



Marketing Science Institute Special Report 07-209

Modeling Co-Existing Business Scenarios with Time Series Panel Data: A New Segmentation Approach for Better Targeting and Maximizing Long-Term Impact of Marketing Activity

Catarina Sismeiro, Natalie Mizik, and Randolph E. Bucklin

© 2007 Catarina Sismeiro, Natalie Mizik, and Randolph E. Bucklin

MSI special reports are in draft form and are distributed online only for the benefit of MSI corporate and academic members. Reports are not to be reproduced or published, in any form or by any means, electronic or mechanical, without written permission.

**Modeling Co-Existing Business Scenarios with Time Series Panel Data:
A New Segmentation Approach for Better Targeting and Maximizing Long-Term Impact
of Marketing Activity**

Catarina Sismeiro[§]

Natalie Mizik

Randolph E. Bucklin

November 2007

[§] Catarina Sismeiro is Lecturer, Tanaka School of Business, Imperial College, London. Natalie Mizik is Gantcher Associate Professor of Business, Graduate School of Business, Columbia University, New York. Randolph E. Bucklin is Peter W. Mullin Professor, UCLA Anderson School, Los Angeles, CA. The authors thank an anonymous collaborating firm for providing the data used in this study. Correspondence to sismeiro@imperial.ac.uk, Tanaka Business School, Imperial College London, South Kensington Campus, London SW7 2AZ, Phone: +44 (0)20 7594 9108, Fax: +44 (0)20 7823 7685.

Abstract

Due to customer segmentation, multiple types of dynamic business scenarios (business-as-usual, escalation, hysteresis, and evolving business practice; Dekimpe and Hanssens 1999) may co-exist within a single product market. The authors develop an approach to model this phenomenon with time series panel data. Unit-root tests are used to group panelists by whether or not outcome (e.g., sales) and marketing activity (e.g., advertising, promotion) variables are stationary or evolving. This produces four clusters corresponding to each business scenario. Next, panel-data vector autoregressive models appropriate for each panelist cluster are estimated to assess the dynamics and the magnitude of the response to marketing effort. The approach is applied to physician panel data on drug prescriptions and direct-to-physician promotions. Estimation results show markedly different response dynamics (as captured by impulse response functions) and elasticities across the physician groups. The approach also produces better in-sample and holdout fits than pooled data models. For firms that track customer-level marketing activity and response over time, a segmentation based on dynamic business scenarios provides a new tool for targeting and efficient marketing resource allocation.

Keywords: Time series analysis, panel data, segmentation, marketing strategy

INTRODUCTION

In markets where sales and/or marketing activity may be evolving, econometricians have emphasized the importance of handling potential non-stationarity in time series data. These “persistence modeling” methods employ unit-root tests to ascertain the stationary or evolving nature of the data and estimate appropriate Vector Autoregressive (VAR) models to represent the market dynamics and long-run effects. Marketing researchers have demonstrated how time series methods on aggregate historical data can identify different dynamic business scenarios. Using the nomenclature advanced by Dekimpe and Hanssens (1999), these scenarios are business-as-usual, escalation, hysteresis, and evolving business practice (or co-evolution). Implications for return on marketing spending, marketing strategy, and profitability can differ dramatically across these scenarios. The possibility that different dynamic business scenarios may co-exist within a single market, however, has not been investigated.

Our objective is to develop and illustrate an approach that uses time-series panel data to investigate whether different dynamic business scenarios may *concurrently* exist across a firm’s customers, and what they imply strategically. If these scenarios concurrently exist, some customers (or segments) present the firm with “business as usual,” others represent the perils of “escalation,” and still others the opportunities in the “hysteresis” or “co-evolution” scenarios. To study this phenomenon, we combine VAR-based persistence modeling with cross-sectional segmentation.

Our approach relaxes the implicit assumption that the time series properties of the data are uniform across panelists or cross-sections. We first test for the order of integration in the data using unit-root tests at the disaggregate level. We conduct two sets of tests, one for the outcome variable and one for the covariates. Then, we form four groups and specify an appropriate panel VAR (PVAR) model for each group. By estimating the separate PVAR models, we can

investigate potential differences in response dynamics across customers (which may be useful for targeting purposes). We can also investigate whether the overall response measures computed from the separate PVAR models differ from the response measures obtained from a pooled PVAR based on the entire sample. Lastly, we can determine which approach (unified pooled or scenario-specific PVARs) produces the best fits in-sample and for holdout. In sum, we seek to improve model selection and inference, increase predictive validity, and enable managers to enhance the productivity of marketing resources by better targeting at the individual and/or segment level.

To test our modeling approach, we use time series panel data from a pharmaceutical prescription drug market. The data at the individual physician level is of high quality for both pharmaceutical prescribing and direct-to-physician promotion (DTP). This allows us to undertake panel VAR modeling and to investigate the potential segmentation in the dynamic response to marketing effort. Another reason for using pharmaceuticals is the likelihood of observing co-existing business scenarios for a single prescription drug. Differences across doctors in age and experience, practice size and type, risk aversion, and adoption timing could lead to differences in the level of time series integration for prescribing decisions at the individual level. As pharmaceutical companies target different levels of marketing activity across physicians, it can give rise to evolution versus stationarity of DTP activity at the individual level.

We find that, indeed, multiple dynamic scenarios co-exist within a single drug market each with dramatically different response patterns and overall response magnitudes. We present evidence that common segmentation heuristics used in the industry fail to produce meaningful response differences across groups. This supports the superiority of a scenario-based segmentation and suggests that it may lead to significant efficiency improvements in marketing

resource allocation. Finally, we also report results of a simulation study where we assess the performance of our procedure under controlled conditions.

In the next section, we outline our modeling approach. We then describe the data used in our empirical application and specify appropriate PVAR models for our data. The following section describes the empirical results obtained from applying our approach, provides an assessment against benchmark models, and discusses implications for segmentation, targeting, and resource allocation. The final section summarizes and concludes.

BACKGROUND

Application of VAR-based persistence models to marketing data has yielded key insights about dynamic response in a series of studies conducted on aggregate-level data (e.g., Dekimpe and Hanssens 1995, 1999; Bronnenberg, Mahajan, and Vanhonacker 2000; Pauwels, Hanssens, and Siddarth 2002). Such differences highlight the importance of (1) accurately diagnosing the scenario under which a firm is conducting business, and (2) estimating a VAR model appropriate for the level of data integration. Horváth and Franses (2003), for example, use the well-known Lydia Pinkham sales and advertising data to provide a compelling empirical demonstration of the importance of dynamic scenario identification and the use of appropriate VAR models with aggregate data.

Another branch of marketing science has extensively studied disaggregate-level data in consumer panels, based largely on UPC scanner data for packaged goods. This stream has emphasized the study of short-run response to marketing activity across individual decision makers and the potential for segmentation in individual level response (e.g., Kamakura and Russell 1989; Bucklin, Gupta, and Siddarth 1998; Kamakura and Wedel 1998). Despite the emphasis on short-run response in individual level studies, a number of authors working with

individual scanner panel data have also attempted to examine dynamic effects or long-run changes in response parameters (e.g., Papatla and Krishnamurthi 1996, Mela, Gupta, and Lehmann 1997). These studies found empirical evidence for long-run changes in the nature of consumer response, but they did not investigate the time series properties of the underlying data (i.e., they did not undertake a persistence modeling approach).

Pauwels, Hanssens and Siddarth (2002) applied VAR-based persistence modeling to UPC scanner data. The authors analyzed aggregate UPC scanner data across multiple packaged goods categories. The analyses revealed that evolution (i.e., the presence of unit-roots) was uncommon in aggregate level scanner data, a phenomenon they attributed to the maturity of most products studied. Such patterns, however, need not be universal for consumer packaged goods and might depend on, for example, the product life-cycle stage. In a study of new product sales and distribution, Bronnenberg, Mahajan, and Vanhonacker (2000) analyzed aggregate-level sales and distribution data for the launch phase of the ready-to-drink tea category. As one might expect in a new product setting, they found empirical patterns consistent with co-evolution in the data for sales and distribution.

Just as different products might be at different stages of the life-cycle, so might be individual consumers or markets. Indeed, most theories of new product diffusion and new product adoption rely on the presence of consumer segments that learn about and adopt the product at different times (Bass 1969, Rogers 2003). As a result, one limitation of using aggregate-level time series data for dynamic scenario analysis is that it requires the investigator to treat *all* of the firm's customers as falling into a single scenario classification. This means that one must describe the dynamics of the entire market in the same way (e.g., business-as-usual). We contrast this with the widespread notion that markets may be segmented, and suggest

that multiple business scenarios may co-exist at the same time.

To take an example from our empirical application, consider the case of a new prescription drug in the final stages of the growth phase in its life cycle. One group of doctors began prescribing the drug to their patients early on. A second group is just beginning to adopt, switching over to the new drug from other treatments. For the first group, a temporary increase in advertising may produce only short-run effects (business as usual) but for the second group, the same investment may produce long-run or permanent effects (hysteresis). If analysis is restricted to aggregate-level data, there is no opportunity to observe the heterogeneity in dynamic response. This limitation highlights the need for time series researchers in marketing to give more emphasis to the analysis of individual customer (or segment) level data when it is available. Indeed, in a recent review paper, Pauwels et al. (2004) explicitly call for more research on the problems associated with cross-sectional heterogeneity in VAR-based models.

Lim, Currim and Andrews (2005) present a VAR-based analysis of scanner panel data that takes a step in this direction. They first assign panelists to *a priori* determined segments based on their brand loyalty (loyals versus switchers) and category usage rates (heavy versus light users). Panelists' choice observations were then aggregated to the segment level where separate VAR models were estimated. Estimates from these models revealed differences in response and adjustment period across segments. Perhaps owing to the nature of the mature product categories involved, unit-roots showed the aggregate time series to be almost universally stationary (similar to the results of Pauwels et al. 2002). This constrained the analysis of response dynamics to differences within the "business-as-usual" scenario.

Another limitation of estimating aggregate-level VAR models is the difficulty in handling the typically large number of endogenous variables and/or lag effects. A lack of degrees of

freedom has led researchers to impose a variety of restrictions on the structure of VAR models in order to hold down the number of parameters. Panel data can be used to dramatically increase the degrees of freedom, under appropriate pooling assumptions (e.g., fixed effects, Horváth and Wieringa 2003). Thus, panel VAR (PVAR) models can also offer the advantage of imposing fewer restrictions on lag structure and explanatory variables.

MODELING APPROACH

In a seminal paper, Granger and Newbold (1974) highlighted the “spurious regression” problem where unrelated unit-root series will appear related with a very high probability if conventional estimation methods are employed. This finding stimulated interest in appropriately modeling time series dynamics and led to a multitude of research studies testing dynamic patterns and addressing the advantages and disadvantages of various modeling approaches to control for the dynamic properties of the series (e.g., Plosser and Schwert 1977, Stock and Watson 1988, Nelson and Kang 1984). More recently, researchers in econometrics have begun scrutinizing the methods involved in the analysis of *panel* data and how these data can be used to improve the study of time series dynamics (e.g., Baltagi and Kao 2000, Horváth and Wierenga 2003). As a result, new methodological advancements in panel data analysis provide a foundation for researchers in marketing to bring together the two streams of research: (1) the study of segmentation with panel data and (2) the study of long-run dynamic effects with (potentially) evolving time series data.

