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On November 28, 2006, Pfizer Inc., in an effort to cut $2 billion in costs by the end of 2008, and adjust to the loss of patents on several blockbuster drugs, announced plans to eliminate 20 percent of its U.S. sales force (Weintraub 2007). Pfizer executives believed that this shift would be beneficial in that it will lead to a culture of productivity and continuous improvement (McGuire 2007). They also believed that it would force them to find more effective sales strategies that ultimately boost the bottom line. In recent years, pharmaceutical companies have been attempting to do more with less by tracking physician prescribing patterns and adjusting their promotional strategies accordingly. As pharmaceutical companies place greater emphasis on reducing costs, they are faced with a need to reduce the size of their sales force. As a result, pharmaceutical firms are motivated to examine how they manage the relationship between their sales force and physicians. For example, one of the areas of interest to pharmaceutical industries is the utilization of the knowledge of physicians’ prescription behavior in improving sales forecasting and marketing-mix strategies—the primary focus of this research.

In this paper, we study the benefits of incorporating the knowledge of physicians’ prescription behavior into the development of marketing-mix strategy and the development of segmented diffusion models for forecasting sales. We primarily attempt to answer the question, “Would the segmented approach to modeling based on the prescription behavior of these three groups of physicians lead to better sales forecasting than previously used methods and in turn a better understanding of marketing-mix strategy?”

The marketing strategies employed in the pharmaceutical industry differ significantly from those typically adopted by other industries for various reasons. First, the pharmaceutical industry is highly regulated. Second, the marketed products (prescription drugs) are credence goods (i.e., physicians prescribe and patients consume them). Finally, manufacturers are required by law to obtain Food and Drug Administration (FDA) approval before a drug can be marketed. In addition, the FDA requires physicians to act as decision makers for their patients when prescribing drugs. The physician searches for prescription drugs based on his or her knowledge of each patient’s needs, and then prescribes products that he or she believes are best suited to address the patient’s problem. Although the physician is engaged in an educated search and decision-making activity, the physician may not be fully prepared to prescribe a product until the product details are formally communicated by pharmaceutical sales representatives, journal advertising, research conferences, and so on (Carter et al. 2006).

The unique characteristics of the pharmaceutical industry have created the need for a large sales force, costing pharmaceutical companies over $6.8 billion in 2006 (IMS Health 2007). Although personal selling (or detailing) is expensive, it does account for the highest return on investment (ROI) (Wittink and Clark 2002) of any marketing activities available to the pharmaceutical company. In recent years, it has become

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critical to understand the prescribing traits of individual physicians as well as identify those who can influence the adoption of a new product (Nickum 2007). Van den Bulte and Joshi (2007) showed the importance of identifying and targeting early on those decision makers who have the tendency to influence others.

Glass and Rosenthal (2004) categorize physicians as influential/clinical trial (ICT) physicians, influential/non-clinical trial (INCT) physicians, or imitator physicians. ICT physicians are those who have an excellent reputation for being thought leaders in their respective communities. They take part in clinical trials, provide scientific evidence for FDA approval, and prescribe the product after FDA approval (Corrigan and Glass 2005). INCT physicians are those who are early prescribers but are not involved in clinical trials. These physicians are respected by the imitator physicians for guidelines for prescribing a new product (Nickum 2007). Neither ICT physicians nor the INCT physicians are necessarily the highest potential prescribers of a new product but are essential for the product to reach its maximum potential. Imitators are physicians who write prescriptions only after influential physicians have tried the product and have had favorable results. The first group of physicians is easier to identify than the other two categories of physicians, which are more difficult to identify and also more critical to the diffusion process. (A list of clinical trial physicians is provided by the FDA at http://clinicaltrials.gov.) Although there are many ways to categorize physicians as influencers and imitators, one way is based on demographics. When segmentation is based on pure demographics, all specialists are categorized as influencers (i.e., innovators) and all primary care physicians are categorized as imitators. However, another method is to categorize physicians as innovators and imitators based on the historical knowledge of their prescription behavior from data providers such as IMS Health and Verispan.

We apply an extension of the current segmented diffusion model based on the knowledge of physicians’ prescription behavior (or SDM-BEH) and calibrate it using a sample of four product histories from the pharmaceutical industry. In addition, we use the diffusion model based on the knowledge of physicians’ prescription behavior as a guideline for incorporating marketing-mix variables (SDM-BEH-MM). The SDM-BEH model is compared with the SDM-DEM model, which is based purely on whether the physicians are specialists or primary care physicians, and with the standard diffusion with retention model (Mahajan, Wind, and Sharma 1983). The comparisons show that the proposed SDM-BEH model is a more accurate predictor than models that are not based on physicians’ prescription behavior, and that marketing-mix variables influence potential influencers and imitators differently. Further, the marketing managers can use the proposed model offered in the study to forecast sales and also to provide diagnostic information on how potential prescribers are likely to respond to marketing activities.

## REPEAT PURCHASE DIFFUSION MODELS APPLIED TO PHARMACEUTICAL INDUSTRY

Past research that has focused on diffusion of pharmaceuticals includes that by Hahn et al. (1994), Lilien, Rao, and Kalish (1981) (LRK), Mahajan, Wind, and Sharma (1983) (MWS), Rao and Yamada (1988), and Ruiz-Conde, Werieringa, and Leeflang (2006). We briefly review these diffusion models, which were calibrated using data from the pharmaceutical industry.

Lilien, Rao, and Kalish (1981) developed a discrete time model using the standard diffusion with retention model to forecast sales of ethical pharmaceutical products. They include the efforts of the sales force (detailing) in an examination of the adoption of drugs by physicians. However, they make the simplifying assumption that the number of physicians in the class is fixed and that all physicians are in the same class. Although the model is structured in terms of prescribing physicians, it uses the total number of written prescriptions in the model. This method of tabulating adoption of a drug appears to overestimate the total number of prescribing physicians because both new prescriptions and refills of existing prescriptions are counted. Moreover, Lilien, Rao, and Kalish (1981) assume that the influence of word of mouth is constant throughout the diffusion process. The same approach has been used by Rao and Yamada (1988) to study the adoption of 20 different drugs (Ratchford, Balasubramanian, and Kamakura 2000).

