



Responsiveness of Physician Prescription Behavior to Salesforce Effort: An Individual Level Analysis

PUNEET MANCHANDA* and PRADEEP K. CHINTAGUNTA

{puneet.manchanda;pradeep.chintagunta}@ChicagoGSB.edu

The University of Chicago, Graduate School of Business, 5807 South Woodlawn Avenue, Chicago, IL 60637, USA

Abstract

Firms in many industries, e.g., pharmaceuticals, spend a significant amount of marketing dollars on salesforce effort. However, there exists very little research examining customer response to salesforce effort at the disaggregate level.

We use data from a pharmaceutical category to examine the response in prescriptions written to salesforce effort (detailing). We use a hierarchical Bayesian count data model that allows us to estimate individual physician-level response parameters.

We find that while detailing has positive impact on prescriptions written, there are diminishing returns to detailing for most physicians in our sample. We use our results to show how detailing reallocation can increase revenues.

Keywords: response models, salesforce effectiveness, micromarketing, pharmaceuticals

1. Introduction

Marketers have long been interested in studying the effects of marketing activities on consumer behavior. Data at various levels of aggregation have been employed to this end. Using data at the aggregate market or national level, several studies have investigated the effects of price (e.g., Wittink et al., 1987), advertising (Lodish et al., 1995; Dekimpe and Hanssens, 1995), promotions (e.g., Blattberg and Wisniewski, 1989), salesforce effort (Parsons and Vanden Abeele, 1981) and distribution (Reibstein and Farris, 1995) on the sales of different brands in a particular product category. The output of such analyses have then been employed for a variety of purposes e.g., to determine optimal levels of marketing activities (e.g., Erickson, 1992), for resource allocation in terms of how much to invest in each of several marketing mix variables (e.g., Chintagunta and Vilcassim, 1994). More recently, the availability of household-level scanner panel data has enabled marketers to investigate the relationship between prices, promotional levels and advertising on the brand choices of individual households. Such disaggregate analyses not only provide a clearer picture of the effects of a firm's marketing mix, but also facilitate micro-

* Corresponding author.

marketing when reasonable estimates are available at the household level. By micromarketing we mean the ability to tailor a firm's marketing mix for the individual household. Bayesian methods, which have seen increased prominence in the marketing literature of late, enable us to obtain such household level estimates of the effects of marketing activities.

While there have been several studies that have examined individual customer response to price and promotion using panel data, there is limited research that has examined customer response to salesforce effort using similar data. Many industries such as pharmaceuticals spend significant amounts of money on salesforce activity (e.g., in the Oral Histamine category, the annual expenditure on salesforce activity was about \$ 500 million in 1998). In addition, for the pharmaceutical industry, salesforce activity is the primary source of promotion e.g., in the Anti-Ulcer product category, these expenditures amount to about 80% of all promotional expenditure – equal to about 20% of sales (Wittink, 2002). Known as detailing, the interaction between the salesperson and the physician is regarded as a primary source of information about new and existing drugs for physicians (Ziegeler et al., 1995; Lexchin, 1989). The prescription behavior of physicians has long been regarded as being influenced by detailing activities of pharmaceutical firms (Lurie et al., 1990; Lexchin, 1989). Given the amount invested in this marketing activity, a firm may wish to understand how each individual physician responds to detailing effort. Given the finite nature of the physician population, such knowledge would enable the firm to better direct salespersons' calls to the appropriate doctors. This will help the firm maximize the return on its investment in its salesforce.

In this paper, we investigate the impact of the number of sales calls on the prescription behavior of individual physicians for a specific drug in a specific therapeutic class. The data are at the quarterly level and are available for a panel of physicians from across the U.S. Given the discrete nature of the prescriptions data, i.e., the number of prescriptions written each quarter, we model the number of prescriptions written by a physician in a quarter as a Poisson regression. The Poisson parameter is allowed to be physician specific and a function of the detailing effort, i.e., the number of sales calls directed towards that physician. The effect of detailing is also allowed to be physician specific and is modeled as a function of the "quality" of detailing directed to the physician (e.g., extent of sampling), observed physician characteristics (e.g., specialty) as well as unobserved factors.

An important concern of managers with respect to salesforce effort is whether the amount of detailing is optimal. This issue has been examined in earlier research at the aggregate level (e.g., Lilien et al., 1981). Specifically, an important concern (especially in the pharmaceutical industry) is whether there are diminishing returns to salesforce effort. However, to the best of our knowledge, this issue has not been investigated in the marketing literature at the individual physician (customer) level. Other research in marketing has proposed that individual response to promotional efforts such as advertising does indeed show diminishing returns (Malaviya et al., 1999). These studies postulate that the (positive) attitude towards an advertisement increases with the number of exposures to that advertisement till it reaches a point from which the attitude actually begins to decline. In our approach, we use revealed behavior data to test for diminishing returns in the number

of prescriptions written as a function of the quantity and quality of salesforce effort. We carry this out through the use of a hierarchical Bayes model formulation which allows the mean rate of prescriptions for each individual physician to be a quadratic function of salesforce effort devoted to that physician. Our approach therefore allows us to determine the extent to which salesforce effort deviates from optimality for each individual physician in our sample.

Our results indicate that detailing has a positive and significant impact on the number of prescriptions written by a physician. Additionally, we find that samples provided to physicians have a main effect that is positive but an interaction effect with detailing that is negative. We also find differential effects across physician specialty but not across physician gender. An interesting finding from our analysis is that, on average, there are diminishing effects of detailing on prescription behavior (i.e., a negative effect of the quadratic term described previously). Specifically, two-thirds of the physicians in our sample exhibit diminishing returns to detailing. The logical issue then is whether there is “over-detailing” for this particular drug. By over-detailing we mean detailing effort beyond the point at which increased detailing results in lower prescription levels (due to the diminishing effects of detailing). For these physicians, our findings indicate that there was over-detailing, on average, in fifteen percent of the quarters in our data. Reallocating the over-detailed calls to the remaining physician-quarters results in a ten percent increase in the number of prescriptions over the current levels.

The remainder of this paper is organized as follows. We review the previous work in this area in Section 2. Section 3 describes our modeling approach. In Section 4, we discuss the data and model specification. Section 5 describes the results and comparison with null models. We discuss the managerial implications of our findings in Section 6 and conclude in Section 7.

