Quantifying the Benefits of Individual Level Targeting
In the Presence of Firm Strategic Behavior

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Abstract

Targeting – setting marketing policy differentially for different customers or segments - is an important marketing practice. Previous approaches to quantifying the benefits from targeting calibrated a response model and used the variation in response parameter estimates to compare the firm’s profits under targeting schemes at different levels of aggregation. Implicit in this approach is the assumption that the data do not reflect any strategic behavior that the firm may be engaged in vis-à-vis the marketing variables being used for targeting. In this paper, we develop a method to quantify the benefits of targeting when the data reflect firm strategic behavior, i.e., when firms are i) already engaged in some form of targeting; and ii) taking into account actions of competing firms. In particular, we are interested in quantifying the improvement in profits to a firm from targeting its activities at the individual customer level (one-to-one marketing) as compared to the allocation of marketing resources at a more aggregate level (e.g., segment or market level).

We focus on detailing – the most important instrument of marketing in pharmaceutical industry. The pharmaceutical firm’s decision is the allocation of detailing visits across individual physicians. As firms already use the information on how detailing affects individual physician behavior in setting their detailing allocation, our proposed approach is appropriate in this context. For our analysis, we develop, at the individual physician level, a model of prescriptions as a function of detailing; and model of detailing under the assumption that firms simultaneously maximize profits from a physician. We estimate our model on a novel physician panel dataset from the Proton Pump Inhibitor category. Estimation of the model parameters is carried out jointly using full-information Bayesian methods to obtain efficient estimates of the parameters of both models at the individual physician level. Our results suggest that accounting for firm strategic behavior improves profitability by 38% relative to segment level targeting; ignoring firm strategic behavior would underestimate the benefit of individual level targeting significantly. We provide reasons for this finding. We also carry out several robustness checks to the various assumptions made in the model.

Keywords: Targeted Marketing, Response Models, Firm Strategic Behavior, Pharmaceutical Industry, Detailing, MCMC Methods
1. Introduction

Targeting – 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 a variety of marketing domains. These domains include direct mail (Bult and Wansbeek (1995), Gonul and Shi (1998), Allenby, Leone and Jen (1999), Kim et al. (2005)), Internet marketing (Montgomery (2000), Ansari and Mela (2003), Murthi and Sarkar (2003)) and couponing (Rossi et al 1996). Typically, these studies calibrate a response model and use 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 (e.g., coupons). To quantify the benefits of targeting, one can then compare firm’s profits under various targeting schemes – at the individual customer level, at the segment level, or via mass marketing (i.e., no targeting). The comparison of these profits is carried out under the assumption that there is no competitive response to these targeting policies or under pre-specified competitive scenarios. We refer to this approach of quantifying the benefits of targeting as the “standard approach”.

Implicit in the standard approach are the following two assumptions regarding firms’ strategic behavior. First, the data being used to estimate the response parameters do not reflect any behavior that the firm may be engaged in vis-à-vis the marketing variables whose responsiveness is being estimated. Second, when evaluating the firm’s profits under alternative targeting schemes, the standard approach typically assumes that firm’s decision does not consider its competitors’ actions. These assumptions may not be valid in many industries (e.g., business-to-business markets) where the firm already has a targeting strategy in place and accounts for competitors’ actions in some fashion (systematic or otherwise). If the data reflect such strategic behavior of firms and it is not accounted for in the estimation, the estimates of the response parameters will be invalid (biased).
Hence, any conclusions drawn regarding the responses parameters themselves, or the implications for targeting are likely to be incorrect.

In this paper, we develop a method to quantify the benefits of targeting while accounting for firm strategic behavior. In particular, we are interested in quantifying the improvement in profits to a firm from targeting its activities at the individual customer level (one-to-one marketing) as compared to the allocation of marketing resources at a more aggregate level (e.g., segment or market level). As mentioned above we are interested in doing this using 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 or personal sales calls made to physicians. The pharmaceutical firm’s 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 allocation. The detailing setting process works as follows. First, firms set detailing at the physician decile (or segment level) where the deciles binning rule is total volume prescribed in the category. All physicians in the same decile are expected to get identical levels of detailing. Second, the firm develops a “calling” plan for each physician in theory. This is accomplished by local managers and sales persons who actually implement the detailing plan and have the freedom to make adjustments to these plans to tailor the detailing to each physician. Thus, the realized number of details received by each physician is a “hybrid” that comprises both the top-down and bottom-up aspects described above.

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2 “Targeting” in the literature sometimes refers to the decision on whether to market to a customer. This situation is nested in our definition i.e., a customer not chosen as part of the target will receive no marketing resources.

3 Detailing accounts for the largest promotional expenditure in this industry ($7 billion in 2003). The industry expenditure on detailing is more than twice as much as the expenditure on any other marketing instrument used by the industry.
Given the above description, it is clear that the standard approach to develop and quantify the value of targeting mentioned earlier will bias the estimates of physicians’ responses and hence the benefits of targeting. Quantifying the benefits of targeting is critical to pharmaceutical companies who invest billions of dollars in detailing with non-negligible costs associated with targeting at the physician level. This quantification will also provide firms an upper bound on the investment they should be willing to make in order 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).

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 written by that physician. The response model needs to reflect the heterogeneity across physicians in their response to detailing – the underlying basis for profitable targeting. The second key building block is a characterization of the data generating mechanism for the observed detailing in the marketplace. Here, we assume that the physician-level detailing for each firm observed in the data are the joint outcomes of all firms acting simultaneously to maximize their profits from each individual physician given the response model previously assumed (as in Shaffer and Zhang 1995). 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 allows us to incorporate a firm’s strategic behavior with respect to detailing explicitly in the analysis.

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4 Note that the current state of practice for a particular 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 current targeting behavior. In our empirical example, assuming one-to-one marketing seems reasonable since firms have access to these detailed physician level data. We will discuss other targeting scenarios in detail in the subsequent sections.

5 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. In our
With the two main building blocks described above - a prescription response model and a strategic detailing equation - at hand, 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. Estimation of the parameters of this system is carried out 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 since individual level estimates are crucial for implementing a one-to-one marketing policy.

To quantify the benefits of targeting, we first need to compute the firm’s profit differential under alternative targeting scenarios. The base case is the individual physician level targeting scenario above. Computing the base case profits is straightforward since that is the situation under which the model parameters are estimated. To obtain the profits under the alternative scenarios we need to compute the prescriptions and levels of detailing under those scenarios. For this, we need to first write down the detailing equation corresponding to each alternative. Then using the model parameters previously estimated, the prescription response equation and the new detailing equation, we simulate the prescription and detailing levels under the new regime. Once those levels are obtained, we can then compute the firm’s profit levels. This approach is similar to the counterfactual simulations described in Chintagunta et al (2005). With the profit levels on hand from the various alternative scenarios, we can then quantify the benefits to the firms from individual physician level targeting relative to those, more aggregate, allocation mechanisms by computing the profit differentials.

