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Are persistent marketing effects most likely to appear right after the introduction of a product? The authors give an affirmative answer to this question by developing a model that explicitly reports how persistent and transient marketing effects evolve over time. The proposed model provides managers with a valuable tool to evaluate their allocation of marketing expenditures over time. An application of the model to many pharmaceutical products, estimated through (exact initial) Kalman filtering, indicates that both persistent and transient effects occur predominantly immediately after a brand's introduction. Subsequently, the size of the effects declines. The authors theoretically and empirically compare their methodology with methodology based on unit root testing and demonstrate that the need for unit root tests creates difficulties in applying conventional persistence modeling. The authors recommend that marketing models should either accommodate persistent effects that change over time or be applied to mature brands or limited time windows only.

Keywords: persistence modeling, long-term marketing effectiveness, time-varying parameters, Kalman filtering, pharmaceutical marketing

Early Marketing Matters: A Time-Varying Parameter Approach to Persistence Modeling

Optimal allocation of marketing budgets over time is an important responsibility. Overspending in periods of low marketing-mix effectiveness or underspending in periods of high effectiveness results in either high costs or a serious amount of money being left on the table. In this study, we distinguish between persistent and transient marketing effects. Persistent effects are those effects that indicate an enduring influence on sales (or a different metric), and transient effects represent (relatively) short-lived sales increases. Given that short-term profit maximization is not the best paradigm for allocating resources (Dekimpe and Hanssens 1999), managers would ideally allocate their budget to periods in which strong persistent effects might be expected (i.e., a high return on the marketing investments). Therefore, it is of great importance to understand temporal differences in persistent marketing effects.

Several theories explain the phenomenon by which marketing-mix effectiveness varies over time. Product life-cycle theory argues that the early growth phase is characterized by relatively high advertising elasticities because of the many new customers in search of product information, whereas in the mature stage, many customers perform repeat purchases and have substantial experience with the product, resulting in lower information needs and increased price sensitivity (Assmus, Farley, and Lehmann 1984). Theory on brand entry indicates that new brands change marketing-mix effectiveness by altering subjective brand judgments, brand preferences, and choice (Pan and Lehmann 1993). However, these studies focus solely on transient effects. It is not clear whether these results also hold for persistent effects.

Dekimpe, Hanssens, and Silva-Risso (1999) show that persistent effects are predominantly absent, though a few studies have uncovered these effects. Examples are the

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studies by Nijs and colleagues (2001), Bronnenberg, Mahajan, and Vanhonacker (2000), and Slotegraaf and Pauwels (2008). These studies indicate that the strongest persistent effects are obtained for developing brands and categories. Yet Pauwels and Hanssens's (2007) study shows that in mature markets, existing brands are also subject to systematic performance improvements and deteriorations, the so-called performance regimes. Pauwels and Hanssens demonstrate that these regimes are related to the brand's marketing actions and policy shifts. Does this mean that persistent marketing effects can be obtained both after introduction of a brand and many years thereafter? This question remains unanswered by Pauwels and Hanssens, who focus solely on mature markets and existing brands. We are not aware of any study revealing how persistent marketing effects evolve over time after a brand's introduction. For managers, this information is highly relevant because it affects the allocation of the marketing budget over the years after introduction of a brand. Pauwels and Hanssens acknowledge the need for research in this area, noting that the issue of performance turnarounds in younger and turbulent markets remains a rich avenue for research. In this article, we pursue this avenue.

We develop a time-varying parameter model that captures both persistent and transient marketing effects over time and apply it to data from the tempestuous market of pharmaceuticals. In our brand-level analyses, we focus on the period from the product's launch until at least four years thereafter and reveal how the effects evolve over time. Moreover, we theoretically and empirically compare our model and its results with the more traditional static parameter approach using unit root testing, vector autoregressive (VAR) modeling, and vector error correction models (VECMs). Thus, we contribute to the field of persistence modeling and to literature on time-varying marketing effects. Our results have valuable implications for both scholars and practitioners. To scholars, they provide new insights into temporal variation in persistent marketing effects. In addition, the theoretical and empirical comparison of our model with the conventional approach may influence the stream of research dealing with persistent marketing effects. The proposed model provides managers with a valuable tool to evaluate their allocation of marketing expenditures over time. Furthermore, we provide insights into marketing-mix effectiveness for managers in the pharmaceutical industry.

BACKGROUND AND HYPOTHESES

Transient Marketing Effects

During the past three decades, marketing research has produced a large body of empirical evidence regarding the presence of temporal differences in marketing-mix effectiveness. A great deal of research has focused on temporal variation in transient (i.e., short- and/or long-term) marketing effects, such as by modeling (lagged) marketing effects on sales directly or with goodwill stock variables that depreciate over time. Parsons (1975) shows that advertising elasticities decline over the product life cycle, which is in line with Sethuraman and Tellis (1991), who demonstrate that the ratio of price and advertising elasticities significantly increases over the product life cycle. Andrews and Franke (1996) analyze advertising, price, and distribution effects and find evidence of temporal variation in sensitivities and elasticities in all marketing-mix variables. Narayanan, Manchanda, and Chintagunta (2005) study temporal differences in marketing effects in a pharmaceutical context. They apply a model with more behavioral detail by distinguishing between the indirect effects (through consumer learning) and the direct effects (through goodwill accumulation) of marketing communication on consumers' choices. Their results indicate that in the early phase of the life cycle of a new product category, marketing mainly shows an indirect effect, whereas the direct effect takes over in later phases. The total effect in later phases is smaller than that in early phases. In an application of brand entry theory, Van Heerde, Mela, and Manchanda (2004) demonstrate that the introduction of an innovative product significantly changes own- and cross-price elasticities. These studies indicate that, in general, transient effect sizes are larger in the early phases after introduction of a brand or product, apart from market shake-ups indicated by Van Heerde, Mela, and Manchanda. Here, note that we do not consider price effects. This prior research leads us to the following hypothesis:

H_1: Transient marketing effects decline in size with the time a brand has been on the market.

Persistent Marketing Effects

Persistent marketing effects, introduced in a marketing context by Dekimpe and Hanssens (1995), are enduring, as opposed to short- and long-term effects, which are transient because they assume a mean reversion of the dependent variable (Pauwels, Hanssens, and Siddarth 2002). Because persistent effects can occur only in nonstationary series (Dekimpe and Hanssens 1995), persistence modeling typically relies on unit root testing, followed by VAR modeling or a VECM.

