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Are Physicians "Easy Marks"? Quantifying the Effects of Detailing and Sampling on New Prescriptions

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Much public attention and considerable controversy surround pharmaceutical marketing practices and their impact on physicians. However, views on the matter have largely been shaped by anecdotal evidence or results from analyses with insufficient controls. Making use of a dynamic fixed-effects distributed lag regression model, we empirically assess the role that two central components of pharmaceutical marketing practices (namely, detailing and sampling) have on physician prescribing behavior. Key differentiating features of our model include its ability to (i) capture persistence in the prescribing process and decompose it into own-growth and competitive-stealing effects, (ii) estimate an unrestricted decay structure of the promotional effects over time, and (iii) control for physician-specific effects that, if not taken into account, induce biased coefficient estimates of detailing and sampling effects. Based on pooled time series cross-sectional data involving three drugs, 24 monthly observations, and 74,075 individual physicians (more than 2 million observations in total), we find that detailing and free drug samples have positive and statistically significant effects on the number of new prescriptions issued by a physician. However, we find that the magnitudes of the effects are modest.

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Introduction

As the cost of prescription drugs continues to escalate, increased public attention is being focused on the marketing practices of the pharmaceutical firms as one source of the problem. Direct-to-physician activities account for the bulk of U.S. pharmaceutical firm promotional spending. IMS Health (2003) estimates that over $5.8 billion was spent in 2002 on detailing, i.e., pharmaceutical sales representatives (PSRs) visiting physicians to promote their firm's drugs. In addition, the retail value of the free drug samples distributed during these visits is estimated at $11.5 billion.

A detailing visit typically lasts two to five minutes during which time a PSR discusses one to three of the company's drugs. Information (and, at times, misinformation) about a drug's composition, therapeutic value, proper dosage, and potential side effects is communicated (Zigler et al. 1995). Often, PSRs will also dispense samples and possibly offer small gifts to the physician. At issue is whether these interactions with PSRs compromise physician integrity and affect their prescribing behavior. More precisely, the key public policy issue is the extent to which the industry's promotional tactics lead to an increase in appropriate versus inappropriate use of drugs in a cost-effective manner.

Concern that pharmaceutical marketing practices have exacerbated increases in public health costs has prompted government actions at the federal and state levels. For example, in 2002 the federal government issued a warning to the drug industry to curtail some of their marketing practices (*Washington Post* 2002). H.R. 2356, which calls for ongoing annual funding of $75 million to conduct comparative cost-effectiveness drug studies, was introduced in Congress in June 2003. A primary intent of this legislation is to provide objective scientific evidence to "reduce doctors' reliance on marketing information from the pharmaceutical industry" (Pear 2003). Given the fact that one of every five dollars spent on pharmaceutical drugs in the United States is paid for by a state program, state governments have also taken steps to counter PSR influence. Most notably, several states have undertaken counterdetailing initiatives (Gold 2001). State employees visit physicians in hopes of persuading them to switch from prescribing branded drugs to prescribing lower-cost generic drugs.

Prescription drug expenditures are projected to remain the fastest-growing sector of health care expenditures. They are expected to account for 14.5% of $3.1 trillion health care expenditures by 2012 (compared with approximately 10% in 2001). With recent legislation providing a Medicare drug benefit expected to cost the federal government $534 billion over the next decade, it is no wonder that the impact of pharmaceutical industry marketing practices is of keen interest to policymakers, the business community, and the general public.

Two competing views have dominated discussion on the matter. The prevailing view contends that PSRs significantly influence physicians' prescribing behavior and that this influence has negative effect on patients' welfare, in that PSRs encourage physicians to prescribe more expensive branded drugs. Many public policy organizations and consumer advocacy groups adhere to this view (see, for example, www.nofreelunch.org). The prominent alternative view argues that PSRs do influence physicians' prescribing behavior, but that this influence is positive in that PSRs provide physicians with valuable information. As a result, physicians are better informed and make better choices for their patients. Pharmaceutical companies and industry groups advocate this second view.

