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

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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:

$$(1) \qquad y_t = \beta_{0t} + \beta_{1t}x_t + \varepsilon_t.$$

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

$$(2) \qquad \beta_{0t} = \beta_{0t-1} + \beta_{2t-1}x_t + \eta_{0t}.$$

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

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

$$(4) \qquad \beta_{2t} = \beta_{2t-1} + \pi_{2t-1} + \eta_{2t},$$

where the stochastic drift components are given by

$$(5) \qquad \pi_{1t} = \pi_{1t-1} + \eta_{3t} \text{ and}$$

$$(6) \qquad \pi_{2t} = \pi_{2t-1} + \eta_{4t},$$

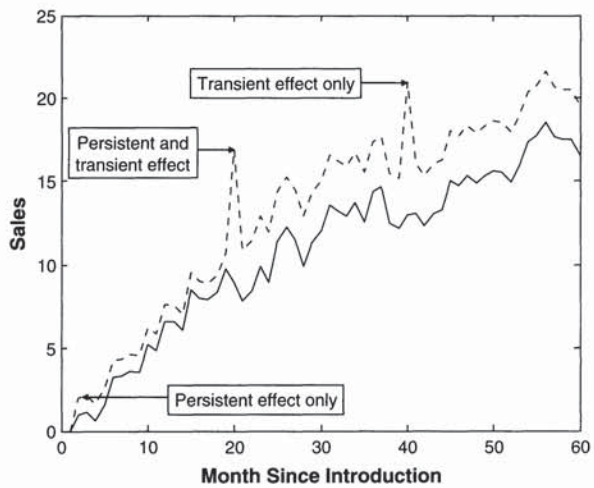
and ε_t and $\eta_{1,\ldots,4,t}$ are normally distributed uncorrelated disturbance terms.[2] The transient marketing effect is given by β_{1t}, and the persistent marketing effect is represented by β_{2t-1}. The subscript $t-1$ for the persistent marketing effect follows from the notion that all components 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).

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