2. Previous Research

Our research builds on the existing stream of research that has investigated the effectiveness of salesforce effort in the pharmaceutical industry. Hence we restrict our literature review to such studies. A complementary stream of research has focused on estimating the effectiveness of individual sales representatives by looking at factors that lead them to work “smarter” (Sujan, 1986; Sujan et al., 1988, 1994). As we discuss in the next section, our panel identifies individual physicians, not individual sales representatives. Thus, we cannot estimate the effectiveness of an individual sales representative.

One of the early studies to empirically investigate the sales response of an established ethical drug to sales calls by a pharmaceutical manufacturer is Parsons and Vanden Abeele (1981). The authors propose a double-log regression model with the number of wholesale units sold in a given month as the dependent variable and the number of sales calls and lagged period sales as independent variables. The effectiveness of sales calls is modeled as a function of a baseline effect and the effect of samples provided by the salesperson. Data used in the estimation are from the Belgian market at the aggregate territory level (across fourteen territories). Territorial differences are accounted for through the use of

covariates such as the number of adult women and doctor specialties within each territory. The authors find that the number of calls, the interaction between calls and samples and the effects of lagged sales all have a significant impact on sales of the drug. Interestingly, they find that the main effect of sales calls is *negative* on the number of prescriptions. This result may be due to the aggregate nature of the data. Our model is similar in spirit to their model since we also allow interactions between sales calls and sampling. However, a major point of departure from that study is that our unit of analysis is the individual physician. The disaggregate nature of our data should allow us to get correct signs for the marketing mix variables. In addition, our results will allow us to carry out resource allocation across individual physicians.

More closely related to the issue of allocation of sales calls to physicians is the study by Lodish (1971, 1976). The proposed model, referred to as CALLPLAN, attempts to first determine the response function to sales calls at a specified level of analysis (e.g., territory or physician). Using managerial judgement, the response function is calibrated. The firm's objective function (to maximize profits) is then set up. The optimal salesperson calling plan schedule is then determined by maximizing the firm's objectives subject to the various constraints imposed by the company's salesforce. Given the complexity of the problem, "near optimal" solutions are sought using certain heuristics. In contrast to CALLPLAN, which uses judgemental data, we make use of actual behavioral data on the physicians' response to calibrate individual level response functions. In addition, our focus is to understand salesforce effort allocation while the Lodish model is focused largely on the issue of sales territory alignment.

A major reason for the absence of research looking at the effects of detailing effort on physician prescription behavior has been the absence of data at the disaggregate level. However, such data are now becoming available from sources such as IMS America, Scott-Levin, Walsh/PMSI and individual pharmaceutical companies. A recent study using disaggregate data is the one by Gonul et al. (2001). The study finds that salesforce effort has a positive and significant effect on the choice of which drug to prescribe. However, the effect of salesforce activity is measured only at the aggregate level (even though the data are available at the disaggregate level).¹ These results are consistent with other recent studies that have used aggregate data (Wittink, 2002).

To summarize, most previous research in this area has looked at aggregate analyses of the sales (prescriptions) – detailing relationship. We have incorporated several of the features of those studies into our model specification. By contrast, our analysis is at the individual physician level. Hence, our work can be seen as complementing and extending previous research in that regard.

3. Modeling Approach

Our interest is in modeling the total number of prescriptions written by each physician in each time period. Let the number of prescriptions written by physician i in time period t be denoted as y_{it} . Since the number of prescriptions written in each quarter is discrete and non-negative, we use the default count data model i.e., the Poisson regression. Specif-

ically, we assume that y_{it} follow a Poisson distribution with a physician-specific mean rate λ_{it} (cf. Winkelmann, 1997, Chap. 2). Thus, the number of prescriptions written by each physician i in period t is given by

$$\Pr(y_{it} = y_{it} \mid \lambda_{it}) = \frac{\lambda_{it}^{y_{it}} \exp(-\lambda_{it})}{y_{it}!} \quad (1)$$

and the joint density, \mathcal{L} , for the complete set of physicians for all the time periods is

$$\mathcal{L} = \prod_{i=1}^I \prod_{t=1}^T \frac{\lambda_{it}^{y_{it}} \exp(-\lambda_{it})}{y_{it}!}. \quad (2)$$

As discussed earlier, we have some evidence from previous research, that salesforce effort plays an important role in the sales (prescriptions) of a pharmaceutical drug. At the individual physician level, therefore, we assume that the mean prescription rate for each physician, λ_{it} , is affected by the marketing efforts of the firm and the physician specific attributes. We follow the usual convention and express the mean rate as $\lambda_{it} = \exp(\beta_i x_{it})$, where x_{it} is a $K \times 1$ vector of variables affecting the physician's prescription behavior and β_i is the $1 \times K$ vector of coefficients specific to physician i . Further, as physicians are assumed to be heterogeneous in how they respond to the explanatory variables, x_{it} , we allow the β_i to vary as follows, $\beta_i = Z_i \mu + \epsilon$, where Z_i is a matrix containing detailing and physician specific variables, μ is a vector of coefficients and ϵ is the vector of errors capturing variations in unobserved differences. $Z_i \mu$ therefore accounts for observed sources of heterogeneity across physicians. ϵ , on the other hand, accounts for unobserved heterogeneity across these physicians. We assume that the ϵ are distributed multivariate normal, $N(0, \Sigma)$, where Σ is a $K \times K$ variance-covariance matrix. In other words, the β_i are distributed multivariate normal, $MVN(Z_i \mu, \Sigma)$.