Having quantified the benefits to targeting while accounting for the manner in which firms set their detailing levels, we turn next to address the question – what is the impact on our profit differential metric (that we use to quantify the benefits of targeting) if we ignore firms’ strategic context, we would need instruments that vary across physicians and time periods. It is not clear whether such valid instruments exist.
behavior when estimating the model parameters? Here we are able to 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 function?) to ensure that our results are robust to model specification and estimation.

Recent literature in marketing and economics has witnessed a surge of interest in estimating the parameters of demand models while explicitly accounting for firm behavior. A majority of these studies focus on product categories such as automobiles, breakfast cereal, yogurt, peanut butter, etc. (Berry, Levinsohn and Pakes (1995), Nevo (2001), Sudhir (2001)). Given data at the market level, these studies typically estimate the demand function at the aggregate market level (or occasionally, at the segment level). Further, since firms’ strategic behavior such as pricing is usually also at the market level (i.e., manufacturers set market level prices for cars), model implications are typically available only at the market level and are not directly applicable in a targeting context. More recently, studies such as Yang, Chen and Allenby (2003) and Chintagunta, Dube and Goh (2005) have estimated demand models at the individual household level. However, in these cases, the strategic behavior of firms continues to be at the aggregate market level making those approaches again less suitable to the study of targeting. A third set of studies exemplified by Besanko, Dube and Gupta (2003) has studied the issue of targeting of coupons under firm strategic behavior. However, in that case, data are at the aggregate level. Consequently the implications for targeting are necessarily limited. By contrast, our study deals with targeting with both the prescription model as well as the firm’s detailing model pertaining to the individual physician for whom the targeting is being undertaken. Further, the data available are at the level of aggregation of interest. Additionally, we are able to exploit the power of the Bayesian estimation machinery given our interest in individual level parameters that are required for addressing the targeting problem. In that regard, our study can be
viewed as an early attempt at estimating a system of demand and firm behavior at the micro-level in order to address an issue (i.e., targeting) which is relevant for that level of aggregation.⁶

2. 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 firm’s strategic detailing decision for each physician. Since 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. The specification of both models is discussed below.

*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.⁷ Conditional on detailing, the number of prescriptions by each physician in each quarter, \(\text{pbtrx}_{pbt}\), is assumed to follow a Poisson distribution, with parameter \(\lambda_{pbt}\) for physician \(p\), brand \(b\) and quarter \(t\).

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⁶ Increasing interest in this general area is also reflected in papers such as Pancras and Sudhir (2005) where the authors’ focus is on strategies of vendors of personalization services.

⁷ 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 will require knowledge of the total patient pool of each physician for whom a prescription is not written. This information is not available to us. Further, since patients arrive over the course of the quarter it may be unreasonable to assume that all the details in that quarter will influence the choice for a patient arriving early in the quarter. Another possibility that does not require the “no-prescription” 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. Since 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 are able to specify a flexible and unconstrained pattern of cross-brand detailing elasticities and estimate these at the physician level.
\[ \text{prob}(rx_{pbt} = y) = \frac{\exp(-\lambda_{pbt}) \times \lambda_{pbt}^y}{y!} \]  

(1)

Where \( rx \) denotes the number of prescriptions, and \( y \) denotes its value. Since \( \lambda_{pbt} \) should be positive for all \( p, b \) and \( t \), a typical log-link function is used and denoted as \( \lambda_{pbt} = \exp(u_{pbt}) \). \( u_{pbt} \) is defined to be linear in parameters, that is

\[ u_{pbt} = \beta_{pb,0} + \beta_{pb,b} f(dt_{pbt}) + \sum_{b \neq b'} \beta_{pb,b'} f(dt_{pb'1}) + \beta_{pb,l} \log(rx_{pb,t-1}) + \xi_{pbt}. \]  

(2)

In this specification, \( \beta_{pb,0} \) is a constant, specific to each individual physician \( p \) and each brand \( b \). The constant accounts for physician and brand specific effects, such as the size of practice for physician \( p \), and physician’s intrinsic preference towards brand \( b \). \( f(dt_{pbt}) \) is a transformation of own detailing, capturing potentially nonlinear effects (typically, diminishing returns) of detailing, as has been documented by the literature (Gonul et al. (2001), Manchanda and Chintagunta (2003)). Given the limited number of observations for each physician, we choose to use a parametric functional form (rather than approximating it via a polynomial function). The requirement for the function, \( \exp(\beta_{pb,b} f(dt_{pbt})) \), is that, with respect to \( dt_{pbt} \), it should allow prescriptions to increase with diminishing returns. For the sake of parsimony, we choose the log-reciprocal transformation (Lilien, Kotler and Moorthy (1992)), that is, \( f(dt_{pbt}) = \frac{1}{1+dt_{pbt}} \) or \( \exp(\beta_{pb,b} f(dt_{pbt})) = \exp\left(\frac{\beta_{pb,b}}{1+dt_{pbt}}\right) \).

Detailing in the data, \( dt_{pbt} \), is incremented by one before the reciprocal transformation to accommodate no (zero) detailing in a physician-quarter for a brand. We expect \( \beta_{pb,b} < 0 \). Note that the log-reciprocal transformation is flexible in that it allows either increasing or diminishing returns based on the parameter estimates as well as the range of data for \( dt_{pbt} \). The conditions under which
this transformation shows diminishing returns are discussed using the second order conditions in equation (8) below.

The next component in equation (2) is \( \sum_{b \neq b'} \beta_{pb,b} f\left( dtl_{pb'/t} \right) \), 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 \( f\left( dtl_{pb'/t} \right) = \frac{1}{1 + dtl_{pb'/t}}, \forall b' \neq b \). We expect \( \beta_{pb,b} > 0 \).

