sr} = \theta_{cbjk}^{sr} + \omega_{cbjkt}^{\theta sr} \quad (5c)$$

(short-run effect) and

$$\theta_{cbjkt}^{lr} = \theta_{cbjk}^{lr} + \omega_{cbjkt}^{\theta lr} \quad (5d)$$

(long-run effect).

Equations (3), (4), (5c), and (5d) allow us to use an estimation step (forward filtering) that updates parameters whenever we observe both the independent and dependent variables. In particular, when there are missing data for the time-varying intercept parameter (missing an independent variable or dependent variable), its posterior mean is not updated while its posterior variance grows, reflecting an increasingly diffuse posterior. When there are data again, both the parameter mean and variance are updated. Full details on the Bayesian model estimation are provided in the electronic companion.

Conceptually speaking, we use the same approach for parameters with fully observed data (Equations (5a) and (5b)) and parameters with partially missing data (Equations (5c) and (5d)) in the sense that both have constant expected values (note that $E(\omega_{cbjkt}^{\theta sr}) = E(\omega_{cbjkt}^{\theta lr}) = 0$). We just use Equations (5c) and (5d) to cope with missing data. Using Equations (5c) and (5d) for all parameters irrespective of whether there are partially missing data is not an option because that would have unpalatable consequences for the size of the state space.

⁵ Our empirical application includes 180 within-category cross effects and 40 within-brand cross-category effects. We refrain from allowing for between-category cross-brand effects as this would entail 180 additional cross effects.

3.4. Derivation of Cannibalization, Brand-Switching, and Primary Demand Effects

The demand for the new product is drawn from secondary demand, primary demand, or both. The secondary demand component is the change in the demand of competing products as a result of the introduction of the focal innovation. The primary demand component is that part of the demand for the innovation that is not drawn from observed competing products and therefore represents new demand. Formalizing these notions, we define ΔES_{cbjt} as the change in base sales for an existing variety j by brand b in category c as a result of the introduction of the focal new product. The change in base sales for new variety j' by brand b' in category c' in period t equals $\Delta ES_{c'b'j't}$, and it is composed as

$$\Delta ES_{c'b'j't} = \underbrace{\sum_{c=1}^C \sum_{b=1}^{B_c} \sum_{j=1}^{J_{cb}} \Delta ES_{cbjt}}_{\text{change in demand for existing products}} + \text{Primary Demand Effect}_t. \quad (15)$$

We gain insights in the demand sources of the new product by decomposing the triple sum in (15):

$$\begin{aligned} \Delta ES_{c'b'j't} &= \underbrace{\sum_{\substack{j=1 \\ j \neq j'}}^{J_{c'b'}} \Delta ES_{c'b'jt}}_{\text{(a) change in demand for other varieties within same brand and category}} + \underbrace{\sum_{\substack{b=1 \\ b \neq b'}}^{B_{c'}} \sum_{j=1}^{J_{c'b}} \Delta ES_{c'b'jt}}_{\text{(b) change in demand for other brands within category}} \\ &+ \underbrace{\sum_{\substack{c=1 \\ c \neq c'}}^C \sum_{j=1}^{J_{cb'}} \Delta ES_{cb'jt}}_{\text{(c) change in demand for other varieties within same brand in other category}} + \underbrace{\sum_{\substack{c=1 \\ c \neq c'}}^C \sum_{\substack{b=1 \\ b \neq b'}}^{B_c} \sum_{j=1}^{J_{cb}} \Delta ES_{cbjt}}_{\text{(d) change in demand for other brands in other categories category}} \\ &+ \underbrace{\text{Primary Demand Effect}_t}_{\text{(e)}}. \end{aligned} \quad (16)$$

Equation (16) says that the demand of a new product can be decomposed, at each time period t , as the sum of (a) within-category cannibalization, (b) within-category brand switching, (c) between-category cannibalization, (d) between-category brand switching, and (e) a primary demand effect. Management of the focal brand will prefer the sources where other brands are affected ((b) and (d)) or no brands are affected (e) over sources that involve cannibalizing its own-brand sales ((a) and (c)).

We operationalize the components of Equation (16) as follows. The *initial* change in base sales for brand b ,

variety j in category c as a result of the introduction equals ψ_{cbjt} (see Equation 3). Because of the autoregressive nature of (3), the initial effect gets amplified to arrive at the base sales effect $\Delta ES_{cbjt} = \psi_{cbjt} / (1 - \lambda_{cbj})$ if $0 < \lambda_{cbj} < 1$ (which is the case for the affected incumbent brands in our empirical application) over time. The left-hand side is the change in base sales of the focal new product as a result of its own introduction, which is given by $\Delta ES_{c'b'j't} = \psi_{c'b'j't} / (1 - \lambda_{c'b'j'})$. We calculate the primary demand effect as the difference between the left-hand side of (16) and the combined secondary demand effect (sum of (a), (b), (c), and (d)).