The only study that explicitly models temporal differences in persistent marketing effects is that of Yoo (2006), who introduces the concept of dynamic impulse response functions to combine time-varying parameters obtained from Kalman filtering with traditional persistence modeling. However, this method has some severe drawbacks. Most important, the specification of the time-varying parameter model is based on unit root tests. When the series are stationary, the method specifies a VAR model in levels, but because this model assumes mean reversion, it will indicate the absence of persistent effects, regardless of the time-varying parameters.

Dekimpe, Hanssens, and Silva-Risso (1999) note that persistent effects are predominantly absent. The only effect that Dekimpe, Hanssens, and Silva-Risso report pertains to the permanent expansion of the soup category because of private-label promotions. Slotegraaf and Pauwels (2008) show that persistent effects may only be obtained for small brands (brands with a market share less than 3%). Sales of larger brands are typically stationary. However, the detection of persistent effects is the exception rather than the rule. Yoo (2006) applies the concept of dynamic impulse response functions to two yogurt brands and finds no persistent effects. Pauwels and Hanssens (2007) propose that

the performance barometer can provide an indicator of persistent effects, though only in specific time windows. They show that within these windows, existing brands may structurally improve or deteriorate in terms of their performance. Bronnenberg, Mahajan, and Vanhonacker (2000) study the feedback between a brand's market share and its distribution during the growth stage of a category. The positive feedback effects they find during the category's growth stage indicate that companies that are able to increase either their market share or their distribution in the product's initial periods can create persistent effects that eventually raise future market share. Finally, Nijs and colleagues (2001) focus on the category demand effects of consumer price promotions, and their results indicate that in categories with successful new product introductions, category demand may increase permanently as a result of promotions.[1] Apart from Pauwels and Hanssens (2007), these studies suggest that persistent effects mainly exist (1) in developing categories and/or markets and (2) for new brands. In line with H_1, we state our second hypothesis as follows:

H_2: Persistent marketing effects decline in size with the time a brand has been on the market.

METHODOLOGY

Theoretical Considerations

We develop a dynamic model that captures transient and persistent effects of marketing expenditures. Pauwels and colleagues (2005) note that the problems associated with neglecting cross-sectional (slope) heterogeneity and aggregation bias are even greater in dynamic models than in static models. Thus, in our model, we account for slope heterogeneity between brands.

Because we investigate temporal differences in persistent marketing effects, we include parameters that change over time. We rely on stochastic time-varying parameters, comparable to the time-varying parameter benchmark model in Pauwels and Hanssens (2007), which provide a good fit even when the prior on the appropriate shape of the pattern is weak (Putsis 1998). Alternatives to a stochastic time-varying parameter model include models that (1) a priori distinguish between growth and mature marketing effectiveness parameters, (2) use an interaction with time or an explicit process function (e.g., Foekens, Leeflang, and Wittink 1999; Mela, Jedidi, and Bowman 1998), or (3) rely on moving-window estimations, as Bronnenberg, Mahajan, and Vanhonacker (2000) and Pauwels and Hanssens (2007) do. We rule out these options because, respectively, (1) the distinction is arbitrary and ignores possible multiple growth periods, as Pauwels and Hanssens find; (2) we have no a priori information about the exact shape of the time-varying process of the parameters or variables that explain this shape; and (3) moving-window regressions can create inefficient estimates because they analyze only a subset of the data each time. In addition, short windows yield unreliable estimates, whereas long windows lead to coarse estimates and may induce autocorrelations when none exist (Van Heerde, Mela, and Manchanda 2004).

Because persistent effects are most likely to occur in growth categories and for successful product introductions, we assume nonstationary rather than stationary processes. We adopt a specification of a random walk with stochastic drift—that is, a local linear trend model (Durbin and Koopman 2001, p. 39)—because this structural time-series model provides a good trade-off between a large degree of flexibility and the number of parameters.

Basic Model

We develop a model at the individual brand level that incorporates stochastic time-varying parameters, following a local linear trend model. We specify a state space model that satisfies the specified conditions and that consists of measurement and transition equations (i.e., equations that describe how parameters evolve over time). For ease of exposition, we first discuss a model with just one endogenous variable (y_t) and one exogenous variable (x_t). In this brand-level model, y_t is the criterion variable (sales), and x_t is a predictor (marketing expenditures), both at time t. We explain y_t by x_t and a stochastic trend β_{0t}, according to the measurement equation:

$$y_t = \beta_{0t} + \beta_{1t} x_t + \varepsilon_t. \tag{1}$$

We specify the following transition equations, in which we assume that the stochastic trend β_{0t} follows a random walk with drift $\beta_{2t-1} x_t$:

$$\beta_{0t} = \beta_{0t-1} + \beta_{2t-1} x_t + \eta_{0t}. \tag{2}$$

The parameters β_{1t} and β_{2t} follow a local linear trend model:

$$\beta_{1t} = \beta_{1t-1} + \pi_{1t-1} + \eta_{1t}, \text{ and} \tag{3}$$

$$\beta_{2t} = \beta_{2t-1} + \pi_{2t-1} + \eta_{2t}, \tag{4}$$

where the stochastic drift components are given by

$$\pi_{1t} = \pi_{1t-1} + \eta_{3t} \text{ and} \tag{5}$$

$$\pi_{2t} = \pi_{2t-1} + \eta_{4t}, \tag{6}$$

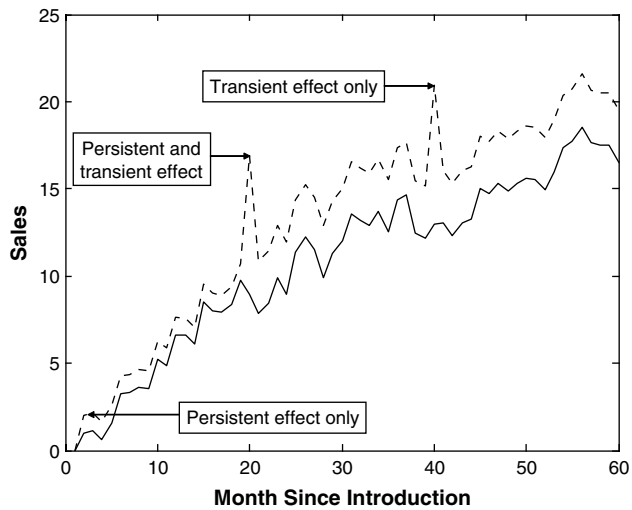
and ε_t and $\eta_{1,\ldots,4,t}$ are normally distributed uncorrelated disturbance terms.[2] The transient marketing effect is given by β_{1t}, and the persistent marketing effect is represented by β_{2t-1}. The subscript $t-1$ for the persistent marketing effect follows from the notion that all components influencing β_{0t} need to be known at time t. However, the subscript $t-1$ should not be interpreted as a lagged effect, because the process for β_2 is latent and linked to current marketing expenditures.