Note that we allow competitive detailing effects to be different across brands. This allows for more flexible competitive brand effects than a share model. The number of estimated detailing effects parameters for our product category with four brands is sixteen (one own effect and three cross effect parameters for each brand).

\[ \log\left( r_{pb,t-1} + 1 \right) \] is a logarithm transformation of the number of prescriptions written during the previous quarter \( t-1 \), by physician \( p \), for brand \( b \). We add one to the lagged variable \( r_{pb,t-1} \) to allow for zero values. This lagged variable accounts for state dependence in physician’s prescription behavior, as well as carry-over effects of detailing, as documented in previous literature (see, for example, Manchanda, Rossi and Chintagunta (2004)). Finally, \( \xi_{pbt} \) in equation (2) is an additive random error term, accounting for any other physician-brand-time varying factors that are not observed or not measurable by the researcher (but are observed by the firm). These might include patient specific characteristics; or factors that are not included in the model because of lack of data, such as availability of free samples at the doctor’s disposal etc. All these factors vary over time and are expected to affect physician \( p \)’s prescription of brand \( b \). Note that, since we model physician’s response to detailing and firm’s strategic detailing decision simultaneously at the individual physician level, the model can accommodate correlations between \( \xi_{pbt} \) and \( dtl_{pbt} \) (we return to this issue subsequently). These random shocks \( \xi_{pbt} \) for all brands are assumed to follow an IID multivariate
normal distribution correlated across brands, with mean zero and covariance matrix $\Sigma_\xi$, if we denote $\xi_{pt} = \{\xi_{pbt}\}$ for all $b$, then $\xi_{pt} \sim N(0, \Sigma_\xi)$.

Another factor that is not considered in the model is direct-to-consumer advertising, or DTC advertising. The effects of DTC advertising in our data can be found in patient requests i.e., when patients specifically request a brand whose advertising they have presumably been exposed to.\footnote{Previous research has shown DTC advertising typically affects patient behavior (participation in the category, visits to the physician and/or patient requests) while it does not have any effect on physician prescription behavior (Xie 2003).} We find that, in our data, prescriptions resulting from a patient request comprise only about 3% of all prescriptions. Thus, we do not expect that the inclusion of DTC advertising will change physicians’ response behavior.

Given the assumptions on $r_{x_{pt}}$ and $\xi_{pbt}$, our model is in the form of the Poisson-lognormal distribution, as discussed by Aitchison and Ho (1989). With this formulation, the model possesses the following three properties that a typical Poisson model potentially ignores, making the latter less suitable for our purposes. These are a) over dispersion of the data (see Chib and Winkelmann (2001) for details); b) correlation among prescriptions of different brands prescribed by the same physician; c) over proportion 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:

1. The firm’s objective function is to maximize profits from each physician in the market. Previous research has documented that even at the individual physician level, firm behavior tends to reflect profit maximizing behavior for a majority of physicians (Manchanda, Rossi and Chintagunta 2004). It is quite possible that at the operational level, detailers are maximizing brand sales (or brand
share). Thus, the data generating process may be more consistent with a sales maximization objective rather than a profit maximization objective. Hence, we carry out a robustness check where we estimate a model assuming a sales maximization objective and examine model fit under this assumption relative to that of a profit maximization objective.

2. Firms maximize only current period profit conditional on observing each physician’s previous quarter’s prescriptions. This assumption can be justified by the quarterly data we use for our analysis and industry managers’ claim that they decide detailing efforts at each quarter with no “forward looking” behavior. Given that the physician’s response model has a lagged prescription term, a theoretically more appealing assumption would be of a rational forward-looking firm that maximizes longer-term profits when making decisions on detailing. However, as our purpose is to simulate the data generating process, we chose the assumption that is most consistent with industry practice for the particular category we analyze. We leave it to future research to verify how far such a period-by-period maximization deviates from a firm’s dynamic detailing policy.

3. Physicians’ prescription decisions are not affected by price. This is what was found empirically by Gonul et al. (2001) using physician level data. In addition, in our data, only 2% of all the patient visits use cash to pay for the drugs, all the other prescriptions are covered by insurance. Therefore, ignoring price will not affect the results. As the price of a drug as charged by its manufacturer does not vary much over time, we assume that when firms make decisions on detailing levels, prices are exogenous and fixed. In other words, we can consider the detailing decision conditional on the pricing decision in our analysis.

4. The firm’s decision variable is the number of details to deliver to physician. While the content of a detail may differ across delivered details, it is hard for firm to decide on content as the interaction is not completely under the detailer’s control. For example, the physician’s time availability and mood at the time of the detail is unknown to the firm in advance. Given this, we
assume that all details for a given brand have the same effect. Note that we allow this effect to be firm (brand) specific.

Based on the above 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. $^9$ The firm’s objective is to find the optimal detailing level for that physician in that quarter:

$$\max_{dtl_{pbt}} \pi_{pbt} = \text{markup}_{pbt} \times E(rx_{pbt} | \xi_{pbt}) - mc_{pbt} \times dtl_{pbt}$$

(3)

In this equation, $\text{markup}_{pbt}$ 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 minus the marginal cost of production. Based on industry feedback, we assume the marginal cost of production to be zero (marginal costs of production are very low and negligible compared to detailing cost). We use price to approximate $\text{markup}_{pbt}$ with the assumption that prices are constant across physicians and across time, that is $price_{pbt} = price_b, \forall b$.

Finally, the variable $mc_{pbt}$ represents the marginal cost of detailing for visiting physician $p$, by firm $b$, in quarter $t$. Following the literature that has estimated marginal cost functions (typically production costs), we use a linear specification for $mc_{pbt}$ as follows.

$$mc_{pbt} = \alpha_b + X_p \alpha + s_b + \eta_{pbt}$$

(4)

In this equation, $\alpha_b$ accounts for intrinsic differences among the pharmaceutical firms in their marginal costs. These differences could be due to differences in sales personnel and managers in the firms. As a consequence, this “intercept” would reflect differences in training, experience, etc. $X_p$ are exogenous, physician specific variables that influence the marginal cost of detailing to that

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$^9$ In this empirical analysis, each firm markets only one brand, therefore we refer to the firm that markets brand $b$ as firm $b$. 
physician. $\alpha$ is the parameter associated with these exogenous variables. $s_b$ accounts for the systematic deviation during a holiday season, and $\eta_{pb}$ is a random error term accounting for any unobserved temporal factors that affect firm $b$'s marginal cost of detailing to physician $p$ at quarter $t$.

An important such factor is the office environment faced by the detailer in each time period. The office environment faced by the detailer 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 other categories (non-PPI) etc. These factors have a direct impact on the quality and quantity of details that an individual detailer can make. Note that these factors are observed by the detailer but not by the researcher. The vectors (with dimension $B$, the number of brands in the same category) of $\eta_p = \{\eta_{p1}, \eta_{p2}, \ldots, \eta_{pB}\}$ are assumed to be independent across physician-quarter and follow a multivariate normal distribution across brands, with zero mean and covariance matrix $\Sigma_\eta$, that is $\eta_p \sim N(0, \Sigma_\eta)$.