Our approach builds on these advancements and is designed to be applied to time series data, encompassing both performance and marketing activity variables, available for a large cross-section of either decision-makers or markets. Methodologically, it is based on unit-root tests and PVAR modeling techniques. It proceeds to (1) determine whether multiple dynamic

business scenarios are concurrently present in a single product market and (2) model these scenarios with the appropriate PVAR formulation. We note that the method is generally applicable to panel or cross-section data sets where different dynamic business scenarios are thought to co-exist. Thus, it is not limited to individual-level data, but can be applied where cross-sectional units are, for example, markets or geographical regions.

The Proposed Procedure

Our approach proceeds as follows. First, we conduct unit-root tests for the outcome and marketing variables for each panelist *at the individual level*. A number of different unit-root tests have been advanced in the time series literature and many issues have been raised about their relative power and reliability (Maddala 1992). The segmentation approach we propose relies on the outcomes of a unit-root test, but does not depend on the specific unit-root test employed. In a given empirical application, the choice of a unit-root test should be determined by the researcher's preferences or objectives (Greene 2003).

Based on the unit-root test results, we classify each panelist into one of the four dynamic business scenarios: evolving business practice (co-evolution), hysteresis, escalation, or business-as-usual.¹ We then specify the PVAR models for each group such that variables enter either in levels (if they were deemed stationary) or in differences (if evolving) depending on the unit-root test results (e.g., Campbell and Perron 1991). Figure 1 depicts our group assignment rules and stylized representations of the dynamic patterns of marketing activity and sales response.

In Figure 1, Group 1 is the “Evolving Business Practice” scenario. Here, all variables are evolving (note the permanent change in the stylized depiction of time series for both sales and

¹ In the appendix, we present the results from a simulation study designed to assess how well the ADF test classifies panelist data into the four scenarios. We find that the test performs well in recovering true assignments. For example, across all 32 cells in our simulation study, the mean percentage of individuals correctly assigned is 80 percent.

marketing activity). As such, in the PVAR model for Group 1 all variables enter the model in differenced form. Group 4 is the “Business-as-Usual” scenario. Here, since all variables are stationary, they all enter the PVAR model in levels. Group 2 is the “Hysteresis” scenario (evolving in sales, stationary in marketing activity) and Group 3 is the “Escalation” scenario (stationary in sales, evolving in marketing activity). Both Group 2 and Group 3 are modeled with mixed PVARs. The outcome variables (e.g., sales) enter the model in levels for Group 3 and in differences for Group 2. Marketing activity variables enter in levels for Group 2 and in differences for Group 3. In order to address potential endogeneity in marketing activity and response, all variables for all groups are treated as endogenous in the PVAR model specifications.

The next step in our approach is to ascertain the presence of any cross-sectional heterogeneity in the levels data. To do this, we conduct Hausman specification tests (Hausman 1978) for the presence of fixed individual-specific effects for each equation entering a PVAR model with a dependent variable in levels. When necessary, the PVAR model is then specified to incorporate fixed effects. Note that for variables entering the PVAR models in differenced form, any individual-level fixed effects are differenced out.

All of our proposed PVAR models also include time-specific indicator variables to control for unobserved time-specific effects and to ensure that the models are robust to structural changes. The potential benefits of intercept corrections such as the indicator variables we employ have been long recognized (e.g., Theil 1961). For example, intercept corrections can act as equilibrium-correction terms and serve to make dynamic models robust to changes and structural breaks (Clements and Hendry 1999).

Further, each PVAR model is also tested for the appropriate number of lagged terms to include. Lag length can be determined by selecting the model with the best Schwarz criterion.

After estimation of the appropriate PVAR models for each scenario, we obtain impulse response functions and gauge the dynamic effect of changes in the marketing variables.

To provide a benchmark for our results, we estimate a pooled PVAR model across all panelists. We estimate the pooled PVAR in both levels and differences. We assess the improvement in prediction (if any) and changes in the nature of dynamic market response by going from a pooled model to a model incorporating co-existing business scenarios. In the next section we review recent empirical studies on pharmaceuticals, the industry we study in our application, and present our empirical application.

RESEARCH ON PHARMACEUTICAL MARKET DYNAMICS

Recent studies on pharmaceutical marketing have used different types of data as well as different methods to investigate the effects of marketing activity on physician prescribing decisions. Using aggregate data, Dekimpe and Hanssens (1999) employed VAR models to investigate the long-run effects of changes in marketing activity and to draw implications for profitability. Their study did not examine the potential for differences in response across physicians. Narayanan et al. (2005) also used aggregate-level data on new prescriptions to investigate temporal differences in the role of detailing and other marketing expenditures. The study, however, did not address the time series properties of the data.

Studies conducted on disaggregate-level data sets have usually investigated the role of heterogeneity in response across physicians. Using data collected from physician diaries, Gonul et al. (2001) studied the effect of detailing and sampling on the choice of drug to prescribe. They estimate a multinomial logit choice model and used latent classes to incorporate heterogeneity in some model parameters. Manchanda and Chintagunta (2004) used a Poisson model to study the effect of marketing activity on the number of prescriptions written by physicians on a quarterly

basis. Manchanda et al. (2004) also focused on heterogeneity but extended the analysis to incorporate potential endogeneity in prescribing and marketing activity. Though the authors estimate carryover effects of the marketing variables, they do not investigate the time series properties of the data. Narayanan and Manchanda (2005) used data from physician self-reports to estimate an individual-level model of prescription choice within a therapeutic class, finding significant differences across physicians in learning rates and response to pharmaceutical detailing. Finally, Mizik and Jacobson (2004) employed fixed effects instrumental variable estimation to address both heterogeneity and endogeneity in physician response to direct-to-physician marketing activities.

In sum, existing disaggregate-level pharmaceutical models have accounted for some dynamic effects (e.g., carryover effects and inclusion of lagged dependent variables). To the best of our knowledge, however, no one has investigated the time series properties of the data at the individual physician level and attempted to model the co-existence of multiple dynamic business scenarios.

EMPIRICAL APPLICATION

Data

The data we use in our application are from an anonymous panel of 5,000 U.S. physicians tracked monthly over a period of approximately two years (October 2001–August 2003) for a single drug. Due to confidentiality requirements, the identity of the drug and the company are masked. For each physician in the panel, the data set includes general demographic information (age, gender, and year of graduation), the number of new prescriptions written in each month, and the number of sales calls (details) and samples received in each month.

To focus on decision-makers who are at least minimally involved with the product, physicians with very low levels of prescribing activity or of marketing activity directed towards them were removed from the sample. Physicians were included if they prescribed the drug two or more times per year and had at least one sales call per year. To avoid undue influence from outliers, we also removed a handful of physicians with extremely high levels of prescribing activity (top one-half of one percent). According to the collaborating firm, the activity assigned to these physicians might reflect large group practices or hospitals, rather than represent individual doctors. After removing non-qualifiers, we retained 3,942 physicians for further analysis (79% of the original sample). We then randomly assigned two-thirds (2,628) of these physicians to the estimation sample and the remaining one-third (1,314) to a holdout sample.

Table 1 presents a summary of descriptive statistics for the final sample of 3,942 physicians, including both estimation and holdout samples. Across physicians, the mean number of new prescriptions written per month is 3.33. The mean number of details is 3.09 and the mean number of samples received is 15.71. It is important to note that the prescriptions data at the individual level are not count data. Because prescription size (i.e., the number of pills) varies significantly across prescriptions, the prescription data are recorded in “standardized” prescription units issued in a given month.

The range statistics included in Table 1 show that the data sample includes a wide cross-section of physicians, with panelists varying significantly in experience, level of prescribing, and attention they receive from pharmaceutical sales representatives. The years since graduation variable is based on the number of years between the physician’s graduation year and the year 2001 (the first year of our sample period). Physicians were also assigned a national decile value by the company based on their past prescribing volume. A decile assignment of 7, for example,

indicates that the doctor is in the 70th percentile for new prescriptions volume. The average decile value was 6.17. According to the collaborating firm, the characteristics of our sample are representative of the general population of physicians who prescribed this drug.

Figure 2 graphs the aggregate time series of key variables over the study period. An examination of the time series patterns in Figure 2 suggests possible evolution in the aggregate series for prescriptions, detailing, and sampling. ADF tests performed on the *aggregate* data shown in Figure 2 are all close to the 95% critical value, with prescriptions marginally evolving and marketing activity stationary.

Unit-Root Tests

We conducted individual-level ADF unit-root tests on all 3,942 physicians in the sample for new prescriptions and the marketing activity variables (details and samples).² We choose to rely on the ADF test to classify our panelists into the evolving or stationary conditions for several reasons. First, our data exhibit significant lag structure and the ADF test has been shown to perform well in Monte Carlo studies under these conditions. Indeed, it increases in power as the number of lags increases (Harris 1992, Haug 1996).³ Second, we select the ADF test because the presence of a unit-root is the null hypothesis. The consequences of modeling a stationary process as having a unit-root are less severe than vice-versa. For example, Plosser and Schwert (1977) emphasized that the negative consequences of ignoring unit-roots amount to false inferences and incorrect conclusions, whereas treating a stationary process as a unit-root (and potentially over-differencing) only leads to a decrease in the efficiency of the estimates. That is,

² As a sensitivity test, we have replicated our analysis using the KPSS test (Kwiatkowski et al. 1992) and report results in the Sensitivity Analysis section. KPSS is another popular unit root test but, in contrast to ADF, stationarity is the null hypothesis. Full KPSS-based results are available upon request.

³ Previous research has shown that the data generating process for drug prescriptions has a high autoregressive order (e.g., Mizik and Jacobson 2004 report six significant lags for the first-differenced prescriptions series for all of the three drugs in their study).

the negative consequences of under-differencing significantly outweigh the consequence of over-differencing.

Finally, we choose the ADF as it has been shown in simulation studies (1) to have very close, albeit slightly more conservative, test statistics for count data (our detailing and sampling data are integer counts), and (2) to perform well in short time series data (i.e., small sample sizes similar to our data). Hellstrom (2001), for example, conducts a large scale simulation study and reports small sample distributions for the ADF test statistic for count data. He derives approximation equations to enable calculation of critical values for any values of time-series length (T) and drift. Given our data characteristics, the Hellstrom (2001) corrections produce very small deviations from the classic ADF statistic.

The ADF tests performed for each physician included an intercept and a trend (visual inspection of the aggregate level data suggests the presence of an upward trend; see Figure 2). The number of lags used, for each physician, was selected based on the Schwarz criterion. For all physicians and all variables tested, the number of observations was 23, which corresponds to the monthly observations in our data. On the basis of the results from these tests, we classify each physician into one of the four groups presented in Figure 1.