Our specification does not necessarily lead to persistent effects. Because of the residual term η_{0t}, the stochastic trend β_{0t} may grow even when the persistent effect β_{2t-1}

[1]Bronnenberg, Dhar, and Dubé (2007) also obtain persistent effects by demonstrating the persistence of geographical differences in market shares for national brands. These findings are beyond the scope of this study because we focus on temporal rather than geographical variation.

[2]We establish that the model is identified by means of a simulation experiment. The results from the experiment are available on request.

Figure 1
ILLUSTRATION OF PERSISTENT AND TRANSIENT MARKETING EFFECTS ON SALES



is 0. In addition, at time t, transient and persistent marketing effects may both be significant, insignificant, or a combination of a significant and an insignificant parameter.

We can incorporate lagged exogenous variables into Equation 1 to capture long-term but transient effects. We do not include lagged endogenous variables, because the stochastic series β_{0t} captures possible trends in y_t, and their inclusion would hinder interpretation of the marketing effects.

Graphic Illustration of the Basic Model

We illustrate our approach in Figure 1, which shows a hypothetical sales curve (y_t) for the first five years after the introduction of a brand (solid line). This synthetic curve follows a local level model specification—that is, a series following a random walk (Durbin and Koopman 2001, p. 10)—generated from normally distributed random numbers. Next, we generate the same series and include three different marketing effects (dashed line).

First, the marketing expenditures in Period 2 generate a (small) persistent effect. Recall that the total effect on sales in Period 2 is represented by $\beta_{2,1}x_2$, as follows from Equation 2 in the basic model. From Figure 1, we discern that the sales curve shifts upward at Time 2 but then has the same pattern over time as the original curve.

Second, the marketing expenditures in Period 20 generate both a (large) persistent effect and a transient effect. The curve shifts upward again, though more than in Period 2, and the pattern of the sales curve remains the same as the original curve. In Period 20, sales peak also for a period and then return to their original pattern (though at a higher level because of the persistent effect). We can express the total marketing effect on sales in Period 20 as $(\beta_{2,19}+\beta_{1,20})x_{20}$, in the terms of the basic model.

Third, in Period 40, marketing expenditures lead only to a transient effect on sales, represented by $\beta_{1,40}x_{40}$ in the basic model. Sales in subsequent periods remain unaffected by the marketing expenditures in Period 40.

Theoretical Comparison with Conventional Persistence Modeling

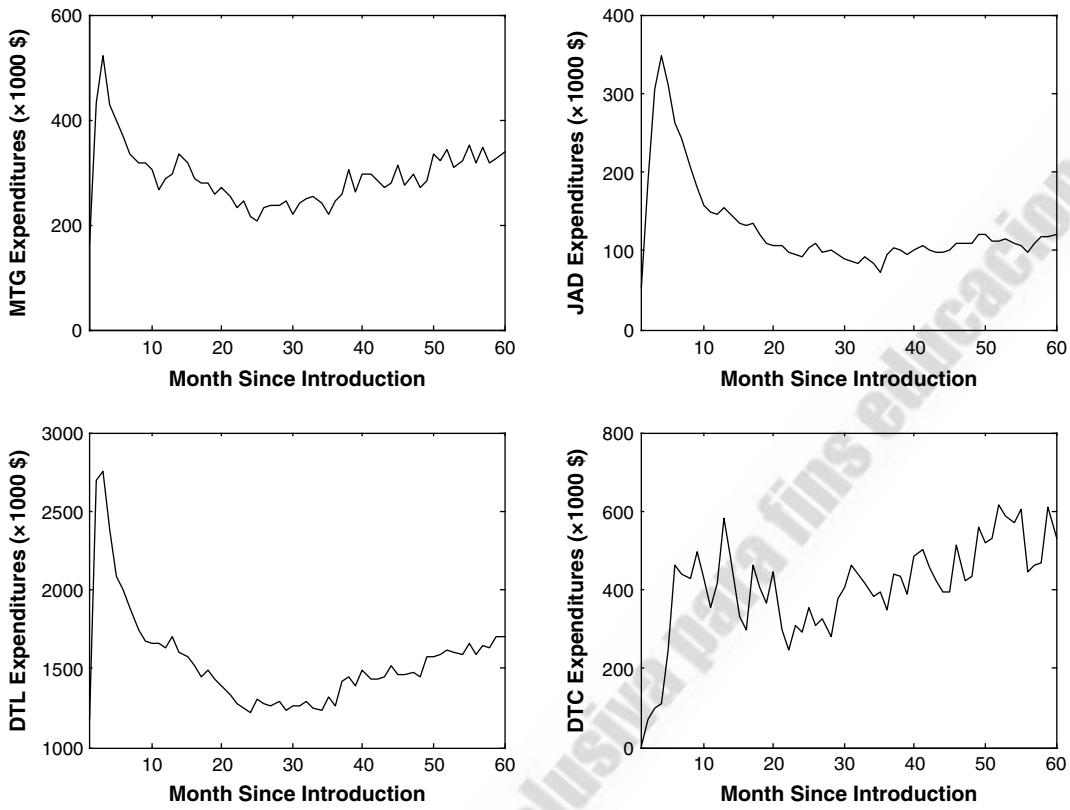
Our proposed methodology offers important advantages over conventional methodology. In particular, our model directly indicates both transient and persistent effects for every dollar spent at time t. Using conventional methodology, modelers must analyze the residual covariance matrix to obtain transient effects and derive persistent effects using unit root tests, VAR modeling, and impulse response analysis. Because our proposed methodology does not require unit root testing, it avoids the tests' known weaknesses, highlighted by Maddala and Kim (1999, p. 45) in their comment that unit root tests "are useless in practice and should not be used." Specifically, unit root tests are (1) sensitive to the assumption that the data have been generated through a pure autoregressive process as opposed to a process with additional moving average terms (Schwert 1987, 2002) and (2) have low power against plausible trend-stationary alternatives (DeJong et al. 1992). In addition, different unit root tests (3) do not necessarily lead to the same conclusion (Tsionas 2000) and (4) provide outcomes that may depend on the chosen time frame, as Bronnenberg, Mahajan, and Vanhonacker (2000) suggest (for an illustration, see Web Appendix A at http://www.marketingpower.com/jmrfeb10). In contrast, our methodology is not subject to this criticism, because, respectively, it (1) extends easily to incorporate a moving average scheme for the disturbances, (2) takes a stochastic trend into account (i.e., we let the data decide whether a trend is present), (3) eliminates the need for unit root tests, and (4) accommodates endogenous series that are partly nonstationary and partly stationary. When β_{2t-1} and η_{0t} are 0, the basic model reduces to a model with a fixed intercept to accommodate a stationary series at time t, but it also accepts an endogenous series following a local level model when η_{0t} is nonzero or a local level model with drift if β_{2t-1} is nonzero as well.