The above formulation represents a random coefficients count data model in which the random effects are assumed to follow a specific parametric distribution – in this case, the Multivariate Normal distribution. The main substantive advantage in assuming a continuous distribution in our case is that, combined with the estimation methodology that we describe next, it is possible for us to obtain individual physician level effects (Allenby and Rossi, 1998). This would then facilitate the resource allocation task that we described in the introduction. From a methodological point of view, the assumption that β_i are distributed normally ensures that we are not constrained by the equi-dispersion implied by the standard Poisson regression model.²

In terms of estimation, we cast our count model in a hierarchical Bayes framework and use Markov chain Monte Carlo methods to arrive at the posterior density of the unknowns (Chib et al., 1998; Winkelmann, 1997; Neelamegham and Chintagunta, 1999). To complete our description of the model under the hierarchical Bayesian framework, we need to specify prior distributions and detail our sampling strategy. Prior distributions need to be specified for the detailing and physician specific parameters, μ and Σ . We assume that the μ are distributed multivariate normal, $N(\mu_0, M)$, and that Σ^{-1} is distributed as Wishart, $W(\rho, (\rho R)^{-1})$. This leads to the joint density of the data, (Y, X, Z_i) , and the unknowns, (β, μ, Σ) , as follows

$$p(y, \beta_i, \mu, \Sigma | X, Z_i) = \prod_{i=1}^I \prod_{t=1}^T p(y_{it} | \beta_i, X) \prod_{t=1}^T p(\beta_i | \mu, \Sigma, Z_i) p(\mu) p(\Sigma). \quad (3)$$

Using this joint density and the specified prior distributions, we derive the full conditional distributions for each of the unknowns. We then use Markov chain Monte Carlo methods to draw iteratively from these full conditional distributions and, after discarding an initial sequence of draws, make inferences about the unknowns β , μ , Σ using the empirical distribution of the retained draws.

The full conditional distributions (and values of the priors) for each of the unknowns are described below:

1. The full conditional distribution for β is given by

$$p(\beta_i | \mu, \Sigma, Y, X, Z_i) \propto \prod_{t=1}^T \exp(\beta_i x_{it})^{y_i} \exp(-\exp(\beta_i x_{it})) \exp((\beta_i - Z_i \mu) \Sigma^{-1} (\beta_i - Z_i \mu)'). \quad (4)$$

2. The full conditional distribution for μ is given by

$$p(\mu | \beta, \mu_0, M, Z_i) = N(\hat{\mu}, \hat{M}), \quad (5)$$

where $\hat{\mu} = \hat{M}^{-1}(M^{-1}\mu_0 + \sum_{i=1}^I Z_i' \Sigma^{-1} \beta_i)$ and $\hat{M}^{-1} = (M^{-1} + \sum_{i=1}^I Z_i' \Sigma^{-1} Z_i)$. We use diffuse but proper priors and set $\mu_0 = 0$ and $M = \text{diag}(100)$.

3. The full conditional distribution for Σ^{-1} is given by

$$p(\Sigma^{-1} | \beta, \mu, \rho, R, Z_i) = W\left(\left[\rho R + \sum_{i=1}^I (\beta_i - Z_i \mu)(\beta_i - Z_i \mu)'\right]^{-1}, \rho + I\right), \quad (6)$$

where I is the number of physicians. We set $\rho = I + 1$ and $R = \text{diag}(0.01)$.

Note that the full conditional distribution for β is known only up to a constant of proportionality. This is in contrast to the full conditional distributions of μ and Σ^{-1} which are known fully. We therefore use a substitution sampler that combines draws using the Metropolis–Hasting algorithm (for β) and Gibbs sampler draws (for μ and Σ^{-1}). Since the Gibbs sampler draws are standard (Geman and Geman, 1984), we describe only the Metropolis–Hastings draws below.

For the Metropolis–Hastings algorithm (Hastings, 1970; Chib and Greenberg, 1995), we need to draw candidates from a proposal density $q(\cdot)$. Let the generated candidate (from this proposal density) be $\beta_i^{(c)}$. Then, if the current value of β_i is $\beta_i^{(n-1)}$, the candidate is accepted with the following probability

$$\min\left\{\frac{p(\beta_i^{(c)} | \mu, \Sigma, Y, X, Z_i) q(\beta_i^{(c)} | \beta_i^{(n-1)})}{p(\beta_i^{(n-1)} | \mu, \Sigma, Y, X, Z_i) q(\beta_i^{(n-1)} | \beta_i^{(c)})}, 1\right\}, \quad (7)$$

where $p(\cdot)$ is the likelihood defined earlier.

Since the β_i are unbounded in our case, we choose $q(\cdot)$ to be the multivariate normal density. We therefore generate candidates using a random walk chain, $\beta_i^{(c)} = \beta_i^{(n-1)} + N(0, \tau\Omega)$. We set the Ω to be equal to the covariance matrix of the parameters obtained through using a simpler version of the model using maximum likelihood estimation. We choose a scalar τ such that the acceptance probability is 30% (the recommended range is 23–40% – see Roberts et al., 1997). Given this symmetric proposal density, the acceptance probability reduces to

$$\min \left\{ \frac{p(\beta_i^{(c)} \mid \mu, \Sigma, Y, X, Z_i)}{p(\beta_i^{(n-1)} \mid \mu, \Sigma, Y, X, Z_i)}, 1 \right\}. \quad (8)$$

The model was estimated using C programs. Repeated draws were made from the series of full conditionals to arrive at the joint posterior density of the unknown quantities using the MCMC sampling scheme. The substitution sampler was run for 30000 iterations and the sequence of output draws was examined to ensure convergence. We used the last 5000 draws for the purpose of making inference.

4. Data and Model Specification

4.1. Data

Data on physician prescription behavior and salesforce effort for a drug in a mature product category were made available to us by a major U.S. pharmaceutical firm. Due to the proprietary nature of the data, the firm has requested that we do not identify the firm, the drug category and the specific drug. The data represent a detailed record of physicians' prescription behavior for the drug in question (which we shall refer to as drug X in subsequent discussion) over the period December 1996 to November 1998. The total number of prescriptions made by each physician for drug X are recorded quarterly. This data has been compiled by the firm. We have eight quarters of prescription behavior for each physician. The total number of physicians in the database is very large and covers the entire United States. The specialty and gender of each physician in the data is also available.

Salesforce effort by the firm's salesforce for each of these physicians for each quarter has been compiled by the firm from its internal records. This makes it one of the most accurate sources of salesforce effort that has been used to examine physicians' prescription behavior so far. The number of calls made to each physician per quarter as well as the number of free samples of drug X given out to each physician during this time period is available in the data.

In our analysis, we use a sample of 1000 physicians drawn at random from the complete database consisting of 116,218 physicians. We ensure that the random sample is matched with the population on both demographics and behavioral variables.