For the dependent variable (number of new prescriptions), panelists are classified as evolving if we fail to reject the null hypothesis of a unit-root at the .05 significance level. Otherwise they are classified as stationary. For the marketing activity variables, we classify panelists as evolving when, for *at least one* of the marketing variables (detailing or sampling), we fail to reject the null hypothesis of a unit-root. We note that our approach is parsimonious in that it holds down the number of resulting segments to four. If desired, this approach can be extended to all possible combinations of evolving vs. non-evolving behavior for all variables (in

our case, with two marketing variables and one performance variable we could create eight dynamic scenarios).

After performing the tests and classifications, we find that each of the four groups is populated by a large, albeit unequal, number of physicians. Group 1 (co-evolution) has 12%, Group 2 (hysteresis) has 10%, Group 3 (escalation) has 40% and Group 4 (business-as-usual) has 38% of the physicians. Thus, evolving prescription behavior for this drug was found in the physician-level data for 22% of the doctors while 78% was stationary. On the other hand, marketing activity was classified as evolving for 52% of the doctors while 48% was classified as stationary.

In Table 2 we present the distribution properties for the ADF test statistic for the four business scenario groups, as well as for the full sample. For the dependent variable, new prescriptions, the test statistic mean for Groups 1 and 2 (evolving outcomes) is substantially larger (i.e., closer to zero) than for Groups 3 and 4 (stationary outcomes). Similarly, for the marketing variables, details and samples, the test statistic mean is larger for groups 1 and 3 (evolving marketing activity) than for groups 2 and 4 (stationary marketing activity). Even for the smallest group, Group 2, the large number of physicians available produces very tight standard errors for the mean.

In Table 3, we present mean values for characteristics of the four business scenario groups. The results reveal few differences across the four groups. The mean number of new prescriptions, by month, is somewhat larger for groups 1 and 2 than for groups 3 and 4, but not significantly so. Experience, as measured by years since graduation to the year 2001, appears to be somewhat higher for groups 3 and 4 than for groups 1 and 2, but again the differences are not significant. Table 4 presents the information on the national decile rankings that are associated

with the physicians assigned to each of the four groups. Pharmaceutical companies use national decile rankings of prescription volume as a key component in targeting marketing efforts to physicians (Manchanda et al. 2004). The table shows the percentage of each group's membership which corresponds to the seven different decile ratings available (numbered four through 10). For example, in Group 1 about 21.2% of the doctors are decile four physicians whereas 2.7% are decile 10 physicians. The table shows little differences in decile rankings across the four groups.

The results from Tables 3 and 4 suggest that readily available descriptive information does not predict the classifications produced by the unit-root tests. If the segmentation based on the unit-root classifications carries through to meaningful differences in response dynamics, it could open new opportunities for segmentation and targeting. For example, at first glance, Group 2 (hysteresis) would seem to be the most interesting and profitable for marketers to identify and target. Indeed, it may take only a temporary increase in marketing activity to produce a permanent increase in new prescription activity. We note, however, that the unit-root classifications (evolving outcomes, stationary marketing) simply make it *possible* for hysteresis to occur but do not ensure that it occurs (evolution in performance variables might not be the result of specific marketing actions, but derived from other phenomena such as learning from usage).

On the other hand, Group 3 panelists may be the least attractive since the scenario here involves permanent increases in marketing effort with only temporary increases in prescribing. Incidentally, Group 3 is the largest in our data sample. Its size might partly reflect the recent intense competitive environment of the pharmaceutical industry. This has been referred to as the "PSR arms race," in which firms fielded large numbers of new pharmaceutical sales representatives (PSRs).

PVAR Specifications

The mathematical specifications of the PVAR models for the four groups are given below. In Group 1 (co-evolution) all variables are evolving and therefore all series are specified in differences whereas in Group 4 (business-as-usual) all series are stationary and thus all equations are specified in levels. Groups 2 and 3 are mixed PVAR models with evolving series entering in differences and stationary entering in levels.⁴

Group 1 (co-evolution):⁵

$$\begin{bmatrix} \Delta Q_{i,t} \\ \Delta D_{i,t} \\ \Delta S_{i,t} \end{bmatrix} = \begin{bmatrix} \alpha_{0Q} \\ \alpha_{0D} \\ \alpha_{0S} \end{bmatrix} + \sum_{j=1}^p \begin{bmatrix} \beta_{11}^j & \beta_{12}^j & \beta_{13}^j \\ \beta_{21}^j & \beta_{22}^j & \beta_{23}^j \\ \beta_{31}^j & \beta_{32}^j & \beta_{33}^j \end{bmatrix} \times \begin{bmatrix} \Delta Q_{i,t-j} \\ \Delta D_{i,t-j} \\ \Delta S_{i,t-j} \end{bmatrix} + \begin{bmatrix} \sum_{t=1}^{T-1} \delta_{Qt} \\ \sum_{t=1}^{T-1} \delta_{Dt} \\ \sum_{t=1}^{T-1} \delta_{St} \end{bmatrix} \times \Delta Time(t) + \begin{bmatrix} \varepsilon_{Q_{i,t}} \\ \varepsilon_{D_{i,t}} \\ \varepsilon_{S_{i,t}} \end{bmatrix}, \quad (10)$$

Group 2 (hysteresis):

$$\begin{bmatrix} \Delta Q_{i,t} \\ D_{i,t} \\ S_{i,t} \end{bmatrix} = \begin{bmatrix} \alpha_{0Q} \\ \alpha_{iD} \\ \alpha_{iS} \end{bmatrix} + \sum_{j=1}^p \begin{bmatrix} \beta_{11}^j & \beta_{12}^j & \beta_{13}^j \\ \beta_{21}^j & \beta_{22}^j & \beta_{23}^j \\ \beta_{31}^j & \beta_{32}^j & \beta_{33}^j \end{bmatrix} \times \begin{bmatrix} \Delta Q_{i,t-j} \\ D_{i,t-j} \\ S_{i,t-j} \end{bmatrix} + \begin{bmatrix} \sum_{t=1}^{T-1} \delta_{Qt} \times \Delta Time(t) \\ \sum_{t=1}^{T-1} \delta_{Dt} \times Time(t) \\ \sum_{t=1}^{T-1} \delta_{St} \times Time(t) \end{bmatrix} + \begin{bmatrix} \varepsilon_{Q_{i,t}} \\ \varepsilon_{D_{i,t}} \\ \varepsilon_{S_{i,t}} \end{bmatrix}, \quad (11)$$

Group 3 (escalation):

$$\begin{bmatrix} Q_{i,t} \\ \Delta D_{i,t} \\ \Delta S_{i,t} \end{bmatrix} = \begin{bmatrix} \alpha_{iQ} \\ \alpha_{0D} \\ \alpha_{0S} \end{bmatrix} + \sum_{j=1}^p \begin{bmatrix} \beta_{11}^j & \beta_{12}^j & \beta_{13}^j \\ \beta_{21}^j & \beta_{22}^j & \beta_{23}^j \\ \beta_{31}^j & \beta_{32}^j & \beta_{33}^j \end{bmatrix} \times \begin{bmatrix} Q_{i,t-j} \\ \Delta D_{i,t-j} \\ \Delta S_{i,t-j} \end{bmatrix} + \begin{bmatrix} \sum_{t=1}^{T-1} \delta_{Qt} \times Time(t) \\ \sum_{t=1}^{T-1} \delta_{Dt} \times \Delta Time(t) \\ \sum_{t=1}^{T-1} \delta_{St} \times \Delta Time(t) \end{bmatrix} + \begin{bmatrix} \varepsilon_{Q_{i,t}} \\ \varepsilon_{D_{i,t}} \\ \varepsilon_{S_{i,t}} \end{bmatrix}, \quad (12)$$

⁴ Δ denotes the difference operator. To keep the model presentation tractable we have dropped the group subscript.

⁵ We tested for and did not find cointegration in Group 1 in our data.

Group 4 (business-as-usual):

$$\begin{bmatrix} Q_{i,t} \\ D_{i,t} \\ S_{i,t} \end{bmatrix} = \begin{bmatrix} \alpha_{iQ} \\ \alpha_{iD} \\ \alpha_{iS} \end{bmatrix} + \sum_{j=1}^p \begin{bmatrix} \beta_{11}^j & \beta_{12}^j & \beta_{13}^j \\ \beta_{21}^j & \beta_{22}^j & \beta_{23}^j \\ \beta_{31}^j & \beta_{32}^j & \beta_{33}^j \end{bmatrix} \times \begin{bmatrix} Q_{i,t-j} \\ D_{i,t-j} \\ S_{i,t-j} \end{bmatrix} + \begin{bmatrix} \sum_{t=1}^{T-1} \delta_{Qt} \\ \sum_{t=1}^{T-1} \delta_{Dt} \\ \sum_{t=1}^{T-1} \delta_{St} \end{bmatrix} \times \text{Time}(t) + \begin{bmatrix} \varepsilon_{Q_{i,t}} \\ \varepsilon_{D_{i,t}} \\ \varepsilon_{S_{i,t}} \end{bmatrix}, \quad (13)$$

In the above equations, $Q_{i,t}$ denotes the number of new prescriptions by physician i in month t , and $D_{i,t}$ and $S_{i,t}$ denote, respectively, the number of details and samples received by physician i in month t . The p matrices of the parameters β depict the effects of past prescriptions, detailing and sampling. The number of lags, p , in each group is selected to minimize the Schwarz criterion in the PVAR estimation. We use Hausman specification tests to assess the presence of fixed effects in our level equations. We denote individual-specific intercepts as α_i and uniform intercepts as α_0 . The subscripts “ Q ”, “ D ”, and “ S ” identify the intercepts for prescriptions, detailing, and samples, respectively. $\varepsilon_{Q_{i,t}}$, $\varepsilon_{D_{i,t}}$, $\varepsilon_{S_{i,t}}$ are the error terms.

To model the time-specific effects we adopt a time indicator specification commonly employed in the time-series models of regime changes (e.g., Clements and Hendry 1999). Thus, our indicator variable $\text{Time}(t)$ is equal to zero before time period t and unity from time t on. In the difference equations, this time indicator variable is also differenced. As a result, the time-specific effects variable, $\Delta\text{Time}(t)$, takes the familiar form of a standard time-period dummy variable equal to 1 if time period is t and zero otherwise. This specification of time indicators accommodates a very general structure of exogenous shocks with various dynamic effects and allows for robust estimation without the prior knowledge of where structural breaks may be occurring.

PVAR Model Estimation and Testing

Estimation, testing, and model selection for the PVARs proceeded as follows. We obtained estimates for each of the four group-level PVAR models, as well as for the pooled PVAR model in levels and differences. Following standard procedures, we first determined the appropriate number of lag terms, p , to include for each model by minimizing the Schwarz criterion.⁶ Table 5 provides a summary of the specifications for each of the PVAR models estimated. The last column of the table shows that the selected PVAR models for Groups 1, 2, 3, and 4 had lag lengths of seven, four, eight, and five, respectively. The final pooled PVAR model in levels had seven lags and the pooled PVAR model in differences had 11 lags.