To address the issue of constant word of mouth, Mahajan, Wind, and Sharma (1983) use the nonuniform influence coefficient of imitation suggested by Easingwood, Mahajan, and Muller (1983). The MWS model could accommodate the assumption that diffusion proceeds in a uniform manner by setting the time-varying coefficient of imitation = 1. The presence of the nonuniform effect would be indicated by the time-varying coefficient of imitation ≠ 1. The values of the time-varying coefficient of imitation between zero and one cause an acceleration of influence leading to an earlier and higher peak in the level of adoptions, which would cause a high initial coefficient of imitation to decrease with penetration. The values of the time-varying coefficient of imitation greater than one delay influence causing a later and lower peak. Unlike the LRK model, the MWS model allows the diffusion curve to attain its maximum rate of adoption at any stage of the diffusion process, and the diffusion curve is independent of the potential market captured by the innovation (Easingwood, Mahajan, and Muller 1983).

Hahn et al. (1994) extend the diffusion framework by incorporating repeat purchase behavior and the effect of competitive marketing efforts used by entering and defend-
ing firms. It is a four-segment trial-and-repeat model that can be calibrated using aggregate data for frequently purchased products in the early stage of the life cycle. Like the MWS model, the framework is simplified before the model is calibrated on aggregate data. All four models discussed so far assume a constant repeat purchase rate and coefficient of imitation. That is, they assume that neither rate is affected by the marketing mix.

The model proposed by Ruiz-Conde, Wieringa, and Leeflang (2006) is an extension of the model of Hahn et al. (1994). Here the model incorporates the effect of company and competitors’ promotional efforts separately. In contrast to other studies that use either aggregate measures for marketing expenditures or expenditures for a single instrument (Hahn et al. 1994; Lilien, Rao, and Kalish 1981; Rao and Yamada 1988), Ruiz-Conde, Wieringa, and Leeflang accommodate heterogeneity in the effects of different marketing instruments. Following existing literature, they assume that the trial rate is time varying and depends on marketing expenditures. However, they do not assume that marketing affects the repeat rate. Although theoretically both options are possible, they do not consider the influence of marketing on the repeat rate using the same argument as Hahn et al. (1994).

As advanced by Bass, Krishnan, and Jain (1994), being able to write the diffusion-specific coefficients as functions of decision variables would be desirable. Moreover, we could explain the influence of decision variables on the dimensions of the adoption rate and repeat purchase rate. Therefore, we use the proposed extension of segmented diffusion framework and show how marketing mix affects the coefficients of innovation \( p \), imitation \( q \), and retention \( r \) in the SDM-BEH-MM model.

**MODEL**

For the past decade, companies such as IMS, Verispan, and Impact RX have been tracking the prescription habits of physicians. The pharmaceutical company may purchase a survey of the targeted physician population and, based on its results, classify the physicians into segments as discussed earlier. Based on this information, it is expected that the pharmaceutical company would be able to forecast sales with greater accuracy. In this paper, we use information gathered from an audit company (IMS) to determine the behavioral tendencies of a physician and focus on how a pharmaceutical firm can leverage this knowledge to improve marketing-mix strategy and sales forecasts. This information is shown to improve sales forecasting by more precisely segmenting the target pool of physicians; in other words, influencers and imitators are treated as separate segments. Although there are three categories of physicians, we were able to conclude that after the product is given FDA approval, the ICT physicians and INCT physicians need not be separated. As a result, we merge the ICT and INCT into one group and call them innovators. Given the small number of ICT physicians (<250 physicians) and the relatively large number of INCT physicians (>10,000 physicians), we believe it to be a reasonable trade-off for a more parsimonious model.

**Prescription-Behavior Knowledge and Forecasting Models**

Given the critical role played by physicians in the commercial success of a prescription medicine, all major pharmaceutical companies concentrate their personal selling efforts on physicians (Berndt et al. 1995). Typical personal selling sessions with physicians last less than three minutes (IMS Health 2007). With the information purchased from the audit companies, the pharmaceutical company gains knowledge about the behavioral patterns of individual physicians and their influence in the community of physicians. In particular, companies may perceive firsthand whether a physician is a potential innovator (i.e., willing to be one of the earlier prescribers of the new product) or an imitator (i.e., relies on others to experience a new product before prescribing the product). On the basis of this information, management can develop better sales forecasting models and better marketing-mix strategies that take into account both the innovator and the imitator physician segments.

However, in the absence of knowledge about the physicians’ prescription behavior, pharmaceutical companies can segment the market based on physician demographics. The most frequently employed segmentation method is to divide physicians into two groups—specialists and primary-care physicians. With this method, it is assumed that all the specialists are potential innovators and that all the primary-care physicians are potential imitators. The assumption, of course, is that these potential innovator physicians will stimulate further demand for the product. Glass and Rosenthal (2004) have shown that not all specialists are potential innovators and not all primary-care physicians behave like imitators. Therefore, unique knowledge about physician prescription behavior should help us to further improve our ability to identify true innovators and imitators, leading to more accurate predictions.

**Segmented Diffusion with Repurchase**

The segmented diffusion model is a trial-repeat model in which both the adoption effects and the repeat purchase are represented. The importance of the latter has been long understood by marketing practitioners and academics (see Ratchford, Balasubramanian, and Kamakura 2000 for a detailed summary of trial-repeat models). The repurchase
phenomenon is incorporated for several reasons. First, it is well known that the phenomenon figures prominently in empirically investigated situations. Second, models that do not include repurchase are known to underestimate cumulative adoption (Mahajan and Muller 1982).

The general framework to include repeat purchasers was proposed by Mahajan, Wind, and Sharma (1983):

\[ N(t+1) = \left( p + \frac{q}{m} N(t) \right) \left( m - N(t) \right) + r N(t), \]  

(1)

where \( p \) (coefficient of innovation) represents an external influence such as advertising, \( q \) (coefficient of imitation) represents an internal social influence such as existing adopters, \( N(t) \) is the total number of buyers at time \( t \), \( m \) is the ceiling or potential number of adopters, \( r \) is the coefficient of retention, and \( N(t+1) \) is the total number of users at time \( t + 1 \).