APPLICATION

Pharmaceutical Marketing

In our application, we determine the dynamic effects of pharmaceutical marketing expenditures. During 1995–2000, total pharmaceutical marketing expenditures in the United States grew at 13% per year to approximately $7.5 billion (Wittink 2002). These marketing budgets span a wide variety of instruments, including direct mail, journal advertising, public relations, postmarketing research, detailing (i.e., visits to physicians by pharmaceutical representatives), physician meetings (hereinafter, referred to simply as meetings), sponsorships, and, since the regulation relaxation in 1997, wide-scale direct-to-consumer (DTC) advertising. Therefore, the proper allocation of the marketing budget over time (and over instruments) is of great interest to pharmaceutical companies (see also Dekimpe and Hanssens 1999).

Figure 2
AVERAGE MARKETING EXPENDITURES SINCE INTRODUCTION PER MONTH



Notes: DTL = detailing, JAD = journal advertising, and MTG = physician meetings.

In Figure 2, we display the average marketing expenditures per month for a large number of drugs on meetings, journal advertising, detailing, and DTC advertising during the five years after introduction of the drug. Marketing efforts appear to be allocated in distinctive patterns over time. The expenditures on meetings, journal advertising, and detailing follow the same pattern: They are highest during the first year after introduction and then gradually decline. In contrast, DTC advertising expenditures are virtually nonexistent immediately after the introduction but trend positively during the subsequent five years. The different pattern in DTC advertising results partly from the regulation relaxation, which falls within our data window.

These observed spending patterns suggest that expenditures on meetings, journal advertising, and detailing are most effective within the first year. Thus, we expect that persistent effects appear during the first (few) year(s) after introduction, in line with the findings of Bronnenberg, Mahajan, and Vanhonacker (2000), Nijs and colleagues (2001), and Slotegraaf and Pauwels (2008).

Data

We estimate models using monthly data related to 89 prescription drugs from 39 categories. The number of drugs in each category appears in Table 1. The two categories containing the most brands are hypertension (11 brands) and rhinitis (10 brands). Our sample contains all drugs introduced between the beginning of 1993 and the end of 2000 with a 2000 annual sales level of $25 million or more in the United States and for which we have a minimum of 50 observations. Key variables in the data set include the number of units sold, retail price, direct-to-physician (DTP) marketing expenditures (sum of detailing, journal advertising, and meetings), and DTC advertising. Moreover, we have data about competitors' physician- and consumer-oriented expenditures. All variables, except journal advertising expenditures, come from Scott-Levin (now Verispan); the journal advertising expenditures come from the PERQ/HCI database. In our model, we distinguish between DTP and DTC expenditures to reduce complexity and circumvent multicollinearity, which is likely to occur if we were to include the separate physician-oriented components in the model (see Figure 2).

We measure sales as the number of prescriptions filled at the retail level. Because price plays a unique role in the pharmaceutical market, compared with many other markets, we do not include a price variable in our analysis. Specifically, when prescribing a product, physicians tend to consider drug efficacy and patients' conditions rather than retail price (Gönül et al. 2001); in many cases, they are unaware of the retail price of specific drugs (Hurwitz

Table 1
NUMBER OF ANALYZED BRANDS PER DRUG CATEGORY

Category	*Number*	*Category*	*Number*	*Category*	*Number*
Acne	2	Asthma	3	Oncology	2
AIDS wasting	2	Cholesterol reducer	1	Ophthalmic anti-infective	1
Analeptic	1	Cystic fibrosis	1	Ophthalmic anti-inflammatory	1
Antiangina	1	Diabetes test	1	Oral contraceptives	5
Anticytomegalovirus	1	Gastrointestinal anti-inflammatory	1	Oral diabetes	3
Anticonvulsant	2	Hemostatic modifier	1	Osteoarthritis and rheumatioid arthritis	3
Antidepressant	5	HIV	3	Osteoporosis	1
Antiglaucoma	3	Hormone replacement therapy	4	Pain management	2
Antiherpes	2	Hypertension	11	Psoriasis	1
Antinauseant	1	Insulin	1	Rhinitis	10
Anti-Parkinson's	1	Migraine	1	Systemic anti-infective	1
Antipsychotic	1	Multiple sclerosis	2	Systemic/topical fungicide	1
Antiulcerant	2	Nail fungus	1	Transplant/immunosuppressive	3

and Caves 1988; Newhouse 1993).[3] In defining competing products as those in the same product category, we distinguish between the marketing efforts of competing brands and the marketing expenditures of competing generics, as we detail subsequently.

Model Specification

For our application, we adapt the basic model from Equations 1–6. We explain sales by one-period lagged DTP marketing and DTC advertising expenditures and allow for both persistent and transient marketing effects. Moreover, we apply time-varying parameters to the persistent and transient effects of the DTP marketing expenditures. Because DTC advertising for a specific brand typically occurs for only a few periods, we do not assign a time-varying parameter to this instrument. We also do not include an interaction between physician- and consumer-oriented marketing, because DTC advertising usually occurs only when physician-oriented expenditures have reached a stable level, so an interaction term would result in severe multicollinearity. Because we analyze monthly data, we do not allow for current marketing effects.[4] Physicians reached by marketing need time to process the message and do not necessarily have a patient who needs the promoted drug immediately. Consumers also need time to process information from DTC advertising to arrange an appointment with a physician, obtain a prescription, and so forth. Finally, it takes time to fill the prescription. These delays hint at the presence of extra lags in DTP and DTC marketing.[5] Therefore, we allow for a wide range of extra lags, which we assume to have transient effects only. To keep the model parsimonious, we do not assign time-varying parameters to these variables. We test whether adding two-, three-, and four-period lagged physician- and consumer-oriented marketing expenditures improves model fit. Finally, we test whether adding a stock variable, defined as $\text{Stock}_t = \delta\text{Stock}_{t-1} + \text{Flow}_t$ (Nerlove and Arrow 1962), where δ is set to .7 (similar to Rizzo 1999), over all remaining lags improves model fit even further. Because we consider combinations of different lag lengths for DTP marketing and DTC advertising, we have 25 different model specifications. We test all 25 specifications and then choose the optimal model for each of the 89 brands separately. As a criterion for model fit, we use the corrected Akaike information criterion, given by $\text{AIC}_C = -2\text{LL} + [2nk/(n-k-1)]$, where LL is the log-likelihood, n is the number of observations, and k equals the number of parameters (Hurvich and Tsai 1989). The AIC_C reduces to regular AIC when n is sufficiently large, but it applies a small sample bias correction for small n, as in our application. For robustness, we compare the AIC_C selection to that based on the Bayesian information criterion (BIC).

