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The authors develop a method to quantify the benefits of individual-level targeting when the data reflect firm strategic behavior—that is, when firms (1) are engaged in targeting and (2) take into account the actions of competing firms. This article studies a pharmaceutical firm's decision on the allocation of detailing visits across individual physicians. For this analysis, the authors develop, at the individual level, a model of prescriptions and a model of detailing. Using physician panel data, they estimate, at the physician level, the parameters of the prescription and detailing models jointly using full-information Bayesian methods. The results suggest that accounting for firm strategic behavior improves profitability by 14%–23% compared with segment-level targeting. In addition, ignoring firm strategic behavior underestimates the benefit of individual-level targeting significantly. The authors provide reasons for this finding. They also carry out several robustness checks to test the validity of the modeling assumptions.

Keywords: target marketing, structural models, pharmaceutical industry, hierarchical Bayesian models, Markov chain Monte Carlo methods

Quantifying the Benefits of Individual-Level Targeting in the Presence of Firm Strategic Behavior

Targeting (i.e., setting marketing policy differentially for different customers or segments) is an important marketing practice. Previous literature has documented that there are positive returns to targeting in various marketing domains. The beginnings of this literature can be attributed to the seminal work of Rossi, McCulloch, and Allenby (1996), who first demonstrated the value of targeting using coupons in the packaged goods industry. Other research then showed similar results across other domains, such as direct mail (e.g., Allenby, Leone, and Jen 1999; Bult and Wansbeek 1995; Gonul and Shi 1998; Kim et al. 2005), pharmaceutical marketing (e.g., Manchanda and Chintagunta 2004), and Internet marketing (e.g., Ansari and Mela 2003; Manchanda et al. 2006; Montgomery 2000; Murthi and Sarkar 2003). Typically, these studies calibrated a response model and used the variation in response parameter estimates (e.g., the effects of prices on brand choices) across cross-sectional units (e.g., segments) to propose a targeting policy for a marketing instrument (e.g., coupons). To quantify the benefits of targeting, research can then compare a firm's profits under various targeting schemes—at the individual customer level, at the segment level, or through mass marketing (i.e., no targeting).

In many industries (e.g., business-to-business markets) firms already have targeting strategies in place and determine their levels of marketing actions using knowledge about their customers' responses and competitors' actions (systematic or otherwise). As many studies have pointed out (e.g., Chintagunta 2001), if the data reflect such strategic behavior, ignoring the endogeneity of marketing actions will lead to incorrect estimates of response parameters and, consequently, to biased inferences regarding the benefits from targeting. Our objective in this article is to quantify the benefits of targeting while accounting for firm strategic

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behavior.[1] In particular, we are interested in quantifying the improvement in profits to a firm when it targets activities at the individual customer level (one-to-one marketing) compared with the allocation of marketing resources at a more aggregate level (e.g., segment or market level), while it also considers competitive response. Specifically, we use data from firms that already use some knowledge about their customers' responses and competitors' actions to set their marketing policy.

Our research domain is the pharmaceutical industry. We concentrate on the major marketing instrument used in this industry—detailing (i.e., personal sales calls to the physicians). Thus, a major difference between this research and the prior literature on targeting that emphasizes price-related marketing instruments is our focus on detailing, which is a nonprice instrument. The pharmaceutical firm's key decision with respect to detailing is the allocation of detailing visits across individual physicians. In this industry, firms are engaged in one-to-one marketing at the physician level. In addition, firms already use the information on how detailing affects individual physician behavior and the behavior of rival firms in setting their detailing allocations. The detailing-setting process works as follows: First, for the period of interest (usually a quarter), firms set detailing at the physician decile (or segment level), in which the decile-binning rule is total volume prescribed in the category. All physicians in the same decile are expected to receive identical levels of detailing. Second, the firm develops a "calling" plan for each physician. This plan is then communicated to the field force, which consists of territory managers and salespeople. The field force then implements the detailing plan. In reality, the field force has some freedom to make adjustments to the communicated plans to tailor the detailing to each physician. Thus, the realized number of details received by each physician is a "hybrid" of top-down (firm calling plan) and bottom-up (local field force adjustments) approaches. Quantifying the benefits of targeting is critical to pharmaceutical companies that invest billions of dollars in detailing with nonnegligible costs associated with targeting at the physician level. This quantification also provides firms an upper bound on the investment they should be willing to make to implement a finer targeting scheme (i.e., at the individual level) relative to a cruder one (e.g., at the segment or market level).[2]

To carry out our analysis, we need two building blocks. The first is a response model that relates the level of individual physician detailing to the number of prescriptions that physician writes. The response model needs to reflect the heterogeneity across physicians in their response to detailing—the underlying basis for profitable targeting. Our response model builds on previous literature (e.g., Manchanda and Chintagunta 2004). The second key building block is the data-generating mechanism for the observed detailing in the marketplace. In line with Shaffer and Zhang (1995), we assume that the physician-level detailing for each firm observed in the data is the joint outcome of all firms acting simultaneously to maximize their profits from each individual physician, given our response model. Using the profit maximization assumption and the prescription model, we specify a model of detailing at the individual physician level for all firms in the market. By allowing each firm to target physicians with their profit-maximizing detailing levels, with all firms in the market doing so jointly, our model structure enables us to incorporate a firm's strategic behavior with respect to detailing explicitly in the analysis.[3] Note that this approach differs from that which Manchanda, Rossi, and Chintagunta (2004) propose, in which firms set detailing levels using a heuristic that depends on the individual physician's own (i.e., not competitive) response parameters.

With these two main building blocks—that is, a prescription response model and a strategic detailing equation—we estimate the model parameters using novel data that contain physician-level prescriptions and detailing levels for all the main drugs in an ethical drug product category. We estimate the parameters of this system jointly using full-information Bayesian methods to obtain efficient estimates of the model parameters at the individual physician level. Bayesian methods are particularly well suited in the current context because individual-level estimates are crucial for implementing a one-to-one marketing policy.

To quantify the benefits of targeting, we compute the firms' profit differential under alternative targeting scenarios. The "base case" is the individual physician-level targeting scenario. Then, we obtain the profits under alternative scenarios by computing prescriptions and levels of detailing under those scenarios, but using our estimated model parameters. This approach is similar to the counterfactual simulations that Chintagunta and colleagues (2006) describe. By computing the profit differentials across the various alternative scenarios, we can then quantify the benefits to the firms from individual physician-level targeting relative to more aggregate allocation mechanisms.

Having quantified the benefits to targeting while accounting for the manner in which firms set their detailing levels, we address the following question: What is the impact on our profit differential metric (which we use to quantify the benefits of targeting) if we ignore firms' strategic behavior when estimating the model parameters? Here, we can demonstrate how the benefits to targeting may be incorrectly quantified if such behavior is not accounted for in the estimation. We also provide reasons for our findings. Finally, we estimate a series of alternative models (e.g., Is the profit maximization objective at the physician level more or less appropriate than alternative objective functions such as sales maximization?) to ensure that our results are robust to model specification and estimation.

Substantively, our research contributes to the targeting literature along the following dimensions: First, this is the first empirical study to consider competitive responses in

[1]In the literature, "targeting" sometimes refers to the decision whether to market to a customer. This is nested in our definition; that is, a customer not chosen as part of the target will receive no marketing resources.

[2]The state of practice for a drug category could involve a cruder form of targeting. Our proposed approach will still be valid as long as the parameter estimation accounts for the appropriate nature of such targeting behavior. In our empirical example, the assumption of one-to-one marketing seems reasonable because firms have access to detailed physician-level data and the nature of decision making described previously. We discuss other targeting scenarios in detail in the subsequent sections.

[3]An alternative approach to accounting for strategic behavior while remaining agnostic about the firm's detailing decision rule would be to use instrumental variables to "proxy" for the detailing variable. An ideal instrumental variable would vary across physicians and periods, but identifying one is a nontrivial task.

evaluating targeting schemes. Second, the theoretical literature on targeting of advertising has found that the ability to do so increases the equilibrium profits of firms (Iyer, Soberman, and Villas-Boas 2005). In our analysis, the firms are competing using detailing (which is essentially advertising). Our results not only provide empirical support for these theoretical findings but also quantify the increases in such profits (using data from the pharmaceutical industry). Third, our study extends and complements the current literature on the analysis of physician prescription behavior. As Manchanda and Chintagunta (2004) note, the two major limitations of the majority of the current literature analyzing physician prescription behavior are that competitive detailing is not explicitly controlled for and that the process by which sales force effort is allocated is not modeled. Our approach explicitly overcomes these two limitations.