Based on the information collected from the audit records, the roles of adopters (i.e., innovators and imitators) are known and repeat buyers are distinguishable from adopters. Consequently, the sizes of these buying segments also are individually observable. That is, \( m \), the market potential, could be separated into two groups—potential prescribers who are known to be innovators \( (m^E) \) and those who have in the past behaved more like imitators \( (m^I) \); \( N_p \), the total number of product prescribers, could be divided into two groups: product prescribers who are innovators and prescribe the focal product during time \( t (N^E) \) and product prescribers who are imitators and prescribe the focal product during time \( t (N^I) \). Keeping in mind that \( N_p = N^E + N^I \) and \( m = m^E + m^I \) and by adopting the framework of Mahajan, Wind, and Sharma (1983), we arrive at the SDM with the following equation:

\[
N_{t+1}^{E} = \left( p + \frac{q}{m} \left( N_{t}^{E} + N_{t}^{I} \right) \right) \left( m^E + m^I - N_{t}^{E} - N_{t}^{I} \right) + r^E N_{t}^{E} + r^I N_{t}^{I}.
\]

(2)

By knowing the adoption roles, we are able to separate pure innovators from pure imitators. As in the traditional diffusion framework, the rate of adoption for innovators is \( p \). Given that these adopters are pure innovators, the imitation effect is absent \( (q = 0) \), which also means that \( r^I = 0 \) and \( m^I = 0 \). This leads to the following model for pure innovators:

\[
N_{t+1}^{E} = p \left( m^E - N_{t}^{E} \right) + r^E N_{t}^{E}.
\]

(3)

In contrast, the rate of adoption for imitators is \( q \). Given that these adopters are pure imitators, the influence’s effect is absent \( (p = 0) \), which also means that \( r^E = 0 \). This leads to the following model for pure imitators:

\[
N_{t+1}^{I} = q \left( N_{t}^{I} \left( m^I - N_{t}^{I} \right) \right) + r^I N_{t}^{I}.
\]

(4)

Because the market is assumed to be heterogeneous with respect to adoption and retention roles, we ascribe different values, \( r^E \neq r^I \), for the retention rates. However, if we assume the market to be heterogeneous only with respect to the adoption roles, we can ascribe the same retention rate, \( r \), to both segments as a special case extension. This assumption would yield the following model:

\[
N_{t+1} = p \left( m^E - N_{t}^{E} \right) + q \left( N_{t}^{I} \left( m^I - N_{t}^{I} \right) \right) + r N_{t}.
\]

(5)

Determination of Potential Innovators and Potential Imitators

As mentioned earlier, the makeup of the segment’s potential innovators \( (m^E) \) and imitators \( (m^I) \) is known to the pharmaceutical company based on the purchased physician survey information. Depending on the information available to the firm, the model can be accomplished in two ways. First, in the absence of knowledge about the prescription behavior of the physicians, all specialists can be classified as potential innovators \( (m^E = m^{SPEC}) \), and all primary-care physicians can be classified as potential imitators \( (m^I = m^{PCP}) \). Second, if the firm has knowledge about the prescription behavior of the physicians, then this behavioral knowledge can be used to estimate \( m^E \) and \( m^I \) more accurately compared to the first method based purely on demographics. Such unique information allows for more accurate sales forecasts. To verify this claim, we will use the history of four products in the pharmaceutical industry.

Using the first method, where \( m^E = m^{SPEC} \) (i.e., total number of specialist physicians who prescribe all products in the class in a specific time period) and \( m^I = m^{PCP} \) (i.e., total number of primary-care physicians who prescribe all products in the class in a specific time period) and assuming \( r^{SPEC} = r^{PCP} \) (\( r^{SPEC} \) is the repeat purchase rate for specialist physicians, and \( r^{PCP} \) is the repeat purchase rate for primary-care physicians), we get the following SDM-DEM model by substituting into Equation (5):

\[
N_{t+1} = p \left( m^{SPEC} - N_{t}^{SPEC} \right)
+ q \left( N_{t}^{SPEC} \left( m^{PCP} - N_{t}^{PCP} \right) \right) + r N_{t}.
\]

(6)

where \( N_{t}^{SPEC} \) is the number of specialist physicians who prescribe the focal product in time period \( t \) and \( N_{t}^{PCP} \) is the number of primary-care physicians who prescribe the focal product in time period \( t \).
Using the second method, where the estimation of innovators and imitators is based on actual knowledge of physician behavior patterns, we estimate \( m^r \) and \( m^i \) differently than in the first method. If we assume that all physicians who prescribe an ethical drug in the first \( \tau \) months of its launch are innovators and those who prescribe after the first \( \tau \) months are imitators, and if \( r^\text{RX} = r^\text{RXAT} \) \( (r^\text{RX} \) is the repeat purchase rate for physicians who prescribe the focal product within the \( \tau \) months that the product is on the market; \( r^\text{RXAT} \) is the repeat purchase rate for physicians who prescribe the focal product after it has been on the market for at least \( \tau \) months), then substituting into Equation (5) yields the following (SDM-BEH):

\[
N_{t+1} = f \left( \frac{N_t}{m} (n_{kX_1} - N_t) r^\text{RX} \right) + q \left( \frac{N_t}{m} (n_{kX_1} - N_t) r^\text{RXAT} \right) + rN_t,
\]

where \( m^\text{RX} \) is the number of physicians whose tendency is to prescribe new products after they have been on the market for at least \( \tau \) months, \( m^\text{RXAT} \) is the number of physicians whose tendency is to prescribe a new product within the \( \tau \) months that the product is on the market, \( N^\text{RX} \) is the number of physicians who prescribe the focal product in the time period \( t \) and whose tendency is to prescribe a new product within the \( \tau \) months that the product is on the market, \( N^\text{RXAT} \) is the number of physicians who prescribe the focal product in the time period \( t \) and whose tendency is to prescribe a new product after it has been on the market for at least \( \tau \) months.