**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 (3)), we need to compute the first order conditions (FOC) as follows:

$$\text{markup}_b \times \frac{\partial E \left( r_{pbt} \mid \xi_{pbt} \right)}{\partial \text{dtl}_{pbt}} = mc_{pbt} \quad (5)$$

Among the various terms in equation (5), $\frac{\partial E \left( r_{pbt} \mid \xi_{pbt} \right)}{\partial \text{dtl}_{pbt}}$ can be obtained from the prescription model in equation (2), that is:

$$\frac{\partial E \left( r_{pbt} \mid \xi_{pbt} \right)}{\partial \text{dtl}_{pbt}} = \exp(\mu_{pbt}) \times \frac{-\beta_{pb,b}}{(\text{dtl}_{pbt} + 1)^2} \quad (6)$$
Equations (4) (the specification for marginal cost of detailing) and (6) (the first derivative of prescription model with respect to detailing) can be substituted into equation (5) (FOC equation), to get the following version of the FOC

$$\text{markup}_b \times \exp\left(u_{pbt}\right) \times \frac{-\beta_{pb, b}}{(\text{dtl}_{pbt} + 1)^2} = \alpha_b + X_p \alpha + s_b + \eta_{pbt}$$

(7)

The above equation can be re-written as

$$\left(\text{dtl}_{pbt} + 1\right)^2 = \text{markup}_b \times \exp\left(u_{pbt}\right) \times \frac{-\beta_{pb, b}}{\left(\alpha_b + X_p \alpha + s_b + \eta_{pbt}\right)}$$

In general, the above is an implicit equation in detailing, $\text{dtl}_{pbt}$, since the function $u_{pbt}$ is a function of $\text{dtl}_{pbt}$. Nevertheless, we can use the above expression to understand its properties. First, note that since $\beta_{pb, b} < 0$ (i.e., detailing has a positive effect on prescriptions), the right hand side (RHS) of the above equation >0 as long as the marginal cost, $mc_{pbt} = \alpha_b + X_p \alpha + s_b + \eta_{pbt} > 0$. In principle if the RHS exceeds one, we have an interior solution for the detailing level. Further, if the RHS is close to 1, we get the zero detailing condition. Note however, since the marginal cost contains the error term $\eta_{pbt}$, it is in principle unbounded at both ends.

The FOC plays a key role in this analysis by connecting the two models - the individual physician response model and firm’s strategic detailing decision model. This setup implies that the details observed in the data satisfy equation (7) for each physician $p$, each brand $b$ at each quarter $t$.

This is different from the assumption in a response model without firm’s strategic detailing model, where we would assume that detailing decisions are exogenous from the response model. For example, Manchanda and Chintagunta (2003) do not make any assumptions on how detailing is decided. They focus only on how physicians respond to firms detailing conditional on detailing levels. Our model is also different from the model in Manchanda, Rossi and Chintagunta (2004),
where a reduced form detailing model is specified in which detailing levels are determined based on physician response parameters. Detailed comparisons with their model are discussed in section 6.

Another point to note in equation (7) is that $u_{pbi}$, which contains all the demand parameters $(\beta_{pb,0}, \ldots, \beta_{pb,l})$ appears in both the prescription model (equation (1)) through $\lambda_{pbi} = \exp(u_{pbi})$, and the detailing model through the FOC. This has two implications. First, by jointly estimating the parameters of the response model and the detailing equation, we are able to get more efficient estimates for the response parameters due to information sharing across the two equations. More importantly, if equation (7) holds, then the firm’s detailing level $dt_{pbi}$, is a function of the prescription equation error, $\xi_{pbi}$. This implies a potential endogeneity bias if the prescription equation parameters are estimated independent of the parameters of the FOC in equation (7). Hence, joint estimation of equations (1) and (7) also helps us to resolve the endogeneity bias. In a later section (Section 4), we show that response parameters estimated with or without the detailing model in equation (7) are substantially different.

Note that the FOC is only a necessary condition for solving firm’s profit maximization problem; the sufficient condition requires the second order condition (SOC) to be negative. By taking the derivative on both sides of equation (6) with respect to $dt_{pbi}$, we obtain the SOC:

$$\text{markup}_b \times \exp(u_{pbi}) \times \left( \frac{2\beta_{pb,b}}{(dt_{pbi} + 1)^3} + \left( \frac{\beta_{pb,b}}{(dt_{pbi} + 1)^2} \right)^2 \right) < 0$$

Solving this inequality, we get, $dt_{pbi} > -\frac{\beta_{pb,b}}{2} - 1$. That is, if physician $p$’s response parameter to brand $b$’s detailing $\beta_{pb,b}$ satisfies the condition, $-2 < \beta_{pb,b} \leq 0$, it is guaranteed that the detailing levels, $dt_{pbi} \geq 0$, observed for all the observations for physician $p$ and brand $b$ satisfy the SOC.
Using our obtained model estimates, we will test to see how many of the observations for each brand satisfy this condition.

Finally, note from the FOC that the estimated marginal cost parameters (in equation (4)) are not invariant to the markup. In other words, if the markup is scaled up by a positive quantity, the parameters will be as well. Our main objective is to compare the profit under various targeting schemes and therefore this is not an issue as long as we assume the same markup under each scheme.

*Bayesian estimation*

We estimate both prescription and detailing models simultaneously using the complete likelihood:

\[
\begin{align*}
    f & \left( \{ \beta_{pb} \}, \{ \xi_{pbt} \}, \{ \alpha, b, s_b \}, \{ \alpha, \Sigma_{\xi}, \Sigma_{\alpha} \} \mid \{ rx_{pbt} \}, \{ dtl_{pbt} \} \right) \\
    \propto & \prod_{p,b,t} \text{prob} \left( rx_{pbt} \mid dtl_{pbt}, \{ \beta_{pb} \}, \xi_{pbt} \right) \\
    & \times \pi_1 \left( dtl_{pbt} \mid \{ \beta_{pb} \}, \xi_{pbt}, \alpha_b, s_b, \alpha, \Sigma_{\alpha} \right) \\
    & \times \pi_2 \left( \beta_{pb} \mid \bar{\beta}, \Sigma_{\beta} \right) \times \pi_3 \left( \xi_{pbt} \mid \Sigma_{\xi} \right) \\
    & \times \pi_4 \left( \bar{\beta}, \Sigma_{\beta}, \Sigma_{\xi}, \alpha_b, s_b, \alpha, \Sigma_{\alpha} \right)
\end{align*}
\]

(9)

Where \( \text{prob} \left( rx_{pbt} \mid dtl_{pbt}, \{ \beta_{pb} \}, \xi_{pbt} \right) \) is the Poisson probability for the number of prescription \( rx_{pbt} \) by physician \( p \) for brand \( b \) at quarter \( t \), as defined in equation (1), with \( \lambda_{pbt} = \exp \left( u_{pbt} \right) \) and \( u_{pbt} \) defined in equation (2) with \( f \left( dtl_{pbt} \right) = \frac{1}{dtl_{pbt} + 1} \).