We can summarize the methodological contributions of our research as follows: The recent literature in marketing and economics that has estimated the parameters of demand models while explicitly accounting for firms' behavior has typically examined strategic behavior at an aggregate level (e.g., Besanko, Gupta, and Jain 1998; Sudhir 2001), though the demand model parameters can be estimated at either the individual level (Chintagunta, Dubé, and Goh 2005; Yang, Chen, and Allenby 2003) or the aggregate level (Berry 1994; Berry, Levinsohn, and Pakes 1995; Nevo 2001). In contrast, our study examines targeting, with both the prescription model and the firms' detailing model pertaining to the individual physician for whom the targeting is being undertaken. Furthermore, the data are at the level of aggregation of interest. In addition, we can exploit the power of the Bayesian estimation machinery given our interest in individual-level parameters that are required for addressing the targeting problem. In this regard, our study can be viewed as an early attempt to estimate a system of demand and firm behavior at the micro level to address an issue (i.e., targeting) that is relevant for that level of aggregation.[4]

MODEL DEVELOPMENT

As noted previously, our proposed approach has two key building blocks: a model of individual physician-level prescription behavior and a model of the firms' strategic detailing decision for each physician. Because firms decide the number of detail calls for each physician quarter, we specify both these models at the quarterly time interval. The prescription model describes an individual physician's prescriptions in response to details received from the pharmaceutical firms in each quarter of the year. The detailing model assumes that firms follow a profit maximization rule when setting their detailing levels for each physician in each quarter.

Individual Physician-Level Prescription Model

Given the integer nature of the number of prescriptions, we use a Poisson regression model to characterize physicians' prescriptions in response to detailing.[5] Conditional on detailing, we assume that the number of prescriptions by each physician in each quarter follows a Poisson distribution, with parameter λ_{pbt} for physician p, brand b, and quarter t:

$$\text{prob}\left(rx_{pbt} = y\right) = \frac{\exp\left(-\lambda_{pbt}\right) \times \lambda_{pbt}^{\,y}}{y!}, \tag{1}$$

where rx denotes the number of prescriptions and y denotes its value. Because λ_{pbt} should be positive for all p, b, and t, we use a typical log-link function, denoted as $\lambda_{pbt} = \exp(u_{pbt})$, where u_{pbt} is linear in parameters; that is,

$$u_{pbt} = \beta_{pb0} + \beta_{pbb} f(dtl_{pbt}) + \sum_{b' \neq b} \beta_{pb,b'} f\left(dtl_{pb't}\right) + \beta_{pbl} \log(rx_{pbt}) + \xi_{pbt}. \tag{2}$$

In this specification, the intercept represents the specific effect for physician p and brand b, such as the size of practice for physician p and the physician's intrinsic preference for brand b. We estimate the individual-specific effect from the hierarchical model:

$$\beta_{pb0} = \theta_{b0} + Z\theta_{b1} + \nu_{pb}, \tag{3}$$

where θ_{b0} and θ_{b1} are the parameters to be estimated, Z represents cross-sectional differences across physicians that affect the mean level of demand, and $\nu_p = \{\nu_{pb}\}$ for $\forall$b is a random variable following a normal distribution $N(0, \Sigma_\nu)$, with zero mean and covariance matrix Σ_ν to be estimated.

In Equation 2, $f(dtl_{pbt})$ is a transformation of own detailing that captures potentially nonlinear effects of detailing (typically, diminishing returns; see Gonul et al. 2001; Manchanda and Chintagunta 2004), and $f(\cdot)$ is operationalized as a log-reciprocal transformation (Lilien, Rao, and Kalish 1981)—that is, $f(dtl_{pbt}) = [1/(1 + dtl_{pbt})]$. In this specification, detailing in the data, dtl_{pbt}, is incremented by one before the reciprocal transformation to accommodate no (zero) detailing in a physician quarter for a brand. We expect that $\beta_{pbb} < 0$. Note that the log-reciprocal transformation is flexible in that it allows either increasing or diminishing returns based on the parameter estimates and the range of data for dtl_{pbt}.

The next component in Equation 2 is $\Sigma_{b' \neq b}\beta_{pb,b'}f(dtl_{pb't})$, which describes the competitive detailing effect corresponding to each competitor in the same category. We use the same functional form as that for the own detailing effect—that is, $f(dtl_{pb't}) = [1/(1 + dtl_{pb't})]$, $\forall b' \neq b$. We expect that $\beta_{pbb'} > 0$. Note that we allow competitive detailing effects to be different across brands. This allows for flexible competitive brand effects. The number of estimated detailing parameters for our product category with four brands is 16 (one own-effect and three cross-effect parameters for each brand). The term $\log(rx_{pbt-1} + 1)$ is a logarithm transformation of the number of prescriptions written during the previous quarter t – 1 by physician p for brand b. Again, we add one to the lagged variable rx_{pbt-1} to allow for zero val-

[4]Increasing interest in this general area is also reflected in articles such as that of Pancras and Sudhir (2007), who focus on vendors' strategies of personalizing services.

[5]A plausible alternative specification, with quarterly data such as those available to us, is an aggregate share model such as the logit. Operationalizing this model would require knowledge of the total patient pool of each physician for which a prescription is not written. However, this information is not available to us. Another possibility that does not require the "noprescription" option data is a hybrid model, with a model for total prescriptions across all drugs in the category combined with a share model for each of the brands in that category. Because the total number of prescriptions will be a count, we need to use a count model regardless. By using a brand-level count model as in Equation 1, we can specify a flexible and unconstrained pattern of cross-brand detailing elasticities and estimate these at the physician level.

ues. This lagged variable accounts for state dependence in the physician's prescription behavior and carryover effects of detailing, as documented in previous literature (e.g., Manchanda, Rossi, and Chintagunta 2004). Finally, ξ_{pbt} in Equation 2 is an additive random error term, accounting for any other physician-, brand-, and time-varying factors that are not observed or not measurable by the researcher (but are observed by the firm). Note that because we model a physician response to detailing and a firm strategic detailing decision simultaneously at the individual physician level, the model can accommodate correlations between ξ_{pbt} and dtl_{pbt} (we return to this issue subsequently). The term ξ_{pbt} might include patient-specific characteristics and/or factors that are not included in the model because of a lack of data, such as availability of free samples at the doctor's disposal. In addition, some of these factors could be common across physicians but could vary by brand and over time.[6] All these factors vary over time and are expected to affect physician p's prescription of brand b. We assume that the random shocks ξ_{pbt} for all brands follow an i.i.d. multivariate normal distribution correlated across brands, with mean zero and covariance matrix Σ_ξ. If we denote $\xi_{pt} = \{\xi_{pbt}\}$ for $\forall b$, then $\xi_{pt} \sim N(0, \Sigma_\xi)$, which is a multivariate normal distribution with dimension as the number of brands.

Given the assumptions on rx_{pbt} and ξ_{pbt}, our model is in the form of the Poisson-lognormal distribution, as Aitchison and Ho (1989) discuss. With this formulation, the model possesses the following three properties that make it more suitable than a typical Poisson model for our purposes: (1) overdispersion of the data (Chib and Winkelmann 2001), (2) correlation among prescriptions of different brands prescribed by the same physician, and (3) overproportion of zero counts (relative to the Poisson) in the data due to the presence of zero prescriptions (Cameron and Trivedi 1998).

Detailing Decision Model at the Individual Physician Level

In the detailing model, we assume that firms simultaneously set detailing levels at the individual physician level given the following assumptions: First, the firms' objective function is to maximize profits from each physician in each quarter. This assumption is based on both industry reports (e.g., Croke 2000) and previous research findings (e.g., Manchanda, Rossi, and Chintagunta 2004). Note that as a robustness check, we assume that the firms' objective function is sales maximization, and we compare the model fit under that assumption with the model fit under the profit-maximizing assumption.

Second, firms maximize only current quarter profit conditional on observing each physician's previous quarter prescriptions. We do this for the following reasons: From reports published in industry journals (e.g., Douglass 1993) and our conversations with managers in this industry, it does not appear that the data-generating process is one in which firms are considering the impact of current detailing decisions on prescription behavior in future periods. In addition, although it is possible to specify a model that incorporates firm forward-looking behavior, the computational burden for estimating such a model using the full-information likelihood method is considerable.

Third, given our previous two assumptions, firms' detailing decisions are the full-information static Nash equilibrium outcomes of a simultaneous move game in any given period. In our case, full information implies that firms know the various parameters of the physician response model and of the profit function, the random shocks in the response model and the random shocks in the cost function, and the previous period prescriptions for all brands in the category (which appear in Equation 2).[7]

Fourth, physicians' prescription decisions are not affected by price. This assumption is based on prior findings in the literature and the institutional features of our setting. Previous studies have found that physicians' prescription decisions are not affected by price (Campo et al. 2006; Gonul et al. 2001; Hellerstein 1998), because patients do not pay retail price but rather a lower amount that is a function of formulary status of the drug and their insurance status. Because all four drugs we consider have broad formulary acceptance, conditional on a patient being insured, the price remains (mostly) invariant across patients. We also checked the insurance status of the patients in our data and found that only 2% were uninsured.

Fifth, the firms' detailing decisions are set conditional on national prices and not on individual prices paid by the patient–physician combination. This is because the pricing decision of firms is different from the price faced by the physician–patient combination, which is typically the copay for the individual patient. Furthermore, these prices are not directly relevant for the firms' profits. Although a firm essentially sets a list price (usually referred to as the wholesale acquisition cost), a complex series of negotiations is carried out between the manufacturer and wholesalers and pharmacies, in which the manufacturer finally records an average manufacturer price, which is the wholesale acquisition cost net of the negotiated discounts (for further details, see Congressional Budget Office 2007). This complex process results in prices that are typically set annually and therefore are relatively stable over time. For example, from IMS Health (2005) data, we find that for Nexium and Prevacid, the price changes essentially mirror the inflation rate.