Next, we conduct group-specific Hausman specification tests and, consistent with prior research (Mizik and Jacobson 2004), we detect the presence of significant fixed effects in the cases where the data enter the PVARs in levels.⁷ As Table 5 indicates, our PVAR models differ across the four groups in terms of the use of individual (i.e., cross-section specific) versus uniform intercepts. We have an individual-level intercepts specification for all equations in Group 4, for marketing activity equations in Group 2, and for the prescribing equation in Group 3. Due to the differencing of the variables, which eliminates any physician specific fixed-effect, the remainder of the equations are specified with uniform intercepts (i.e., without fixed effects). For these selected formulations reported in Table 5 (i.e., fixed effects, lag lengths), the quality of in-sample prediction for all models was then assessed by evaluating the Schwarz criterion.

⁶ To save space, the detailed results regarding lag length determinations for the PVAR models are not reported here but may be requested from the authors. Parameter estimates of the various PVAR models are also not reported since they are difficult to interpret in raw form; instead, we subsequently present impulse response functions and elasticities.

⁷ In other applications the use of random effects might also be appropriate to account for individual level heterogeneity. We use fixed effects because previous research has found that marketing activity levels are correlated with the level of prescribing activity for each physician (Mizik and Jacobson 2004, Manchanda et al. 2004) and random effects do not accommodate such correlation. We also note that Horvath and Wierenga (2003) found that the fixed effects formulation performed better than the random effects formulation in an application of the PVAR model.

In Table 6, we report values for the Schwarz criterion (SC) for each of the group models as well as the pooled models. Though the group-level PVAR models are estimated separately, we also report the SC value computed for all groups. This facilitates comparison with the pooled PVAR models. Conversely, the pooled PVAR models are estimated across all physicians in the estimation sample (i.e., all four groups at once). Again, to facilitate comparison, the table also reports the computed SC values that are produced by the pooled models when applied to each physician group. The results in Table 6 show that the group-level models are preferred to the pooled models in all cases. The group-level PVAR models gave the minimum SC values both overall as well as for each group taken separately.

We also compared the performance of the group-level models with the pooled models using the holdout sample of physicians. Using the PVAR model parameters from the estimation sample, we computed the predicted number of new prescriptions for the physicians in the holdout sample. We did this at both the group level as well for the entire sample. In Table 7 we report these results. The table gives two measures of predictive validity, root mean squared error (RMSE) and mean absolute deviation (MAD). The group-level PVAR model estimates produced lower RMSE and MAD values than either pooled PVAR models with one exception. The MAD corresponding to the group-level model for Group 3 is equal to the corresponding MAD from the pooled model in differences. We note, however, that the RMSE still favors the group-level model for the physicians in Group 3.

In sum, the model comparison results for this data set consistently support the selection of the group-level PVAR models over the pooled PVAR models. For the estimation sample, the Schwarz criterion was minimized by the group-level modeling approach, both for all four groups separately as well as for the estimation sample taken as a whole. For the holdout sample, the

forecast errors, as measured by RMSE and MAD, were lower for the group-level models versus the pooled models. Collectively, these results demonstrate the potential for superior fit and forecasting in time series panel data given by a model which incorporates the potential for co-existing business scenarios.

Nature of Dynamic Response

To examine whether our group-level approach produces substantive differences in dynamic response patterns, we compute impulse response functions (IRFs) for the effect of changes in detailing and sampling on prescriptions. We follow previous research (Dekimpe and Hanssens 1999; Nijs et al. 2001) to derive generalized impulses to compute each IRF. These generalized impulses do not impose any particular ordering to the effect of the endogenous variables. To compute the standard errors of the IRF estimates we use a bootstrap procedure repeated 250 times (see Srinivasan et al. 2004 for a discussion). We report the impulse response functions for new prescriptions with respect to one standard deviation change in detailing in Figure 3 and for new prescriptions with respect to one standard deviation change in sampling in Figure 4. The solid lines give the impulse response function. The dashed lines show the 95% confidence interval for the IRF.

The patterns of dynamic response represented by the IRFs are broadly similar for detailing and sampling and are also consistent with the nature of the business scenario classifications pertaining to each group (Dekimpe and Hanssens 1999). For Group 1, the co-evolution scenario, the responses over time are positive, significant and permanent for both detailing and sampling. Group 4, the business-as-usual scenario, shows significant short-run response in both cases, but a return to zero after about six periods. In Group 3, escalation, a non-

significant response to both detailing and sampling is well contained within the error bands at all times.

For Group 2, hysteresis, we also find that response is not significantly different from zero. For detailing, the IRF values are positive for most periods, but the error bands always include zero. This suggests that the sales calls made to physicians in this group, on average, are not producing sufficient short-run response to capitalize on the potential for a permanent effect from evolution in the prescriptions series. In other words, we do not find a marketing-based hysteresis in our data (i.e., the evolving nature of the sales series in this group is not caused by the marketing effort). Indeed, evolution in sales can be due to factors other than marketing stimuli (e.g., physicians learning through usage). Our finding of the absence of marketing-induced hysteresis is consistent with prior research, in that, hysteresis is a very rarely observed phenomenon.⁸

The IRFs for the pooled PVAR models show quite different patterns of response (bottom two panels of each figure). For details and samples, the pooled model in levels shows a significant, positive short-run effect, reverting to zero after about eight periods. On the other hand, the pooled model in differences shows that the effects of detailing and sampling are not only positive and significant, but permanent. The nature of dynamic response implied by the group-level models, however, differs substantially from what is suggested by either pooled model. In particular, the group-level models permit the impulse response functions to capture different dynamics at the segment level—revealing heterogeneity in the response dynamics within the same market—while the pooled models cannot.

⁸ We thank Dominique Hanssens for very helpful discussions on the nature of the hysteresis scenario and frequency of its occurrence. As we note in the discussion of directions for future research, within group heterogeneity in response may still exist within dynamic scenarios. This issue, however, it is beyond the scope of the present study and we leave for future research.

Elasticities

To better understand the magnitude of the effect sizes for each group and for the sample as a whole, we compute detailing and sampling elasticities at different time points (1-month, 6-months, and 12-months). These elasticities are presented in Table 8. We begin by noting that the magnitude of the elasticities differs markedly across the four groups. Consistent with the patterns given by the IRFs, both detailing and sampling elasticities are largest for Group 1, smallest for Group 3, while Groups 2 and 4 fall in between. The detailing elasticities for Group 3 are negatively signed, though very close to zero (when we recomputed the elasticities excluding insignificant effects, all of the elasticity values for Group 3, as well as most of the elasticities for Group 2, were equal to zero). In sum, the group-level results for the elasticities further reinforce the insights from the IRFs regarding the segmentation and targeting potential of using co-existing business scenarios.

Table 8 also reports the overall elasticity obtained from the group-level PVAR models (computed as a weighted average of group elasticities) as well as the two pooled PVAR models. The two pooled models produce differing elasticity values, with those from the pooled model in differences substantially greater than the pooled model in levels. Indeed, at 12 months, the differenced model gives elasticities for the entire sample about three times larger than those from the group-level model. Since the overall properties of the panel data suggested possible evolution in the time series, choice of a pooled model in differences might be justified. However, the elasticity results we present show that such a pooled model could produce very different implications for market response and resource allocation.

SENSITIVITY ANALYSES

Alternative Computation of Elasticities

The elasticities presented in Table 8 (for both the segmented and pooled models) are computed with respect to the initial exogenous shocks of detailing and sampling following the standard approach. That is, the elasticity numerator takes into account the impact on prescriptions from subsequent changes of the marketing variables (i.e., it is based on the generalized IRF), but the elasticity denominator does not incorporate the accumulated marketing changes. These cumulative changes, however, can contribute significantly to the total cost of the original marketing action, in particular when marketing is evolving.⁹ To incorporate the full marketing cost considerations in the elasticity computation, we have re-computed the 6-month and 12-month detailing elasticities including the effect of a detailing shock on future detailing.¹⁰

Overall, these new elasticities tend to be lower than the ones reported in Table 8 but they follow similar patterns, retaining the significant differences across groups. The re-computed elasticities also confirm that pooled models produce different implications for market response. For example, the re-computed detailing elasticities for the pooled model in differences are 0.082 and 0.110 for the 6-month and the 12-month windows, respectively. The corresponding re-computed values obtained for the segmented approach are 0.046 and 0.055. (Full results are available from the authors upon request.)

Alternative Unit-Root Tests

As we noted before, the selection of the unit-root test for classification of panelists into multiple business scenarios should be left up to the investigator. ADF is the appropriate test given our data characteristics (discreteness in some variables and long lags). The results we report are based on the use of the ADF test, where the presence of a unit-root is the null hypothesis. To test the robustness of our findings to the selection of a particular unit-root test, we

⁹ We would like to thank Professor Els Gijbrecchts for her comments on the alternative elasticity computations.

¹⁰ We do not report similar analysis for sampling as it is typically treated as having zero marginal cost in the industry.

also ran our analysis based on segments formed using the KPSS test, in which the absence of a unit-root is the null.

Overall, we find similar results. We find that (1) the proportion of physicians assigned to each business scenario group changes little when using KPSS instead of ADF; (2) the KPSS-based segments outperformed the pooled models; and (3) the segment elasticities are very similar between ADF and KPSS-based groupings. Full KPSS sensitivity results are available from the authors upon request.

Alternative Classification Heuristics

We have examined the performance of alternative classification heuristics and compared it with our proposed dynamic segmentation approach. Specifically, we assessed the differences in elasticities across different decile groupings (the common segmentation and targeting heuristic in the pharmaceutical industry) and different clusters formed based on the available demographic characteristics of our panelists. We did not find meaningful differences in response across such groupings and clusters. These results further highlight the substantive benefits of examining and addressing dynamic response using the proposed segmentation approach.

Scalability: the Role of Additional Factors

A potential extension for the PVAR models we present is to include additional factors that might influence physician prescribing, including other promotional tools or competitive marketing effort. The approach we propose is scalable and can easily accommodate such additional factors.

Unfortunately, we did not have information about other marketing effort or competitive detailing and sampling activity in our dataset. The competitive information is unavailable to the pharmaceutical firm that provided us with the data. The lack of information on competitive

marketing effort at the individual physician level is a common problem in many situations. The intense competitive rivalry inhibits data sharing and requires the drug firms to carefully guard sensitive information. In this sense, the data available to us closely parallels the data available to practitioners in this industry. Several recent academic studies have also lacked competitive information and have presented a variety of compelling arguments for proceeding without it (e.g., Mizik and Jacobson 2004, Manchanda and Chintagunta 2004, and Manchanda et al. 2004).

A couple of studies in marketing have analyzed data sets based on self-reports or surveys of physicians (e.g., Gonul 2001, Narayanan and Manchanda 2005). They include competitive information, but lack continuous time series data for each individual doctor as physicians move in and out of the survey panel or do not participate on a continuous basis. As such, these data sets may not enable researchers to address dynamics. Using aggregated data, other studies have investigated the dynamics of competition in specific therapeutic classes at the brand level and included a full competitive information set (e.g., Berndt et al. 2003). It is not clear, however, how the results are affected by pooling across individual decision makers. In sum, all of the currently available pharmaceutical research data sets of which we are aware present investigators with limitations of one sort or another.