Gibbs sampling (Geman and Geman (1984)) with data augmentation techniques (Tanner and Wong (1987)) are employed to facilitate estimation of the model parameters. Gibbs sampling allows 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...
including individual level parameters, i.e. the \( \{\beta_{pb}\} \)'s. Data augmentation techniques allow us to draw the random component \( \xi_{pb} \) in the prescription model, which facilitates the simulation draws for the covariance matrix \( \Sigma_{\xi} \), as well as all the \( \{\beta_{pb}\} \)'s. The details of the full conditional posterior distributions for groups of the parameters are presented in the Appendix. Here we highlight two points. First, the conditional distribution of detailing is obtained based on the FOC in equation (7). 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, \( \eta_{pb} \sim N(0, \Sigma_{\eta}) \) using the technique of change-of-variables. 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, the covariance matrices of demand and supply random shocks \( \Sigma_{\xi} \) and \( \Sigma_{\eta} \) 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 allows us to account for the correlations between the random shocks in the two models.

3. Data and Estimation

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 (in contrast to 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 (PPI) category at a quarterly level from August 1, 2001 to May 1, 2004. These data are novel in that the marketing activity of each
competitor is recorded by the individual physicians. PPI treats gastroesophageal reflux disease (GERD, also known as Acid Reflux Disease), which is one of the conditions that cause chronic heartburn. More than 60 million American adults suffer from heartburn at least once a month, and about 25 million American adults suffer from heartburn on a daily basis. The PPI category generated $12.5 billion in revenue in 2004, making it the second largest prescription drug category in sales in the US market (IMS Health). In our data, four brands account for over 99% of all details received and over 97% of all the prescriptions written by the physicians in the panel. We therefore focus our attention on these four brands: Aciphex, Nexium, Prevacid and Protonix.

Our sample consists of physicians who have received at least one detail (across 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. It shows that Nexium, the newest brand, possesses the largest prescription market share in this category. It is also the most detailed brand among these four brands. These data probably reflect physicians’ beliefs about Nexium having the least side effects as well the heavy marketing push by AstraZeneca (Wall Street Journal 2002). Prevacid is the oldest drug among these four brands and has the second largest share of prescriptions in this category. The launch dates of Aciphex and Protonix are very close to each other, and the market shares for these two brands are also similar. Finally, it is interesting to notice that prescriptions and details are ordered in the same manner across the four drugs.

--------------------- Insert Table 1 about here ---------------------

One of the challenges in this analysis is to find some reasonable cost shifters that vary the marginal cost of detailing across physicians (see equation (4)). Given that our data have only zip code location information for each physician, we enriched the data with four other data sources that provide aggregate information at zip code level. The four sources are a national (proprietary)
physician prescription database to obtain the distribution of physician types (PCPs and Gastroenterologists (GE)) in each zip code, census data (from US Census Bureau http://www.census.gov) to obtain demographic information (such as population density, income levels), a database for the rural-urban commuting area codes (from the Economic Research Service of United States Department of Agriculture http://www.ers.usda.gov) to obtain travel information, such as average commuting time and the American hospital directory http://www.ahd.com to obtain number of hospitals in each zip code.

We use data from the first eleven quarters for estimation purposes. We use MCMC methods to estimate the models. To achieve the best possible mixing, we computed the relative numerical efficiency parameters (Allenby, McCulloch and Rossi (2005)) at different values of the scaling parameters in the Metropolis steps (drawing $\beta_{pb}$ for each $p$ and drawing the latent demand random shocks $\xi_{pb}$ for each physician-quarter). We use the ones that give the lowest relative numerical efficiency parameter as the optimal scaling.

4. Results and Discussion

In this section, we discuss the results from our estimation process, first from the prescription model and then from the detailing model.

*Estimation results for the prescription model*

Table 2 presents the population level mean $\bar{\beta}$ from the prescription model, and the parenthesis lists the (2.5%, 97.5%) percentile values of the parameters. The first column lists the estimates for the constants, which follow the order similar to the market shares of these brands. The last column shows the parameter estimates for the log-transformation of lagged prescription. All four parameters are positive and significantly different from zero, indicating the existence of carry over effects in physician’s prescription behavior. This finding is consistent with that from previous studies, such as Crawford and Shum (1998). The middle part in this 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. Interestingly, these parameters are all similar across the four brands, suggesting similar own detailing effects. All the own detailing parameter values are between -2 and 0. As discussed in section 2, this indicates prescriptions are increasing with diminishing returns in the level of detailing. To illustrate the nonlinear effects of own detailing, we plot the function \( y = \exp \left( \frac{\beta_{b,b}}{dtl + 1} \right) \) in Figure 1, using the four parameter values of \( \beta_{b,b} \) for the population level estimates, as those listed in the diagonal. Again, the mean detailing effects are similar across these four brands. Note however 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 very 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 2 are the competitive detailing parameters, which vary across brands. Note that among the twelve parameters for competitive detailing effects, eleven are significantly different from zero and have the expected sign. The only exception is the competitive detailing effects of Aciphex on Protonix, which contains zero in the 95% probability interval.
Figure 3 illustrates the competitive detailing effects on Nexium’s prescription using the parameter estimates. It shows that the competitive effects are different from competitors and the effect sizes are different at different values of competitive details. This is true for all four brands, as shown in Table 3, which computes the mean elasticities across all physicians. From Table 3, we can see that the competitive effects are different across competitors (columns) and across brands (rows), and the cross-elasticities are asymmetric.

Comparing the competitive effects in Table 3, we note the following:

a) Nexium’s detailing impacts Prevacid’s prescription the most but Prevacid’s detailing does not impact Nexium’s prescriptions as much as it impacts Aciphex’s and Protonix’s prescriptions.

b) Protonix’s detailing impacts Aciphex’s prescriptions the most; but Aciphex’s detailing has almost no effect on Protonix’s prescription.

c) The competitive detailing effect sizes of Prevacid’s detailing on Aciphex’s and Protonix’s prescriptions are quite close; and this is also true of Nexium’s detailing on Aciphex’s and Protonix’s prescriptions.

a) and b) indicate that the four brands can be classified weakly into two groups of competitors: Nexium and Prevacid in one group, and Aciphex and Protonix in another. However, because of the asymmetry in competitive effects, this grouping is not fully supported. But we do see the similarities in Aciphex’s and Protonix’s prescriptions in their response to the competitive...
detailing from the other two brands. This grouping is also consistent with the market share data for each brand, and that Aciphex and Protonix were launched only about six months apart.