Marketing-Mix Variables

We now address the issue of capturing the effects of the marketing mix. The separability of the adoption roles for current prescribers—innovators and imitators—should allow managers to allocate promotion efforts among them. In addition to detailing, pharmaceutical firms employ other marketing-mix elements to improve the total number of prescriptions. The segmented diffusion models specified in this paper capture the effects of marketing activities. The advertising efforts are operationalized by the number \( (j) \) of advertising pages purchased by the drug manufacturer. Although much of the extant literature (e.g., Iizuka and Jin 2003; Leeflang, Mijatovic, and Saunders 1992; Wittink and Clark 2002) uses journal advertising expenditures as a measure of advertising intensity, the use of the number of pages seems to be a more appropriate measure of advertising intensity for the pharmaceutical industry (Azoulay 2002; Berndt et al. 1995; Carter et al. 2006; Cleary 1992; Parsons and Abeele 1981). In a departure from much of the marketing literature, we allow not only the innovation process to be affected by advertising but the imitation and repeat purchase process as well. They are noted as \( j^i_s, j^s_i, \) and \( j^r_i, \) where \( j^i_s \) is the number of advertising pages targeted at non-prescribing innovators, \( j^s_i \) is the number of advertising pages targeted at nonprescribing imitators, and \( j^r_i \) is the number of advertising pages targeted at current prescribers. Allowing the influencer, imitator, and repeat purchase processes to be affected by advertising is dictated by the unique nature of the pharmaceutical industry, in which advertising is largely used to support the efforts of the sales representatives.

The promotional activities of the company are represented by the samples that a representative of the company offers the physician in a typical sales call. A review of the extant literature shows that researchers have long recognized the importance of this variable (Carter et al. 2006; Gönlü et al. 2001; Iizuka and Jin 2003; Manchanda and Chintagunta 2004; Mizik and Jacobson 2004; Parsons and Abeele 1981). This form of promotion is of particular importance in the pharmaceutical industry: the physician’s acceptance of the sample represents a certain degree of commitment to use the product. Furthermore, the sample often is used by the physician to provide the patient an initial supply of the drug. The aggregate number of samples delivered to physicians’ offices is denoted by \( s. \) Noting that samples are dispensed differently by each segment, we allow the innovator, imitator, and repeat purchase processes to be affected by sampling differently. These are specified as \( s^i_s, s^i_i, \) and \( s^i_r, \) where \( s^i_s \) is the number of samples distributed to nonprescribing innovators, \( s^i_i \) is the number of samples distributed to nonprescribing imitators, and \( s^i_r \) is the number of samples distributed to current prescribers.

Finally, the detailing activities of the producer under study are of central importance. Indeed, it is through personal selling that a long-term relationship between a producer and a prescriber is consummated and maintained. The intensity of detailing has been shown to be of central importance by researchers studying the impact of the pharmaceutical marketing mix (Carter et al. 2006; Hahn et al. 1994; Manchanda and Chintagunta 2004; Manchanda, Rossi, and Chintagunta 2004; Mizik and Jacobson 2004; Narayanan, Manchanda, and Chintagunta 2005; Parsons and Abeele 1981). A major input in the present model is, therefore, the detailing intensity, which we operationalize by the number of completed sales calls per period of time (denoted by \( d. \) ) Detailing strategy varies by segment. Therefore, we allow the potential innovator, potential imitator, and repeat purchase processes to be affected by sampling differently. These are specified as \( d^i_s, d^i_i, \) and \( d^i_r, \) respectively, where \( d^i_s \) is the number of details to nonprescribing innovators, \( d^i_i \) is the number of details to nonprescribing imitators, and \( d^i_r \) is the number of details to current prescribers.
Because marketing efforts provide long-lived information, it is important that cumulative information stocks be distinguished from current period new information flows (Berndt et al. 1995). For each prescription that physicians write, they are likely to be influenced by past marketing activity (Gönül et al. 2001). Noting that physicians are influenced more by recent activity than past, we define the cumulative detailing, journal advertising, and samples:

\[ X_t = \sum_{t=0}^{\infty} \delta^{t} x_t, \tag{8} \]

where \( X_t \) is the cumulative detailing, journal advertising, or samples at time \( t \); \( x_t \) is the flow of each at time \( t \); and \( \delta \) is the monthly discount factor. We set the monthly discount factor to 0.70 to yield a reasonable annual discount rate as did Narayanan, Manchanda, and Chintagunta (2005), which is consistent with the industry belief that the effect of these expenditures lasts for approximately six months. We denote the cumulative detailing and journal advertising as \( D_t \) and \( J_t \), respectively. Henceforth, for brevity, we use the terms detailing and samples and journal advertising to refer to the cumulative discounted detailing \( (D_t) \) and journal advertising \( (J_t) \) and cumulative samples \((S_t)\), respectively.

Here we use as a guideline the generalized Bass model (GBM) (Bass, Krishnan, and Jain 1994). As advanced by the GBM, the diffusion model with marketing variables should, under plausible regularity conditions involving the variables, reduce to the Bass model as a special case. The GBM also gives us guidelines for writing \( p \) and \( q \) as specific functions of decision variables. This would allow us to explain the influence of decision variables on the dimensions of the adoption and retention rates.

Although it may be convenient to proceed with the linear regression model (i.e., choosing the function \( f \) to the identity), that model is inadequate. It does not guarantee that the function \( f \) would exhibit diminishing returns. Diminishing returns may be modeled in a number of ways. In the present model, we impose yet another condition to retain, to the greatest extent possible, direct interpretability. Specifically, we require that the model coincide with linear regression when the marketing activity endogenous to the model is low.

To maintain the properties mentioned, we apply an \( \arctan \) (inverse tangent) specification of the marketing-mix variables, as did Freeman and Tse (1992). As noted by Freeman and Tse, \( \lim_{x \to \infty} \arctan x = \pi/2 \), this monotone function exhibits proper diminishing returns. At the same time, for the small values of the argument—that is, when the marketing activity is low, \( f \) reverts to the linear model, \( f(x) = x \).