Despite the substantial resources that pharmaceutical companies invest in promoting their products and the controversy associated with pharmaceutical marketing practices, surprisingly little is known about the magnitude of the impact that PSR visits and free drug samples have on physician prescribing behavior. Narayanan et al. (2003) report a pharmaceutical executive as stating, "No one is really sure if sending the legions of reps to doctors' offices really works. Everyone is afraid to stop it, because they don't know what difference it's making" (p. 4).

In point of fact, much of the evidence on PSR effectiveness is anecdotal. The empirical studies investigating the issue have been subject to data or methodological limitations that restricted their ability to control for potential biases and have come to contradictory conclusions regarding even the central issues: the effects of detailing on prescriptions (e.g., Parsons and Abeele 1981 versus Gonul et al. 2001), of detailing on price elasticity (e.g., Rizzo 1999 versus Gonul et al. 2001), and even of price on sales (e.g., Rizzo 1999 versus Gonul et al. 2001).

We have obtained access to a unique database that allows us to undertake econometric analysis that overcomes a number of fundamental limitations existing in past research. In particular, making use of a dynamic fixed-effects distributed lag model that accounts for physician-specific effects likely to induce bias if left uncontrolled, we assess the effect of detailing and sampling on physician prescribing behavior. The large number of observations in the database (it involves a total of more than 2 million observations) allows us to accurately pinpoint the impact that interactions with PSRs have on the number of new prescriptions issued by physicians.

We find that, although detailing and free drug samples have a positive and statistically significant association with the number of new prescriptions issued by a physician, the magnitudes of the effects are modest. As such, our results challenge the two dominant views and support the contention that, rather than being easy marks, physicians are tough sells. This realization is important because the public policy debate continues over how best to address the high cost of prescription drugs.

PSR Influence on Physicians

Most discussions of PSRs have focused on the factors facilitating their influence. Unquestionably, PSRs provide physicians with information about new drugs, new indications, dosages, and interactions for existing medicines. Azoulay (2002) finds evidence that detailing diffuses product information. Avorn et al. (1982) report that 20% of surveyed physicians view information provided by PSRs as "very important" in influencing their prescribing behavior. Furthermore, PSRs are trained in persuading physicians. Detailing takes the form of presenting facts and, as has been documented (Zigler et al. 1995), misrepresenting facts about the drug in an effective manner. Finally, mere exposure or salience effects might lead to a temporary increase in prescribing following a PSR visit. Numerous studies have reported high physician responsiveness to PSR activity attributed it to PSR persuasiveness (Avorn et al. 1982, Powers 1998).

Less attention has been paid to the factors limiting PSR effectiveness. The key consideration here is that PSRs are not the only or even the primary source of information about drugs for physicians. Scientific papers, advice from colleagues, and a physician's own training and experience also influence prescribing practices. Indeed, most physicians view these other influences as far more important than that of PSRs (Peay and Peay 1990).

PSR influence is limited by the fact that many physicians have skeptical or negative attitudes toward PSRs (Lichstein et al. 1992, McKinley et al. 1990). Attribution theory suggests that with low source credibility, which is determined by factors such as a source's trustworthiness and expertise (Dholakia and Sternthal 1977), arguments in a message will be discounted (Eagley and Chaiken 1975). Physicians recognize that PSRs are neither experts nor com-

pletely trustworthy. They realize that information presented is biased toward the promoted drug and is unlikely to be objective or even accurate (Connelly et al. 1990). Thus, physicians will discount information received from a PSR.

Some additional characteristics of physicians would seem to make them particularly tough sells. Friestad and Wright's (1994) persuasion knowledge model suggests that targets of persuasion use their knowledge about the persuasion agent and can effectively cope with and even achieve their own goals during a persuasion attempt, e.g., obtaining free drug samples that can be later distributed to patients. Campbell and Kirmani's (2000) tests of the persuasion knowledge model reveal that busy targets with accessible agent motivation (a profile that would fit most physicians) are particularly effective in resisting persuasion.

When cast within the workings of other sources of influence, we would expect the ability of PSRs to influence physician behavior to be relatively small. As such, we hypothesize a relatively small effect of PSR activity on physician prescribing behavior.