4. Empirical Application

We study the March 1998 introduction of the Lexus RX300 in the U.S. market. It is widely seen as a pioneering innovation, as it was the first crossover between an SUV and a sedan. Even though in terms of emissions and fuel economy regulations, the Lexus RX300 was considered a sedan (Gardner and Winter 1998), it was explicitly designed to compete in the luxury SUV category (Lassa 1998). As such, it is conceivable that the Lexus RX300 could draw secondary demand from two categories: (i) luxury SUVs and (ii) luxury sedans. As Lexus was already active in both categories (with prior shares of 12.3% and 25.3%, respectively), there was a clear cannibalization potential. Although Lexus' management was aware of this, the cannibalization threat was not perceived as problematic. As put by Steve Sturm, corporate marketing manager of Lexus United States, "Perhaps the only risk is that it could cannibalize a few Lexus Sedan sales" (Gardner and Winter 1998, p. 1; italics our own). The RX300 could also create additional primary demand. Possible sources for primary demand effects include new (first-time) buyers (Goldberg 1996), sales to existing used-vehicle owners (Berkovec 1985), as well as extra automobiles for some households (Manning and Winston 1985). Modeling primary demand effects is important in the light of the growth of new car sales in the United States from 15 million units (1995–1998) to an average of 17 million units since 2000 (Silva-Risso and Ionova 2008).

Data on both categories were provided by a leading data supplier in the automotive industry (hereafter DSA). We obtained weekly pre- and postentry data on the aggregate sales of all brands in California and on the price series of the major brands. Advertising expenditures were obtained from TNS Media Intelligence. To align the advertising and sales data, we scaled down the originally national advertising figures to the California level using an internal scaling factor advocated by the DSA. The Lexus RX300

Table 2 Luxury Sedans and Luxury SUVs: Market Share, Prices, and Weekly Advertising of Brands

Category	Start of sample period	Brand	Within-category market share (%)	Price (\$)	Advertising (×1,000)
Luxury sedan	10/13/1996	Acura	17.4	27,300	30
	10/13/1996	Infiniti	4.4	30,060	14
	10/13/1996	Lexus	10.2	39,630	46
	10/13/1996	Lincoln	7.3	37,920	12
	10/13/1996	Mercedes-Benz	22.6	48,370	14
Rest			38.1		
Total			100.0		
Luxury SUV	11/24/1996	Infiniti	16.4	33,470	34
	10/13/1996	Lexus (other)	25.1	60,710	9
	03/22/1998	Lexus RX300	10.6	34,420	147
	07/06/1997	Lincoln	25.1	41,600	55
	09/21/1997	Mercedes-Benz	22.8	39,240	30
Total			100.0		

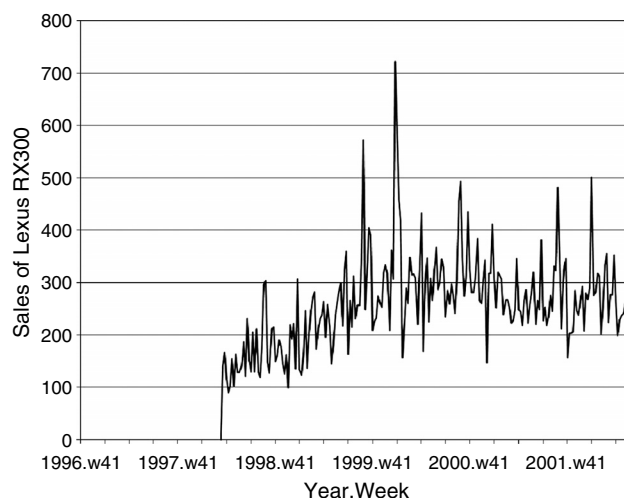
is classified by the DSA in the luxury SUV category.⁶ As such, we first describe this category. Four other brands were available in the market at the time of the RX300's introduction: other Lexus luxury SUVs (the 450 and 470), Lincoln (Navigator), Mercedes-Benz (M series), and Infiniti (QX4). The market share, prices, and advertising expenditures of the five brands in this category are described in Table 2. Figure 1 displays the observed sales data for the Lexus RX300.

In the luxury sedan category, we model the top five brands separately, i.e., Acura, Infiniti, Lincoln, Lexus, and Mercedes-Benz (see Table 2). In combination, these brands account for 62% of the luxury sedan market. To avoid interpreting brand switching from the remaining 38% as a primary demand effect, we also model the sales evolution of this Rest group. Because of the fragmentation of this market, no information on the price and advertising level was available for the smaller brands. The corresponding Rest equation therefore captures directly the cross effects from the five leading brands, whereas own effects from brands belonging to the Rest group are captured in the error term. Across the two categories, we estimate a system of 11 equations (five luxury SUVs and six luxury sedans). As Table 2 shows, not all brands are available for the entire duration of the data, which underscores the importance of our Bayesian estimation to avoid the excessive listwise deletion with traditional estimation procedures.

Automobile sales are known to exhibit seasonal fluctuations. In line with Srinivasan et al. (2009), we add a number of holiday dummy variables, which

⁶ Hence, the primary locus of the cannibalization threat as seen by the company (luxury sedans) differs from the one adopted by a key industry observer (luxury SUVs), which is, as argued before, not uncommon when dealing with pioneering innovations.