Sixth, the firm's decision variable is the number of details to deliver to a physician in each period. Although the content of a detail may differ across delivered details, it

[6]Examples of two such factors are direct-to-consumer (DTC) advertising and time to patent expiry. The effects of DTC advertising on patients, if any, would manifest in requests by patients for specific drugs. In our data, we find that only 3% of all prescriptions result from such requests. Finally, any residual or idiosyncratic (e.g., at the physician level) effects of DTC advertising will be captured by the term in Equation 2. We also found that the smallest time to patent expiry across the four brands we consider was three years, and we did not find any evidence that firms were strategically setting detailing as a function of time to expiry.

[7]Note that firms do not need to observe the competitive detailing levels in a given period to set their own detailing levels. The knowledge of the response parameters, demand and supply shocks, the equilibrium, and past prescriptions for all brands is all that is needed to set detailing levels. However, it is possible that for some therapeutic categories, firms never observe all competitive activity at the physician level. In such situations, our approach should be modified to reflect the specific institutional practice.

is difficult for the firm to decide on content because the interaction is not completely under the detailer's control. For example, both the physician's time availability and mood at the time of the detail are unknown to the firm in advance. Given this, we assume that all details for a given brand have the same effect. However, note that we allow this effect to be firm (brand) specific.

On the basis of the previous assumptions, firm b's profit maximization problem for each physician p at each quarter t is the total profit generated by the expected number of prescriptions in that quarter, less the total costs of all detailing visits to that physician. The firm's objective is to find the optimal detailing level for that physician in that quarter:

$$(4)\qquad \max_{dtl_{pbt}} \pi_{pbt} = markup_{pbt} \times E(rx_{pbt}|\xi_{pbt}) - mc_{pbt} \times dtl_{pbt}.$$

In this equation, $markup_{pbt}$ is the markup that firm b gets from fulfilling physician p's prescriptions in quarter t. The markup is computed as the wholesale price of each prescription less the marginal cost of production. On the basis of industry feedback, we assume that the marginal cost of production is zero (though any exogenously specified marginal cost level will do). Therefore, we use price to approximate $markup_{pbt}$ with the assumption that prices are constant across physicians and across time, that is $price_{pbt} = price_b \ \forall b$. The variable mc_{pbt} represents the marginal cost of detailing for visiting physician p by firm b in quarter t. Following the literature that estimates marginal cost functions (typically production costs), we use a linear specification for mc_{pbt} as follows:

$$(5)\qquad mc_{pbt} = \alpha_{b0} + X_{pt}\alpha_{bx} + s_b + \eta_{pbt}.$$

In this equation, α_{b0} accounts for intrinsic differences among the pharmaceutical firms in their marginal detailing costs due to differences in sales personnel and managers in the firms and would reflect differences in training, experience, and so forth; X_{pt} are exogenous, physician quarter–specific variables that influence the marginal cost of detailing to that physician; α_{bx} is the parameter associated with these exogenous variables; s_b accounts for the systematic deviation during a holiday season; and η_{pbt} is a random error term that accounts for any unobserved temporal factors that affect firm b's marginal cost of detailing to physician p at quarter t. Note that these factors are observed by the detailer but not by the researcher. One such factor is the office environment the detailer faces in each period. This is typically a function of the staff in the office, the relationship between the detailer and the physicians, the relationship between the detailer and the staff, the amount of detailing received by the physician for categories other than that under investigation, and so forth. These factors have a direct impact on the quality and quantity of details an individual detailer can make. The vectors of $\eta_{pt} = \{\eta_{pbt}\}$ for $\forall b$ are assumed to be independent across physician quarters and follow a multivariate normal distribution across brands, with zero mean and covariance matrix Σ_η—that is, $\eta_{pt} \sim N(0, \Sigma_\eta)$.

Linking the Prescription and Detailing Models

We now link the prescription and detailing models into a joint system. To solve the firm's profit maximization objective (Equation 4), we need to compute the first-order conditions (FOC) as follows:

$$(6)\qquad markup_b \times \frac{\partial E\left(rx_{pbt}|\xi_{pbt}\right)}{\partial dtl_{pbt}} = mc_{pbt}.$$

Among the various terms in Equation 6,

$$\frac{\partial E\left(rx_{pbt}|\xi_{pbt}\right)}{\partial dtl_{pbt}}$$

can be obtained from the prescription model in Equation 2; that is,

$$(7)\qquad \frac{\partial E\left(rx_{pbt}|\xi_{pbt}\right)}{\partial dtl_{pbt}} = \exp\left(u_{pbt}\right) \times \frac{-\beta_{pb,b}}{\left(dtl_{pbt}+1\right)^2}.$$

Equations 5 (the specification for the marginal cost of detailing) and 7 (the first derivative of the prescription model with respect to detailing) can be substituted into Equation 6 to obtain the following version of the FOC:

$$(8)\qquad markup_b \times \exp\left(u_{pbt}\right) \times \frac{-\beta_{pb,b}}{\left(dtl_{pbt}+1\right)^2} = \alpha_{b0} + X_{pt}\alpha_{bx} + s_b + \eta_{pbt}.$$

We can then rewrite this equation as

$$\left(dtl_{pbt}+1\right)^2 = markup_b \times \exp\left(u_{pbt}\right) \times \frac{-\beta_{pb,b}}{(\alpha_{b0} + X_{pt}\alpha_{bx} + s_b + \eta_{pbt})}.$$

In general, this equation is an implicit equation in detailing, dtl_{pbt}, because the function u_{pbt} is a function of dtl_{pbt}. Nevertheless, we can use this expression to understand its properties. Note that because $\beta_{pb,b} < 0$ (i.e., detailing has a positive effect on prescriptions), the right-hand side of this equation is greater than zero as long as the marginal cost, $mc_{pbt} = \alpha_{b0} + X_{pt}\alpha_{bx} + s_b + \eta_{pbt} > 0$. In principle, if the right-hand side exceeds one, we have an interior solution for the detailing level. Furthermore, if the right-hand side is close to one, we get the zero detailing condition. However, note that because the marginal cost contains the error term, η_{pbt}, it is in principle unbounded at both ends.

The FOC plays a key role in this analysis by connecting the individual physician response model and the firm's strategic detailing decision model. Four points are noteworthy here. First, this setup implies that the details observed in the data satisfy Equation 8 for each physician p and each brand b at each quarter t. Second, in Equation 8, u_{pbt} contains all the demand parameters ($\beta_{pb,0}$, …, $\beta_{pb,l}$) and appears in both the prescription model (Equation 1) (through $\lambda_{pbt} = \exp[u_{pbt}]$) and the detailing model (through the FOC). By jointly estimating the parameters of the response model and the detailing equation, we obtain more efficient estimates for the response parameters because of information sharing across the two equations. More important, if Equation 8 holds, the firm's detailing level dtl_{pbt} is a function of the prescription equation error ξ_{pbt}. This implies a potential endogeneity bias if the prescription equation parameters are estimated independent of the parameters of the FOC in Equation 8. Thus, joint estimation of Equations 1 and 8 also helps us resolve the endogeneity bias. In a subsequent section, we show that response parameters estimated with or without the detailing model in Equation 8 are

substantially different. Third, note that the error term in the detailing equation, η_{pbt}, can be correlated with the error term in the prescription equation, ξ_{pbt}. Fourth, the left-hand side of Equation 8 contains u_{pbt}, which is a function of dtl_{pbt} for all brands (see Equation 2). Thus, the action of any firm influences the outcomes of all firms in the market. The Appendix demonstrates how estimation is carried out under this equilibrium assumption.

The FOC is only a necessary condition for solving the firm's profit maximization problem; the sufficient condition requires the second-order condition (SOC) to be satisfied. By taking the derivative on both sides of Equation 7 with respect to dtl_{pbt}, we obtain the SOC:

$$(9)\quad \text{markup}_b \times \exp\left(u_{pbt}\right) \times \left[\frac{2\beta_{pb,b}}{\left(dtl_{pbt}+1\right)^3} + \frac{\beta_{pb,b}{}^2}{\left(dtl_{pbt}+1\right)^4}\right] < 0.$$

Solving this inequality (see the Web Appendix at http://www.marketingpower.com/jmrapril09), we get

$$dtl_{pbt} > \frac{-\beta_{pb,b}}{2} - 1.$$

We follow the approach used in the literature in terms of ensuring that the SOC is satisfied. This approach typically estimates the model without imposing any constraints and checks to determine whether the estimated parameters satisfy the constraints imposed by the SOC (e.g., Besanko, Gupta, and Jain 1998). In our case, these constraints are satisfied for more than 98% of all observations. Thus, we do not directly impose the constraints. As we show in the Web Appendix (http://www.marketingpower.com/jmrapril09), the nature of the constraint makes the specification of a Markov chain Monte Carlo (MCMC) sampler with constraints difficult to implement.