Because we do not have competitive data, we can not undertake direct sensitivity tests, but given the finding in the previous research we believe our results are unlikely to be substantially altered by the inclusion of competitor data if it were available. The major reason for this is that our PVAR models account for physician-specific effects. Prior research has shown that the level of a physician's prescribing is the major determinant of the frequency of detailing visits (Manchanda, Rossi, and Chintagunta 2004). By controlling for physician-specific effects, we remove a major common source of bivariate correlation between own and competitive

marketing effort. Using the Berndt et al. (2003) brand-level data, Mizik and Jacobson (2004) assess the impact of omitting competitive marketing effort from the estimation model and provide empirical support that the use of physician-specific effects is sufficient. In sum, given the body of empirical evidence, we believe that the results we report would not be significantly affected by the lack of competitive marketing data.

DISCUSSION AND CONCLUSION

In cases where marketing outcomes and marketing variables are potentially evolving, researchers have used persistence modeling techniques to identify and study the nature of the business scenario that characterizes time series data (Dekimpe and Hanssens 1995, 1999). These scenarios (business-as-usual, escalation, hysteresis, and evolving business practice) can have radically different implications for management and for the efficient allocation of scarce marketing resources. The objective of this research has been to combine persistence modeling techniques with the possibility that customers can be segmented. In particular, we explore the notion that different customers are at different stages of product adoption and/or firms escalate marketing activity only to certain customer segments or parts of the market, that is, multiple business scenarios co-exist in a single market.

We propose and illustrate an approach to model potentially *co-existing* business scenarios within the same product market. First, we conduct unit-root tests on the outcome and marketing activity variables at the level of the individual panelist and classify these variables, for each panelist, as either evolving or stationary. Using this classification, we group the panelists into clusters corresponding to the four business scenarios and specify and estimate appropriate PVAR models for each group. Finally, impulse response functions are used to study the dynamic properties of the data and elasticities are computed to guide marketing resource allocation.

We illustrated the approach using physician panel data provided by a pharmaceutical company. The segmentation obtained from the unit-root tests showed that each of the four business scenarios was populated by a substantial proportion of doctors. We also found that the PVAR models estimated at the group level provided a better fit to the data than pooled PVAR models (both in-sample and in holdout). This finding documents the ability of a multiple scenario approach to represent the data better than conventional benchmark models.

In addition to producing superior fit, most importantly, the IRFs and dynamic response elasticities derived from the multiple scenario approach highlighted large differences across the groups. These differences demonstrate the substantive benefits of the proposed approach. Firms can draw important implications for segmentation, targeting, and marketing resource allocation. We found, for example, that the differences across business scenario groups did not align with traditional targeting variables used in the industry (e.g., physician demographics and decile rankings) and that common simpler segmentation heuristics did not create meaningful groupings with differentiated response. This suggests that these traditional approaches might not be useful for segmentation purposes: they are not a substitute for proper modeling of individual-level dynamics. We further note that many businesses today store customer-relationship and transaction data, but often do not have access to reliable demographic descriptors of their customers. Our results suggest that meaningful segments can be constructed and used for targeting and marketing activity allocation based on these data using our proposed dynamic segmentation approach.

Finally, we would like to highlight that the proposed approach not only studies the properties of the response to marketing variables, it also addresses simultaneously the dynamic properties of marketing effort *and* performance measures and the dependencies (feedback)

among all series. This allows for a truly comprehensive assessment of the returns to marketing actions. For example, in the case of evolving marketing effort and stationary outcomes (escalation scenario), any (short-run) benefits from marketing will be eventually overshadowed by the ever increasing escalation of marketing spending. The tool we propose provides a diagnosis of the evolution of both performance measures and marketing actions, and it allows firms to better understand the dynamic market structure and better target their marketing efforts.

There are several limitations to our study. First, we rely on unit-root tests to determine the stationary or evolving nature of each panelist's outcome and marketing activity variables. To the extent that the power of these tests is weak, there is a misclassification risk. Our simulation study, reported in the Appendix, showed that this risk may be greatest in small sample sizes but attenuates quickly with additional data.

Further, customer membership in a group might not be stable over time. In fact, we would expect customers to migrate from evolving consumption to stationary and then back to evolving as the product moves through the adoption, maturity, and decline stages of its life cycle. As such, we view our approach as best implemented as a continuous process rather than a one-time exercise. The approach is easy to implement and can be updated every time new data become available (e.g., every quarter or every month). Such a continuous screening process will produce customer switching across the four groups. Future research might model customers migrating from one business scenario to another over time (e.g., from evolving practice to business as usual). Re-classifying customers and tracking potential changes in classification could enhance the approach, and could enable managers to draw more specific implications for when – and to whom – to accelerate, decelerate, or even stop marketing activity.

Finally, further improvements to this segmentation methodology might be developed by incorporating individual-level response heterogeneity within each business scenario. However, we would argue that a non-segmented approach (i.e., single full-heterogeneity model specified across all panelists) would not be appropriate if different dynamic scenarios co-exist in the data. Because traditional Bayesian estimation shrinks individual estimates toward a prior and a common mean (or means) without an *a priori* screening for dynamic patterns, a Bayesian procedure can mask and blend the different dynamic patterns. This could result in the estimation, for many panelists, of a dynamic profile similar to that of the dominant (largest size) business scenario in the data. In addition, the presence of unit roots in the data series prevents the inversion of matrices that define the typical distributions used in Bayesian MCMC estimation. As such, using a pure Bayesian approach to model heterogeneity in individual dynamic data—rather than the panel VAR approach with prior unit-root testing we propose—requires that all individual series be modeled in differences (note that modeling any evolving series in levels would lead to the “spurious regression” problem). Hence, we argue that prior unit-root testing (i.e., the core idea of the proposed approach) is always essential for the proper modeling of dynamic data, even if Bayesian methods are to be applied subsequently to each dynamic group identified.

References

- Baltagi, B.H. and Kao, C. (2000), "Nonstationary Panels, Cointegration in Panels and Dynamic Panels: A Survey," *Advances in Econometrics*, 15, 7–51.
- Bass, F.M. (1969), "A New Product Growth Model for Consumer Durables," *Management Science*, 15(5), 215–27.
- Berndt, E.R., R.S. Pindyck and P. Azoulay (2003), "Consumption Externalities and Diffusion in Pharmaceutical Markets: Antiulcer drugs," *The Journal of Industrial Economics*, 51(2), 243–270.
- Bronnenberg, B.J., V. Mahajan and W.R. Vanhonacker (2000), "The Emergence of Market Structure in New Repeat-Purchase Categories: The Interplay of Market Share and Retailer Distribution," *Journal of Marketing Research*, 37(February), 16–31.
- Bucklin, R.E., S. Gupta and S. Siddarth (1998), "Determining Segmentation in Sales Response Across Consumer Purchase Behaviors," *Journal of Marketing Research*, 35(May), 189–97.
- Campbell J. Y. and P. Perron (1991), "Pitfalls and Opportunities: What Macroeconomists Should Know about Unit Roots," *NBER Macroeconomics Annual*, 141–204.
- Clements, M.P. and D.F. Hendry (1999). *Forecasting Non-Stationary Economic Time Series*. The MIT Press.
- , ———, R.T. Baillie, F.X. Diebold, et al. (1993), "On the Limitations of Comparing Mean Square Forecast Errors; Comments; Reply," *Journal of Forecasting*, 8(12), 617–676.
- Dekimpe, M.G. and Hanssens, D.H. (1995), "The Persistence of Marketing Effects on Sales," *Marketing Science*, 14(1), 1–21.
- and ——— (1999), "Sustained Spending and Persistent Response: A New Look at Long-Term Marketing Profitability," *Journal of Marketing Research*, 36 (November), 397–412.
- Granger C.W.J. and P. Newbold (1974), "Spurious Regressions in Econometrics," *Journal of Econometrics*, 2, 11–120.
- Greene, W.H. (2003), *Econometric Analysis*. Prentice-Hall.
- Hamilton, J.D. (1994), *Time Series Analysis*, Princeton University Press.
- Harris, R.I.D. (1992), "Testing for Unit Roots Using the Augmented Dickey-Fuller Test: Some Issues Relating to the Size, Power and Lag Structure of the Test," *Economics Letters*, 38, 381–386.
- Haug, A.A. (1996), "Tests for Cointegration: A Monte Carlo Comparison," *Journal of Econometrics*, 71, 89–115
- Hausman, J.A. (1978), "Specification Tests in Econometrics," *Econometrica*, 46(November), 1251–1272.
- Hellstrom, J. (2001), "Unit Root Testing in Interer-Valued AR(1) Models," *Economic Letters* 70, 9–14.
- Horváth, C. and J.E. Wieringa (2003), "Combining Time Series and Cross-Sectional Data for the Analysis of Dynamic Marketing Systems," SOM Research Report, University of Groningen.

- and P.H. Franses (2003), “Deriving Dynamic Marketing Effectiveness from Econometric Time Series Models,” Working Paper, Erasmus University.
- Kamakura, W.A. and G.J. Russell (1989), “A Probabilistic Choice Model for Market Segmentation and Elasticity Structure,” *Journal of Marketing Research*, 26(November), 379–90.
- and M. Wedel (1998), *Market Segmentation: Conceptual and Methodological Foundations*, Kluwer Academic Press.
- Kwiatkowski, Denis, P.C.B. Phillips, Peter Schmidt and Yongcheol Shin (1992), “Testing the Null Hypothesis of Stationarity Against the Alternative of a Unit Root: How Sure Are We That Economic Time Series Have a Unit Root?” *Journal of Econometrics*, 54(Oct-Dec), 159–178.
- Lim, J., Currim, I.S., and Andrews, R.L. (2005), “Consumer Heterogeneity in the Longer-term Effects of Price Promotions,” *International Journal of Research in Marketing*, 22(December), 441–458.
- Maddala, G.S. (1992), *Introduction to Econometrics*, 2nd Ed., Macmillan, N.Y.
- Manchanda, P. and P. Chintagunta (2004), “Responsiveness of Physician Prescription Behavior to Salesforce Effort: An Individual Level Analysis,” *Marketing Letters*, 15(2–3), 129–146.
- , Peter Rossi, and Pradeep Chintagunta (2004), “Response Modeling with Non-Random Marketing Mix Variables,” *Journal of Marketing Research*, 41(November), 467–478.
- Mela, C.F., S. Gupta, and D.R. Lehmann (1997), “The Long-Term Impact of Promotion and Advertising on Consumer Brand Choice,” *Journal of Marketing Research*, 34(May), 248–261.
- Mizik, N. and R. Jacobson (2004), “Are Physicians ‘Easy Marks’? Quantifying the Effects of Detailing and Sampling on New Prescriptions,” *Management Science*, 50(12), 1704–1715.
- Narayanan, Sridhar and Puneet Manchanda (2005), “Heterogeneous Learning and the Targeting of Marketing Communication for New Products,” Working Paper, Stanford University..
- , ———, and P. Chintagunta (2005), “Temporal Differences in the Role of Marketing Communication in New Product Categories,” *Journal of Marketing Research*, 42(August), 278–290.
- Nelson, C.R. and H. Kang (1984), “Pitfalls in the Use of Time as an Explanatory Variable in Regressions,” *Journal of Business and Economic Statistics*, 2, 73–82.
- Nijs, V.R., Marnik G. Dekimpe, Jan-Benedict E.M. Steenkamp, D.M. Hanssens (2001), “The Category-Demand Effects of Price Promotions,” *Marketing Science*, 20(1), Winter, 1–22.
- Papatla, P. and L. Krishnamurthi (1996), “Measuring the Dynamic Effects of Promotions on Brand Choice,” *Journal of Marketing Research*, 33 (February), 20-35.
- Pauwels, K.H., I. Currim, M.G. Dekimpe, Eric Ghysels, D.M. Hanssens, N. Mizik and P. Naik (2004), “Modeling Marketing Dynamics by Time Series Econometrics,” *Marketing Letters*, 15(4), 167–84.
- , D.H. Hanssens and S. Siddarth (2002), “The Long-Term Effects of Price Promotions on Category Incidence, Brand Choice and Purchase Quantity,” *Journal of Marketing Research*, 39(November), 421–39.