One-period lagged competitive marketing expenditures may have both a transient and a persistent effect on sales. We distinguish between marketing expenditures of competing brands ($\text{MKTG}_{\text{comp.br.}}$) and those of competing generics ($\text{MKTG}_{\text{comp.gen.}}$) and not between physician- and consumer-oriented efforts. Competing brands usually enter the category before competing generics, and brands typically enjoy larger marketing budgets than generics. Furthermore, in general, a brand entering a category represents an innovative product in terms of its active ingredients or dosage form, whereas in most cases, a generic is an equivalent of a branded product whose patent has expired. Finally, whereas generics seldom employ DTC advertising, new brands often receive support from both physician- and consumer-oriented marketing. To keep the model parsimonious, we do not allow for a wide range of lag lengths in competitive variables; instead, we test whether a flow or stock variable is more appropriate in the case of transient effects. Here, a problem arises because we do not necessarily observe the first marketing effort and cannot define the first observation of the stock variable. We solve this problem by taking the same approach as Rizzo (1999); namely, we define the first observation as $\text{Stock}_1 = \sum_{t=0}^{T-1} \delta^t \text{Flow}_1$ for a brand that has been on the market for T periods already. Again, we use the AIC_C to select the model with the best fit. We visually inspect sales of all 89 brands for seasonality and include three quarterly dummies if seasonality appears.

[3]We verify whether including price in our model changes the results. The results appear to be robust.

[4]Robustness checks indicate that allowing for current effects does not influence any of our substantive conclusions.

[5]We thank an anonymous reviewer for pointing us in this direction.

Because we do not include current marketing effects in the sales model, endogeneity is of less concern. However, we specify an equation explaining DTP marketing. Correlation between the associated error term and that of the sales equation accommodates shocks that may affect the whole system, similar to a seemingly unrelated regression framework in static modeling.

We expect that DTP marketing expenditures are influenced by the previous periods' expenditures (inertia), current expenditures on DTC advertising (budget allocation effects), lagged competitors' marketing expenditures (competitive reaction effects), and lagged sales (internal feedback effect) (Dekimpe and Hanssens 1999). In addition, we include lagged competitors' sales to accommodate cross-brand feedback effects (Horváth et al. 2005). With regard to competitive reaction effects, we again distinguish between marketing expenditures of competing brands and those of competing generics. We do not make a similar distinction for cross-brand feedback effects because sales of competing brands often correlate strongly with those of competing generics. In case of seasonality in sales, we include three quarterly dummies in the DTP marketing equation because brands may spend more during, or just before, their peak sales months.

For brand i, we present the measurement equations in Equations 7 and 8 and specify the transition equations as Equations 9–13. With regard to the sales equation, we specify only one extra lag each for DTP and DTC marketing efforts. Extensions to models with more lags are straightforward. The competitive marketing expenditures in Equation 7 are represented by either a flow or a stock variable, depending on the best fit. We omit the seasonal dummies from Equations 7 and 8. Not all brands use DTC advertising or have (generic) competitors, in which case we do not include the corresponding variables in the model specification. We define the transition equations for the static parameters by setting the value of a parameter at time t equal to its value at time t − 1. We do not present these equations here.

$$\text{(7)}\quad \ln(\text{SALES}_{it}) = \beta_{0it} + \beta_{1it}\ln(\text{DTP}_{it-1}) + \beta_{2i}\ln(\text{DTP}_{it-2}) + \beta_{3i}\ln(\text{DTC}_{it-1}) + \beta_{4i}\ln(\text{DTC}_{it-2}) + \beta_{5i}\ln(\text{MKTG}_{\text{comp.br.},it-1}) + \beta_{6i}\ln(\text{MKTG}_{\text{comp.gen.},it-1}) + \varepsilon_{1it}.$$

$$\text{(8)}\quad \ln(\text{DTP}_{it}) = \beta_{7i} + \beta_{8i}\ln(\text{DTP}_{it-1}) + \beta_{9i}\ln(\text{DTC}_{it}) + \beta_{10i}\ln(\text{MKTG}_{\text{comp.br.},it-1}) + \beta_{11i}\ln(\text{MKTG}_{\text{comp.gen.},it-1}) + \beta_{12i}\ln(\text{SALES}_{it-1}) + \beta_{13i}\ln(\text{SALES}_{\text{comp.},it-1}) + \varepsilon_{2it}.$$

Here, DTP and DTC represent DTP marketing and DTC advertising expenditures, respectively. The stochastic trend β_{0it} behaves according to the following specification:

$$\text{(9)}\quad \beta_{0it} = \beta_{0it-1} + \gamma_{1it-1}\ln(\text{DTP}_{it-1}) + \gamma_{2i}\ln(\text{DTC}_{it-1}) + \gamma_{3i}\ln(\text{MKTG}_{\text{comp.br.},it-1}) + \gamma_{4i}\ln(\text{MKTG}_{\text{comp.gen.},it-1}) + \eta_{1it}.$$

The parameters β_{1it} and γ_{1it} follow a local linear trend model:

$$\text{(10)}\quad \beta_{1it} = \beta_{1it-1} + \pi_{1it-1} + \eta_{2it}, \text{ and}$$

$$\text{(11)}\quad \gamma_{1it} = \gamma_{1it-1} + \pi_{2it-1} + \eta_{3it},$$

where

$$\text{(12)}\quad \pi_{1it} = \pi_{1it-1} + \eta_{4it} \text{ and}$$

$$\text{(13)}\quad \pi_{2it} = \pi_{2it-1} + \eta_{5it},$$

where ε_{it} and η_{it} are normally distributed uncorrelated disturbance terms. We allow for correlation between the error terms of the transient and persistent effects to accommodate the possibility that they evolve similarly over time. Finally, in Equations 7–9, we add a constant of 1 to all variables that represent marketing expenditures and competitor sales before we take the natural logarithm, because these variables may reveal 0 values for one or more periods (competitive sales are 0 when the focal brand is the first to enter the category).