Bayesian Estimation

We estimate both prescription and detailing models simultaneously using the full-information likelihood:

$$\begin{aligned}(10)\quad & f\left(\{\beta_{pb}\}, \{\xi_{pbt}\}, \{\theta, \Sigma_\upsilon\}, \{\alpha_b, s_b\}, \Sigma_\xi, \Sigma_\eta | \{rx_{pbt}\}, \{dtl_{pbt}\}\right)\\ &\propto \prod_{p,b,t} \text{prob}\left(rx_{pbt} | dtl_{pbt}, \{\beta_{pb}\}, \xi_{pbt}\right)\\ &\times \pi_1\left(dtl_{pbt} | \{\beta_{pb}\}, \xi_{pbt}, \alpha_b, s_b, \Sigma_\eta\right)\\ &\times \pi_2\left(\beta_{pb} | \bar{\beta}, \Sigma_\beta\right) \times \pi_3\left(\xi_{pbt} | \Sigma_\xi\right)\\ &\times \pi_4\left(\beta_{pb,0} | \theta, \Sigma_\upsilon, Z\right)\\ &\times \pi_5\left(\bar{\beta}, \Sigma_\beta, \Sigma_\upsilon, \Sigma_\xi, \alpha_b, s_b, \Sigma_\eta\right),\end{aligned}$$

where $\text{prob}(rx_{pbt}|dtl_{pbt}, \{\beta_{pb}\}, \xi_{pbt})$ is the Poisson probability for the number of prescriptions rx_{pbt} by physician p for brand b at quarter t, conditional on ξ_{pbt}, as defined in Equation 1, with $\lambda_{pbt} = \exp(u_{pbt})$ and u_{pbt}, as defined in Equation 2, with $f(dtl_{pbt}) = [1/(dtl_{pbt} + 1)]$, $\theta = \{\theta_0, \theta_1\}$, and $\alpha_b = \{\alpha_{b0}, \alpha_{bx}\}$.

We employ Gibbs sampling (Geman and Geman 1984) with data augmentation techniques (Tanner and Wong 1987) to facilitate estimation of the model parameters. Gibbs sampling enables us to make a sequence of draws from the full conditional distribution for each group of parameters conditional on all the other parameters. By iterating over all groups of parameters, we can obtain the joint posterior distribution of the complete set of the parameters. This method greatly simplifies the effort involved in simulating draws from such a complex joint distribution (Equation 10), including individual-level parameters (i.e., the $\{\beta_{pb}\}$). Data augmentation techniques enable us to draw the random component ξ_{pbt} in the prescription model, which facilitates the simulation draws for the covariance matrix Σ_ξ, as well as all the $\{\beta_{pb}\}$ and the η_{pbt}. The details of the full conditional posterior distributions for groups of the parameters appear in the Web Appendix (http://www.marketingpower.com/jmrapril09). Here, we highlight three points. First, we obtain the conditional distribution of detailing based on the FOC in Equation 8. In deriving this distribution, we use the assumption that firm b has full information. With this assumption, the distribution of detailing can be derived from the normal distribution assumption of the random component in the detailing model, using the change-of-variable technique. In other words, in this derivation, we believe that all the stochasticity of the observed detailing across time, for the same physician by the same firm, comes only from the randomness of the marginal cost shocks. This is true only when firms actually observe the realizations of the demand shocks. Second, using the change-of-variable technique based on the joint distribution across all four brands, our model accommodates strategic response from competitors as a result of the firm's targeting scheme changes (for details, see the Appendix). Third, the covariance matrices of the prescription model errors and the marginal cost errors, Σ_ξ and Σ_η, are drawn simultaneously by putting the latent draws of the random shocks from both prescription and detailing models together when deriving the posterior Wishart distribution. This enables us to account for the correlations between the random shocks in the two models.

DATA

Our data are collected and made available to us by a pharmaceutical market research firm, ImpactRx Inc. The data are unique in that they are collected from a national primary care physician (PCP) panel (rather than being assembled from pharmacy audits and firm-level call data) and are purchased by most leading pharmaceutical firms. Each physician reports the number of details and prescriptions of each brand in the proton pump inhibitor category at a quarterly level, from the start of the third quarter in 2001 to the end of the second quarter in 2004. These data are novel in that the marketing activity of each competitor is available as it is recorded by the individual physician. The proton pump inhibitor treats gastroesophageal reflux disease (also known as acid reflux disease), which is one of the conditions that cause chronic heartburn. More than 60 million adults in the United States suffer from heartburn at least once a month, and approximately 25 million suffer from heartburn on a daily basis. The proton pump inhibitor category generated $12.5 billion in revenue in 2004, making it the second-largest prescription drug category in sales

Table 1
SUMMARY STATISTICS

		Prescriptions		Detailing		
Brand	*Marketed by*	*M*	*SD*	*M*	*SD*	*Approval Date*
Nexium	Astra Zeneca	11.7	(12.7)	3.8	(3.1)	February 2001
Prevacid	TAP	8.5	(9.7)	3.5	(3.3)	May 1995
Aciphex	Janssens and Eisai	6.5	(8.3)	2.8	(2.7)	August 1999
Protonix	Wyeth	5.9	(7.4)	2.8	(3.3)	February 2000

in the U.S. market (IMS Health 2005). In our data, four brands account for more than 99% of all details received and more than 97% of all the prescriptions written by the physicians in the panel. Therefore, we focus our attention on these four brands: Nexium, Prevacid, Aciphex, and Protonix.

Our sample consists of physicians who have received at least one detail (among all four brands) in each quarter. This results in a sample of 330 physicians with 12 quarterly observations for each physician. Table 1 presents some descriptive statistics of the data and the Food and Drug Administration approval dates for the four brands. It shows that Nexium, the newest brand, possesses the largest prescription market share in this category. It is also the most detailed brand among the four brands. These data probably reflect physicians' beliefs about Nexium having the fewest side effects as well the heavy marketing push by AstraZeneca. Prevacid is the oldest drug among the four brands and has the second-largest share of prescriptions in this category. The launch dates of Aciphex and Protonix are close to each other, and the market shares for these two brands are also similar. Finally, note that prescriptions and details are ordered in the same manner across the four drugs.

Physicians are likely to differ in their average propensity to prescribe drugs in this category according to the size of their practices. We do not have data on the size of the practice for each physician, but we proxy for it using the total category prescriptions across three other (i.e., non–proton pump inhibitor) large therapeutic categories—antihistamines, antidepressants, and erectile dysfunction—written by each physician. This number for each physician is the Z variable in Equation 3.

Another challenge in this analysis is to find some reasonable cost shifters that vary the marginal cost of detailing across physicians and quarters (see Equation 5). Given that our data have only zip code location information for each physician, we enriched the data with five other data sources that provide aggregate information at the zip code level: (1) a national (proprietary) physician prescription database to obtain the distribution of physician types (PCPs and gastroenterologists) in each zip code; (2) census data (from the U.S. Census Bureau at http://www.census.gov) to obtain demographic information (e.g., population density, income levels); (3) a database for the rural–urban commuting area codes (from the Economic Research Service of the U.S Department of Agriculture at http://www.ers.usda.gov) to obtain travel information, such as average commuting time; (4) the American Hospital Directory (http://www.ahd.com) to obtain the number of hospitals in each zip code; and (5) average weekly wage at each state in each quarter from the Bureau of Labor Statistics (http://www.bls.gov). Note that the cost shifters 1–4 essentially capture differences in cost in detailing across physicians, while cost shifter 5 captures the aggregate variation in detailing cost over time. The summary statistics of these cost shifters appear in Table 2.

Table 2
SUMMARY STATISTICS FOR THE COST SHIFTERS

Average Weekly Wage ($)	*Population Density (per Square Miles)*	*Number of PCPs*	*Number of Gastroenterologists*
685	229	27	2
(100)	(44)	(24)	(3)

Notes: Standard deviations are in parentheses.

We use MCMC methods to estimate the models. To achieve the best possible mixing, we follow the work of Rossi, Allenby, and McCulloch (2006) in computing the relative numerical efficiency parameters and obtaining the best value of the scaling parameters in the Metropolis steps (drawing β_{pb} for each p and drawing the latent demand random shocks ξ_{pbt} for each physician quarter).

RESULTS AND DISCUSSION

Estimation Results for the Prescription Model

Table 3 presents the population-level means $\bar{\beta}$ from the prescription model and the 95% probability interval for the parameters, ranging from the 2.5th to the 97.5th percentile. The first column lists the estimates for the intercepts, and the last column shows the parameter estimates for the log-transformation of the lagged prescriptions. All four parameters are positive and significantly different from zero, indicating the existence of carryover effects in physicians' prescription behavior. This finding is consistent with that from previous studies (e.g., Crawford and Shum 1998). The middle part in the table shows the parameters for own and competitive detailing. Among them, the own-detailing parameters all have negative signs, indicating increasing effects of own detailing on prescriptions. Notably, these parameters are similar across the four brands, suggesting similar own-detailing effects. To illustrate the nonlinear effects of own detailing, we plot the function

$$y = \exp\left(\frac{\bar{\beta}_{b,b}}{dtl + 1}\right)$$

in Figure 1, using the population level mean $\bar{\beta}_{b,b}$ for Nexium as an example. Again, the mean detailing effects are

Table 3
POPULATION-LEVEL MEAN ESTIMATES FOR THE PRESCRIPTION MODEL

Prescriptions	*Intercept*	$[1/(1 + dtl_{Nexium})]$	$[1/(1 + dtl_{Prevacid})]$	$[1/(1 + dtl_{Aciphex})]$	$[1/(1 + dtl_{Protonix})]$	$ln(1 + Rx_{t-1})$
Nexium	1.49	–.81	.02	.28	.11	.18
	(1.41, 1.58)	(–.92, –.71)	(–.09, .12)	(.19, .36)	(–.01, .21)	(.13, .22)
Prevacid	1.53	.17	–.94	.02	.03	.09
	(1.46, 1.61)	(.08, .25)	(–1.06, –.81)	(–.09, .11)	(–.08, .13)	(.05, .13)
Aciphex	1.12	–.05	.13	–.87	.38	.10
	(1.03, 1.22)	(–.15, .05)	(.03, .22)	(–.98, –.77)	(.28, .47)	(.06, .15)
Protonix	1.23	.26	.01	–.24	–.89	.14
	(1.16, 1.31)	(.17, .35)	(–.09, .11)	(–.36, –.11)	(–1.01, –.77)	(.10, .19)

Notes: (2.5%, 97.5%) percentiles are in parentheses.

similar across the four brands. However, note that this is not necessarily true for a given physician.