Plosser, C.I. and G.W. Schwert (1977), "Estimation of Non-Invertible Moving Average Processes: The Case of Overdifferencing," *Journal of Econometrics*, 6, 199–224.

Rogers, Everett (2003), *Diffusion of Innovations*, 5th edition, Free Press.

Srinivasan, S., K.H. Pauwels, D.M. Hanssens and M. Dekimpe (2004), "Do Promotions Increase Profitability and for Whom?" *Management Science*, 50(5), 617–629.

Stock, J.H. and M.W. Watson (1988), "Testing for Common Trends," *Journal of the American Statistical Association* 83, 10097–1107.

Theil, H. (1961), *Economic Forecasts and Policy*, 2nd edition. Amsterdam: North Holland Publishing Company.

Figure 1
The Four Basic Business Scenarios

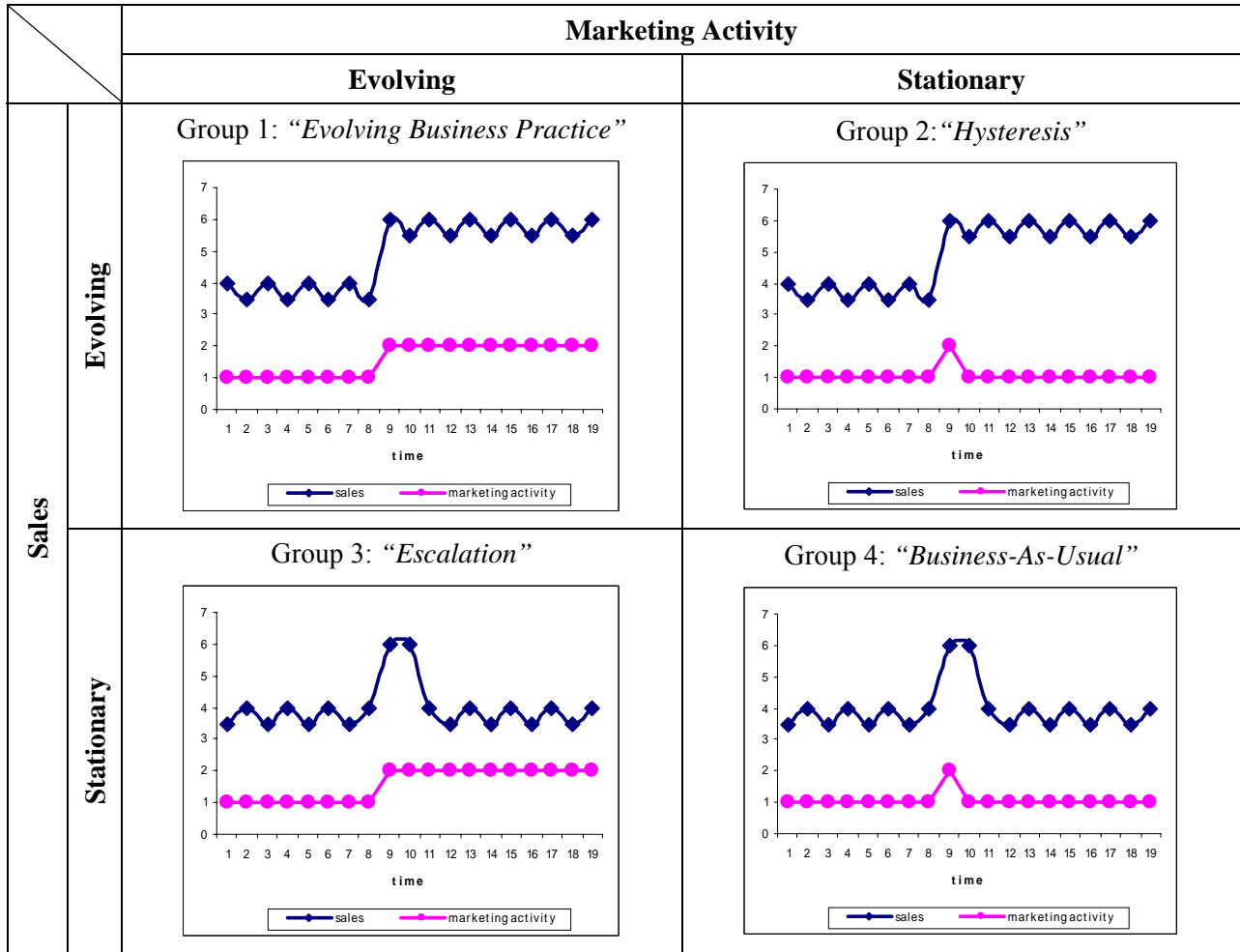


Figure 2
Number of New Prescriptions, Details, and Samples by Month

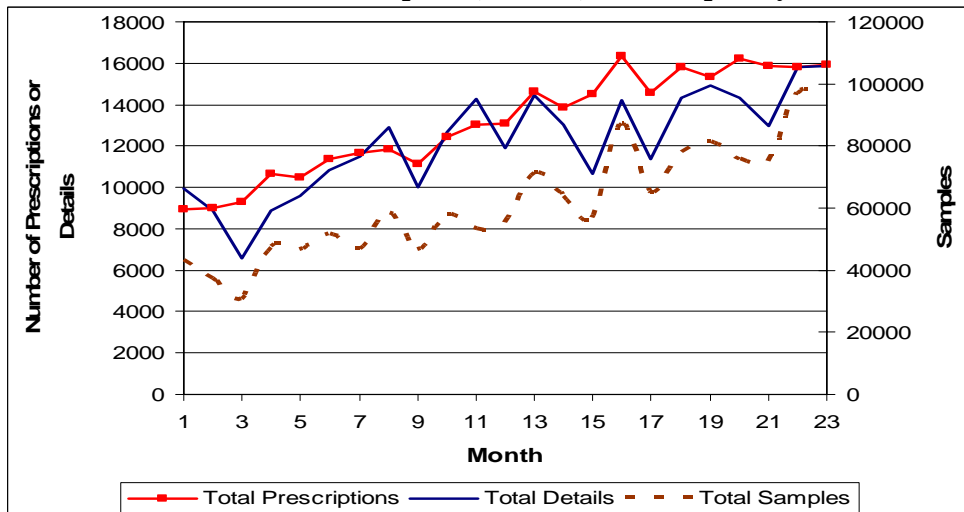
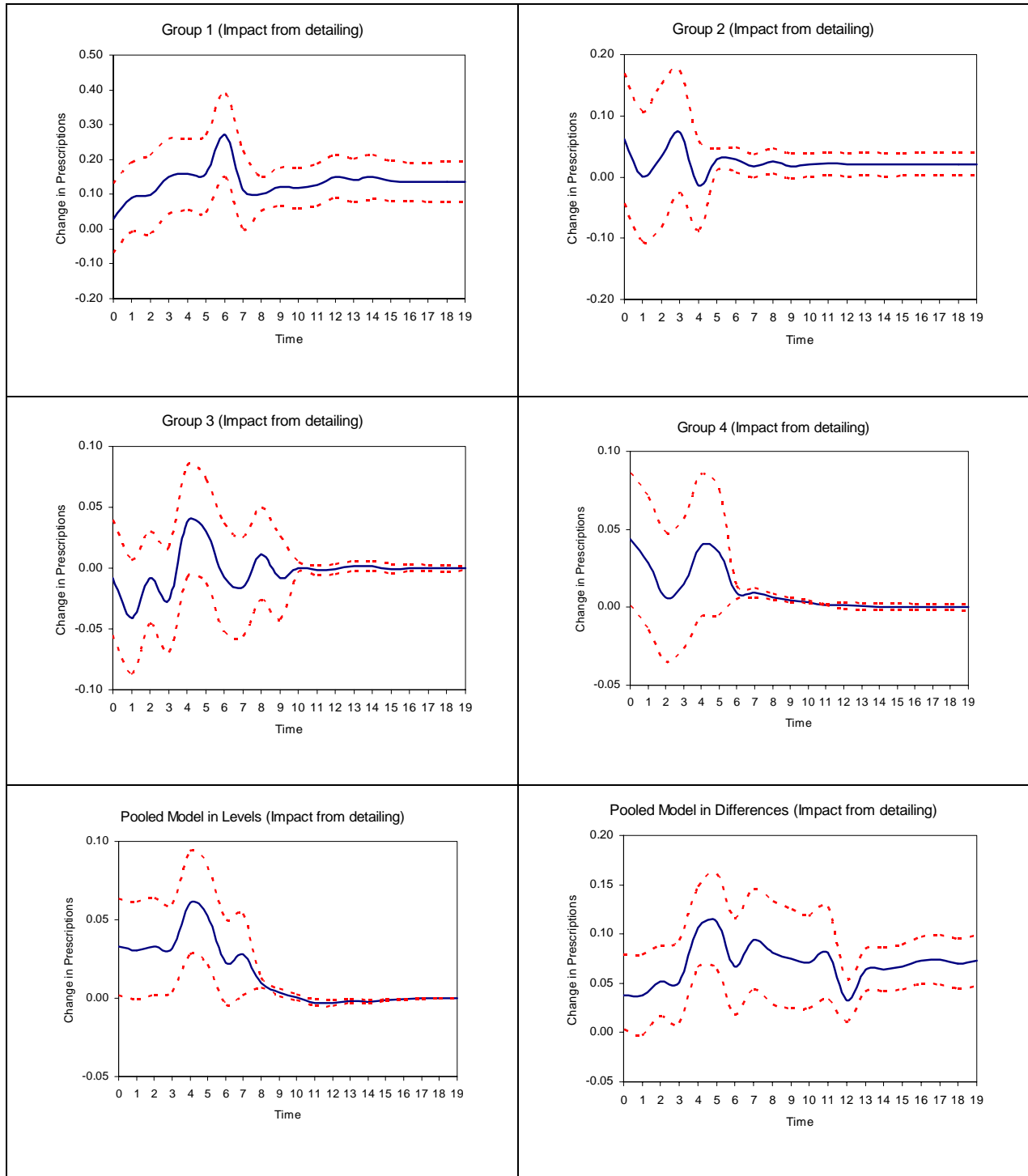
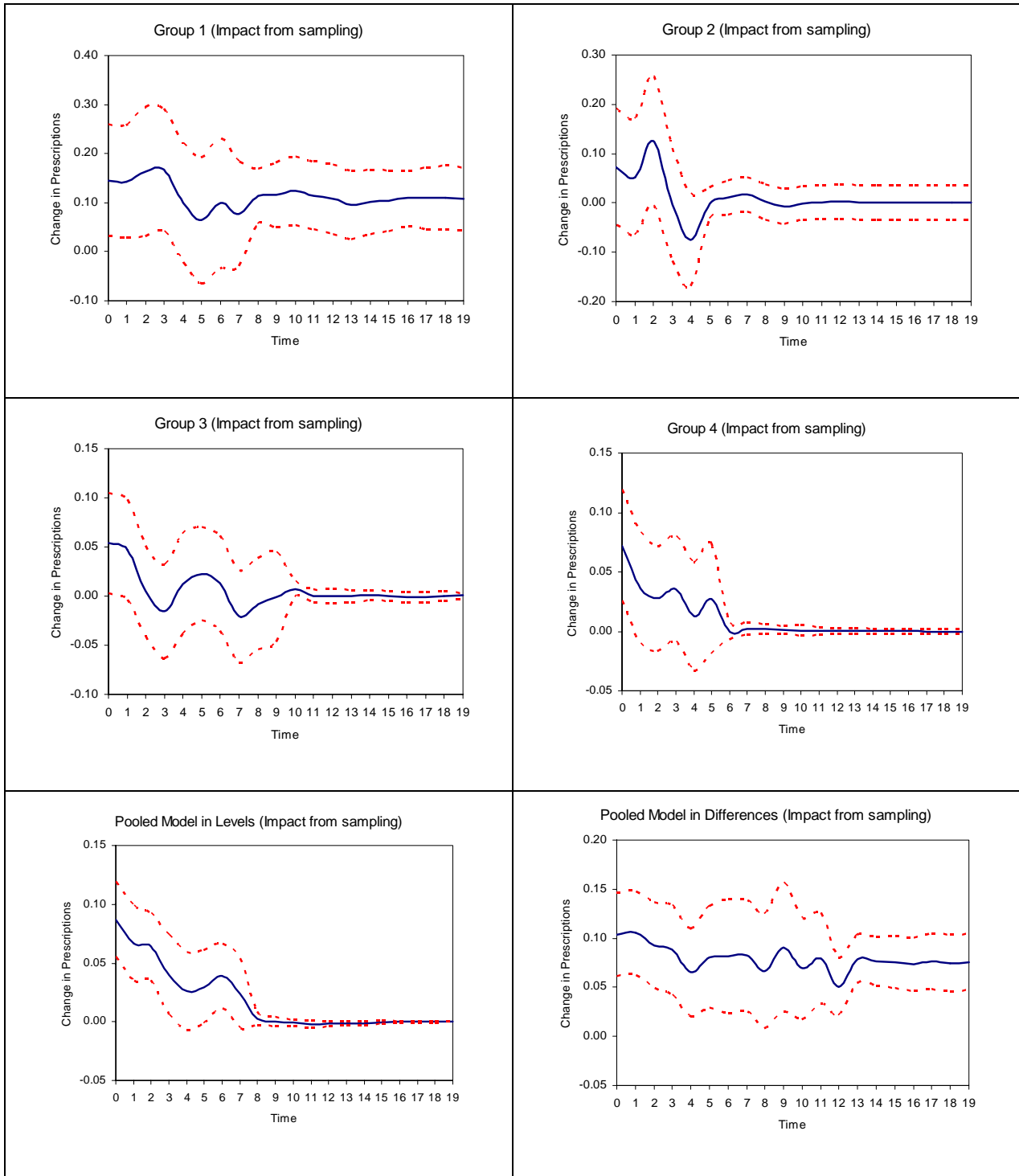