Previous Empirical Research

The various studies assessing the effect of PSR activity on physician prescribing behavior have generated conflicting results. Indeed, on some of the most central issues—ranging from the effects of detailing on prescriptions, of detailing on price elasticity, and even of price on sales—studies have come to diametrically opposite conclusions. Data and methodological limitations, however, raise concerns about the inferences drawn from these analyses.

A few quasi-experimental studies of the issue originate in the medical community. These studies compare physicians who did not see PSRs or were visited less frequently by PSRs to physicians who saw PSRs or were visited more frequently by PSRs (Chren and Landefeld 1994, Powers 1998). The limitation of these studies is that they are not randomized: PSRs do not determine which physicians to visit on a random basis. Rather, PSRs tend to see physicians who are more likely to utilize the drug or who prescribe in higher volume. This consideration invalidates these attempts to assess the effect of PSRs independent of controls accounting for motivation influencing PSR behavior.

The ability to potentially control for other influences is an advantage of regression-based analysis. Past research has made use of different regression techniques to assess PSR influence. Unfortunately, it has been inadequate in controlling for physician-specific effects. Parsons and Abeele (1981) use data for 24 months and 14 territories to model the number of prescriptions sold in a given territory for a given month as a function of sales calls. Interestingly, the estimated main effect of detailing was negative. The most dominant explanatory factor in the model is sales lagged one period, which would reflect persistence in behaviors and carryover effects magnifying the influence of detailing. Alternatively, lagged sales could be reflective of territory-specific effects that are not modeled and, as such, could lead to biased estimates. Wotruba (1982), for example, raises this possibility of territory-specific effects to question the reported effects of detailing.

Rizzo (1999) uses annual data for the period 1988–1993 and for 46 drugs to estimate a brand-level model linking prescriptions for a drug for a given year to pharmaceutical company marketing activities. He finds that price is negatively related to sales and that detailing is anticompetitive in that it decreases price sensitivity. Detailing is also found to have a direct positive effect on sales. Surprisingly, no consideration is given to the dynamic properties of sales. The classic spurious regression characteristics, i.e., very high R^2 in the presence of substantial unmodeled autocorrelation, appear to be present. As such, questions exist about the validity of both the point estimates and standard errors reported in the analysis.

Gonul et al. (2001) use data involving 1,785 patient visits to estimate a multinomial logit model assessing factors influencing physician prescribing behavior. Exactly opposite to the findings of Rizzo (1999), they report that price has a positive effect on prescription probabilities and that detailing increases price sensitivity. They find positive effects of detailing and sampling, but do not discuss the implications of their magnitudes. These magnitudes, calculated based on descriptive statistics, imply elasticities that are surprisingly large.[1] The elasticity estimates for the seven drugs studied, evaluated at the mean level of detailing and sampling, average 41% for detailing and 48% for sampling. Particularly for samples, which have a negligible marginal cost, their estimated coefficients imply enormous returns to enhanced PSR activity. In point of fact, these substantial effects could arise, not from the influence of PSR activity, but rather as an outgrowth of a joint correlation with an omitted factor from the model, e.g., larger practices prescribe more and receive more free samples.

A concern, which Gonul et al. (2001) explicitly acknowledge, is over the role of physician-specific effects that can induce a bias in the estimated coefficients. They state (p. 84),

> prescription behavior patterns might be strongly influenced by factors other than the explanatory variables we include in our model. Examples are physi-

[1] The elasticity of prescription probability P_j to covariate x_{jk} in a conditional logit model is calculated as $(\partial P_j/P_j)/(\partial x_{jk}/x_{jk}) = \beta_k * x_{jk} * (1 - P_j)$.

> cians' unobservable personal characteristics.... Ignoring these factors might bias the coefficients of the included explanatory variables.

The extent to which their estimates are biased by the failure to control for unobservable factors remains unanswered, but this is one consideration that might account for the large estimated effects.