To illustrate heterogeneity across physicians in detailing response, we pick two physicians in our data and plot their prescription response curves (Figure 2). These two physicians respond to detailing in different ways. For example, at two details per quarter, Physician B has already shown a "leveling off" of the detailing effect, while Physician A is still very responsive to the detailing calls. This existence of heterogeneity in response is what leads to targeting benefits.

The off-diagonal elements in Table 3 are the competitive detailing parameters, which vary across brands and competitors. In general, we find that competitive detailing affects prescription behavior adversely; for 11 of the 12 competitive detailing parameters, an increase in competitive detailing reduces the mean prescriptions of the focal brand.[8] To illustrate the range of a typical competitive effect, we plot the effect of the three remaining drugs on Nexium prescription, holding everything else constant, in Figure 3.

As Figure 3 shows, the competitive effects are the highest in the 0–2 detailing range. In addition, they are different for different competitors. For example, Prevacid detailing has a very small effect on Nexium prescriptions, while Aciphex has a much larger effect. This difference exists for all four brands, as is apparent in the mean own- and cross-detailing elasticities of detailing (Table 4). In addition, all the cross-detailing elasticities are asymmetric. Finally, we find that physicians in practices with larger patient pools (as measured by the Z variable described previously) tend to write more prescriptions on average (Table 5).

Estimation Results for the Detailing Model

In estimating the detailing model, we first obtain the fixed prices for each brand from http://www.rxaminer.com. The prices for a 90-day prescription (the typical course of therapy in this category) with the smallest daily dosage range from $280 to $360 across the four brands.

Table 6 shows the effects of the variables used as cost drivers. We list the estimation results and the 95% credible interval for each estimate. The parameters without zero in the credible interval appear in bold. We find that the cost shifters have some explanatory power. Population density tends to decrease marginal cost of detailing. This is reasonable because higher density makes it easier for salespeople

[8]The only exception is the competitive detailing effects of Aciphex on Protonix. Protonix is smallest brand in terms of share and volume (Table 1), and Aciphex detailing may be causing a positive spillover onto the prescriptions of the smallest brand.

Figure 1
NONLINEAR TRANSFORMATION OF DETAILING IN THE DEMAND MODEL

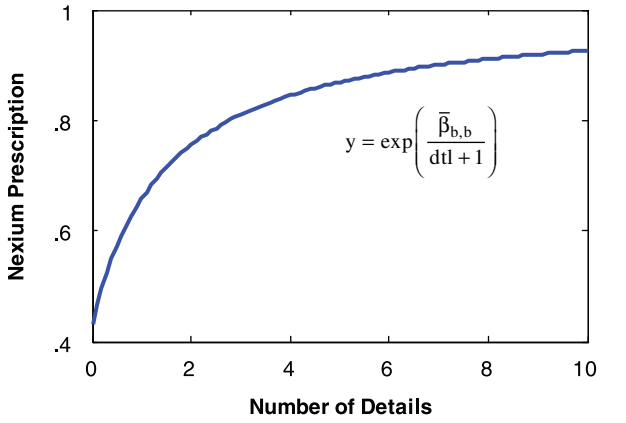

Figure 2
RESPONSE CURVES FOR TWO INDIVIDUAL PHYSICIANS

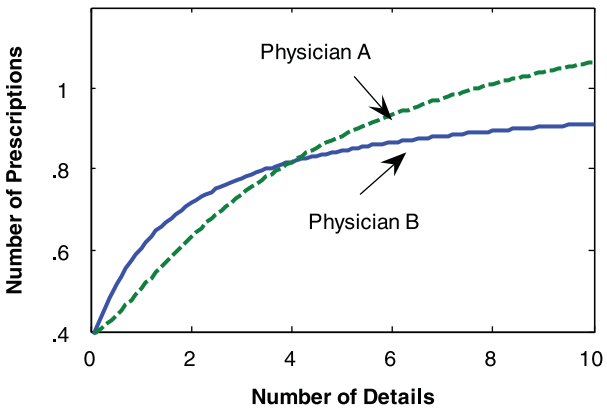

Figure 3
COMPETITIVE DETAILING EFFECTS ON NEXIUM PRESCRIPTION

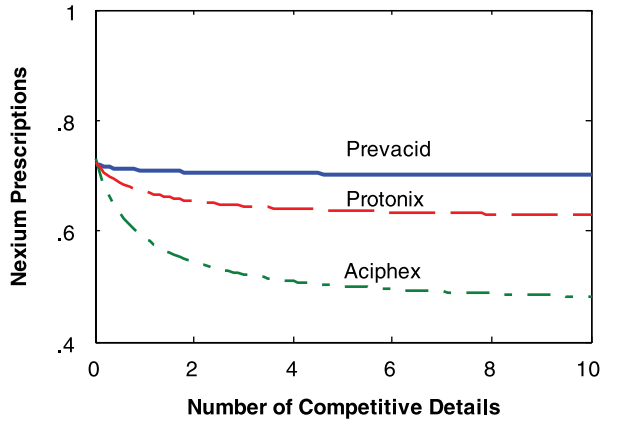

Table 4
MEAN ELASTICITIES

	Nexium	*Prevacid*	*Aciphex*	*Protonix*
Nexium	.115	.000	–.045	–.014
Prevacid	–.027	.128	–.002	–.004
Aciphex	.007	–.017	.131	–.050
Protonix	–.039	–.002	.039	.120

Table 5
PARAMETER ESTIMATES FOR THE β_0 HIERARCHY

	Intercept (θ_0)	*Other Category Prescriptions (1/1000)* (θ_1)
Nexium	.90	1.62
	(.72, 1.09)	(.55, 2.66)
Prevacid	1.22	2.01
	(1.08, 1.37)	(1.18, 2.82)
Aciphex	1.23	2.28
	(1.09, 1.36)	(1.43, 3.11)
Protonix	1.07	1.16
	(.94, 1.21)	(.41, 1.93)

Notes: (2.5%, 97.5%) percentiles are in parentheses.

to make the additional detailing calls. A greater number of PCPs in the same zip code tends to decrease the marginal cost of detailing, though this effect is reversed for the number of gastroenterologists. When there are more PCPs in a zip code, it is less costly to visit an additional PCP in the same zip code than in zip codes with fewer PCPs. Finally, the industry tends to use more qualified and better compensated salespeople to call on specialists, leading to a higher marginal cost of detailing in zip codes with more gastroenterologists. However, the temporal variation in state-level wages is not significant for any brand.

On the basis of these parameter estimates, we compute the marginal cost of detailing to each physician; the average values across all physicians for each brand range from $83 (Protonix) to $115 (Nexium). These cost estimates are consistent with the industry reports. For example, a Global Business Insights report (Seget 2004) mentions that the marginal cost of a detail is $106.[9]

Finally, our model allows the shocks from the prescription model ξ_{pbt} to be correlated with those from the marginal cost function η_{pbt}. The estimated correlations range from .13 to .15 across the four brands, and they are all statistically significantly different from zero. Although these correlations are not particularly large in magnitude, they underscore the importance of accounting for the detailing decision while estimating the parameters of the physician response parameters.

Thus far, we have presented all the model parameters from estimating both the prescription and the detailing models simultaneously. To solve the objective function in Equation 4, we need to check the SOC using these model estimates. To do that, we substitute the individual-level parameter estimates for the prescription model into Equation 9 and evaluate the left-hand side of the SOC at the levels of dtl_{pbt} in the data for each brand at each observation. The results show that for each of the four brands, more than 98% of the observations satisfy the SOC—specifically,

[9]Note from Equation 8 that our costs are scaled to the assumed prices (markups). However, our analysis of profits under a different targeting scenario assumes the same price under each scenario. We also carried out sensitivity analyses with different prices and found that our results were essentially the same. Finally, the prices we use give rise to recovered cost estimates that are close to the industry estimates. This lends some additional credence to our choice of prices.