Figure 3
New Prescriptions Impulse Response to Change in Detailing by Group



*Solid lines correspond to the responses to a generalized impulse of one standard deviation of detailing. Dashed lines represent the 95% confidence intervals.

Figure 4
New Prescriptions Impulse Response to Change in Sampling by Group



Solid lines correspond to the responses to a generalized impulse of one standard deviation of sampling. Dashed lines represent the 95% confidence intervals.

Table 1
Summary of Descriptive Statistics*

	Mean	Standard Error of the Mean	Minimum	Lower 10%	Median	Upper 90%	Maximum
Average Monthly New Prescriptions per Physician	3.33	0.05	0.15	0.79	2.55	6.77	21.02
Average Monthly Details per Physician	3.09	0.03	0.09	0.91	2.91	5.52	9.91
Average Monthly Samples per Physician	15.71	0.22	0.22	3.09	11.65	33.76	93.87
Physician National Deciles	6.17	0.03	4.00	4.00	6.00	9.00	10.00
Years Since Graduation	20.09	0.15	3.00	8.00	20.00	32.00	58.00

*Descriptive statistics computed across the sample of 3942 physicians; for each physician, average monthly new prescriptions, average monthly details, and average monthly samples were computed using the 23 months of observations in our data. Physicians were assigned a national decile by the company based on their prescribing volume. A decile assignment of 7, for example, indicates that the doctor is in the 70th percentile for new prescription volume. The variable “years since graduation” uses 2001, the first year of our sample, as the reference year.

Table 2
Distribution Properties of the ADF Statistic for Groups and Full Sample

	ADF Test Statistic for New Prescriptions	ADF Test Statistic for Details	ADF Test Statistic for Samples
Group 1			
Mean	-2.760	-3.190	-3.753
SEM*	0.044	0.052	0.082
Minimum	-3.677	-8.396	-12.678
Lower 2.5%	-3.625	-5.793	-6.380
Upper 97.5%	-0.218	-0.822	0.789
Maximum	4.923	0.669	6.426
Group 2			
Mean	-2.845	-4.619	-5.033
SEM*	0.045	0.040	0.050
Minimum	-3.677	-7.949	-10.446
Lower 2.5%	-3.606	-6.537	-7.203
Upper 97.5%	-0.306	-3.682	-3.698
Maximum	0.828	-3.638	-3.640
Group 3			
Mean	-4.856	-3.135	-3.882
SEM*	0.022	0.030	0.044
Minimum	-8.928	-7.852	-9.619
Lower 2.5%	-6.820	-5.566	-6.710
Upper 97.5%	-3.706	-0.488	-0.012
Maximum	-3.642	4.296	14.390
Group 4			
Mean	-4.865	-4.706	-5.097
SEM*	0.023	0.022	0.030
Minimum	-9.742	-11.140	-25.384
Lower 2.5%	-6.962	-6.843	-7.493
Upper 97.5%	-3.699	-3.684	-3.716
Maximum	-3.634	-3.634	-3.635
Full Sample			
Mean	-4.418	-3.887	-4.443
SEM*	0.019	0.020	0.026
Minimum	-9.742	-11.140	-25.384
Lower 2.5%	-6.746	-6.327	-7.085
Upper 97.5%	-1.782	-1.164	-0.894
Maximum	4.923	4.296	14.390

*Standard error of the mean

Table 3
Summary of Descriptive Statistics by Group

	Group Description			Averages				Number of Physicians
	New Prescriptns	Marketing	Number of New Prescriptns	Details	Samples	National Deciles	Years Since Graduation	
Group1	Evolving	Evolving	3.62	3.02	15.30	6.18	19.15	476
Group2	Evolving	Stationary	3.66	2.92	15.69	6.24	19.75	375
Group3	Stationary	Evolving	3.27	3.08	15.33	6.16	20.26	1,571
Group4	Stationary	Stationary	3.22	3.16	16.23	6.17	20.36	1,520

Table 4
Percentage of Physicians by Group and Decile

Decile	Group 1 (%)	Group 2 (%)	Group 3 (%)	Group 4 (%)
4	21.2	24.0	23.7	24.1
5	18.3	16.0	17.2	18.0
6	18.7	17.1	19.0	18.1
7	18.1	15.5	15.7	13.8
8	13.2	13.1	12.0	12.4
9	7.8	11.2	8.8	9.7
10	2.7	3.2	3.6	3.8
Total	100.0	100.0	100.0	100.0

Table 5
Summary of the Estimated Models*

	Variable Specification		Period Effects		Cross-Sectional Fixed Effects		Number of Lags
	Prescriptions	Marketing	Prescriptions	Marketing	Prescriptions	Marketing	
Segmented							
Group 1	Difference	Difference	$\Delta\text{Time}(t)$	$\Delta\text{Time}(t)$	No	No	7
Group 2	Difference	Level	$\Delta\text{Time}(t)$	$\text{Time}(t)$	No	Yes	4
Group 3	Level	Difference	$\text{Time}(t)$	$\Delta\text{Time}(t)$	Yes	No	8
Group 4	Level	Level	$\text{Time}(t)$	$\text{Time}(t)$	Yes	Yes	5
Pooled							
Differences	Difference	Difference	$\Delta\text{Time}(t)$	$\Delta\text{Time}(t)$	No	No	11
Levels	Level	Level	$\text{Time}(t)$	$\text{Time}(t)$	Yes	Yes	7

* $\text{Time}(t)$ represents an indicator variable that is equal to zero before time period t and unity from time t on; $\Delta\text{Time}(t)$ represents the first-difference of $\text{Time}(t)$ and it is the same as monthly dummy variables. The number of lags for each final model was selected based on Schwarz criterion. The variables entering the models in differences do not include cross-sectional fixed effects because these are cancelled out through first-differencing.

Table 6
Estimation Sample Model Fit and Model Selection*

	SC Values for	SC Values for Pooled Models	
	Group-Level PVARs	Levels	Differences
Group 1	18.378	25.772	18.579
Group 2	18.404	28.304	18.487
Group 3	18.836	25.387	18.922
Group 4	17.956	20.440	17.969
All Groups	18.395	21.779	18.476

*Schwarz criterion (SC) values for all models are based on the estimation sample of physicians. SC is defined as $-2(l/T)+k \log(T)/T$ where l is the log likelihood, k is the number of parameters, and T is the number of observations.

Table 7
Model Comparisons of Out-of-Sample Forecast Errors for New Prescriptions

	Group-Level Models		Pooled Model: Levels		Pooled Model: Differences	
	RMSE*	MAD*	RMSE	MAD	RMSE	MAD
Group 1	3.398	2.344	3.418	2.400	3.456	2.417
Group 2	3.769	2.576	3.792	2.593	3.827	2.606
Group 3	3.202	2.238	3.217	2.251	3.208	2.238
Group 4	3.083	2.227	3.099	2.250	3.086	2.235
All Groups	3.240	2.279	3.257	2.301	3.257	2.288

*RMSE is the root mean square forecast error and MAD is the mean absolute forecast error. Forecasts are performed one-step-ahead. Because we are predicting for physicians not used in estimation, we predicted prescription levels using the models without fixed-effects (these provide the best prediction of the out-of-sample prescriptions for all the alternative formulations).