In terms of demographics, we have access to physician gender and specialty. Of the 1000 physicians, 80% are male. In terms of specialty, we classify all the physicians in our sample into three specialty groups based on our discussion with the firm providing the data. The three specialty groups are labeled as SPE, PCP and OTH. SPE stands for

the specialty directly related to the drug benefit or patient problem addressed by drug X,³ PCP denotes Primary Care Physician and OTH refers to all other specialties. 11% of the physicians in our sample belong to specialty SPE, 59% to specialty PCP and the balance 30% to specialty OTH.

In terms of the behavioral variables, our data provide information on total prescriptions written and sales calls (details) and samples received by each physician for each of the eight quarters. Across all physician-quarters (8000 observations), the mean (standard deviation) of total prescriptions written is 48.10 (46.17), details received is 3.93 (4.91) and samples received is 18.44 (24.33).

Note that while the practice in the pharmaceutical industry has been that more than one drug is detailed during a call, recent trends indicate that the number of drugs detailed during a call is one or two (*Medical Marketing and Media*, January 17, 2000, p. 10). In our data, a call is recorded *only if* drug X has been detailed in that call. We therefore treat each call as equal to each detail. Also, each sample in our data consists of medication that represents a typical course of treatment of drug X.

4.2. Model Specification

There is much evidence in the literature that detailing plays a strong role in physicians' understanding of drug characteristics and subsequent prescription behavior (Ziegeler et al., 1995; Lexchin, 1989; Parsons and Vanden Abeele, 1981). However, as we have mentioned earlier, there is some concern in the pharmaceutical industry regarding over-detailing. We expect that this will manifest itself (after an initial level of detailing) in a flat response in prescriptions (at best) or a declining level of prescriptions for each additional detailing call (at worst). In other words, we expect the mean rate to be a concave function of detailing. We therefore introduce a non-linear term as a covariate in the equation for the mean. Consistent with previous literature (Gonul et al., 2001; Lilien et al., 1981), we use the quadratic formulation where the mean prescription rate is a function of the number of detailing calls (NDET) and the square of the number of detailing calls (NDET²). The quadratic specification has also been used to test for concavity or convexity in Poisson count data models in other domains (e.g., see the labor mobility application in (Winkelmann, 1997, p. 169)).⁴ The sign of the coefficient for the squared number of detailing calls will provide us some indication of the overall returns to detailing. Let NDET refer to the number of times a physician was detailed in a particular quarter. Then,

$$\lambda_{it} = \exp(\beta_{0i} + \beta_{1i} \cdot \text{NDET}_{it} + \beta_{2i} \cdot \text{NDET}_{it} \cdot \text{NDET}_{it}).$$

In the above equation, we expect $\beta_{1i} > 0$. $\beta_{2i} = 0$ implies that a physician's mean prescription rate is linear in the amount of detailing. On the other hand, a value greater than zero implies increasing returns to detailing while $\beta_{2i} < 0$ suggests that beyond a particular level of detailing, the physician starts prescribing less of the detailed drug. The key benefit of the methodology that we use in this paper is that we can classify each physician i into one of three groups depending on whether $\beta_{2i} < 0$, $= 0$ or > 0 .

As discussed section 3, the mean prescription rate may vary across physicians due to observable and unobservable factors. In other words, $\beta_i = Z_i \mu + \epsilon$, in which as just described, $\beta_i = (\beta_{0i}, \beta_{1i}, \beta_{2i})$. In order to characterize the Z_i , we identify two sets of observable variables – quality of detailing effort and physician specific effects.

Quality of detailing Physicians meet the salesforce of various drug companies for a variety of reasons. These reasons include gathering of information about specific drugs, to obtain free samples and to stay in touch with developments in the medical practice (Lexchin, 1989). Thus the quality of detailing in terms of prescription effectiveness depends, among other factors, on the number of free samples handed out to the physician. Therefore, the mean prescription rate may be influenced by the mean number of samples handed out to a physician. We therefore allow the mean number of samples to influence the mean prescription rate of each physician through all three β coefficients (i.e., $\beta_0, \beta_1, \beta_2$). Thus, the main effect of mean sampling on mean prescription rates is captured through the coefficient of sampling (denoted by MSAM) on β_0 while the interaction effects of sampling are captured through the coefficients of sampling and detailing on β_1 and β_2 .

Physician specific effects Since we have physician level data, we consider two other variables that could affect physician response to detailing.

1. *Specialty*: Our discussion with the firm that provided the data indicated that for the drug in question, physicians' prescription behavior could be systematically different across three types of specialty groups mentioned earlier – SPE, PCP and OTH.
2. *Gender*: Much research in marketing has shown that there may be systematic differences in how persuasion is affected by gender (e.g., Meyers-Levy, 1988). We therefore include information on whether the physician was male or female.

Note that we allow Specialty and Gender to appear as main and interaction effects as well. Thus the specification of the β 's is as follows:

$$\begin{aligned} \beta_{0i} = & \mu_1^0 + \mu_2^0 \cdot \text{SG1} + \mu_3^0 \cdot \text{SG2} + \mu_4^0 \cdot \text{SG3} + \mu_5^0 \cdot \text{SG4} \\ & + \mu_6^0 \cdot \text{SG5} + \mu_7^0 \cdot \text{MSAM} + \epsilon_0, \end{aligned} \quad (9)$$

$$\begin{aligned} \beta_{1i} = & \mu_1^1 + \mu_2^1 \cdot \text{SG1} + \mu_3^1 \cdot \text{SG2} + \mu_4^1 \cdot \text{SG3} + \mu_5^1 \cdot \text{SG4} \\ & + \mu_6^1 \cdot \text{SG5} + \mu_7^1 \cdot \text{MSAM} + \epsilon_1, \end{aligned} \quad (10)$$

$$\begin{aligned} \beta_{2i} = & \mu_1^2 + \mu_2^2 \cdot \text{SG1} + \mu_3^2 \cdot \text{SG2} + \mu_4^2 \cdot \text{SG3} + \mu_5^2 \cdot \text{SG4} \\ & + \mu_6^2 \cdot \text{SG5} + \mu_7^2 \cdot \text{MSAM} + \epsilon_2. \end{aligned} \quad (11)$$

μ_i^0 represent the base case representing male physicians who belong to the OTH classification. The remaining binary variables capturing the specialty/gender interaction are – SG1 (Male/SPE), SG2 (Male/PCP), SG3 (Female/OTH), SG4 (Female/SPE) and SG5 (Female/PCP).