Table 6
PARAMETER ESTIMATES FOR THE DETAILING MODEL

Detailing	*Intercept*	*Average Weekly Wage ($/1000)*	*Population Density (per Square Miles/1000)*	*Number of PCPs (1/100)*	*Number of Gastroenterologists (1/10)*	*Holiday Season Dummy*
Nexium	.37	.04	–.05	–.03	.00	.12
	(.28, .46)	(–.10, .17)	(–.38, .28)	(–.12, .05)	(–.05, .06)	(.08, .16)
Prevacid	.34	.05	.28	–.12	.04	.13
	(.24, .43)	(–.07, .19)	(–.10, .65)	(–.20, –.03)	(–.00, .08)	(.10, .17)
Aciphex	.40	–.06	.16	–.04	–.01	.03
	(.32, .50)	(–.18, .06)	(–.16, .50)	(–.11, .03)	(–.06, .04)	(.00, .07)
Protonix	.29	.00	–.39	.03	.00	.02
	(.22, .36)	(–.11, .10)	(–.62, –.16)	(–.03, .10)	(–.05, .04)	(–.01, .05)

Notes: (2.5%, 97.5%) percentiles are in parentheses.

99.7% for Nexium, 99.0% for Prevacid, 98.8% for Aciphex, and 98.4% for Protonix.

QUANTIFYING THE BENEFITS OF TARGETING

The main objective of this article is to compare the profitability under different targeting mechanisms. Using the parameters presented previously, we can obtain the marginal cost of detailing for each individual physician from Equation 5. Recall from our description of the detailing-setting process in this industry that the realized number of details for a physician is a hybrid of segment- and individual-level targeting. In our model and estimation thus far, we have assumed that firms maximize profits at the physician level. This provides one extreme of the targeting process. We compare the profitability under this extreme case with the other extreme—namely, targeting at the segment level, at which we obtain the segments of physicians by grouping them into ten deciles on the basis of the physician's total prescriptions in the therapeutic class under consideration. We also compare the profitability with that of an intermediate case that exploits some information on physician responsiveness. In particular, we again create segments by clustering the response parameters of the physicians obtained from the prescription model into ten groups. Computing firms' profits under the physician-level targeting plan is straightforward, given our model parameters. How do we compute profits under segment-level targeting?

Note that if the model parameters are estimated under the "true" data-generating process, we can use these parameters to simulate the results from alternative or "counterfactual" scenarios (see Chintagunta, Kadiyali, and Vilcassim 2004). This implies that we need to simulate the prescriptions and detailing levels when firms target at the segment level, given our model parameters. Under this scenario, the prescription model remains identical to the model in Equation 1, but detailing levels are obtained by maximizing segment-level profits. This implies that detailing levels are identical for all physicians in the same segment. To do this, we need to define the segment membership for each physician. We use the two segmentation definitions described previously in this section. For each of the ten segments, we obtain the optimal detailing levels by solving the following optimization problem:

$$(11)\quad \max_{\mathrm{dtl}_{sbt}} \pi_{sbt} = \sum_{p \in s}\left[\mathrm{markup}_b \times \mathrm{E}\left(\mathrm{rx}_{pbt}|\xi_{pbt}\right) - \mathrm{mc}_{pbt} \times \mathrm{dtl}_{sbt}\right],$$

where s indexes segment. The functional form for $\ln[\mathrm{E}(\mathrm{rx}_{pbt}|\xi_{pbt})]$ is the same as Equation 2, except that the values of dtl_{sbt} are the same for all physicians in a segment. The FOC is changed from Equation 8 for individual-level targeting to the following for the segment-level optimization:

$$\mathrm{markup}_b \times \sum_{p \in s}\left[\exp\left(u_{pbt}\right) \times \frac{-\beta_{pb,b}}{\left(\mathrm{dtl}_{sbt}+1\right)^2}\right]$$

$$= \sum_{p \in s}\left[\alpha_{b0} + X_{pt}\alpha_{bx} + s_b + \eta_{pbt}\right];$$

that is, the condition of total marginal revenue equals total marginal cost is achieved at the segment level as the sum across all physicians in the same segment. Given this detailing equation and our physician response function, we solve this system of equations to yield the levels of prescriptions and detailing under the counterfactual scenario.

We compute the average quarterly profits under the three targeting schemes. The results show that targeting at the individual level is more profitable than that at the segment level, and this is true across all four brands. The increase in profits by targeting at the individual level, compared with targeting at the segment level using the decile-based segmentation rule, ranges from 19% to 24% across the four brands, with an average increase of 23%. This represents a big increase in profits and underscores the power of targeting. Because we used the same cost estimates to compute the profits for both targeting scenarios, the increase in profits is not due to cost savings but rather to (better) accounting for response heterogeneity across physicians. In other words, the availability of individual-level physician response estimates enables the firm to adjust its detailing at a granular level, leading to increased profitability. Turning to the segmentation rule based on the physician response parameters, we find that the average increase in profits is now 14% (with a range of 11%–18% across the four brands). The lower profit differential is to be expected because the counterfactual scenario is now using information on the response parameters. Nevertheless, the benefits to targeting are still substantial.

Our result of higher profits under finer targeting appears to be at odds with the result in Chen, Narasimhan, and Zhang (2001). There are two reasons for this finding. First, in Chen, Narasimhan, and Zhang, firms are competing using price; in our context, they are competing using detailing (which is essentially advertising). The intuition for the results when price is the basis of competition is fairly straightforward: To win customers (the "switchers" in Chen, Narasimhan, and Zhang), firms must undercut competitors on price. As a result, when targetability is extremely high (e.g., at the individual customer level), the competition is severe, leading to a "prisoner's dilemma" situation. In our case, firms compete using a nonprice instrument. The importance of this difference is evident when the theoretical findings from the literature are examined. For example, as Iyer, Soberman, and Villas-Boas (2005, p. 462, emphasis added) note, "When firms have the ability to choose different advertising levels for different groups of consumers, *it leads to higher profits independent of whether or not firms have the ability to set targeted prices*." Therefore, our work can be viewed as providing empirical support for these theoretical predictions. Firms can exploit both the location and the shape of the responsiveness distribution to own and competitive detailing to achieve higher profits. This is consistent with the intuition that Iyer, Soberman, and Villas-Boas provide—that "the targeting of advertising also provides firms with the direct benefit of eliminating wasted advertising" (p. 473). More generally, our work can also be viewed as providing empirical insights into the effectiveness of nonprice targeting. The second point of difference with Chen, Narasimhan, and Zhang's (2001) study is that in their model, the total demand across competing firms is assumed to be the same for different targeting schemes. In other words, the only way a firm can increase sales is by "stealing" customers (i.e., by attracting the nonloyal customers [switchers] to move from another

firm to it). In our study, we model the number of prescriptions for each brand in each period instead of market share. Thus, our model allows for category expansion at different levels of targeting. As a result, a more efficient targeting strategy by each competing firm could lead to expansion of the total market and a potential win-win situation.

Parameters Estimated Without Accounting for Firms' Strategic Behavior

We also conduct the profitability comparison using parameter estimates obtained when we ignore firms' strategic decisions in the estimation process. Because this approach does not involve the detailing equation, we cannot obtain cost estimates in this case. Thus, we use the same cost estimates as those obtained from the proposed approach. Using the response parameter estimates thus obtained and the costs from the proposed approach, we compute the average quarterly profits for the two targeting scenarios. As we expected, targeting at the individual level is still more profitable than targeting at the segment level, but the increase in this case is only 5% across all four brands for the deciles segmentation case and 3% for the response parameter–based segmentation case. In contrast, the increase in profitability is 23% and 14% using the proposed model. This could be why in practice, unlike the firms in these data, many firms still continue to target at the segment level, even with the availability of individual physician–level data. This is because the modest increase in profits may not be enough to cover the cost of implementing an individual-level targeting strategy.[10]

Why Are the Estimated Benefits from Targeting Different When Strategic Behavior Is Considered or Ignored?

To understand why the two approaches yield such large differences in profit gains of individual-level targeting, we now compare the model estimates between these two approaches on the basis of the results listed in Tables 7, 8, and 9. In each of these tables, some estimates from the two approaches are listed together with the 95% credible intervals. To compare the differences between these two approaches, we also present the posterior mean of the differences and the 95% credible intervals of these differences. If zero is not contained in an interval, the difference is statistically significant.

Table 7 lists the mean elasticities from each approach. As the table shows, the approach that ignores firm strategic behavior underestimates own elasticities.[11] That is, ignoring firm strategic behavior underestimates the effects of detailing. This is consistent with findings in the price endogeneity literature, in which ignoring price endogeneity underestimates the price effect. Several studies have documented this finding (e.g., Chintagunta 2001; Villas-Boas and Winer 1999).

[10]It might also be worthwhile to compare the profits from individual-level targeting under both approaches. Although these numbers are not directly comparable because of differences in the assumptions regarding the data generation process, we find that, on average, the proposed approach gives rise to 5% increase in profit relative to the approach that ignores firm strategic behavior.

[11]This is true except for Aciphex, for which the difference between the elasticities from these two approaches is not significantly different from zero.