*Estimation results for the detailing model*

In estimating the detailing model, we first obtain the fixed prices for each brand from [www.rxaminer.com](http://www.rxaminer.com). The prices for a 90 day prescription (the typical prescription duration in this category) with the smallest daily dosage are listed in Table 4. As can be seen from the table, except for Protonix, the prices for the three brands are similar.

--------------------- Insert Table 4 about here ---------------------

The estimation results are listed in Table 5, and the 95% intervals are listed in parentheses. The parameters that have over 90% of the simulation draws on one side of zero are in bold. Table 5 shows the effects of the variables that are used as cost drivers. Among all the variables, we found that only population density, number of PCPs and GEs in the same zip code have impact on the marginal cost of detailing for some of the brands. We find that higher population density tends to decrease the marginal cost of detailing. Higher number of PCPs in the same zip code decreases the marginal cost of detailing, and number of GEs has the opposite effects. When there are more PCPs in a zip code, it is less costly to visit another PCP in the same zip code compared to zip codes with fewer PCPs. Therefore, the marginal cost to detail the PCP who has more PCPs around (in the same zip code) is lower than another PCP who has fewer PCPs around. When the number of specialists in that zip code is higher, the PCP in that zip code has a higher chance to be visited by a sales rep who also visits the specialists in that zip code. We know that those sales representatives who visit specialists typically receive better training and higher salary. As a result, the visit to the PCP in the zip code with more specialists is likely to be more expensive.
Based on these parameter estimates, we can compute the marginal cost of detailing to each physician - the average values across all physicians for each brand are listed in Table 6. These range from $90 to $125. This is consistent with the industry practice which typically assumes that the marginal cost of a detail is about $100. As mentioned earlier, these costs are not invariant to the assumed prices (markups). However, given that our estimates are close to the industry estimate, our chosen prices are probably the correct prices.

Thus far, we have presented all the model parameters from estimating both the prescription and detailing models simultaneously. To solve the objective function in equation (3), 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 (8), and evaluate the left hand side of the SOC at the data level $dtl_{pbt}$ for each brand at each observation. The results show that all the four brands have over 90% of the observations satisfying the SOC. Given the stochastic property of the parameter estimates, this finding appears reasonable.

5. Quantifying the benefits of targeting

The main objective of this paper is to compare the profitability under different targeting mechanisms. Using the parameters presented above, we can obtain the marginal cost of detailing for each individual physician from equation (4). Recall from our earlier description of the detailing setting process in this industry, 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 us one extreme of the targeting process. We compare the profitability under this extreme case with the other extreme – targeting at the segment level.\footnote{Since we impose physician level targeting in the estimation, this also suggests that we need to check for robustness of our results when estimation is carried out under the other extreme. We do this in a subsequent section.} Computing firms’ profits under the physician-level targeting plan is straightforward given our model parameters. The question then is: how do we compute profits under segment-level targeting?\footnote{Computing firms’ profits under the physician-level targeting plan is straightforward given our model parameters. The question then is: how do we compute profits under segment-level targeting?}

Following the literature on structural models (see for example, Chintagunta et al 2005 for a review), if the model parameters are estimated under the “true” data generating process, then we can use these parameters to simulate the results from alternative or “counterfactual” scenarios. This implies that we need to simulate the prescriptions and detailing levels when firms target at the segment level given our model parameters. Now the prescription model will remain the same as the model in equation (1). But detailing levels are obtained by maximizing segment level profits, and so detailing levels are identical for all physicians in the same segment. In order to do this, we need to first define the segment membership for each physician. Following industry practice, we compute the total category prescriptions for each physician, based on which the physicians are grouped into 10 segments. For each of these 10 segments, the optimal detailing levels are obtained by solving the following optimization problem:

\[
\max_{dtl_{sb}} \pi_{sb} = \sum_{p \in s} \left[ markup_p \times E \left( rx_{pb} | \xi_{pb} \right) - mc_{pb} \times dtl_{sb} \right]
\]

Where \(s\) indexes for segment. The functional firm for \(\ln \left( E \left( rx_{pb} | \xi_{pb} \right) \right)\) is the same as equation (2), except that the values of \(dtl_{sb}\) are the same for all physicians in the same segment. The FOC is changed from equation (7) for individual level targeting to the following for the segment level optimization
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.

We compute the profits under the two targeting schemes for both the estimation sample as well as for the 1-quarter hold-out data. Results presented here are for the holdout data with comparable results from the estimation data as well.\footnote{The profits are computed ignoring the switching or operation costs related to implementing the targeting strategies.} Figure 4 and Table 7 shows the results. Table 7 also presents in the parentheses the percentage increase in profits by targeting at the individual level relative to targeting at the segment level. It shows that targeting at the individual level is more profitable than at the segment level and this result is true across all four brands. Relative to targeting at the segment level, the average increase in profits by targeting at the individual level is 38% across all four brands. This represents a big increase in profits and underscores the power of targeting. Since the same cost estimates are used in computing the profits for both targeting scenarios, the increase in profits is not because of cost savings, but because of accounting for heterogeneity among physicians. In other words, it is the capability of targeting at individual physician level that allows firm to adjust their detailing decisions on a finer basis and allocate their resources more efficiently, therefore increases the profitability.
Parameters estimated without accounting for firms’ strategic behavior

We also conduct the profitability comparison using parameter estimates from the standard approach, which ignores firm strategic decisions in the estimation process. Since the traditional estimation approach does not involve the detailing equation, we can not obtain cost estimates in this case. Hence we use the same cost estimates as those obtained from the proposed approach. Using the estimates from the standard approach and the costs from the proposed approach, we compute the average profits for the two targeting scenarios, as shown in Figure 5 and Table 8. As 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, which is much lower than what we obtained from the proposed model at 38%. This could be one reason that in practice, unlike the firms in these data, we still see many firms continuing to target at the segment level, even with the availability of individual physician level data. It is quite possible that firms that conduct analyses using standard approach obtain only a small increase in profits. This increase may not cover the costs of implementing an individual level targeting strategy.

Comparison of the proposed approach and the standard approach

To understand why the two approaches give such large differences in profit gains of individual level targeting (38% vs. 5%), we now compare the model estimates between these two approaches. Table 9 lists the mean elasticities from each model, and the (2.5%, 97.5%) range are shown in parentheses. The results show that the traditional model underestimates own elasticities. That is, ignoring firm strategic behavior underestimates the effects of detailing. This is consistent with findings in the price endogeneity literature. There, ignoring price endogeneity underestimates the price effect. Several
studies have documented this finding, e.g. Villas-Boas and Winer (1999). Villas-Boas and Winer (1999) also shows that ignoring price endogeneity overestimates the point estimates for the effects of lagged purchase choices, although there are no statistically significant differences in these estimates. We find similar results, as shown in Table 10; the four mean values of the parameters for lagged prescription variables are all higher in the model that ignores firms’ strategic behavior in the estimation. However, when we check the (2.5%, 97.5%) interval for the posterior distributions of these estimates, we can see that statistically there are no significant differences in these parameters estimates. Hence, our results are largely consistent with those of Villas-Boas and Winer (1999).