We now offer new parameters for \( p, q, r \), and \( r \), and substituting into Equation (7), we get the segmented diffusion with marketing-mix (SDM-BEH-MM) model:

\[
N_{t+1} = \frac{2}{\pi} \arctan \left( \beta_0^E + \beta_1^E D_t^E + \beta_2^E S_t^E \right) \nonumber \\
+ \frac{2}{\pi} \arctan \left( \beta_0^R + \beta_1^R D_t^R + \beta_2^R S_t^R + \beta_3^R R_t^R \right) N_t. \tag{9} \]

The calibration results for the SDM-DEM (6), SDM-BEH (7), and SDM-BEH-MM (9) models are presented in the next section.

**CALIBRATION, FIT, AND PREDICTIVE ABILITY OF THE MODEL**

**Data**

To determine the physician behavioral information, we used a database supplied by IMS, a firm that collects data on physicians’ prescribing activity. We used the IMS data to classify the physicians based on their prior history in the therapeutic class. Once classified, we were able to follow the physicians’ prescribing behavior for the entire therapeutic class. We were then able to estimate of the number of monthly prescribers for each product studied \((N, N', N'')\). The class of drugs we selected for the analysis is ACE inhibitors. ACE inhibitors are considered part of vascular agents (USC 31000), which includes beta blockers and calcium channel blockers, and are prescribed to lower blood pressure. The ACE inhibitors class started in 1982 with Capoten, the first and only product on the market until Vasotec was introduced in 1985. Other competitors such as Prinivil (launched in 1987), Zestril (launched in 1988), Altace (launched in 1991), Lotensin (launched in 1991), and Accupril (launched in 1991) followed. In addition to physician characteristics data, such as specialty, years in practice, patients seen per week, and prescriptions written per week, information on the number of details of a product to a physician in a given month as well as the number of samples of each product left with the physician was reported.

We first selected physicians who prescribed any of the new products classified as vascular agents that were introduced in the previous 12 months that Capoten, the first ACE inhibitor, was introduced to the market. We then verified our selection by identifying physicians who prescribed Capoten as either potential innovators or potential imitators. Potential innovators were those prescribed Capoten at some time during the first six months after launch and continued to prescribe it for the next 12 months. We chose an initial timeline of six months.
because it is the commonly used industry convention (Glass and Rosenthal, 2004). All other physicians were characterized as being not new adopters or potential imitators. We assume that all physicians who were prescribers were included in this database. There were a total of 201,000 physicians (170,000 primary-care physicians and 31,000 specialists) in the database with 29,000 prescribing in the first six months (22,000 primary-care physicians and 7,000 specialists). Therefore, we have 29,000 potential innovators and 172,000 potential imitators.

For promotional expenditures, we also used IMS data. Reported data include the number of total new prescriptions written, the number journal advertising pages, the number of samples left by the sales representative, the number of details, and the average number of prescriptions written per physician. Because of the nature of the class of drugs, there was no direct-to-consumer advertising reported and that is therefore not included in this study. The data set from IMS provides data for the first 60 months that the product was on the market. We use 48 months of data for calibration while reserving 12 months of data for the test of predictive validity. We combine both IMS audits and formulate the SDM-BEH-MM model using the framework proposed by Carter et al. (2006). The framework facilitates an understanding of how new products are introduced into the pharmaceutical industry, including how resources are allocated. We used this allocation scheme to calculate the amount of each marketing activity that was targeted at each segment. For example, in the case of journal advertising, there were a total of 288,000 pages (J_2) during the second time period for Vasotec. Because there were a total of 17.6 percent of the innovators prescribing Vasotec by this period, it is reasonable to assume that the manager would allocate 17.6 percent of the journal pages to repeat purchases—that is, 50,909 (J_2)^2 pages and the remaining 229,091 pages to target nonprescribing innovators (J_2^8). Table 1 shows the descriptive statistics for the four products analyzed in the study.

Calibration Procedure and Fit of the Model

To capture both the main effect of segmented diffusion and its interaction with the marketing-mix variables, we estimate the three versions of the segmented model as:

1. SDM-DEM model (6), the segmented counterpart of the benchmark MWS model, where the potential prescribers are segmented into innovators and imitators. Here, specialists are categorized as innovators and primary-care physicians are categorized as imitators;
2. SDM-BEH model (7), where the potential prescribers are segmented by prescription behavior with time of adoption; and
3. SDM-BEH-MM model (9), an extension that includes the effects of segmentation by prescription behavior with time of adoption and marketing-mix.

The SDM-DEM and the SDM-BEH models are compared with the MWS model (Equation (1)). The SDM-BEH-MM model is then estimated to show the degree of improvement in sales forecasting and marketing-mix effectiveness as a result of segmenting physicians into potential innovators and imitators. These results are summarized in Tables 2 and 3.

Using a commercially available package (SPSS), we first estimate the pooled linear regression of each of the models and use the values of the coefficients as starting values for the nonlinear versions of the product-specific models.

As noted by Desiraju, Nair, and Chintagunta (2004), we can expect some serial correlation in the residuals, given that the cumulative variables are regressors, a priori. If that were the case, our models would be canonical linear models with a lagged dependent variable and serially correlated errors and would give inconsistent errors (Desiraju, Nair, and Chintagunta 2004). To test for serial correlation, we use a regression of the residuals from the base model on lagged values and run the Durbin (1970) h-test. Based on our results, we cannot reject the null hypothesis of no first-order autocorrelation in the residuals.

As stated by other researchers (Gatignon, Weitz, and Bansal 1990; Hahn et al. 1994; Lilien, Rao, and Kalish 1981; Ruiz-Conde, Wieringa, and Leeuward 2006), we should also be concerned about the possibility of multicollinearity of the marketing instruments even though multicollinearity does not actually bias results. If there was multicollinearity in the marketing instruments, the separated effects of expenditures in detailing, medical journal advertising, and samples could not be detected. Hence, we would not be able to determine the effect of each marketing instrument on the trial rate. A first indication for multicollinearity would be high first-stage (bivariate) correlation among independent variables, which was not the case for our data. Also, using the variance inflation factor (Stine 1995), the estimation of the SDM-BEH-MM model does not suffer from multicollinearity.