Table 1. Effects of Detailing^a

Parameter	Mean	5th percentile	95th percentile
INTERCEPT (β_0)	3.23	0.72	4.91
NDET (β_1)	0.83	-1.58	3.98
NDET · NDET (β_2)	-0.49	-2.44	1.21

^a Across 1000 physicians.

Table 2. Σ Matrix

	INTERCEPT (β_0)	NDET (β_1)	NDET · NDET (β_2)
INTERCEPT (β_0)	1.14 (0.11)	-1.11 (0.08)	0.57 (0.05)
NDET (β_1)		3.23 (0.17)	-2.05 (0.11)
NDET · NDET (β_2)			1.42 (0.07)

Mean and (posterior standard deviation).

5. Results and Managerial Implications

5.1. Results

We first examine the effect of detailing on mean prescriptions (Table 1). Our results show that the mean prescription rate is positively affected by detailing activity, as can be seen from the positive sign of β_1 . However, the mean prescription rate is concave in the amount of detailing as can be seen from the negative sign of β_2 . In other words, detailing is effective in increasing the mean prescription rate up to a point after which it has an adverse effect on mean prescriptions. One possible explanation for this finding is detailing “wearout”. Given the mature nature of the product category, increasing contact with a physician beyond a particular point in a given quarter may not provide any additional benefit to the physician. In fact, it may result in a backlash. This is especially likely if we consider the fact that the opportunity cost of time is quite high for physicians in general.

Our results also show considerable differences across physicians in their response to the amount of detailing. This may be seen from the diagonal elements of the Σ matrix (Table 2). These results therefore indicate that the use of the hierarchical specification is justified.

We now examine how the observable differences across detailing and physicians affect the mean prescription rate. Table 3 details the estimates of the μ vector for each of the three β coefficients. We find that the main effect of sampling, μ_7 , is positive i.e., increased sampling leads to higher mean prescriptions. However, the interaction effect with detailing is negative and that with detailing squared is insignificant. This implies that increased

Table 3. Hierarchical Means

Parameter	INT (μ_1)	SG1 (μ_2)	SG2 (μ_3)	SG3 (μ_4)	SG4 (μ_5)	SG5 (μ_6)	MSAM (μ_7)
INTERCEPT (β_0)	2.35 (0.08)	0.93 (0.14)	0.42 (0.09)	-0.18 (0.17)	1.28 (0.28)	0.35 (0.12)	2.79 (0.18)
NDET (β_1)	1.10 (0.15)	0.24 (0.11)	-0.07 (0.17)	-0.04 (0.30)	0.03 (0.38)	0.09 (0.19)	-1.30 (0.30)
NDET · NDET (β_2)	-0.66 (0.10)	-0.12 (0.16)	0.08 (0.12)	0.09 (0.19)	-0.31 (0.27)	-0.03 (0.10)	0.82 (0.20)

Mean and posterior standard deviation.

Table 4. Gender and Specialty Effects

Parameter	Gender		Specialty		
	Male	Female	OTH	SPE	PCP
INTERCEPT (β_0)	3.70	3.98	2.35	4.56	3.12
NDET (β_1)	1.34	1.22	1.10	1.46	1.10
NDET · NDET (β_2)	-0.66	-0.66	-0.66	-0.66	-0.66

sampling leads to a lower detail efficacy. This may be because the physician may not be responsive to details that consist of (increasing) sample drop-offs. This is borne out by industry studies which note that sales representatives use samples to gain admission to the physician's office (since samples are attractive to the physician – as suggested by the positive main effect) and therefore do not add any “value” to the detail (Stinebaugh and Sabin, 2003).

We translate the specialty and gender effects to a more meaningful form (Table 4). Our findings indicate that the highest mean prescription rate is for physicians of specialty SPE, followed by PCP and then OTH (all differences are significant). This is not unexpected. We also find that SPE specialty physicians are the most responsive to detailing while there is no difference on this dimension for the other two specialties. Also, on average, diminishing returns do not vary across specialties. Finally, we find no significant differences in the base level of prescriptions, responsiveness to detailing and diminishing returns across male and female physicians.

As mentioned earlier, the power of our approach is not just in describing average effect sizes, but in being able to investigate individual level effects. The main coefficient of interest in our analysis is that of the quadratic term (β_2). When we examine the posterior distribution of the 1000 individual coefficients, we find that even though the mean β_2 across the sample of physicians is negative, the mean individual response coefficient, $E(\beta_{2i})$ is negative for *only* 664 of the 1000 physicians. This implies that, on average, the response to detailing exhibits diminishing returns – however, it does so for about two-thirds of the physicians. This has important implications for resource allocation. We discuss these in detail in the section on managerial implications below.

5.2. Model Performance

We compare our model specification with two null models. The first null model is a non-hierarchical version of our model (null model 1). The second null model is the hierarchical version of our model without the quadratic term (null model 2).

We compare our model using a cross-validated (or “leave one out”) approach where the fitted value for a set of holdout observations is computed conditional on all the data (except the holdout set) (Gelfand et al., 1992; Gelfand and Dey, 1994). In order to do this, we make use of the conditional predictive density which is given by:

$$f(y_r | Y_{(r)}) = \int f(y_r | \theta, Y_{(r)}) f(\theta | Y_{(r)}) d\theta,$$

where Y represents the data, θ represents the unknowns and $Y_{(r)}$ denotes all elements of Y except y_r . In our case, we use the last observation for each physician as our holdout observation. The density at each of these observations is known as the *Conditional Predictive Ordinate* or *CPO*. The logarithm of the CPO (for the r th data point) represents the incremental benefit of the model for that data point relative to the prior predictive density at all the other points. Therefore, we can sum the $\log(\text{CPO})$ over all r points to determine model performance – the higher this number, the better the model.

We estimate each of the models using 7000 observations (keeping 1000 observations as holdout). The $\sum \log(\text{CPO})$ of the proposed model is -4072.06 , for null model 2 it is -4203.14 and null model 1 it is -4587.10 . Thus our model provides considerable improvement in predictive performance over both null models.