Table 8
Elasticities for Group and Pooled Models

	Detailing Elasticity			Sampling Elasticity		
	1 month	6 months	12 months	1 month	6 months	12 months
Group 1	0.014	0.325	0.727	0.028	0.152	0.276
Group 2	0.032	0.095	0.163	0.016	0.033	0.043
Group 3	-0.004	-0.008	-0.019	0.012	0.024	0.025
Group 4	0.029	0.111	0.135	0.019	0.041	0.056
All Groups*	0.014	0.088	0.147	0.017	0.047	0.069
Pooled (Levels)	0.020	0.145	0.182	0.021	0.061	0.089
Pooled (Differences)	0.021	0.221	0.481	0.022	0.104	0.211

* The “All Groups” elasticities are computed as a weighted average of the group elasticities.

Appendix: Simulation Study

We conducted a simulation study to assess our ability to correctly classify individual panelists with unit-root tests under a variety of conditions. We assumed a population of 1,000 individuals equally distributed across the four scenarios (Evolving Business Practice, Hysteresis, Escalation, and Business-as-Usual), giving 250 individuals per scenario. We simulated two endogenous variables (a performance variable y_1 and a marketing variable y_2) measured periodically and related through a VAR system with individual-specific intercepts and time-specific effects.

We follow Ashley and Verbrugge (2004) and use a similar structure for our VAR model simulation. We assume a one-lag VAR specified as follows:

$$\begin{bmatrix} y_{1it} \\ y_{2it} \end{bmatrix} = \begin{bmatrix} \alpha_{1i} \\ \alpha_{2i} \end{bmatrix} + \phi_1^s \begin{bmatrix} y_{1it-1} \\ y_{2it-1} \end{bmatrix} + \begin{bmatrix} \delta_{1t} \\ \delta_{2t} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1it} \\ \varepsilon_{2it} \end{bmatrix}, \quad (1)$$

where y_{1it} and y_{2it} are the endogenous variables of individual i ($i = 1, \dots, 1,000$) in period t ($t = 1, \dots, T$), α_{1i} and α_{2i} are individual-specific intercepts, ϕ_1^s is the (2×2) matrix of parameters for the first order effects for scenario s ($s = 1, 2, 3$ and 4), δ_{1t} and δ_{2t} are time-specific effects, and ε_{1it} and ε_{2it} are error terms. Errors are assumed to be normally distributed such that:

$$\varepsilon_{it} \sim N(0, \Sigma), \quad (2)$$

where Σ is a (2×2) variance-covariance matrix and $\varepsilon_{it} = (\varepsilon_{1it}, \varepsilon_{2it})'$ is a (2×1) vector of error terms. To simulate individual and monthly effects, we assume normal distributions as follows:

$$\alpha_{ji} \sim N(a_j, \sigma_{\alpha_j}), \text{ for } j = 1, 2 \text{ and} \quad (3)$$

$$\delta_{jt} \sim N(d_j, \sigma_{\delta_j}), \text{ for } j = 1, 2. \quad (4)$$

Simulations were set up for a variety of values for the means and standard deviations of the individual-level and monthly effects. Because we found similar results for the range of parameters simulated, we report findings for only one set of these parameter values, given below:

$$a_1 = 1.5 \text{ and } \sigma_{\alpha_1} = 0.8 \quad (5)$$

$$a_2 = 2 \text{ and } \sigma_{\alpha_2} = 0.5 \quad (6)$$

$$d_1 = 1 \text{ and } \sigma_{\delta_1} = 0.3 \quad (7)$$

$$d_2 = 2 \text{ and } \sigma_{\delta_2} = 0.6 \quad (8)$$

In the one-lag VAR model, at least one unit-root is present if:

$$|I_n - \phi_1| = 0. \quad (9)$$

In other words, the determinant of the n -dimensional identity matrix minus the parameter matrix must equal zero, where n is the number of endogenous variables in the system (see Hamilton 1994, p. 549). In our one-lag model we ensure that this constraint is satisfied for those scenarios in which unit-roots are to be present, and that it is not satisfied for the remaining scenarios.

To test how the availability of more information could improve the classification of individual panelists we considered four alternative conditions. We began with a baseline condition in which only two years of monthly data are available (24 monthly observations). We then examined conditions where three, four and five years of data are available (corresponding to 36, 48 and 60 monthly observations, respectively).

We present the simulation results based on the parameters given in the chart below.¹¹ These values were selected to reflect moderate levels of persistence for the non unit-root conditions, corresponding to typical levels of carryover observed for marketing activity in the extant literature.

<p>Group 1</p> <p>Evolving Business Practice</p> $\phi_1^1 = \begin{bmatrix} 1 & 0.1 \\ 0 & 1 \end{bmatrix}$	<p>Group 2</p> <p>Hysteresis</p> $\phi_1^2 = \begin{bmatrix} 1 & 0.1 \\ 0 & 0.4 \end{bmatrix}$
<p>Group 3</p> <p>Escalation</p> $\phi_1^3 = \begin{bmatrix} 0.6 & 0.1 \\ 0 & 1 \end{bmatrix}$	<p>Group 4</p> <p>Business-as-Usual</p> $\phi_1^4 = \begin{bmatrix} 0.6 & 0.1 \\ 0 & 0.4 \end{bmatrix}$

The error terms, ε_{1it} and ε_{2it} , are normal with zero mean and standard deviation of 0.5. We allowed the correlation between the error terms of y_1 and y_2 to take three values: 0, 0.2, and 0.8. We report results only for the high and low correlations as the results do not change materially for the zero correlation case. We also note that simulations using alternative values for the individual and monthly effects (and their standard deviations) did not materially change the results.

Results of the Simulation Study

We present the results using the Augmented Dickey Fuller (ADF) test to classify individual panelists into the evolving (unit-root present) or stationary (no unit-root) conditions. The results based on the KPSS test (Kwiatkowski et al. 1992) were not materially different and are available from the authors upon request. We present the ADF-based results because it is the most popular unit-root test (perhaps due to its simplicity) and a default in many time series statistical packages. We again emphasize that the choice of unit-root test should be up to the investigator in an applied setting.

We report the results from 32 simulation scenarios. Across the four group conditions, we consider sample sizes of 24, 36, 48, and 60 observations and an error correlation of either 0.2 or 0.8. We replicated each of these specifications 100 times. Each time we simulated the data and then conducted the ADF tests (with intercept, trend, and automatic selection of lags) for the two endogenous variables (y_1 and y_2). Based on the test results we assigned

¹¹ We have also examined alternative values and specifications as well as different numbers of observations. No material effect on the results was observed for any of these other test conditions. Details are available from the authors upon request.

each individual to one of the four business scenarios. We then stored the number of individuals assigned to each scenario by actual group of origin (i.e., for each of the four scenarios, we determine how many individuals were assigned to the true scenario as well as the other three). We then compute the mean across the 100 replications.

Table A1 gives the percentages, organized by group, for the corresponding assignment results. For individuals simulated as true members of Group 1 (evolving business practice), the first panel in Table 1 gives the percentage of Group 1 individuals classified into each of the four groups across the different correlation and sample size conditions. For example, in the case of 24 data points and a correlation level of 0.2, 83.6 percent of the 250 simulated individuals were correctly classified into Group 1, 13 percent were classified into Group 2, 3.4 percent into Group 3, and none into Group 4. For individuals simulated as members of Group 2, the second panel presents corresponding results. In this case 59.7 percent of Group 2 individuals were correctly assigned to that group when the sample size was 24 and the correlation 0.2. The third and fourth panels of the table give the results for individuals simulated as true members of Group 3 and Group 4.

Discussion of the Simulation Study

The ADF test performs generally well in recovering the true assignments. Across all 32 test cells, the average percentage of individuals correctly assigned is 80 percent. There is little difference in the results across the high and low correlation levels. Turning to sample size, when the number of data points is equal to 24, the worst assignment performance is 50 percent accuracy (for Group 3) and the average assignment accuracy is 63.3 percent. When the sample size is equal to 36, the worst performance is 61.2 percent (also for Group 3) and the average is 80.3. In Groups 2, 3, and 4, there is a large increase in classification accuracy from 24 to 36 data points while the improvement is flatter between 36 and 48. This suggests the potential value in retaining 36 months of customer-level data versus the often observed industry practice of keeping 24 months.

In our empirical application, we have two years of monthly data. The simulation results suggest that the performance we observe in our empirical study could be enhanced with modest increases in sample size per panelist.

Table A1
Simulation Study Results

Group 1 Individuals (Evolving Business Practice)

Correlation Level (ρ)	Number of Data points	Percentage of Group 1 Individuals Classified as:				Total
		Group 1	Group 2	Group 3	Group 4	
0.2	24	83.6	13.0	3.4	0.0	100.0
0.2	36	86.0	11.0	3.0	0.0	100.0
0.2	48	90.0	9.0	1.0	0.0	100.0
0.2	60	89.0	10.0	1.0	0.0	100.0
0.8	24	84.0	12.0	4.0	0.0	100.0
0.8	36	83.0	16.0	1.0	0.0	100.0
0.8	48	83.0	14.0	3.0	0.0	100.0
0.8	60	90.0	9.0	1.0	0.0	100.0

Group 2 Individuals (Hysteresis)

Correlation Level (ρ)	Number of Data points	Percentage of Group 2 Individuals Classified as:				Total
		Group 1	Group 2	Group 3	Group 4	
0.2	24	29.9	59.7	3.4	0.0	100.0
0.2	36	8.2	83.9	0.0	7.9	100.0
0.2	48	1.4	92.3	0.0	6.3	100.0
0.2	60	1.0	92.7	0.0	6.3	100.0
0.8	24	25.8	58.2	3.5	12.6	100.0
0.8	36	6.0	86.2	1.0	6.8	100.0
0.8	48	2.6	90.7	0.0	6.8	100.0
0.8	60	0.4	90.4	0.0	9.2	100.0

Group 3 Individuals (Escalation)

Correlation Level (ρ)	Number of Data points	Percentage of Group 3 Individuals Classified as:				Total
		Group 1	Group 2	Group 3	Group 4	
0.2	24	37.0	6.7	50.0	6.3	100.0
0.2	36	22.1	2.6	66.9	8.4	100.0
0.2	48	17.8	1.2	73.2	7.8	100.0
0.2	60	13.8	1.3	76.2	8.7	100.0
0.8	24	37.3	5.1	50.7	6.9	100.0
0.8	36	22.8	3.6	61.2	12.4	100.0
0.8	48	13.1	1.5	72.9	12.5	100.0
0.8	60	15.0	0.1	76.0	8.9	100.0

Group 4 Individuals (Business-as-Usual)

Correlation Level (ρ)	Number of Data points	Percentage of Group 4 Individuals Classified as:				Total
		Group 1	Group 2	Group 3	Group 4	
0.2	24	6.2	11.6	25.0	57.2	100.0
0.2	36	1.0	3.6	7.2	88.2	100.0
0.2	48	0.0	0.5	1.4	98.0	100.0
0.2	60	0.0	0.2	1.0	98.8	100.0
0.8	24	6.6	7.5	22.7	63.2	100.0
0.8	36	2.0	5.9	5.0	87.1	100.0
0.8	48	0.0	2.3	2.6	95.2	100.0
0.8	60	0.0	0.1	0.4	99.5	100.0