The comparisons among the calibrations of the aforementioned models center around two main measures—overall goodness of fit and the differences in values of specific parameters. As expected with diffusion models that include the peak in the data sets, the mean corrected $R^2$ values were high. We used Akaike’s information criterion (AIC = $-2 \times \text{log-likelihood} + 2 \times \text{number of parameters}$) to compare the models (Akaike 1974). The AIC reduces the likelihood of fit by adjusting for the number of parameters. The lower the AIC, the better fit the model, as we observed with the SDM-DEM model when compared to the MWS model.

The second dimension of usefulness of segmented diffusion is what we learn about the essential diffusion parameters.
<table>
<thead>
<tr>
<th></th>
<th>Prinivil</th>
<th>Zestril</th>
<th>Altace</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Standard Deviation</td>
<td>Mean</td>
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<tr>
<td>Prescribers</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Innovators</td>
<td>16,527.47</td>
<td>6,893.74</td>
<td>24,522.67</td>
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<tr>
<td>Imitators</td>
<td>6,809.60</td>
<td>1,762.15</td>
<td>12,788.27</td>
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<td>Trial Imitators</td>
<td>9,718.07</td>
<td>6,031.25</td>
<td>11,734.60</td>
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<tr>
<td></td>
<td>939.2</td>
<td>2,033.03</td>
<td>1,357.40</td>
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<td></td>
<td>5,916.02</td>
<td>2,079.66</td>
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</tr>
<tr>
<td>Dt (cumulative details)</td>
<td>1,400.70</td>
<td>1,522.54</td>
<td>1,198.81</td>
</tr>
<tr>
<td>DtI (cumulative journal pages)</td>
<td>1,522.54</td>
<td>1,198.81</td>
<td>1,094.10</td>
</tr>
<tr>
<td>DtR (cumulative journal pages)</td>
<td>1,198.81</td>
<td>1,094.10</td>
<td>698.32</td>
</tr>
<tr>
<td>Je (cumulative samples)</td>
<td>3,751.98</td>
<td>4,849.64</td>
<td>4,760.54</td>
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<tr>
<td>Ji (cumulative samples)</td>
<td>74,084.75</td>
<td>52,730.37</td>
<td>112,418.84</td>
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<tr>
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<tr>
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<tr>
<td>StI (cumulative journal pages)</td>
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<td>112,418.84</td>
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<tr>
<td>StR (cumulative journal pages)</td>
<td>76,829.19</td>
<td>49,222.22</td>
<td>134,232.27</td>
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</table>
### Table 2
**Coefficient Estimates and Fit Statistics: MWS Versus SDM-DEM Versus SDM-BEH**

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Vasotec</th>
<th>Prinivil</th>
<th>Zestril</th>
<th>Altace</th>
</tr>
</thead>
<tbody>
<tr>
<td>p</td>
<td>0.000</td>
<td>0.004</td>
<td>0.200&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.068&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td>q</td>
<td>0.206&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.236&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.176&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.000</td>
</tr>
<tr>
<td>r</td>
<td>0.930&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.923&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.783&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.980&lt;sup&gt;b&lt;/sup&gt;</td>
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<tr>
<td>AIC</td>
<td>14.52</td>
<td>14.39</td>
<td>13.96</td>
<td>30.66</td>
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<tr>
<td>Holdout Sample MAPE&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.102</td>
<td>0.083</td>
<td>0.074</td>
<td>0.186</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Vasotec</th>
<th>Prinivil</th>
<th>Zestril</th>
<th>Altace</th>
</tr>
</thead>
<tbody>
<tr>
<td>P</td>
<td>0.031&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.028&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.013&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.033&lt;sup&gt;c&lt;/sup&gt;</td>
</tr>
<tr>
<td>Q</td>
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<td>0.457&lt;sup&gt;f&lt;/sup&gt;</td>
<td>0.285&lt;sup&gt;f&lt;/sup&gt;</td>
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</tr>
<tr>
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<td>0.907&lt;sup&gt;b&lt;/sup&gt;</td>
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<td>0.952&lt;sup&gt;c&lt;/sup&gt;</td>
</tr>
<tr>
<td>AIC</td>
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<td>8.31</td>
<td>5.39</td>
</tr>
<tr>
<td>Holdout Sample MAPE&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.147</td>
<td>0.146</td>
<td>0.115</td>
<td>0.135</td>
</tr>
</tbody>
</table>

Notes: Holdout: 12 months; AIC = Akaike information criteria = (2/number of observations) * (log-likelihood-number of parameters). * Mean absolute percentage error (MAPE) = 100/\(\sum (N_t - N_t') / N_t\), where \(N_t - N_t'\) is the difference between the actual number of prescribers \(N_t\) and the forecast \(N_t'\). The MWS model is as in Equation (1); the SDM-DEM model is as in Equation (6); the SDM-BEH model is as in Equation (7).<sup>a</sup> p < 0.25; <sup>b</sup> p < 0.1; <sup>c</sup> p < 0.05; <sup>d</sup> p < 0.025; <sup>e</sup> p < 0.01; <sup>f</sup> p < 0.001.

The impact of the segmentation here is most dramatic. Specifically, we noted that the calibration of the MWS model suggests that propagation of the product is essentially retention driven. The retention rates for all four products are very high, notably higher than the typical rate \(r = 0.8\) reported by industry experts (Carter et al. 2006). Among the four products, the estimates of \(r\) vary insignificantly between 0.93 and 0.98. On the basis of this model, a product...
manager would concentrate on ensuring retention among his or her customers.

A segmented diffusion model on the basis of physician's specialization yields better results. For Altace, the product for which the effect is the most visible, the SDM-DEM model estimates retention at the rate of 81 percent. From a descriptive standpoint, this value is very close to the actual one in the pharmaceutical industry. Normatively, a product manager is more likely to spread the resources among the adoption and retention mechanisms rather than to concentrate on retention alone.

The differences between the MWS and the SDM models are not limited to retention. For all products that have not been on the market for an extended period (Prinivil, Zestril, and Altace), the coefficient of imitation in the SDM model is significantly different from that of the MWS model. Specifically, the MWS model suggests that imitation is entirely inessential (q = 0 for Prinivil). In contrast, the SDM-DEM model does not assign a zero rate to any segment. In fact, for the segment of imitators (that is, where imitation is concentrated), the rate is substantial (q = 0.18).