Figure 1 Observed Sales of Focal New Product: Lexus RX300



take the value of one in the week prior, during, and following Labor Day and Memorial Day weekends. To account for end-of-quarter promotions, four additional control dummies (defined in a similar way as the holiday dummies) were added. To control for the impact (if any) of the introduction on the short-run dynamics, we also add a pulse dummy (the first difference of the introduction step dummy) as a control variable. Finally, to control for the impact of some further (nonpioneering) innovations, some additional step dummies were added to the model. For minor innovations, we modeled their impact on own brand sales, whereas for somewhat more pronounced innovations (e.g., the 2001 Acura MDX in the luxury SUV category), we directly modeled the effects on both own and cross-brand sales.⁷

5. Empirical Results

This section reports the model estimation results. First, we compare our model with some benchmark models, and briefly summarize the marketing mix effects. We then elaborate on the cannibalization and brand-switching results, which are of central interest to this study. Finally, we discuss some implications for the innovation's competitors.

5.1. Benchmark Models

Besides the full model (DLM 0), we estimated a number of benchmark models (DLM 1–DLM 3) that are nested in the full model. Each of the benchmark models restricts a certain model feature that we included in our specification and therefore allows us to test whether we really need that feature. DLM 1 assumes a diagonal rather than full covariance matrix between

⁷ Full details on these additional control variables are available from the authors upon request.

the multivariate error terms of the sales equations; DLM 2 assumes that the adjustment to new base sales levels is instantaneous rather than gradual ($\lambda_{cbj} = 0$ in (3)); and DLM 3 allows no stochastic variation in cannibalization and brand-switching effects: ψ_{cbjt} in (4) is nonstochastic: $\psi_{cbjt} = \psi_{1cbj}$.

Table 3 reports on the predictive fit of the models. Because in a real-world setting it is important that the model can predict early cannibalization rates, our forecast criterion looks at the one-step-ahead forecast errors for the first 26 weeks after the introduction of the focal radical innovation. We compare the median model forecasts to actual sales using common predictive fit statistics (Franses 2005): mean squared error (MSE), correlation, and Theil's U . Theil's U looks at predictive performance relative to an often quite effective predictive model: $\hat{y}_{t+1} = y_t$ (Leeftang et al. 2000, p. 507). This model does not require independent variables and hence does not suffer from missing values in these variables (something that would break down conventional approaches). If Theil's U is smaller than one, then a model predicts better than this benchmark model. Based on Theil's U , each of the four DLM variants (DLM 0–DLM 3) outperforms this benchmark model because Theil's $U < 1$ in all cases.

The full model DLM 0 outperforms DLM 2 and DLM 3 based on all three fit criteria. DLM 0 has a slight edge over DLM 1 by winning on two criteria (MSE and correlation) yet losing on one (Theil's U). Because further inspection shows very little difference in the substantive results between DLM 0 and DLM 1, and because several off-diagonal error covariances are significant (see Table 5), we stick to DLM 0 as our focal model. Therefore, we conclude that we need all three model components: gradual and stochastic

cannibalization and brand-switching effects, and, to a lesser extent, a full error covariance matrix. We report on the full model in the rest of this section.

5.2. Marketing Mix Effects

Our model includes 260 marketing mix effects, allowing for own effects and (within-category and within-brand across-category) cross effects of price and advertising, both in the short (θ_t^{sr}) and the long (θ_t^{lr}) run. To save space, we focus on a few key findings. The face validity of the significant estimates is good, with more than six times as many expected signs than unexpected signs. The percentage of significant estimates with unexpected signs is 3%, which is less than can be expected by chance (at a 10% two-sided significance level). Among the significant estimates with expected signs, the median price elasticity is -3.54 . This is very comparable to the meta-analysis of Bijmolt et al. (2005), who report an average price elasticity of -3.81 for durable goods in the mature life cycle stage. The median cross-price elasticity is 1.37 , which is in the expected range (Sethuraman et al. 1999). The median own-advertising elasticity is 0.07 , which is in line with previous findings (Tellis 2007, p. 269), whereas the median cross-advertising elasticity (0.00) indicates a balance between negative (substitution) effects and positive (primary demand or spillover) effects. Primary demand effects for advertising are indeed not uncommon, as also observed in Lancaster (1984), Schultz and Wittink (1976), and van Heerde et al. (2007).

As expected, the fraction of significant own effects is higher than the fraction of significant cross effects. Nevertheless, we find that it is important to control for cross effects. For example, in the focal category (luxury SUV), we find that there is a significant positive cross effect of Lincoln's price on the sales of the focal new product (Lexus RX300), both in the short run (cross elasticity = 0.96 , $p < 0.05$) and in the long run (cross elasticity = 1.58 , $p < 0.05$). Furthermore, the significant effects are quite evenly distributed across the marketing mix instruments (price versus advertising), across the time span of their impact (short run versus long run), and across the two product categories. There are also significant within-brand *cross-category* effects, such as the spillover effect of advertising for Lincoln's luxury sedans on the sales of its luxury SUVs (long-run elasticity = 0.06 , $p < 0.05$). These results underline that it is important to control for a wide variety of own effects and cross effects while deriving cannibalization and brand-switching rates.

The model specification allows for a full covariance matrix \mathbf{V} for the errors across categories and brands. Table 4 shows that quite a number of the covariance terms are significantly different from zero (based on 90% posterior intervals). This holds not only for

Table 3 Model Comparisons Based on One-Step-Ahead Forecasts for the First 26 Weeks, After the Introduction of Pioneering Innovation

Model	Description	Rationale	MSE	Correlation	Theil's U
DLM 0	Full model		<u>0.867</u>	<u>0.376</u>	0.778
DLM 1	Diagonal \mathbf{V} matrix	To test whether we need to correlate the errors of the sales models.	0.891	0.350	<u>0.763</u>
DLM 2	Without gradual adjustment: $\lambda_{cbj} = 0$ (hence instantaneous adjustment)	To test whether the adjustment to the new base sales level is instantaneous or gradual.	0.984	0.312	0.824
DLM 3	Parameter ψ_{cbjt} in (4) is nonstochastic: $\psi_{cbjt} = \psi_{1cbj}$	To test whether we need a stochastic term in brand-switching and cannibalization rates. This feature is new relative to previous DLMs in marketing.	0.874	0.372	0.780

Note. The best values are underlined.