Empirical Analysis

A key benefit of utilizing pooled time series cross-sectional (panel) data is the ability to test for and control the effect of unobserved fixed factors. These unobserved factors, if left uncontrolled, can induce bias in the coefficient estimates of the explanatory factors included in the model. Past research has either not used panel data or not made full use of the benefits of panel data analysis. We make use of pooled time series cross-section observations (24 months of observations across 74,075 physicians) and panel data statistical methods (i.e., a dynamic fixed-effects distributed lag regression model) to assess the effect of detailing and sampling on physician prescribing behavior.

Data

Access to the data was gained from a U.S. pharmaceutical manufacturer with the only condition of ensuring the anonymity of the firm and the drugs in the study. Two different sets of data were merged to form the database. One data set pertains to the number of new prescriptions for the studied drugs and their competitors issued by physicians during a month. The *new prescription* measure reflects both new and repeat usage, but does not reflect refills accompanying the prescriptions. These data cover a 24-month period for three widely prescribed drugs. The second data set pertains to detailing and sampling activity by PSRs for the same three drugs. The two data sets were merged into one database containing prescribing and promotional activity information by month and physician.

To reduce the possible influence of extreme values (outliers) that would arise from, for example, data entry errors and the common practice of one physician signing for all samples that later get distributed to a group of physicians attending a conference, we excluded the top 0.5% of observations for the number of details, samples, and new prescriptions. We later undertook sensitivity analysis on alternative definitions of outliers (e.g., 0%, 1%, 5%) and found results in close correspondence across these alternative samples.

Table 1 presents basic background information and descriptive statistics for the drugs included in our study. The drugs differ on a variety of dimensions: They have been on the market from less than 1 year to 11 years; annual sales range from under \$0.5 billion to more than \$1 billion; they come from different therapeutic areas. Although the effect of detailing can vary across drugs, analysis of these three drugs offers some generalizable insights, not only because they provide a cross-section of drugs in the marketplace, but because they represent more than 4 million PSR interactions with physicians.

Model

We employ the following dynamic fixed-effects distributed lag regression model to assess the effect of detailing and sampling on new prescriptions:

$$\begin{aligned} Prescribe_{it} &= \alpha_i + \sum_{j=0}^{6} \beta_j * Details_{it-j} + \sum_{j=0}^{6} \gamma_j * Samples_{it-j} \\ &+ \sum_{j=0}^{6} \lambda_j * Competitor_{it-j} + \sum_{j=1}^{6} \phi_j * Prescribe_{it-j} \\ &+ \sum_{\tau=1}^{T} \delta_\tau * Time(\tau) + \sum_{s=1}^{11} \kappa_S * Specialty(s) * Trend_t \\ &+ \varepsilon_{it}, \end{aligned} \tag{1}$$

where $Prescribe_{it}$, $Details_{it}$, $Samples_{it}$, and $Competitor_{it}$ are, respectively, the number of new prescriptions issued, the number of PSR visits, the number of free drug samples received, and the number of new prescriptions issued for competitive drugs by physician i at time period t. $Time(\tau)$ is an indicator function that takes on the value 0 prior to the time period τ and 1 from the time period τ on, $Specialty(s)$ is an indicator function that takes on the value 1 when the specialty area of the physician is s, 0 otherwise (i.e., separate dummy variables for each of the 11 specialty areas), and Trend is the observation number for a given month and year. Because it includes both current-term and lagged variables in the model, Equation (1) allows for a wide range of possible effects and influences, e.g., serial correlation (current-effects) and state-dependent (persisting) dynamic relationships.

A key characteristic of Equation (1) is that it allows for a physician-specific effect, i.e., the intercept α_i is allowed to vary by physician. This consideration acknowledges that physician behavior patterns are influenced by unobserved or unobservable factors, e.g., physician characteristics. To the extent that these unobserved factors are correlated with detailing and sampling, analysis not controlling for their effects will result in biased estimated effects for the marketing phenomena. Although a Hausman (1978) specification test can empirically assess the role played by fixed effects, we have a priori reason to believe that these unobserved factors will in fact be correlated with marketing activity. For instance, larger practices will generate more prescriptions and will also attract more

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