ESTIMATION

We estimate the model by means of Kalman filtering, applied previously in a marketing context by, for example, Naik, Mantrala, and Sawyer (1998), Cain (2005), Sriram, Chintagunta, and Neelamegham (2006), and Sriram and Kalwani (2007). In addition, Bayesian (learning) models including the dynamic linear model (see West and Harrison 1997) use Kalman filtering recursions. Published examples of the Bayesian approach include Erdem and Keane (1996), Akçura, Gönül, and Petrova (2004), Van Heerde, Mela, and Manchanda (2004), and Ataman, Mela, and Van Heerde (2008). Bayesian dynamic linear modeling has an advantage over the classical approach to Kalman filtering, in that different assumptions about the distribution of the error terms can be incorporated easily. An important disadvantage of the Bayesian approach is the significant computing time as a consequence of sampling (see also Leeflang et al. 2009). Because we assume all error terms to be normally distributed, and given the many different model specifications to be tested for each individual brand, we rely on the classical approach.

To estimate the model, we first write the measurement and transition equations of the state space model in matrix form; we illustrate this process for Equations 1–6 of the basic model in Web Appendix B (http://www.marketingpower.com/jmrfeb10). Next, we estimate the sales equation for all possible lag length combinations of physician- and consumer-oriented marketing expenditures. We select the optimal model for each brand and test whether the competitive marketing expenditures should be expressed as flow or stock variables. Again, we select the optimal specification for each brand. We estimate the sales and DTP marketing equations separately and use the resulting parameter values as starting values for the full model. In our estimation process, we perform standard filtering and smoothing recursions and use a numerical optimization method for the log-likelihood (for technical details, see Durbin and Koopman 2001).[6]

We pay particular attention to the filtering and smoothing routines for the first periods. Usually, such routines use the unconditional mean and (co)variances of the states,

[6]We estimate models using several starting values; the results appear to be robust.

but in our case, these values cannot be given because they are undetermined (stochastic time-varying parameters) or unknown (fixed coefficients). Therefore, we rely on exact initialization (Koopman 1997; Koopman and Durbin 2003), which is more accurate than naive methods and computationally more efficient than the augmented Kalman filter (Koopman 1997). Our exact initialization basically means that we start our routines with a flat prior, implying that we have lowest power at the beginning of the sample. In addition, the power of the Kalman filter is lowest in the beginning and at the end of the sample because of the inability to extract information from neighboring information at those points. Therefore, if we obtain effects in the initial periods, those effects are rather strong.

After optimizing the model, we use the smoothed coefficients, which contain information from all periods, because our model is descriptive and not predictive. Finally, we perform diagnostic checks on the standardized smoothed residuals, which Harvey and Koopman (1992) refer to as auxiliary residuals. We test the errors for nonnormality and heteroskedasticity over time. We do not check for serial correlation, because the smoothed residuals are autocorrelated by nature (Harvey and Koopman 1992). In the case of nonnormality, we visually inspect the auxiliary residuals to detect possible outliers and then replace the outliers with missing values using a state space approach (Koopman and Durbin 2001, p. 92). In the case of heteroskedasticity over time, we apply an adapted version of the ad hoc correction suggested by Harvey and Koopman (2000). We fit a stochastic volatility model (Durbin and Koopman 2001, p. 185) through the measurement equation's disturbances to obtain time-varying variance estimates. We then reestimate our model (Equations 7–13) using the time-varying variances.

RESULTS

Model Outcomes

Our model estimation is successful for 88 of the 89 sample brands;[7] for 1 brand, the estimation procedure does not converge. The model with the maximum number of lags, including the stock variable, for physician-oriented expenditures and just one lag for consumer-oriented marketing expenditures appears to be most successful, being chosen in almost half of the cases. A wide range of other specifications performs better for other brands, stressing the need for a brand-level analysis. For 75% of the brands, the model in which competitive marketing is represented by a stock variable returns the lowest AIC_C; for the other brands, the flow variables perform better. We compare these results with those indicated by the BIC and find that the AIC_C and BIC outcomes correspond in 73% of the cases with regard to the lag length selection for the own marketing expenditures and in all cases for the stock versus the flow variable for competitive marketing.

In Table 2, we summarize the means and standard deviations from the mean for the significant (at the 5% level) static coefficients of the 88 brands and the percentage of brands for which the particular coefficient is significant, together with the total number of coefficients estimated per variable. The number of coefficients differs per variable because not every brand employs DTC advertising and confronts (different types of) competitors. In addition, the lag length differs per brand. For the time-varying parameters, we provide the mean and range of the significant coefficients over brands and over time, as well as the percentage of brands for which we obtain at least one significant coefficient.

We obtain significant persistent effects of DTP marketing on sales for 47% of the brands under study and uncover a positive effect on average over all brands. All transient effects of the physician-oriented expenditures are positive, on average, across brands. The use of lagged components declines with lag length, as does the percentage of brands that indicate a significant effect, except for the five-period lagged stock variable.

Direct-to-consumer advertising has a persistent effect on sales for a mere 13% of the brands, and the average effect is small and negative. However, DTC advertising reveals positive transient effects. In addition, the use of DTC advertising components decreases with lag length.

On average, the marketing efforts of competing brands and generics have a negative persistent effect on the focal brand's sales. However, the standard deviations from the mean for these coefficients indicate considerable dispersion in the obtained effects across brands. Notably, for competing brands, we obtain more positive (17) than negative (11) significant coefficients. For competing generics, we observe 3 positive versus 10 negative significant coefficients, indicating that competing generics' marketing efforts are more detrimental to own brand's sales than those of competing brands.

With regard to the transient effects of competing brands' and generics' marketing spending, we reveal a fair amount of dispersion across brands. With regard to competing brands, we find 62 positive, significant effects versus 1 negative, significant effect; for competing generics, we obtain 10 positive, significant effects and 5 negative, significant effects, indicating many cases of category expansion from which all brands (may) benefit. These results reflect findings in fast-moving consumer goods categories (Pauwels 2004; Steenkamp et al. 2005), which imply that managers should not worry too much about competitive cancellation of their (otherwise persistent) marketing efforts.[8]

From the DTP marketing equation, we recognize that more than 77% of brands display inertia in their physician-oriented expenditures. In addition, 28% of the firms take the DTC advertising budget in the same month into account, such that a firm's DTP expenditures typically correlate positively with its DTC expenditures. Increased marketing expenditures by competing brands (generics) lead to higher (lower) physician-oriented marketing expenditures on average. According to the results from the sales equation, brands tend to overreact to competing brands' marketing efforts. Finally, brands decrease their DTP expenditures as the previous month's own and competitive sales increase.

[7]After we apply corrections, all auxiliary residuals meet assumptions about normality and homoskedasticity, except for two brands that show signs of heteroskedasticity over time in the DTP equation's residuals. Our results are robust to the exclusion of these two brands.

[8]We thank an anonymous reviewer for indicating this similarity.