6. Managerial Implications

We now discuss the managerial implications of our findings. We first focus on trying to understand the reasons for the variation in the quadratic term. As discussed earlier, the mean coefficient of $\text{NDET} \cdot \text{NDET}(\beta_2)$ is negative for 664 out of the 1000 physicians. Therefore we do not observe diminishing returns to detailing for 336 physicians. In the analysis that follows, given that the individual coefficients are being utilized, it is important to document how well the posterior mean is estimated for each physician. We computed the posterior standard deviations of the thousand β_{2i} parameters and found that for a majority of the parameters (53%), the distribution was massed away from zero. In fact, for the 664 negative β_{2i} parameters, the posterior distribution of 403 (or 61%) was massed away from zero.⁵ The first group of 663 physicians (for whom the mean β_{2i} parameter is negative) represents the worst-case scenario for the firm as a larger number of physicians seem to show evidence of diminishing returns. In contrast, the second group of 403 physicians (for whom the mean β_{2i} parameter is negative and significant) represents the best-case scenario for the firm. Thus, in our analysis below, we will focus on both groups so as to provide an upper and lower bound on our findings. For the sake of exposition, we will label these two groups as Group W(orst) and Group B(est), respectively.

It is possible that the differences in the β_2 parameter can be explained by observable differences across physicians. In our data the observable differences comprise the demo-

graphics (specialty and gender) and the marketing activity variables (detailing and sampling).

We first examine the specialty composition of the different groups of physicians (note that gender differences were not significant). The composition of Group W is 61% PCP, 26% OTH and 13% SPE relative to the remaining physicians (non Group W) who are split as 67% PCP, 24% OTH and 9% SPE. If we look at Group B, the composition is 60% PCP, 25% OTH and 15% SPE and 65% PCP, 26% OTH and 9% SPE for the remaining (non Group B) physicians.

We next examine the activity data for these groups of physicians. Group W gets an average of 3.79 calls/quarter relative to 4.20 calls/quarter for the non Group W physicians. In terms of sampling, we find that Group W gets an average of 17.12 samples/quarter as compared to 21.06 for the remaining physicians. If we restrict our analysis to Group B, we find that they get 3.72 calls/quarter relative to the remaining physicians who get 4.07. For sampling, Group B gets 16.98 samples/quarter while the remaining physicians get 19.44.

Taken together, these data suggest the following. First, diminishing returns are observed somewhat more frequently among SPE physicians. Second, on average, the firm seems to be directing more of its marketing activity towards physicians that do not exhibit diminishing returns (in the range of the available data).

As mentioned earlier, a major benefit of our methodology is that it allows us to examine managerial implications at the individual physician level. We therefore focus now on individual physician (and quarter) analyses to understand the extent of “over-detailing.” By over-detailing we mean that these physicians get more calls than are “optimal” for them. The optimal point is computed for each individual physician as, $(-\beta_{1i}/2\beta_{2i})$, and represents the level of detailing beyond which the mean prescription rate for the physician declines.

We first focus on the Group W physicians. For this set of physicians, we find that 181 (or 27%) of these physicians have been over-detailed in at least one quarter out of the eight quarters. The average number of prescriptions written by these 181 physicians is 72 which is about 50% higher than the sample average. In fact, if we just examine the top 25% of these over-detailed physicians, we find that they write 90 prescriptions per quarter – close to double the sample average. The results for Group B are also similar, with 104 (or 26%) of physicians being over-detailed in at least one quarter. The average number of prescriptions written by these 104 is 60% higher than the sample average and the top 25% of these write 96 prescriptions per quarter (double the average). These findings are consistent with industry biases that have been reported in the literature i.e., “heavier” prescribers are detailed disproportionately by the salesforce (Lexchin, 1989).

Next we turn to measures of effect size. At the mean level of detailing, on average our results show that detailing results in increased mean prescriptions. Based on our results, the population-level detailing elasticity (at the mean level of detailing and parameters) is 0.17. This magnitude is consistent with that reported in other studies (e.g., Narayanan et al., 2002). The elasticity can be translated into a more meaningful managerial measure such as the return on (detailing) investment. From our discussion with firm executives, each prescription in this category brings in about \$ 100.00 while the average cost of a

detail is \$ 80.00. This translates into a return on investment of about 23% (at the current mean level of detailing).

We would also like to use the obtained individual level parameters to compute other managerially relevant metrics for this category. The firm's objective function is to maximize profit. However, our discussions with the firm have informed us that it is reasonable to assume that the marginal cost of each prescription is zero. Thus, revenue (prescription) maximization and profit maximization are equivalent in this case. To examine the impact of different detailing plans on revenue maximization, we carry out two set of analyses. In the first analysis, we reduce the number of "wasted" calls (defined below) to zero in each physician-quarter but do not reallocate the surplus calls. In the second analysis, we carry out a simple reallocation exercise where we reduce the wasted calls to zero and reallocate these calls across physicians using a simple rule.

For the first analysis, we compute the optimal number of calls for each physician in Group W and Group B. We then compare this with the actual number of calls made in each quarter for each physician and find out how many, if any, "wasted" calls were made to that physician. We find that the optimal number of sales calls was exceeded in 14% and 16% of physician-quarters for Group W and Group B, respectively. For both Group B and Group W, the number of wasted calls was 9% of the total calls made to these physicians (1815 out of 21301 for Group W and 1028 out of 11993 for Group B). For Group W, the median (mean) number of wasted calls in these physician-quarters was 1.8 (2.4) while it was 1.6 (2.0) for Group B.

Now, for the over-detailed physician-quarters, we fix the number of calls to the optimal number and predict the total number of prescriptions using the estimated parameters. We then predict the number of prescriptions using the actual number of calls. This exercise shows that fixing the number of calls at the optimal point results in an extra 3983 prescriptions (a 1.6% increase) for Group W and an extra 3105 prescriptions (a 2% increase for Group B).⁶

These results show that there are significant benefits to be achieved once firms are able to identify the optimal level of detailing for its physicians. The benefits accrue from both saved expense on detailing and the increase in prescriptions.⁷

Finally, in the second analysis, we examine the impact of detailing reallocation on sales-force effort. As before, we cut down the wasted calls to the over-detailed physicians. We then evenly spread out the number of wasted calls over all other physician-quarters in which the optimal number of calls was not made and predict the total number of prescriptions. Assuming that the reallocation is costless, we find that the total number of these prescriptions is about 9% higher than the number with the current call allocation for Group W and 11% for Group B. It is likely that this effect will be greater with an allocation rule that is more optimized and hence our estimate should be seen as close to a lower bound.