Both the proposed estimation approach and the standard approach allow for heterogeneity in physicians’ response, hence Table 11 compares the heterogeneity distributions obtained from each model. It shows the estimated variances of the own-detailing parameters at the population level from these two approaches. The comparison shows that the standard approach tends to underestimate heterogeneity. The reason of this reduction of heterogeneity can be found Table 12, which lists the variances of the random shocks in the prescription model for both models. Traditional model shows higher variances for these random shocks than the proposed model across all four brands. This indicates that the traditional model overestimates the variance of the random shocks in the prescription model by absorbing some heterogeneity. This is consistent with the finding by Chintagunta, Dube and Goh (2005), where they find that ignoring unobserved common factors (similar to the random shocks for the prescription model in this paper) overestimates

---------------------     Insert Table 9 about here     --------------------
---------------------     Insert Table 10 about here     --------------------

12 The (2.5%, 97.5%) range of these estimates shows that Prevacid and Protonix have significantly lower estimated variance for the traditional model than the proposed model; estimated variances for Nexium have some overlap between these two models; those for Aciphex do not differ much.
heterogeneity. They explain this result arises from the fact that 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 more consistent with the study of Chintagunta, Dube and Goh (2005), both papers demonstrate that an erroneously specified model (either ignoring firms strategic behavior or ignoring the unobserved common factors) will bias the estimates for heterogeneity. Furthermore, both studies show evidence of influence between the estimated variance of the parameters and variance of the random shocks.

The underestimation of the both own detailing effects and heterogeneity can be also seen from Figure 6, 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. We therefore expect the parameter of own-detailing to be negative. Under the proposed approach, almost all the individual level own detailing parameters are of the right sign. In contrast, the standard approach shows a large number of individuals 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 (such as using a log-normal distribution instead of a normal distribution).
Summarizing, our analysis suggests that the standard approach (which ignores firm strategic behavior), underestimates the elasticities, carry-over effects, and heterogeneity. This underestimation (in the elasticities and the heterogeneity specifically) drives the finding that the traditional model underestimates the gains to targeting at the individual level vs. targeting at the segment level.

6. Robustness checks

Sections 4 and 5 show the importance of incorporating firm strategic behavior, as ignoring it results in biased estimates and hence a biased comparison between targeting strategies. This section aims at testing key assumptions in the proposed model – (1) profit maximization at the physician versus the segment level in the estimation model; (2) profit maximization versus sales maximization; (3) heuristic versus strategic detailing levels; and (4) marginal costs of detailing that are estimated from the data rather than assumed a priori. The first assumption we test in two ways. First, we see if the gain of individual level targeting relative to segment level targeting remains large even if we assume in our estimation model that the details are generated from firms targeting at the segment level. Second, we compare the fit and predictive abilities of these two approaches to see which is more consistent with the data. The second assumption we test by assuming that the firm’s objective function is sales maximization, then derive and estimate the model and examine model fit relative to the proposed model. The third assumption is that the firm is behaving strategically at all. In other words, detailing behavior of firms may be better described via a heuristic model such as Manchanda et al (2004) rather than based on profit or sales maximization. Again, we use the model fit criterion to assess this assumption. Finally, we compare the results under different a priori values assumed for marginal costs.

Estimation model assumes segment level targeting rather than physician level targeting

In the proposed model, we assume that firms target at the individual physician level, and then based on the estimation results, we simulated the profitability of targeting at the segment level. As shown
in Figure 4, targeting at the individual level increases profitability by 38% compared to targeting at the segment level. Here, we change the assumption to the firm targeting at the segment level in setting detailing and we then simulate the profitability from targeting at the individual level. Our results show that on average the increase in profits from targeting at the individual level is 47% relative to targeting at the segment level. We consider this result to be close enough to the 38% obtained with the individual level profit maximization assumption, which indicates that the gains to targeting is robust to the assumption on whether targeting in the detailing happens at the individual level or segment level. When comparing this difference with that of 38% vs. 5%, we learn that as long as firm strategic behavior is incorporated, the profitability analysis between the two targeting schemes is robust to model assumptions, either individual level optimization or segment level optimization.

Sales versus profit maximization

As mentioned earlier, we have assumed that the firm’s objective is to maximize profits. However, given that contact with physicians involves the sales force, it may be the case that the true data generating process is based on local sales maximization (reflecting the behavior of individual salespeople if incentives are based on sales quotas). We therefore estimate a model that takes sales maximization as the given objective (details on the model are available from the authors on request). We then compute an out of sample fit metric to examine how well a model based on this assumption recovers the data. As can be seen from the RMSE measures reported in Table 14, a model generated under this assumption fits the data poorly relative to our assumed model specification.

Heuristic versus strategic decision making

In the proposed model while accounting for strategic behavior, we assume firms target at the individual physician level. There are at least two other ways to describe how firm makes its detailing decisions: targeting at the segment level and using the heuristic rule as discussed by Manchanda,
Rossi and Chintagunta (2004). In the second test, we aim at comparing these three models by checking their relative model fits. For that, we estimate all the three models using data from the first 11 quarters, and then conduct a hold-out sample test, predicting the number of details for the final quarter. The Root Mean Squared Errors (RMSEs) for the predicted details with the observed data are listed in Table 13, which shows that the proposed model (targeting at the individual level) predicts the best.

---------------------     Insert Table 13 about here     --------------------

Marginal cost estimates

One benefit of incorporating firm strategic behavior in the modeling process is that the model allows us to obtain the marginal cost of detailing. Based on those cost estimates, we can conduct different policy experiments and compare profits under different scenarios (Chintagunta et al. (2005)). To ensure that our results are not sensitive to the estimated marginal costs, we conducted a robustness check by comparing the profit gains for both the proposed approach and the standard approach under different cost values (Table 14).

---------------------     Insert Table 14 about here     --------------------

In the base model, we use the estimated marginal cost of detailing in comparing the profit gains of individual level targeting vs. segment level targeting. As we have seen before, the profits gains are 38% using the proposed approach and 5% using the standard approach. We then fix the cost to be $100, the typical value used in the industry - the profit gains are 37% and 4% using the two approaches. We also fix the cost to be at the highest and lowest estimated average cost across the four brands - $123 and $93. The results show that when the marginal cost values vary, there are
only minor changes in the computed profit gains for individual level targeting vs. segment level targeting.