Table 4 Error Covariances Within and Between Categories

Category	Luxury sedan						Luxury SUV				
	Acura	Infiniti	Lexus	Lincoln	Mercedes-Benz	Rest	Infiniti	Lincoln	Lexus (other)	Lexus RX300	Mercedes-Benz
Luxury sedan											
Acura	0.89	0.34	0.43	0.36	0.28	0.50	−0.10	−0.08	−0.08	−0.09	−0.07
Infiniti		0.71	0.39	0.41	0.39	0.40	−0.09	0.01	0.01	−0.07	−0.04
Lexus			0.82	0.44	0.43	0.48	−0.07	−0.05	−0.10	−0.11	−0.11
Lincoln				0.78	0.39	0.51	−0.11	−0.07	−0.12	−0.08	−0.07
Mercedes-Benz					0.86	0.48	−0.05	−0.05	−0.08	−0.03	−0.08
Rest						0.84	−0.15	−0.10	−0.08	−0.06	−0.11
Luxury SUV											
Infiniti							0.57	0.04	0.09	0.00	0.05
Lincoln								0.54	0.07	0.08	0.10
Lexus (other)									0.60	0.10	0.07
Lexus RX300										0.52	0.12
Mercedes-Benz											0.61

Notes. We report error covariances based on standardized dependent variables. Numbers in bold indicate significance at 10%.

covariances within categories but also for covariances between categories. For example, the covariance between the error term of the focal new product (Lexus RX300) and Lexus in the luxury sedan category is -0.11 (and its 90% posterior interval excludes zero).

5.3. Sources of the Demand for the Innovation

The sources of the demand for the pioneering innovation are derived from changes in base sales (long-run intercepts) of the new product itself, and of same-brand and cross-brand varieties in the same and other categories. Defining a change as significant if the 90% posterior interval of the effect of the introduction excludes zero, the introduction of the Lexus RX300 significantly affects the base sales of five other cars (see Table 5). There is within-category brand switching (from Mercedes-Benz and Lincoln luxury SUVs), between-category brand switching (from Acura and Lincoln luxury sedans), and between-category cannibalization (of Lexus luxury sedans). Interestingly,

there is no cannibalization of other Lexus models in the luxury SUV category. This is consistent with the fact that the “Lexus (other)” SUV is in a much higher price tier than the Lexus RX300 (Table 2).

Equation (3) for the time-varying intercepts includes the autoregressive parameter λ_{cbj} . Table 5 reports the posterior distribution of λ_{cbj} and the implied 90% duration interval (Leone 1995). Whereas for one brand (Infiniti luxury SUV) base sales are nonstationary (the posterior interval for λ_{cbj} includes one), for all other brands base sales are stationary as $\lambda_{cbj} < 1$. For the five brands that are significantly affected by the introduction of the Lexus RX300, it takes between 18 and 73 weeks for the base sales to settle.

Figures 2 and 3 show graphically how base sales vary over time. Figure 2 shows that the sales of the focal new product, the Lexus RX300, take off quickly and reach a base sales level of 235 units per week. Figure 3 represents the base sales of some other car models (left-hand side graphs) and the effect of the

Table 5 Autoregressive Parameters (λ) for the Base Sales Levels and the Implied Duration Intervals

Category	Make	Significantly affected by Lexus RX300 introduction?	Posterior distribution of λ_{cbj}					Median 90% duration interval (weeks)
			2.5 percentile	5 percentile	Median	95 percentile	97.5 percentile	
Luxury sedan	Acura	Yes	0.903	0.903	0.904	0.908	0.909	23
	Infiniti	No	0.975	0.976	0.983	0.997	0.998	137
	Lexus	Yes	0.902	0.902	0.902	0.903	0.903	22
	Lincoln	Yes	0.898	0.899	0.899	0.900	0.900	22
	Mercedes-Benz	No	0.893	0.895	0.897	0.897	0.897	21
	Rest	No	0.960	0.960	0.964	0.969	0.969	62
Luxury SUV	Infiniti	No	0.985	0.986	0.996	1.002	1.002	— ^a
	Lexus (other)	No	0.894	0.894	0.896	0.898	0.898	21
	Lexus RX300	Yes	0.957	0.958	0.969	0.972	0.972	73
	Lincoln	Yes	0.862	0.864	0.877	0.885	0.885	18
	Mercedes-Benz	Yes	0.898	0.898	0.898	0.899	0.899	21

^aBecause the posterior for this autoregressive parameter includes one, base sales are nonstationary, and a median duration interval cannot be computed.