7. Conclusion

In this study, we have attempted to estimate the response of the individual physician to the detailing efforts of a pharmaceutical firm. The firm is the largest player in the mar-

ket and also does the most amount of detailing. By specifying and estimating a count data model at the disaggregate level, we are able to provide some insights into whether some of the physicians are being over-detailed. Over-detailing is an issue of concern to pharmaceutical companies as it reflects “wasted” expenditure. It is also of concern to consumer advocacy groups that feel that physicians’ prescriptions may be unduly influenced by pharmaceutical sales representatives. In addition, our results may also be of interest to policy makers in helping them design guidelines for ethical marketing of pharmaceuticals.

We formulate a count data model in which the count of quarterly prescriptions of a physician are modeled as a function of the amount of detailing effort directed at that physician. We allow for diminishing returns to the effects of detailing on the number of prescriptions. Further, the effects of detailing are made functions of the number of samples given out during the sales call as well as physician characteristics. Using hierarchical Bayesian methods we are able to estimate the effects of detailing at the physician level. Our results indicate that there does seem to be over-detailing in this product category. But there is also reason for both pharmaceutical companies as well as advocacy groups to be pleased with the results. For the pharmaceutical companies, we find ways in which these firms can increase the amount of prescriptions (i.e., increase revenues) or reduce the number of salesperson calls (i.e., lower costs) via a more efficient allocation of salesforce effort. From the viewpoint of the advocacy groups we find that too much detailing could actually dissuade a physician from prescribing a drug. This means that physicians, at some level, are conscious about the pressure being put on them by the companies’ salesforce and too much detailing could result in a physician backlash.

Note that, given our data, our analysis and results apply to the relationship between prescription behavior of an “average” physician (conditioned on specialty and gender) and an “average” detail received by this physician in a mature product category. Explicitly accounting for characteristics such as the age of the physician, individual differences across sales representatives, the number of drugs and the sequence in which a drug is detailed, and age of category could shed more light on this relationship. Another important caveat to our model and analysis is that we do not observe the levels of competitive detailing in the data and consequently, their effects are not controlled for in the analysis. Hence, an alternative explanation for our finding of over-detailing could be due to competitive pressures in the marketplace that force firms and their salespersons to expend more effort on certain physicians. Interestingly, data on competitive detailing efforts are not available to most pharmaceutical firms at the physician level. Thus, in many respects, our data are very similar, if not identical, to the data used by these firms in making their decisions. Also, due to data limitations, we do not control for other forms of promotional activity directed at physicians such as advertising in medical journals and event-based marketing as well as other marketing expenditure such as direct-to-consumer advertising. Finally, do not model the process by which salesforce effort is allocated – we only try to verify if it is indeed “optimal” based on our estimated demand parameters (see (Manchanda et al., 2004) for a richer description of the detailing setting process). Addressing these limitations remain potential areas for future research.

Acknowledgment

The authors would like to thank the Co-Editors, two anonymous reviewers, Susan Gertzis, Eric Anderson, Peter Rossi, Sridhar Narayanan and participants at the Marketing Science Conference in Los Angeles for helpful comments and a major pharmaceutical firm for providing the data. Both authors would like to thank the Kilts Center for Marketing at the Graduate School of Business, University of Chicago, for research support.

Notes

1. Note that while they use a latent class model to capture differences across physicians, only the intercept term and the price coefficient are allowed to be different across physician segments.
2. This can be easily illustrated by a nested formulation of the model we propose. Let $\lambda_{it} = \exp(\beta_{0i} + \beta_1 x_{it})$, i.e., the random effect is specified only on the intercept (in contrast, we allow each element of the β vector to be distributed across physicians). Let β_{0i} be distributed as $N(\bar{\beta}_0, \sigma^2)$. Then $\text{Var}(y_{it}|x_{it}, \bar{\beta}_0, \sigma^2) = E(y_{it}|x_{it})[1 + \sigma^2 E(y_{it}|x_{it})]$ i.e., the formulation accommodates over-dispersion.
3. As an example, for Anti-Ulcer drugs, this specialty would be gastroenterology.
4. An alternative specification to capture the concavity in detailing response would be to use $\log(\text{NDET})$ instead. Given that $\text{NDET} = 0$ for 21% of the observations in the data, the typical transformation is $\log(C + \text{NDET})$ where C is a constant. However, the results are usually not invariant to the choice of this constant. Hence we prefer to use the quadratic specification.
5. We would like to thank an anonymous reviewer for highlighting this important issue.
6. We also computed this increase using the fitted prescriptions instead of the observed prescriptions in the data and found almost no difference between the two numbers.
7. It should be noted that, as mentioned earlier, we are making the assumption that the effect of a detail applies only to prescriptions in this category. If the same detail results in prescriptions in another category, the economics may be somewhat different. However, note that industry studies point to big "inefficiencies" in detailing in general (Elling et al., 2002).