Note that the SDM-DEM model estimates of p and q are expected to have greater values than those of the MWS model. Whereas the SDM-DEM model estimates shown in Table 2 are for the relevant segment alone (p for innovators and q for imitators), the MWS model reports an averaged, nonsegmented value. Perhaps more crucial, the SDM-DEM model recovers from the boundary solution p and q reported for some products in the case of the MSW model. Thus, the main effects of segmentation by adoption roles are manifest not so much in improvement of the model fit to the data, but rather in a more accurate picture of the adoption process. In particular, the SDM-DEM model corrects for the overestimation of retention by the MWS model (at least for the data sets under study) and its underestimation of imitation rates.

For all products that have not been on the market for an extended period (Prinivil, Zestril, and Altace), the coefficient of imitation in the SDM-BEH model is significantly different from that of the SDM-DEM model. Specifically, the SDM-DEM model suggests that imitation is immaterial (q = 0 for Vasotec and Prinivil). In contrast, the SDM-BEH model assigns the rate of 0.122 and 0.413 to Vasotec and Prinivil, respectively.

Segmented Diffusion and Marketing Mix

The segmented diffusion models based on the knowledge of physicians' prescription behavior gains further importance when it is combined with the effects of the marketing mix. Intuitively, this importance is an expected effect as prescribers, innovators, and imitators are expected to have different response functions to the marketing mix. When the marketing-mix variables are included endogenously, the SDM-BEH-MM model uses the behavioral differences of innovators and imitators more accurately.

The parameter sign indicates whether the marketing activity has been increasing or decreasing the trial and repeat prescribing. For personal selling (i.e., the number of completed calls), a positive sign suggests that calls have been productive and a zero value for the coefficient indicates that calls were not very productive. A positive sign could indicate higher than expected average minutes per call. We would expect, however, that for the two more recently introduced products (Zestril and Altace), detailing would be more important in terms of establishing the product. Additionally, positive signs for both personal selling and product sampling may indicate commitment from physicians, but those signs might also indicate oversampling. In this case, the physician may prescribe the product but not distribute a sample with each new prescription. In any event, personal selling is expected to be a positive influence for each segment accompanied with a positive sign for product sampling as well (i.e., the sales representative drops more samples to the higher volume offices).

For the products we studied, 10 of the 12 personal selling parameters (βₕ₁, βₙᵢ, and βₛᵣ) were significant. Of the 10, five had negative signs. All of the retention personal selling parameters (βₛᵣ) were significant, with three of the four positive. The negative parameter for Altace suggests that the strategy for this product appears to have been to efficiently spend time converting innovators and oversellers for retention. On the other hand, managers for Zestril seem to have decided to match the personal selling strategies of older products and were less efficient in converting innovators than were those for Prinivil. This difference in strategy could explain why Altace, introduced at the same time as Prinivil, outperformed Prinivil in obtaining and retaining prescribing physicians.

Medical journal advertising is generally expected to have either a positive or no influence. Positive signs for advertisements are generally seen for innovators when the goal of promotion is education. One of the four journal advertising parameter estimates (βₙᵢ) was positive in the proposed model. Where the parameter estimates are positive and significant for r, the overall retention rate is high (see Zestril). A highly significant journal advertising coefficient is a strong indicator of a strong retention rate (r > 70 percent).

The constants βₕᵢ, βₚᵣ, and βₛᵣ were significant in eight of nine cases, with negative signs in one instance. The retention constant (βₛᵣ) was highly significant for each product, which suggests that the likelihood of retention is captured by some marketing and exogenous factors.

Likelihood of Adoption and Retention

Because the values of rates p, q, and r are marketing-mix dependent in the SDM-MM-BEH model, the comparison of
their values cannot be made directly from Table 3. These rates as functions of time are depicted in Figures 1–4.

If we let \( p \) equal the likelihood of trial by innovators and \( q \) equal the likelihood of trial by imitators, we can note that these likelihoods should decrease over time. That is, the longer the product has been on the market, the less likely sales will be generated by new prescribers because more resources are allocated to repeat prescribers than to nonprescribers. The industry experts have noted that \( r \) (the likelihood of retention) should reach the peak of 100 percent before it begins to fluctuate, never dropping below 80 percent after reaching the peak. The retention rate is determined by the percentage of resources allocated for that purpose as overall resources allocated for the product decrease. Also, the reduction in retention could be attributed to first-time prescribers who move back to the potential prescriber group. This action will be evident by a corresponding increase in \( r \) because retention resources are allocated first.

From the figures, we see that the plots of the time-varying values for the likelihood of trial by innovators and imitators clearly indicate that the likelihood of trial declines over time as companies allocate the majority of their resources to retaining prescribers and combating competitive activities. This finding is consistent with industry experience that prescriber retention becomes more significant the closer the product gets to patent expiration. As expected, for all four products, \( p \) was consistently much lower than \( q \) or \( r \). Thus, we conclude that the conversion rate of innovators falls far below that of imitators.

As shown in Figure 4, retention rates stabilize over time. Industry experts note that as the market and the product mature, prescriber retention becomes more difficult because new products compete for company resources and many new...
products are introduced. Declining rates of retention were proportional to the increases in imitator trial. As prescribers move from potential to trial, they may require more detailing time to be established as retained prescribers. Our model does not differentiate between types of retention (i.e., whether they are short-term or long-term prescribers) because each requires a different effort.

Predictive Validity of the Model

In the previous section, we discussed the overall fit and predictions of the segmented and aggregate models. Next, we turn to the issue of predictive validity that we have verified in a holdout sample of product histories with duration of 12 months. The results are summarized in Table 3.