Table 2
GENERAL ESTIMATION RESULTS

	Significant Coefficients			
	M	*SD*	%	*Number of Coefficients*
Sales Equation				
Persistent Effects				
Intercept	8.162	17.098[a]	100.0	88
DTP (t−1)	.012	.252[a]	46.6	88
DTC (t−1)	−.006	.003	12.5	40
Marketing of competing brands (t−1)	−.008	.008	32.6	86
Marketing of competing generics (t−1)	−.001	.001	22.4	58
Transient Effects				
DTP (t−1)	.087	1.002[a]	71.6	88
DTP (t−2)	.052	.006	64.6	82
DTP (t−3)	.034	.005	54.3	81
DTP (t−4)	.027	.005	36.2	69
DTP (stock, t−5)	.050	.009	43.8	48
DTC (t−1)	.008	.002	20.0	40
DTC (t−2)	.006	.002	31.6	19
DTC (t−3)	.009	.000	8.3	12
DTC (t−4)	.003	.004	33.3	9
DTC (stock, t−5)	.016	.000	12.5	8
Marketing of competing brands (flow, t−1)	.117	.017	81.3	16
Marketing of competing generics (flow, t−1)	N.A.	N.A.	0	2
Marketing of competing brands (stock, t−1)	.149	.012	71.4	70
Marketing of competing generics (stock, t−1)	.018	.013	26.8	56
DTP Equation				
Intercept	12.315	2.261	88.6	88
DTP (t−1)	.530	.024	77.3	88
DTC (t)	.023	.010	27.5	40
Marketing of competing brands (t−1)	.278	.379	29.1	86
Marketing of competing generics (t−1)	−.004	.021	31.0	58
Sales (t−1)	−.192	.045	61.4	88
Sales of competing brands and generics (t−1)	−.723	.368	44.2	86

[a]For the time-varying coefficients, we present the range instead of the standard deviation of the significant coefficients.
Notes: N.A. = not available.

Temporal Differences

In Figures 3 and 4, we depict the persistent and transient effects of DTP marketing expenditures, respectively, for the first 60 months after introduction of the brand, on the basis of the means of the significant coefficients across all brands. Although we have eight years of data, we plot estimates for only the first five years. We possess fewer estimates of effects in the later years because many brands were introduced after January 1993, the first period for which we have data. These figures clearly demonstrate that the average size of both persistent and transient effects declines over time, confirming both our hypotheses. The findings in Figure 3 also indicate that the mean of the significant persistent effects across all brands is positive and significantly different from 0 during the first two years after introduction. The transient effect across all brands differs significantly from 0 for the full five years after introduction but converges in effect size after the first two years. These results correspond with the marketing expenditure patterns in Figure 2. Physician-oriented spending is highest after introduction; approximately 25 months after the introduction, expenditures stop declining and fluctuate around a stable level. More specifically, expenditures on meetings display a slight upward trend when the brand has been in the market for more than 25 months. However, this effect does not induce an upward trend in overall DTP marketing expenditures, because meeting expenditures are minor compared with detailing expenditures.

We now investigate whether the percentage of significant effects changes over time. In total, we obtain persistent and transient DTP marketing effects for 39% and 66% of the brands, respectively, but not all these effects occur in the same period after introduction. In Figure 5, we display the percentages of significant persistent and transient coefficients over time. We obtain significant persistent effects for almost 40% of the brands after introduction. After four years, this percentage falls below 20%. With regard to transient effects, we find significance for nearly 60% of the brands during the first periods after introduction and for less than 40% two years after introduction. Bronnenberg, Mahajan, and Vanhonacker (2000) and Nijs and colleagues (2001) indicate that mature markets are less likely to exhibit persistent marketing effects than emerging markets; our findings confirm this premise at the individual brand level (see also Slotegraaf and Pauwels 2008). That is, brands are more likely to exhibit persistent effects right after their introduction than in later stages.

Figure 3
PERSISTENT EFFECTS OF DTP MARKETING OVER TIME

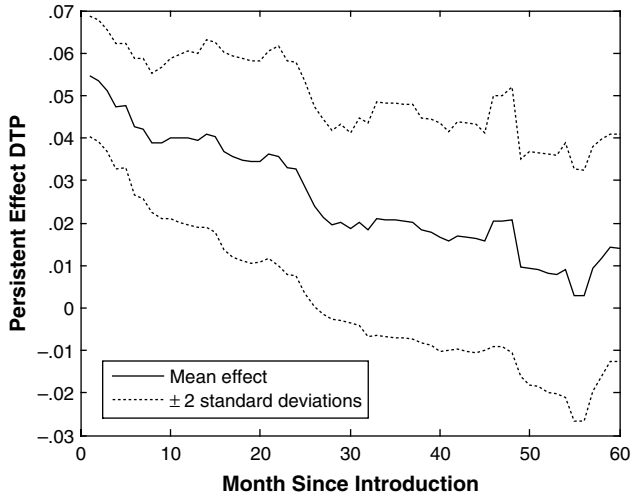
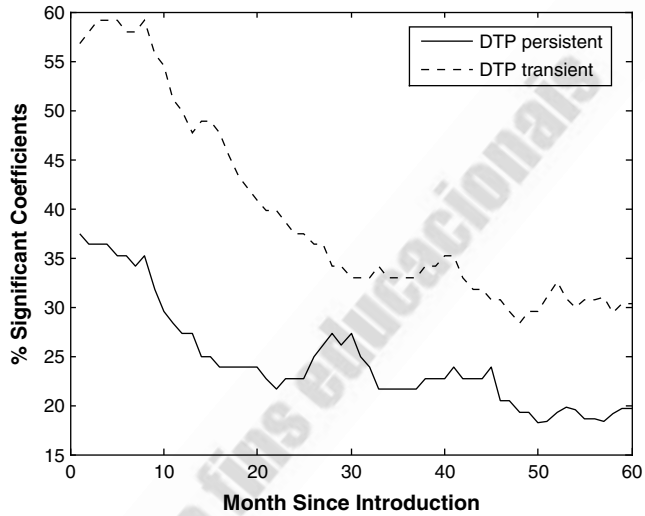