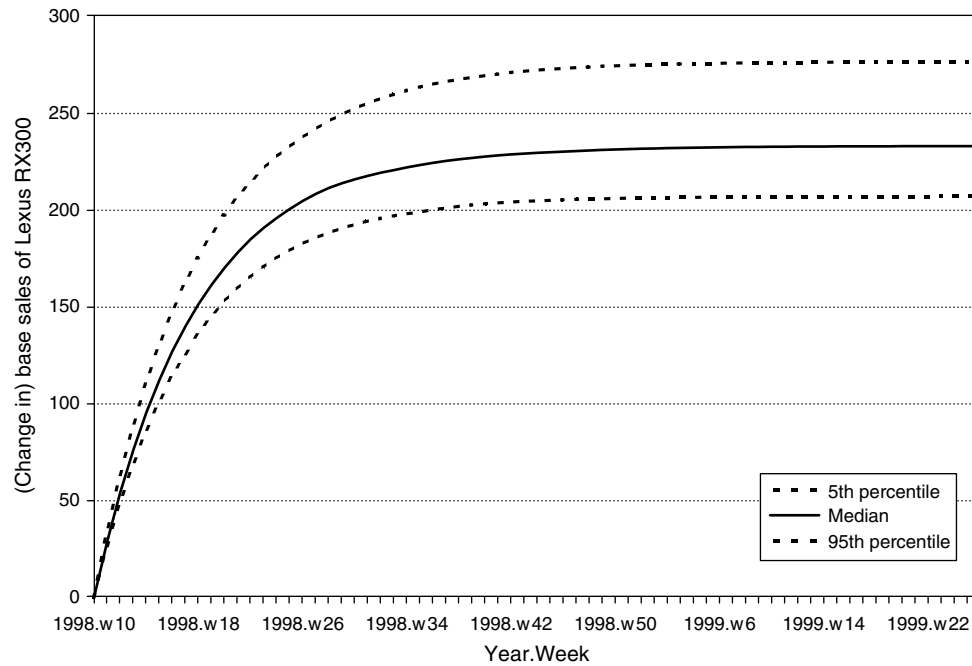
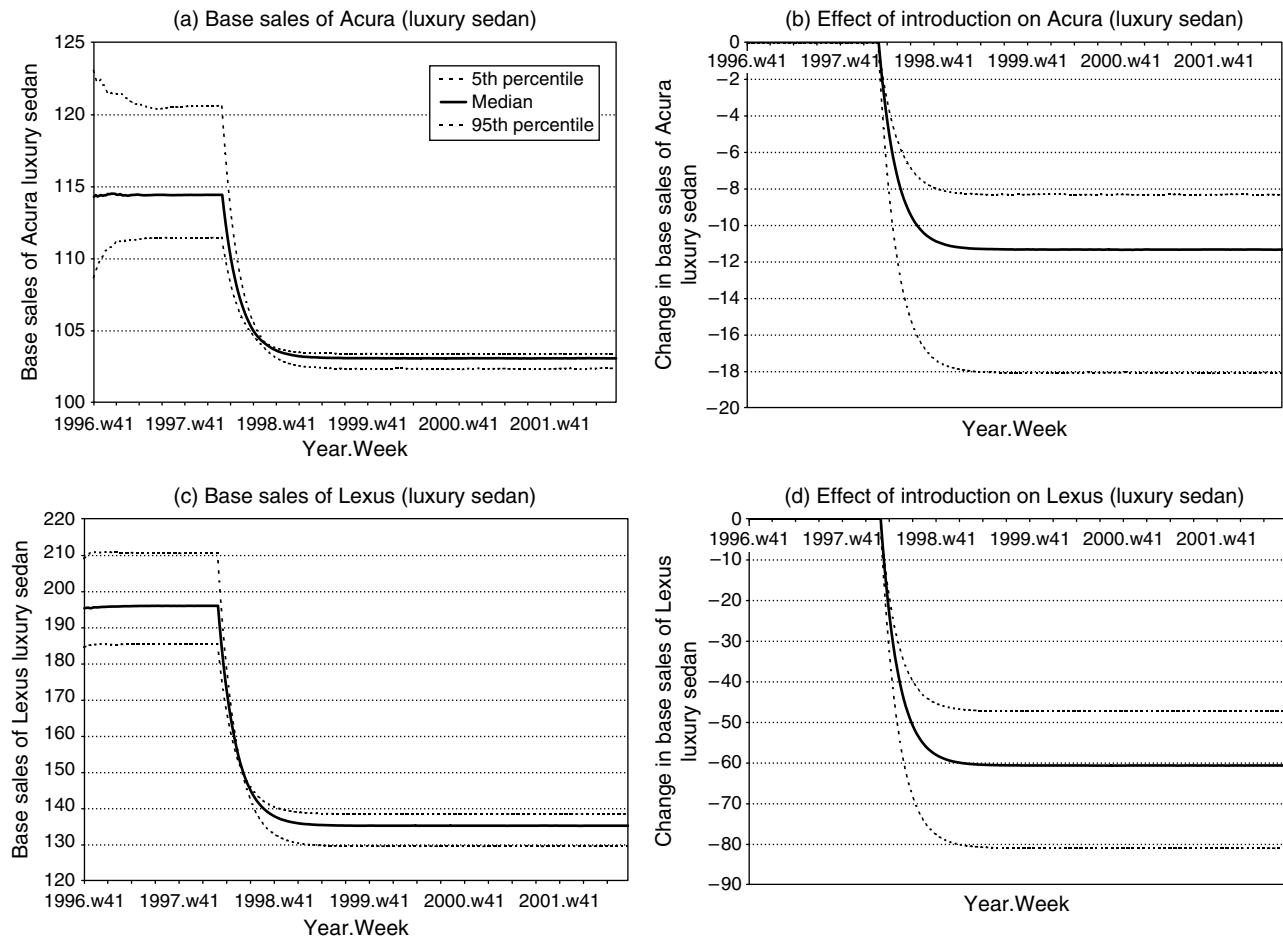
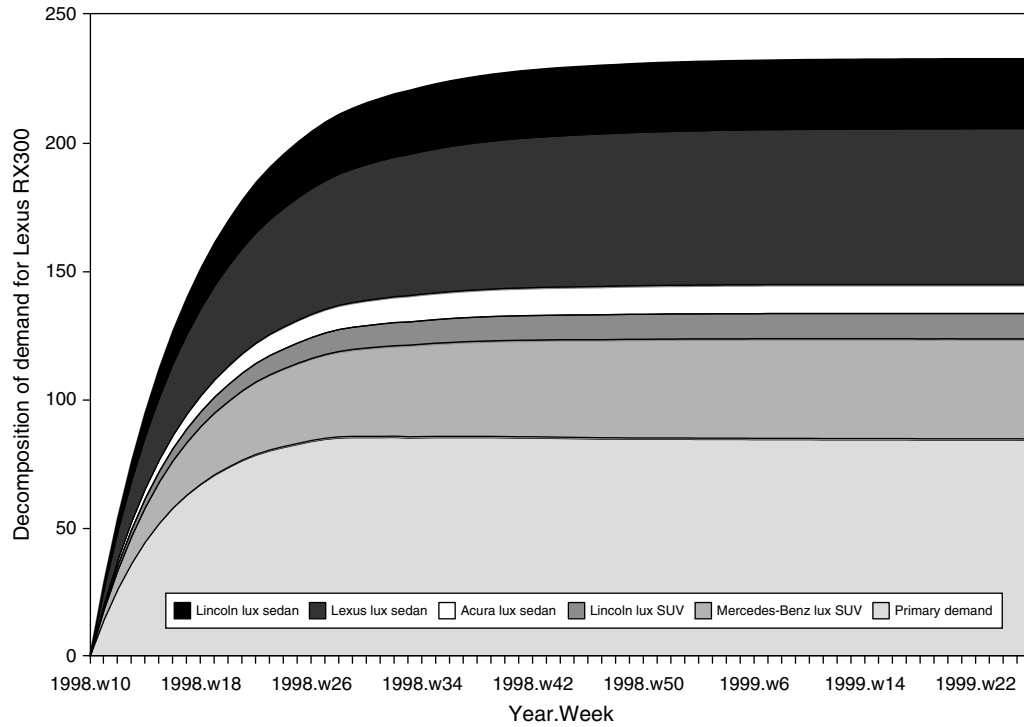
Figure 2 Base Sales of Focal New Product: Lexus RX300**Figure 3** Estimates of Time-Varying Base Sales (LHS Plots) and Their Change as a Result of the Introduction of Lexus RX300 (RHS Plots)