Both approaches allow for heterogeneity in physicians' response. Table 8 compares the heterogeneity distributions obtained from each model by documenting the estimated variances of the own-detailing parameters at the population level from these two approaches. The comparison shows that the approach that ignores strategic behavior tends to underestimate the extent of heterogeneity. The reason for this reduction of heterogeneity can be found in Table 9, which lists the variances of the random shocks in the prescription model for both models. The model results in higher variances for these random shocks than the proposed model for all four brands. This indicates that the model without strategic detailing overestimates the variance of the random shocks in the prescription model by absorbing some heterogeneity. This result is consistent with Chintagunta, Dubé, and Goh's (2005) finding that ignoring unobserved common factors (similar to the random shocks for the prescription model) overestimates heterogeneity. Their explanation for this is that it arises because the parameters identifying taste differences across individuals pick up some variations from the unobserved factors. Although our analysis does not estimate a model without the random shocks in the prescription model (which would have been

Table 7
COMPARISON OF MEAN OWN ELASTICITIES FROM THE TWO APPROACHES

	Nexium	*Prevacid*	*Aciphex*	*Protonix*
Proposed approach	.11	.13	.13	.12
	(.11, .12)	(.12, .13)	(.13, .14)	(.12, .13)
Approach ignoring firm strategic behavior	.10	.06	.14	.08
	(.08, .12)	(.05, .07)	(.12, .16)	(.07, .10)
Difference	.02	.07	–.01	.04
	(.01, .03)	(.06, .08)	(–.02, .01)	(.02, .05)

Notes: (2.5%, 97.5%) percentiles are in parentheses.

Table 8
COMPARISON OF VARIANCE OF OWN-DETAILING PARAMETER ACROSS INDIVIDUAL PHYSICIANS

	Nexium	*Prevacid*	*Aciphex*	*Protonix*
Proposed approach	.77	1.12	.89	1.05
	(.64, .94)	(.89, 1.36)	(.76, 1.04)	(.85, 1.27)
Approach ignoring firm strategic behavior	.60	.63	.94	.82
	(.48, .74)	(.51, .78)	(.67, 1.18)	(.66, 1.02)
Difference	.17	.49	–.05	.22
	(–.03, .41)	(.26, .72)	(–.33, .17)	(.01, .49)

Notes: (2.5%, 97.5%) percentiles are in parentheses.

Table 9
VARIANCE OF RANDOM SHOCKS IN THE PRESCRIPTION MODEL

	Nexium	*Prevacid*	*Aciphex*	*Protonix*
Proposed approach	.25	.22	.30	.27
	(.23, .27)	(.20, .24)	(.28, .32)	(.25, .30)
Approach ignoring firm strategic behavior	.35	.43	.65	.62
	(.32, .38)	(.40, .47)	(.59, .72)	(.56, .68)
Difference	–.10	–.21	–.35	–.35
	(–.13, –.06)	(–.25, –.17)	(–.43, –.29)	(–.41, –.28)

Notes: (2.5%, 97.5%) percentiles are in parentheses.

more consistent with Chintagunta, Dubé, and Goh's study), both studies demonstrate that an erroneously specified model (either ignoring firm strategic behavior or ignoring the unobserved common factors) biases the estimates for heterogeneity. Furthermore, both studies show evidence of the relationship between the estimated variance of the parameters and the variance of the random shocks.

The underestimation of both own-detailing effects and heterogeneity is also evident in Figure 4, which plots the histograms of the individual-level parameters for own-detailing effects for all the brands under the two models. Recall that the model uses the inverse transformation of detailing. Therefore, we expect that the parameter of own detailing is negative. Under the proposed approach, almost all the individual-level own-detailing parameters are of the right sign. In contrast, the approach that ignores firm strategic behavior shows several physicians who have the wrong sign. Note that this outcome of the right sign for individual-level parameters from the proposed model is a result of an economic constraint (by incorporating firm strategic behavior) and not a statistical constraint (e.g., using a log-normal distribution instead of a normal distribution). Another way to consider this is that our model "shrinks" the parameters obtained from a misspecified model in a manner that is consistent with economic prediction. This suggests that firms are indeed behaving in a profit-maximizing way at the individual physician level.

Villas-Boas and Winer (1999) also show that ignoring price endogeneity overestimates the point estimates for the effects of lagged purchase choices. We find similar results, as Table 10 shows. From the preceding analysis, we learn that ignoring endogeneity underestimates heterogeneity.

Figure 4
COMPARISON OF THE DISTRIBUTION OF INDIVIDUAL-LEVEL PARAMETERS

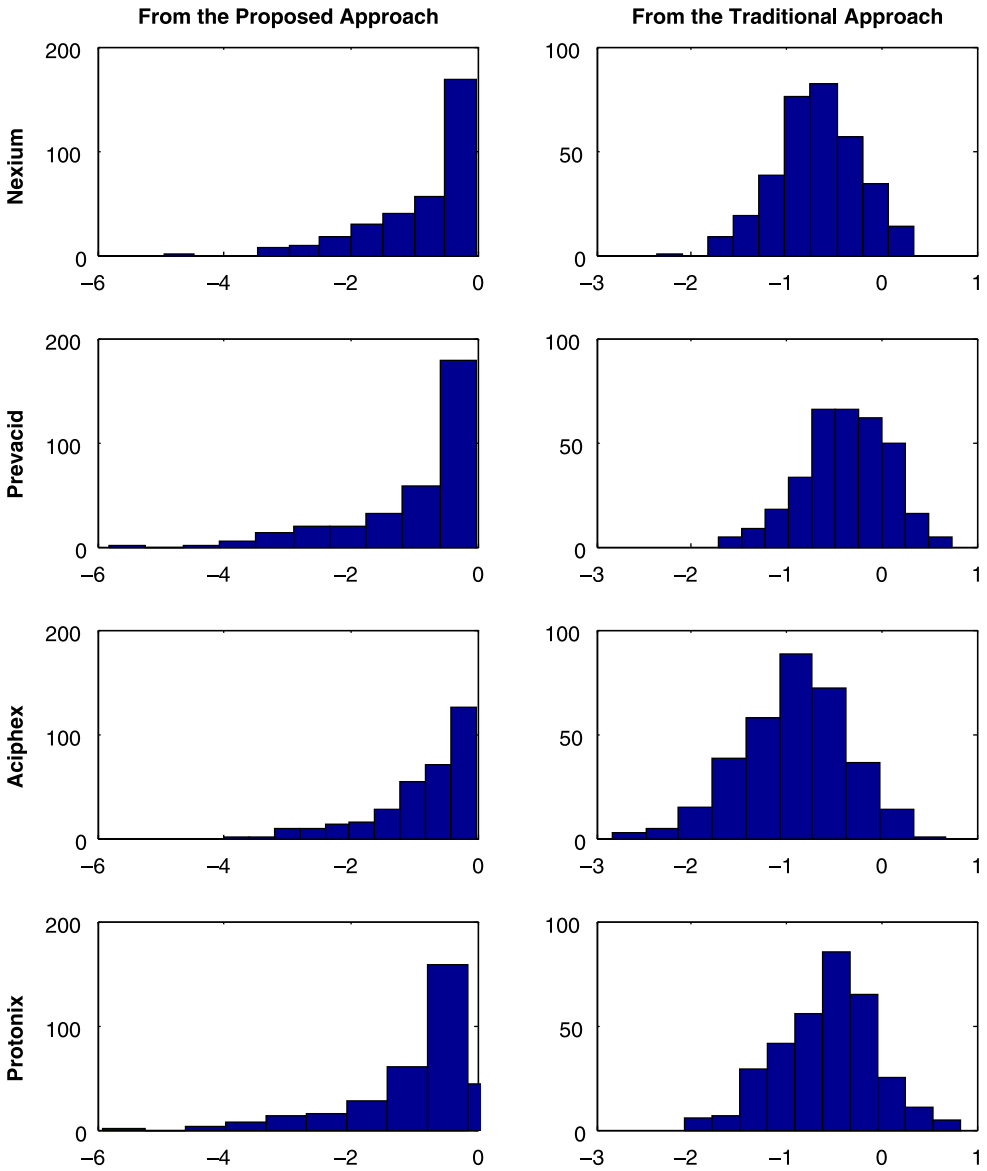

Table 10
COMPARISON OF PARAMETER FOR LAGGED PRESCRIPTION

	Nexium	*Prevacid*	*Aciphex*	*Protonix*
Proposed approach	.18 (.13, .22)	.09 (.05, .13)	.10 (.06, .15)	.14 (.10, .19)
Approach ignoring firm strategic behavior	.17 (.13, .21)	.12 (.07, .17)	.16 (.11, .22)	.19 (.14, .25)
Difference	.01 (–.06, .07)	–.04 (–.10, .03)	–.06 (–.13, .01)	–.05 (–.12, .02)

Notes: (2.5%, 97.5%) percentiles are in parentheses.

Because state dependence is one way to capture heterogeneity, these results indicate that accounting for firm strategic behavior (similar to price endogeneity) realigns the importance of state dependence and heterogeneity. That is, accounting for firm strategic behavior increases estimated heterogeneity and, at the same time, decreases the estimated state dependence.

We also compared the two approaches using the holdout sample test. In this test, we estimate the individual-level response model parameters using the first 11 quarters for each physician (under the approach that ignores firm strategic behavior and the proposed approach) and then compare the prescription likelihood for the final quarter in the data using the estimated individual-level parameters in each case. Specifically, we compute the likelihood value for the final quarter at each draw in the MCMC process for both approaches (Bodapati 2008). We then compute the posterior mean of the log-likelihood across all the simulation draws—this is –6184 for the approach that ignores strategic firm behavior and –5707 for the proposed approach. These results suggest that the proposed approach captures the data-generating process much better.