The holdout samples for each product provide an opportunity to challenge how well the model predicts the number of users during the time periods subsequent to the calibrated period. We also can observe how well the model predicts the actual values by noting the ratio of predicted to actual users. As shown in Table 3, we calculate the mean absolute percentage error (MAPE = 100/nΣNt−Nt′/Nt, where Nt−Nt′ is the difference between the actual number of prescribers Nt and the forecast Nt′). MAPE is a measure that corrects the “canceling out” effects and also takes into account the different scales at which this measure can be computed and thus can be used to compare different predictions. The lower the MAPE, the better the fit of the model. This is similar to what we observed with the SDM-BEH model when compared to both the SDM-DEM and MWS models. This allows us to assess the prediction accuracy among the three models using a 12-month (holdout sample) forecast. The measures are designed to evaluate ex post forecasts—that is, forecasts for which the exogenous variables do not have to be forecasted.

Based on the MAPE, the SDM-BEH-MM model outperformed the SDM-BEH, SDM-BEH, and the MWS models. Moreover, the SDM-BEH-MM model offers more diagnostic information, which is important to managers who are not willing to trade forecast accuracy for useful diagnostic information.

DISCUSSION

We investigated the influence of the knowledge of physicians’ prescription behavior on the accuracy of sales forecasts and its influence on marketing-mix strategy. The paper calibrates segmented diffusion with retention sales forecasting models. The results with data from four pharmaceutical products show
that segmented diffusion models that incorporate physicians’ prescription behavior significantly improve the accuracy of sales forecasts. The results also demonstrate the impact of segmentation based on knowledge of prescription behavior on marketing-mix strategy.

Primary Contribution

The paper’s findings contribute to the literature in marketing by demonstrating that in a detail-intensive industry, segmentation based on the knowledge of physicians’ prescription behavior does improve the accuracy of sales forecasts. The paper specifies three models that are tested with data from four products in the pharmaceutical industry. The three analytical models are (1) segmented diffusion model based on physicians’ demographic information (SDM-DEM), (2) segmented diffusion model based on the knowledge of physicians’ prescription behavior (SDM-BEH), and (3) segmented diffusion model that incorporates knowledge of physicians’ prescription behavior as well as marketing-mix information (SDM-BEH-MM). The results show that the SDM-DEM model is more accurate in forecasting sales compared to the standard diffusion with retention model. However, the SDM-BEH is the most accurate model. It provides more accurate sales forecasts compared to the standard diffusion with retention model and the SDM-DEM model. We also find that the segmented approach to marketing-mix strategy significantly improves the fit of the model.

Managerial Implications

As the pharmaceutical industry comes under attack for its marketing practices, it is imperative that the industry focus on taking advantage of the unique knowledge that is available from physicians’ surveys about their prescription tendencies based on years of detailing by the sales force. With the volatility of repeat purchase rates and of marketing-mix activity, the use of segmentation based on the past prescribing behavior of those physicians seems to offer increased value. The SDM-BEH model framework proposed in this paper shows that pharmaceutical companies can significantly improve the accuracy of their sales forecast.

Marketing managers can use the proposed model offered in the study not only to forecast sales but also to provide diagnostic information on how potential prescribers are likely to respond to marketing stimuli. The parameter signs indicate marketing strategy, such as oversampling, as well as how each segment responds to certain marketing activities. Other models appear to provide limited diagnostic information regarding marketing-mix variables. The model presented here can be used by managers before they introduce a new product so that they may adjust both their percentages of calls and the marketing resources allocated to each segment to optimize sales. With unlimited resources, products could reach maximum potential, although the following constraints can limit the volume of sales: (1) the budget allocated for marketing and sales expenditures, (2) the percentage of the total sales force allocated to the product, (3) the number of sales representatives, (4) the number of calls per day, and (5) revenue goals and management priorities.

To show the practical application of the proposed model, we selected Accupril, an ACE inhibitor that was introduced into the market after the calibration period for Prinivil. We take advantage of the knowledge gained from the parameter estimates of Prinivil and apply it to generate the forecast for the new product. The parameters of the proposed model were used to forecast the number of prescribers for Accupril. A comparison of the actual and forecasted prescriber levels for the Accupril is presented in Figure 5. Except in the first few months, the model generated a ratio of predicted to actual prescribers of 0.95. It is important to note that there is generally very high promotional activity in the first few months of new product
introduction in this industry. Because our model is dependent on personal selling activity, it will predict higher than actual levels of usage in the first few periods. Nevertheless, managers could use the model to adjust the mix of each element of marketing expenditures and to determine the optimal levels of marketing activity.

Although the relationship between the pharmaceutical company and the physician has many effects on both parties involved, we focused in this paper on the informational outcomes of the relationship. The paper argues that as a result of the ongoing relationship between the pharmaceutical company and the potential prescribers, the adoption roles of the latter become observable, thus enabling the company to segment the market on that basis. The segmented diffusion models, SDM-BEH and SDM-BEH-MM, incorporate the segmentation scheme based on the information available. As expected, the results show that the additional information regarding the adoption roles makes a positive impact on the performance of the model. The overall fit improves most notably in the SDM-BEH-MM model, which also incorporates the marketing-mix variables, and the characteristic rates of the process (i.e., those of innovation, imitation, and retention) are predicted more closely to the values empirically observed.

Limitations and Future Research

The specified models were tested with pharmaceutical products alone. This limits the generalizability of our findings to only the pharmaceutical industry. The paper demonstrates how the additional information on adoption roles affects forecasting of the total number of users. The total value of sales depends not only on this number but also on the rate of purchase. In addition to the present aggregate-level model, it would be useful, therefore, to formulate an individual-level model that incorporates the additional information and predicts the buying rate. Taken together, these two models are capable of forecasting the (dollar) value of sales.

Another meaningful direction for future research emerges from the observation that the models in this paper are descriptive. Segmentation by adoption roles poses the additional question of optimal allocation of resources across segments. Furthermore, one would expect that the additional information translates into an increase in a firm’s profits. It would be interesting, therefore, to explicate the economic (in contrast to measurement or forecasting) value of knowledge about physicians’ prescription behavior and about activities that supply this information.

Finally, the modeling aspects of incorporating the marketing-mix variables into the MWS model have not been the main focus of the paper. We have been interested in them inasmuch as they have interaction effects with segmentation. The results indicate, however, that this issue may be of independent interest because of the impact of the marketing controls, at least jointly with the proposed segmentation strategy based on historical prescription behavior.

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