Figure 4 Time-Varying Decomposition of the Demand for Lexus RX300



introduction of the Lexus RX300 on base sales of that car (right-hand side graphs).⁸ To obtain Figures 2 and 3, we calculate each curve for every draw of the estimation chain, and next show the 2.5th, the 50th, and the 97.5th percentiles across draws. Figure 3 shows the impact on the luxury sedans of Acura (Figures 3(a) and 3(b)) and Lexus (Figures 3(c) and 3(d)) and confirms the prior expectation from Lexus' management that their luxury sedan category might be affected by the RX300 introduction (Gardner and Wildner 1998).

Figure 4 graphically shows how the demand for the Lexus RX300 is composed of secondary demand effects and primary demand effects and how the composition changes over time. We refrain from showing posterior intervals in Figure 4 to avoid too much clutter. Four weeks after the introduction of the new product (week $t_0 + 4$), Equation (16) looks like the following:

$$\begin{aligned} \Delta ES_{\text{Lexus RX300}, t=t_0+4} \\ = 114 \text{ units} &= \underbrace{0 \text{ units}}_{(0\%)} \\ &\quad \text{(a) within-category cannibalization} \end{aligned}$$

⁸ We present the graphs for these brands as we will focus on these brands in the policy simulations discussed in §5.4. Similar graphs for the other three affected brands are available from the first author upon request.

$$\begin{aligned} &+ \underbrace{20 \text{ units}}_{(18\%)} + \underbrace{25 \text{ units}}_{(22\%)} \\ &\quad \text{(b) within-category brand switching} \quad \text{(c) between-category cannibalization} \\ &+ \underbrace{16 \text{ units}}_{(14\%)} + \underbrace{53 \text{ units.}}_{(46\%)} \quad (17) \\ &\quad \text{(d) between-category brand switching} \quad \text{(e) Primary demand effect} \end{aligned}$$

Although there is no within-category cannibalization, there is a significant cross-category cannibalization effect. That is, base sales of Lexus in the luxury sedan category are reduced by 25 weekly units, corresponding to 22% of the 114 units of demand of the Lexus RX300. Within-category brand-switching effects contribute 18%, whereas between-category brand-switching effects (14%) are substantive as well. Primary demand effects represent 46% of the demand for the Lexus RX300 in these early weeks of its existence.