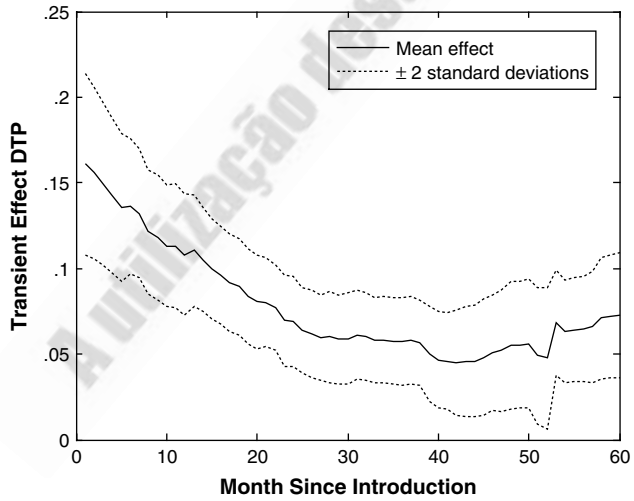
Figure 5
PERCENTAGE OF SIGNIFICANT EFFECTS OF DTP MARKETING EFFORTS OVER TIME



Empirical Comparison with Conventional Persistence Modeling

Compared with conventional methodology, a theoretical advantage of our approach is that it does not rely on unit root testing and therefore avoids the known weaknesses of these tests. In conventional persistence modeling, the outcome of unit root tests is crucial, in that it determines the model specification for the second-stage analysis (i.e., choice of a VAR model in levels, in the case of a stationary series, versus a VAR model in differences or a VECM, in the case of evolving series). We verify whether our theoretical concerns can be supported empirically by performing two types of full-sample unit root tests and then conducting moving-window unit root tests for the sales series, where we first take the natural logarithm to be consistent with our application, of each of the 88 brands.[9]

Figure 4
TRANSIENT EFFECTS OF DTP MARKETING OVER TIME



To determine whether the different unit root tests lead to different test results (Tsionas 2000), we perform full-sample augmented Dickey–Fuller and Phillips–Perron tests. Assuming a trend and a constant, the full-sample augmented Dickey–Fuller tests indicate a unit root for 28 of the 88 brands, whereas the Phillips–Perron test results show evidence for a unit root for only 2 brands. This picture does not change when we assume only a constant. Thus, these findings support our theoretical concerns.

Next, we perform moving-window unit root tests, setting the window size to 36 months and shifting the windows by a month, to assess whether the series consist of both stationary and evolving parts. Bronnenberg, Mahajan, and Vanhonacker (2000) perform similar analyses and find that the evidence for unit roots remains constant over the observation period. However, our results are significantly different, which again supports our theoretical concerns. Both the moving-window augmented Dickey–Fuller and the moving-window Phillips–Perron test results indicate that the percentage of brands for which a unit root emerges fluctuates significantly across different time windows, ranging from 5% to 75%. As we mentioned previously, we need different second-stage model specifications (VAR model in levels or differences or a VECM) for different unit root test outcomes. To limit the number of models to estimate, researchers might specify a single model for each set of consecutive windows that shows the same test result, ignoring possible parameter instability within such sets of windows. The ideal situation from a modeler's perspective involves equal test results across all windows, which occurs

[9]We thank an anonymous reviewer for suggesting moving-window unit root tests.

for only 2 brands. For 4 brands, 12 different models must be estimated. The total number of models to be estimated to cover all 88 brands is 527, according to the augmented Dickey–Fuller, or 417, according to the Phillips–Perron test results. Not only does this number increase the computational demands, but it also greatly decreases the ease of interpretation of the second-stage results. For example, a persistent effect may appear in a certain window but be absent in the next, even though these windows have 35 of 36 observations in common. Thus, questions arise about how to interpret these results and communicate them to management. Our approach avoids these problems altogether by avoiding any reliance on unit root testing.

CONCLUSION

We develop a model that indicates how persistent and transient marketing effects evolve over time. By applying this model to sales data and data on marketing expenditures of 89 pharmaceutical brands, we find that both persistent and transient marketing effects are most likely to occur right after the brand's introduction and that they decline in size over time. Our findings regarding persistent effects confirm the findings of Bronnenberg, Mahajan, and Vanhonacker (2000), Nijs and colleagues (2001), and Slotegraaf and Pauwels (2008). They also explain how Dekimpe, Hanssens, and Silva-Risso (1999) came to their conclusion that persistent effects are predominantly absent, namely, by assuming parameters that are static over time and focusing on mature brands. The results obtained for the time-varying transient effects are in line with existing literature and specifically with Narayanan, Manchanda, and Chintagunta (2005), who report similar time-varying patterns in transient effects in the field of pharmaceuticals.

A major advantage of our approach over conventional methodology is that we do not rely on unit root testing and thus avoid the known weaknesses of these tests. Test results show that, as we argue in our theoretical comparison, different unit root tests may lead to different outcomes and that series may consist of evolving and stationary parts. These results demonstrate the difficulty and subjectivity associated with applying conventional persistence modeling. In turn, our findings imply that marketing models must accommodate persistent effects that change over time. Alternatively, models can be applied to mature brands or limited time windows only in which the parameters are constant over time.

Our model offers a valuable tool for managers responsible for allocating marketing budgets, in that it enables them to assign marketing expenditures to the periods that exhibit the greatest persistent effects. The model also can be used to evaluate previous campaigns and derive input for new campaigns. For example, our empirical results suggest that drug manufacturers should use physician-oriented marketing in the periods right after an introduction of a brand because during these periods, both persistent and temporary marketing effects are significant and largest in effect size. Later, manufacturers should decrease the brand's marketing expenditures because the effects become insignificant or only marginally effective. These recommendations correspond to the spending patterns actually observed for many brands (see Figure 2). An alternative explanation for our results, and these spending patterns, is that marketing expenditures need to reach a threshold to become persistent.[10] Although we cannot completely rule out this explanation, our intuition is that the temporal pattern we obtain for persistent effects is rather robust. Many brands show a fairly flat spending pattern a few years after introduction. However, sudden expenditures peaks are not unusual. In general, we do not observe an increase in persistent effect size at the time of these peaks.

We acknowledge several limitations of our study. First, we omit several variables, such as sampling, drug innovativeness, and clinical test results, from our application. In addition, we model the influence of marketing expenditures directly on sales. In reality, many parties participate in the drug prescription process. We treat this process as a black box. Further research could improve the proposed model by including additional explanatory variables and taking more behavioral details into account. Second, we do not know whether our results hold across different industries. Third, in our model, we assign time-varying parameters to only two variables.

In addition to those suggested by the limitations, we imagine several further research opportunities. For example, researchers might consider the factors that determine the differences in persistent effects among individual brands. Why does one brand exhibit persistent effects but another does not? What factors influence the size of the persistent effect? Factors that might play a role include the year in which the drug was introduced (e.g., whether persistent effects become more rare as the pharmaceutical market gets more crowded), the message conveyed in marketing communication efforts, the degree of innovativeness of a new drug, or the quality with which the pharmaceutical company targets individual physicians (see Manchanda, Rossi, and Chintagunta 2004). Alternatively, additional research could attempt to model the persistent effects of marketing expenditures on other metrics, such as profits or appropriate indicators for the value of the firm.

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[10]We thank an anonymous reviewer for bringing this explanation to our attention.

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