In summary, our analysis suggests that the approach that ignores firm strategic behavior underestimates the detailing response heterogeneity and the elasticities and overestimates the carryover effects. This underestimation (in the response heterogeneity and the elasticities specifically) drives the finding that ignoring strategic behavior underestimates the gains to targeting at the individual level versus targeting at the segment level.

ROBUSTNESS CHECKS

The previous sections show the importance of incorporating firm strategic behavior because ignoring it results in biased estimates and, thus, a biased comparison between targeting strategies. However, an important concern for any study that incorporates a "supply-side" model in estimating demand model parameters is that the FOC cannot be misspecified (for further details, see Bronnenberg, Rossi, and Vilcassim 2005; Chintagunta et al. 2006; Chintagunta, Kadiyali, and Vilcassim 2004; Kadiyali, Sudhir, and Rao 2000).[12] To ensure that the FOC is not misspecified, in this section, we checked the robustness of our results to the following variations of the proposed model (detailed results are available on request, though a summary is available in the Web Appendix at http://www.marketingpower.com/jmrapril09):

- Profit maximization at the segment (rather than the physician) level in the estimation model, with estimated parameters used to simulate profitability from targeting at the individual level.
- Sales maximization objective for firms (versus profit maximization).
- Detailing levels set using the heuristic rule that Manchanda, Rossi, and Chintagunta (2004) propose (instead of the profit maximization rule of firms assumed in the proposed model).
- Marginal costs of detailing, which are assumed to be known quantities a priori (with sensitivity analysis on the assumed levels) rather than estimated from the data.
- Limited and approximate forward-looking detailing decisions by firms (versus static decision making assumed in the proposed model).
- Latent class assumption for the heterogeneity distribution (instead of a continuous distribution).

In general, we find that our results are robust to alternative specifications and that the proposed model performed better on the criteria of model fit and predictive ability than the alternative specifications required for some of the robustness checks.

CONCLUSION

In this study, we quantify the benefit of targeting at the individual level in the presence of firm strategic behavior. Our application domain is firms' detailing decisions in the pharmaceutical industry. Detailing enables firms to target physicians at the individual level, which in turn enables us to analyze individual-level targeting. It also poses a modeling challenge because detailing levels observed in the data are generated from firms' strategic behavior. We develop a model that accounts for both heterogeneity among individual physicians' responses to detailing and firms' strategic behavior at the individual physician level. Our model contributes to the literature by analyzing both physicians' responses and firms' decisions at the individual level. The analysis also overcomes the potential shortcoming in the current literature on targeting by explicitly accounting for the actions of competitors. Furthermore, the model enables us to obtain the economic marginal cost of detailing. Finally, we estimate all the parameters simultaneously for efficiency.

The results show that when firm strategic behavior is accounted for, targeting at the individual level yields substantial gains (14%–23%) in profit compared with targeting at the segment level. However, ignoring firm strategic behavior in the modeling process biases the parameter estimates and, thus, the benefit of individual-level targeting. The main reason for our finding is that ignoring strategic behavior underestimates the detailing elasticity and the extent of heterogeneity in detailing responsiveness across physicians. We also find that our results are robust to alternative modeling assumptions made in the course of our

[12]Another approach to address this problem would be to use instrumental variables. Although it may be tempting to do this, the solution may not be much better than the problem. As Bronnenberg, Rossi, and Vilcassim (2005, p. 24) note, "Because of the problems with the specification of the supply side, there is growing sentiment to eliminate this part of the model and deal with possible endogeneity problems through instrumental variables. This solution, however, may simply be replacing one possible source of specification error with another. There are no general methods of ascertaining whether an instrumental variable is valid." In addition, as we mentioned previously, it is difficult to find an instrumental variable to "proxy" for the detailing variable because such an instrument needs to vary across physicians, brands, and periods.

analysis. Although these empirical results are confined to a particular data set and the domain is restricted to the pharmaceutical industry, taken together with the results from the recent endogeneity literature, we expect that our basic result—namely, that ignoring firm strategic behavior underestimates the benefit of individual level targeting—is likely to generalize beyond the context of our application. At the same time, extending our analysis to account for possible forward-looking behavior of firms under alternative demand specifications and accounting for multiple marketing instruments in the analysis remain fertile areas for further research.

APPENDIX

The Bayesian estimation is based on the full-information likelihood function in Equation 10. In this likelihood function, the first term, $\text{prob}(rx_{pbt}|dtl_{pbt}, \{\beta_{pb}\}, \xi_{pbt})$, is the distribution of the number of prescriptions conditional on the number of detailing visits, parameters in the prescription model, and the random (demand) shocks; the second term, $f_1(dtl_{pbt}|\{\beta_{pb}\}, \xi_{pbt}, \alpha_b, sb, \Sigma_\eta)$, is the distribution of detailing conditional on parameters from both the prescription and the detailing models. This conditional distribution of detailing is derived from the FOC on the basis of the equilibrium concept. In other words, the FOC "constrains" the distribution of parameters in the detailing equation. In addition, the use of the full-information likelihood function results in estimation efficiency.

This becomes clearer if we consider two alternative model structures. The first would be the approach that we describe as being typically used in the literature. In this approach, detailing is considered data. Thus, the likelihood would consist only of $\text{prob}(rx_{pbt}|dtl_{pbt}, \{\beta_{pb}\}, \xi_{pbt})$. The second could be a model in which detailing is affected only by exogenous variables (and not by any of the demand parameters). In this case, there would be two terms in the likelihood function: $\text{prob}(rx_{pbt}|dtl_{pbt}, \{\beta_{pb}\}, \xi_{pbt})$ and $f_1(dtl_{pbt}|\alpha_b, s_b, \Sigma_\eta)$. In this case, the full conditional distributions for the parameters of the detailing function are independent of the parameters of the prescription equation, and therefore these distributions are "unconstrained."

In terms of the relationship between own and competitive detailing, the firms' decisions are assumed to be simultaneous moves. The FOCs are solved simultaneously in this model. We agree that this may not be easily observable from Equation 10. To clarify, the FOC in Equation 8 is as follows:

$$\text{markup}_b \times \exp\left(u_{pbt}\right) \times \frac{-\beta_{pb,b}}{\left(dtl_{pbt}+1\right)^2} = \alpha_{b0} + X_{pt}\alpha_{bx} + s_b + \eta_{pbt}.$$

Note that u_{pbt} (as specified in Equation 2) is a function of detailing levels of all brands. This implies that the FOC for brand b is not only a function of own detailing, dtl_{pbt}, but also a function of competitive detailing visits, $dtl_{pb't}$, $\forall b' \neq b$, as noted in Equation 2. In this case, to solve the FOC to obtain optimal solutions for detailing for each brand, it is necessary to solve all four FOCs simultaneously. This is exactly what would be done in a game with simultaneous moves. We indeed solve the four FOCs simultaneously to obtain the joint distribution of the four detailing variables using the transformation-of-variable technique.

Specifically, note that η_{pbt} in the preceding equation is assumed to follow multivariate normal distribution with zero mean and covariance matrix Σ_η, where Σ_η has a dimension of four, which is the number of brands.

By leaving η_{pbt} on the right-hand side of the equation, we get the following:

$$\text{markup}_b \times \exp\left(u_{pbt}\right) \times \frac{-\beta_{pb,b}}{\left(dtl_{pbt}+1\right)^2} - \left(\alpha_{b0} + X_{pt}\alpha_{bx} + s_b\right) = \eta_{pbt},\ \forall b.$$

We denote the left-hand side of the preceding equation as r_{pbt}; that is

$$r_{pbt}\left(dtl_{pt}\right) = \text{markup}_b \times \exp\left(u_{pbt}\right) \times \frac{-\beta_{pb,b}}{\left(dtl_{pbt}+1\right)^2} - \left(\alpha_{b0} + X_{pt}\alpha_{bx} + s_b\right),\ \forall b,$$

where $dtl_{pt} = \{dtl_{pbt}, \forall b\}$, and we define $r_{pt} = \{r_{pbt}, \forall b\}$.

When using the transformation-of-variable technique, we need to compute the Jacobian of

$$\left|\frac{\partial r_{pt}}{\partial dtl_{pt}}\right|$$

for all four brands. That is, in the Jacobian, the diagonal is composed of the values of

$$\frac{\partial r_{pbt}}{\partial dtl_{pbt}},$$

which is the derivative computed for the own detailing, and the off-diagonal is the derivative with respect to competitive detailing. According to the transformation-of-variable technique, the product of this Jacobian and the multivariate distribution of the random shocks, $\eta_{pt} \sim N(0, \Sigma_\eta)$, gives rise to the joint distribution of the observed detailing for all four brands.

To summarize, the equilibrium concept is incorporated in the estimation process as follows:

1. The FOCs are solved simultaneously because the equilibrium arises from the assumption that all four firms move simultaneously.
2. It is the joint conditional distribution of detailing across all four brands that enters the full-information likelihood function in Equation 10. Thus, we do not need to use own detailing conditional on all other detailing.

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