The effects have settled in new base sales levels 73 weeks after the introduction:

$$\begin{aligned} \Delta ES_{\text{Lexus RX300}, t=t_0+73} \\ = 235 \text{ units} &= \underbrace{0 \text{ units}}_{(0\%)} + \underbrace{49 \text{ units}}_{(21\%)} \\ &\quad \text{(a) within-category cannibalization} \quad \text{(b) within-category brand switching} \\ &+ \underbrace{62 \text{ units}}_{(26\%)} + \underbrace{39 \text{ units}}_{(16\%)} + \underbrace{85 \text{ units.}}_{(36\%)} \quad (18) \\ &\quad \text{(c) between-category cannibalization} \quad \text{(d) between-category brand switching} \quad \text{(e) primary demand effect} \end{aligned}$$

The absolute and relative contribution for each of the effects has changed relative to the snapshot at week $t_0 + 4$. Whereas total demand for the Lexus RX300 equals 235 units, net extra demand for Lexus as a whole equals 173 units, since 62 units (26%) are lost because of a (between-category) cannibalization effect. Thus, Equation (18) can be used by Lexus management to assess the net success of the Lexus RX300 introduction.

The primary demand effect (36%) represents that part of the own demand that cannot be attributed to sales reductions of other products. To make sure we have not overlooked other products that may have lost sales as a result of the introduction of the focal new product, we extended our analysis to a third product category, nonluxury SUVs. This category is less likely to compete for the same upmarket customers as luxury sedans or luxury SUVs. Consistent with this assumption, this category does not suffer from a significant competitive draw by the Lexus RX300 introduction. On top of that, including this category in the full VEC system does not noticeably affect the results for the two core categories.

5.4. Implications for Competitors

In this section, we illustrate how competitors may use our results to reduce their sales losses resulting from the introduction of the focal new product. Let us first consider the Acura in the luxury sedan category. As Table 6 shows, Acura luxury sedan base sales dropped from 114 to 103 cars a week (see also Figures 3(a) and 3(b)). Our model allows Acura management to contemplate ways to recoup this loss of 11 cars per week (or 572 cars per year).

However, prior to conducting such what-if analyses, we have to test for the Lucas critique (Lucas 1976, van Heerde et al. 2005): policy changes may lead to changes in parameter estimates. Therefore, we tested for superexogeneity (Engle et al. 1983), closely following Ahumada (1992). First, we tested after the pioneering innovation's introduction whether there were any policy changes in a given marketing instrument. Specifically, we used moving-window Chow breakpoint tests (at $\alpha = 0.10$) in a first-order autoregressive model for the instrument. Second, we tested whether the corresponding response parameter of interest stayed constant for those observations in which there may have been a policy change (i.e., where the Chow test's p -values were smaller than α). Specifically, we included step dummies (becoming one at the observations identified in step 1) in the process function for the response parameter, and we assessed whether the associated parameters were significant. Superexogeneity is established when the test of the instrument says there have been policy changes, whereas the corresponding response parameter did not change significantly. Applying the tests for each of the implications

Table 6 Possible Responses by Competitors to Recoup the Sales Loss as a Result of the Product Introduction

	Acura luxury sedan	Lexus luxury sedan
Base sales before introduction Lexus RX300	114	197
Base sales after introduction Lexus RX300	103	135
Difference	−11	−62
Mean price	\$27,300	\$39,630
Long-term own-price effect	−0.028	n.s.
Required price change to recoup sales loss	−\$399	n.a.
Required new price to recoup sales loss	\$26,901	n.a.
Mean advertising level ($\times \$1,000$)	30	46
Long-term own-advertising effect	n.s.	0.471
Required advertising change to recoup sales loss ($\times \$1,000$)	n.a.	+131
Required new advertising level to recoup sales loss ($\times \$1,000$)	n.a.	177

Note. n.s., not significant (90% posterior interval includes 0); n.a., not applicable.

derived below yields the conclusion that superexogeneity is indeed present and, hence, that the Lucas critique does not apply.⁹ Therefore we can proceed with the what-if analyses.

Because Acura's long-term own price effect is −0.028 (a significant estimate), it would take a price reduction of \$399 on its average price of \$27,300 to bring its base sales level to the original level (recoup the 11 cars lost per week). However, this move is not necessarily profitable (Dekimpe and Hanssens 1999), as there will be a margin loss on all sold cars (we lack margin data though). Spending more on advertising is not a solution for this brand, as its long-term own-advertising effect is insignificant. Increasing its advertising would therefore, in the terminology of Steenkamp et al. (2005), have resulted in spoiled arms.

In the luxury sedan category, the sister model Lexus is the most affected brand: base sales become 135 units a week after the introduction of the Lexus RX300 SUV, down from 197 weekly units. For this brand, reducing price is not an option to recoup the lost

⁹ In both case, one candidate for a policy shift was found in the autoregressive model. However, the parameters for the associated step dummies in the process function were not significant ($p = 0.34$ for the long-run own-price effect of the Acura luxury sedan and $p = 0.54$ for the long-run own-advertising effect of the Lexus luxury sedan), establishing superexogeneity. Moreover, the identified policy-shift candidates were not related to the introduction of the focal new product.