References

- Allenby, Greg M. and Peter E. Rossi. (1998). "Marketing Models of Heterogeneity," *Journal of Econometrics*, 89, 57–78.
- Blattberg, R. C. and K. J. Wisniewski. (1989). "Price-Induced Patterns of Competition," *Marketing Science*, 8, 291–309.
- Chib, Siddhartha and Edward Greenberg. (1995). "Understanding the Metropolis-Hastings Algorithm," *American Statistician*, 49, 327–335.
- Chib, Siddhartha, Edward Greenberg, and Rainer Winkelmann. (1998). "Posterior Simulation and Bayes Factors in Panel Count Data Models," *Journal of Econometrics*, 86, 33–54.
- Chintagunta, Pradeep K. and Naufel J. Vilcassim. (1994). "Marketing Investment Decisions in a Dynamic Duopoly: A Model and Empirical Analysis," *International Journal of Research in Marketing*, 11, 287–306.
- Dekimpe, Marnik G. and Dominique M. Hanssens. (1995). "The Persistence of Marketing Effects on Sales," *Marketing Science*, 14, 1–21.
- Elling, Martin E., Holly Fogle, Charles S. McKhann, and Chris Simon. (2002). "Making More of Pharma's Sales Force," *The McKinsey Quarterly*, 3, 87–95.
- Erickson, Gary M. (1992). "Empirical Analysis of Closed-Loop Duopoly Advertising Strategies," *Management Science*, 1732–1749.
- Geman, S. and D. Geman. (1984). "Stochastic Relaxation, Gibbs Distributions and the Bayesian Restoration of Images," *IEEE Transactions of Pattern Analysis and Machine Intelligence*, 6, 721–741.
- Gelfand, A. E. and D. K. Dey. (1994). "Bayesian Model Choice: Asymptotics and Exact Calculations," *Journal of the Royal Statistical Society, Series B*, 56, 501–514.

- Gelfand, A. E., D. K. Dey, and H. Chang. (1992). "Model Determination Using Predictive Distributions with Implementation via Sampling-Based Methods (with Discussion)." In J. M. Bernardo, J. O. Berger, A. P. David, and A. F. M. Smith (eds.), *Bayesian Statistics*, Vol. 4. Oxford: Oxford University Press, pp. 147–167.
- Gonul, F., F. Carter, E. Petrova, and K. Srinivasan. (2001). "Promotion of Prescription Drugs and Its Impact on Physicians' Choice Behavior," *Journal of Marketing*, 65, 79–90.
- Hastings, W. K. (1970). "Monte Carlo Sampling Methods Using Markov Chains and Their Applications," *Biometrika*, 57, 97–109.
- Lexchin, Joel. (1989). "Doctors and Detailers: Therapeutic Education or Pharmaceutical Promotion," *International Journal of Health Services*, 19, 663–679.
- Lilien, Gary L., Ambar G. Rao, and Shlomo Kalish. (1981). "Bayesian Estimation and Control of Detailing Effort in a Repeat Purchase Environment," *Management Science*, 27, 493–507.
- Lodish, Leonard M. (1971). "CALLPLAN: An Interactive Salesman's Call Planning System," *Management Science*, 18, 25–40.
- Lodish, Leonard M. (1976). "Assigning Salesmen to Accounts to Maximize Profit," *Journal of Marketing Research*, 13, 440–444.
- Lodish, Leonard M., Magid Abraham, Stuart Kalmenson, Stuart Jeanne Livelsberger et al. (1995). "How T.V. Advertising Works: A Meta-Analysis of 389 Real World Split Cable T.V. Advertising Experiments," *Journal of Marketing Research*, 32, 125–139.
- Lurie N., E. C. Rich, D. E. Simpson et al. (1990). "Pharmaceutical Representatives in Academic Medical Centers: Interaction with Faculty and Housestaff," *Journal of General Internal Medicine*, 5, 240–243.
- Malaviya, Prashant, Joan Meyers-Levy, and Brian Sternthal. (1999). "Ad Repetition in a Cluttered Environment: The Influence of Type of Processing," *Psychology and Marketing*, 16, 99–118.
- Manchanda, Puneet, Peter E. Rossi, and Pradeep K. Chintagunta. (2004). "Response Modeling with Non-Random Marketing Mix Variables," *Journal of Marketing Research*, forthcoming.
- Meyers-Levy, Joan. (1988). "The Influence of Sex Roles in Judgement," *Journal of Consumer Research*, 14, 522–530.
- Narayanan, Sridhar, Puneet Manchanda, and Pradeep K. Chintagunta. (2002). "Temporal Differences in the Role of Marketing Communication in New Product Categories." Working Paper, University of Chicago.
- Neelamegham, Ramya and Pradeep K. Chintagunta. (1999). "A Bayesian Model to Forecast New Product Performance in Domestic and International Markets," *Marketing Science*, 18, 115–136.
- Parsons, Leonard Jon and Piet Vanden Abeele. (1981). "Analysis of Sales Call Effectiveness," *Journal of Marketing Research*, 18, 107–113.
- Reibstein, David J. and Paul W. Farris. (1995). "Market Share and Distribution: A Generalization, a Speculation and Some Implications," *Marketing Science*, 14, G190–G202.
- Roberts, G. O., A. Gelman, and W. R. Gilks. (1997). "Weak Convergence and Optimal Scaling of Random Walk Metropolis Algorithms," *Annals of Applied Probability*, 7, 110–120.
- Stinebaugh, Craig and Glenn Sabin. (2003). "Better Sampling Boosts the Bottom Line," *Pharmaceutical Executive*, March.
- Sujan, Harish. (1986). "Smarter Versus Harder: An Exploratory Attributional Analysis of Salespeople's Motivation," *Journal of Marketing Research*, 43, 41–49.
- Sujan, Harish, Barton A. Weitz, and Mita Sujan. (1988). "Increasing Sales Productivity by Getting Salespeople to Work Smarter," *Journal of Personal Selling and Sales Management*, August, 9–19.
- Sujan, Harish, Barton A. Weitz, and Nirmalya Kumar. (1994). "Learning Orientation, Working Smart, and Effective Selling," *Journal of Marketing*, 58, 39–52.
- Winkelmann, Rainer. (1997). *Econometric Analysis of Count Data*. Berlin-Heidelberg: Springer Verlag.
- Wittink, Dick R. (2002). "Analysis of ROI for Pharmaceutical Promotions," unpublished study conducted for the Association of Medical Publications, available at <http://www.rxpromoroi.org/arpp/index.html>.
- Wittink, Dick R., Michael J. Addona, William J. Hawkes, and John C. Porter. (1987). "SCAN-PRO: A Model to Measure Short-Term Effects of Promotional Activities on Brand Sales Based on Store-Level Scanner Data," Working Paper, Johnson Graduate School of Management, Cornell University, Ithaca, NY.
- Ziegeler, M. G., P. Lew, and B. C. Singer. (1995). "The Accuracy of Drug Information from Pharmaceutical Sales Representatives," *Journal of the American Medical Association*, 273, 1296–1298.