62 cars a week (or 3,224 cars per year), because its long-term price effect is insignificant. Instead, it may consider increasing advertising spending to overcome the sales loss, because its long-term advertising parameter (0.471) is significant. To increase weekly car sales by 62 units, Lexus needs to almost quadruple its weekly advertising for its luxury sedan: from \$46,320 to \$178,000. This comes down to \$903 of advertising per car ($=\$178,000/197$), which are sold at an average price of \$39,630. Of course, whether or not competitors implement these suggestions depends on various other considerations (costs, margins, positioning); the key is that our model allows for an informed strategic response.

6. Conclusions

Although the marketing literature on new products and their diffusion is particularly rich, it does not provide sufficient insights into how the demand for a new product draws from other products. Still, such an assessment is critical to evaluate the ultimate success of the innovation. In this paper, we develop a new approach to split the demand for a pioneering innovation into cannibalization, brand switching, and primary demand expansion. As pioneering innovations may transcend conventional category boundaries, their effects should be assessed across multiple categories (Moreau et al. 2001), which lead us to distinguish between within- and across-category cannibalization and brand switching. A key contribution of our approach is that it considers the time-varying long-term decomposition of the demand for the new product, which distinguishes our decomposition from the time-invariant short-term approaches that have appeared in the promotional literature (e.g., van Heerde et al. 2004a). In a recent review, Steenburgh (2007, p. 645) called for more research identifying the sources of demand that looks beyond the instantaneous effects and considers instead how the effects of marketing investments persist over time. Our method does exactly that.

We obtain our results while controlling for the own- and cross-marketing mix effects. The Bayesian estimation method readily handles partially missing data resulting from product introductions and deletions. These missing data would lead to a significant information loss in the estimation of cross-marketing effects when using conventional estimation techniques. In this respect, our paper fits in an increasingly broad stream of papers in marketing explicitly dealing with partially missing data (e.g., Bradlow et al. 2004, Schweidel et al. 2008).

Managers of the pioneering brand can use our approach to evaluate the net sales of the new product, after accounting for within- and across-category cannibalization. Managers of competing brands may use

our method to assess the extent to which their products (across different categories) are affected and how they may recoup potential losses. Moreover, management may also learn about the ability of new products to generate new (primary) demand.

We illustrate our method in the context of the Lexus RX300, which crossed the traditional boundaries between luxury SUVs and luxury sedans. Even though Jim Press, CEO of Lexus United States, considered the RX300 “a huge hit” (*BrandWeek* 1998), our results show that 26% of its sales (or 62 weekly units in our Californian sample) were drawn from Lexus’ luxury sedan sales. Although this number may look quite large, this “sibling rivalry” was actually a small price for Lexus to pay. Indeed, they felt that without the RX300 introduction, 15% of their Lexus sedan owners would defect anyway to the SUV category (Phelan 1998). This loss corresponds to approximately 30 units ($=0.15 \times 197$). As such, the “net” cannibalization becomes much smaller (i.e., $62 - 30 = 32$ units), especially in light of the 88 units of brand switching and the 85 units of primary demand expansion.

These calculations illustrate that cannibalization may often be a necessary evil, as reflected also in the motivation of Apple’s Steve Jobs (Graham and Baig 2007, p. 1) when introducing the iPhone: “If anyone is going to cannibalize us, I want it to be us. I don’t want it to be a competitor.” As in our setting, the iPhone crossed the boundaries of two categories (portable media players and mobile phones), with a clear cannibalization potential for the pioneering firm, along with an anticipated primary demand expansion (see, e.g., LeClaire 2007). As such, the iPhone introduction represents another exciting case study for applying our modeling approach. In this and other cases in which a radical innovation is difficult to assign to one category a priori (e.g., the Febreze and Purell cases mentioned in §1), our method can provide real-time information in which category cannibalization and brand-switching rates are the strongest. Applying our method across multiple settings would allow not only to derive empirical generalizations on the relative magnitude of the cannibalization rates and other demand components but also to identify potential drivers of any observed variability in this relative magnitude, both cross-sectionally and longitudinally.

Even though our model already captures multiple features, one could envision several extensions. First, in line with Fok et al. (2006) and van Heerde et al. (2007), we treated the performance series as key dependent variables. One could consider extending our system with additional equations for the marketing mix variables. In our application, this would have resulted in 20 extra equations, which would have considerably increased the parameter space and,

consequently, the estimation burden. In smaller-sized applications, however, this may be a fruitful way to extend our approach. Second, in our model, we allowed for time-varying base sales. However, we did not allow all response parameters to change over time as well, as this would again have increased the state space tremendously, leading to excessive estimation times (months rather than days). In our application, we found that for those response parameters where we had to allow for time variation because of partially missing data, there was no indication that they actually did vary considerably. This may not be the case in other settings, in which case this parsimony restriction may have to be relaxed. Third, although we do allow for a full error covariance matrix across brands and categories, for parsimony reasons we did not include cross-brand, cross-category effects of market instruments. Future research may try to integrate the parsimonious componential specification for cross effects of Wedel and Zhang (2004) in our time-varying VEC model.

In sum, we believe that the new method proposed and tested in this paper constitutes a useful management tool to assess the success of pioneering innovations. We hope that future academic work will provide further extensions and generalizations.

7. Electronic Companion

An electronic companion to this paper is available as part of the online version that can be found at <http://mktsci.pubs.informs.org/>.

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