7. 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. The fact that detailing allows firms to target physicians at the individual level allows us to analyze individual level targeting. It also poses a modeling challenge, resulting from the fact that the detailing levels observed in the data are generated from firms’ strategic behaviors. We develop a model that accounts for both heterogeneity among individual physician’s response to detailing and firms’ strategic behavior at the individual physician level. Our model contributes to the literature by analyzing both physicians’ response and firm’s 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. Further, the model allows us to obtain the economic marginal cost of detailing. Finally, all the parameters are estimated simultaneously for efficiency.

The results show that when accounting for firm strategic behavior, targeting at the individual level brings in substantial gains (38%) in profit relative to targeting at the segment level; however, ignoring firm strategic behavior in the modeling process will bias the parameter estimates and hence the benefit of individual level targeting. The main reason for our finding is that ignoring strategic behavior underestimates the detailing elasticity as well as the extent of heterogeneity in detailing responsiveness across physicians. We also find that our results are quite robust to alternative modeling assumptions made in the course of our analysis.


Pancras, Joseph and K. Sudhir (2005), "The personalization services firm: what to sell, whom to sell to and for how much?" *Working paper*.


Xie, Ying (2003), Essays on Promotion Mix Management: An Application to the Prescription Pharmaceutical Industry, PhD dissertation, Northwestern University, Evanston, IL.

Appendix

Gibbs sampler overview:

1. Define \( \beta_p = \{ \beta_{pb,0}, \beta_{pb,b}, \beta_{pb,b} \} \) for \( \forall b \), draw \( \beta_p \) for each physician, all brands.

\[
\begin{align*}
\beta_p | \star & \propto \\
\prod_{t,b} \text{Poisson}(\lambda_{pbt}) & \quad \text{Likelihood from prescription model} \\
\times \prod_{t,b} \left( \frac{\partial r}{\partial dt_{pbt}} \right) & \left[ \text{markup}_b \times \exp\left(u_{pbt} \times \frac{-\beta_{pbt}}{dt_{pbt} + 1} \right) \right] \times \left( \alpha_b + \alpha_p + s_b \right) \sim N\left(0, \Sigma_{q}\right) \\
& \quad \text{Likelihood from detailing model} \\
\times \beta_p & \sim N\left(\overline{\beta}, \Sigma_{p}\right) \quad \text{Prior}
\end{align*}
\]

Where \( r \) is the function defined as the left hand side of the FOC in equation (7), that is

\[
r = \text{markup}_b \times \exp\left(u_{pbt} \times \frac{-\beta_{pbt}^2}{dt_{pbt} + 1} \right)
\]

2. Define \( \xi_{pt} = \{ \xi_{pbt} \} \), for \( \forall b \), draw \( \xi_{pt} \), a \( B \) dimensional vector for the random demand shock for each physician-quarter observation.

\[
\begin{align*}
\xi_{pt} | \star & \propto \\
\prod_{b} \text{Poisson}(\lambda_{pbt}) & \quad \text{Likelihood from prescription model} \\
\times \prod_{b} \left( \frac{\partial r}{\partial dt_{pbt}} \right) & \left[ \text{markup}_b \times \exp\left(u_{pbt} \times \frac{-\beta_{pbt}^2}{dt_{pbt} + 1} \right) \right] \times \left( \alpha_b + \alpha_p + s_b \right) \sim N\left(0, \Sigma_{q}\right) \\
& \quad \text{Likelihood from detailing model} \\
\times \xi_{pt} & \sim N\left(0, \Sigma_{\xi}\right) \quad \text{Prior}
\end{align*}
\]

Note that the full conditional posterior distributions for demand parameters \( \beta_p \) and the random shock vectors in the prescription model \( \xi_{pt} \) are quite similar in their likelihood functions, in that both have the Poisson likelihood and the likelihood based on the derived distribution of detailing from the FOC. The differences are in the data that are incorporated in the likelihood: the likelihood for \( \beta_p \) consists of all the observations for the same physician, the likelihood for \( \xi_{pt} \) contains each observation for the physician-quarter data. Also, their prior distributions are different in both parameters and number of dimensions.

3. Draw \( \Sigma_{\xi} \), with a Inverted Wishart conjugate prior, using the posterior draws of \( \xi_{pt} \) as the data.

4. Draw \( \overline{\beta}, \Sigma_p \) with normal and wishart conjugate prior, using the draws of \( \beta_p \) as the data.
Above are the demand side estimates, and next will be the supply side.

5. Draw $\alpha_b$ and $s_b$
Conditional on all the other parameters, including the physician level response parameters $\beta_p$, random shocks in the prescription model $\xi_{pt}$, we can compute the total marginal cost $mc_{pb}$ as defined in equation (4) using the FOC in equation (7). Conditional on $\alpha_p$, we can get the data for $\alpha_b$ and $s_b$ as $mc_{pb} - \alpha_p$ for all $p$ and $b$. If we call this to be $Y$, the dimension of the matrix $Y$ is $N \times B$, where $N$ is the total number of physician-quarter observations, and $B$ is the number of brands. And define a matrix $X$ with dimension $N \times 2B$, where the first $B$ columns are ones, and last $B$ columns are mainly zeros, except those rows that corresponds to the holiday season for every physician, the values are ones. Then $\alpha_b$s and $s_b$s are the parameters for this multivariate normal regression. That is $Y = X \times \begin{bmatrix} \text{diag}(\alpha_b) \\ \text{diag}(s_b) \end{bmatrix} + \eta$, where $\eta \sim N\left(0, \Sigma_\eta\right)$ is the supply random shock.

6. Draw $\alpha$
Similar to drawing $\alpha_b$ and $s_b$, we first compute the marginal cost $mc_{pb}$ using the demand side parameters and demand random shocks, then compute $mc_{pb} - \alpha_b - s_b$ for all $p$ and $b$, and define this data matrix as $Y$, with dimension $N \times B$. And also define a matrix $X$ with dimension $N \times B$, where $T$ denotes the number of observations for each physician. Then we can write $Y = X_p \alpha + \eta$, where $\eta \sim N\left(0, \Sigma_\eta\right)$, and $\alpha$ can be therefore obtained using multivariate normal regression with normal prior.

7. Draw supply side variance $\Sigma_\eta$
Compute the random shocks for the detailing model by substituting all the other parameters into the FOC in equation (7). Using these random shocks as data, we can draw $\Sigma_\eta$ from the inverted Wishart distribution with conjugate prior.
Table 1: Summary statistics

<table>
<thead>
<tr>
<th>Brand</th>
<th>Marketed by</th>
<th>Mean Rx</th>
<th>Sd. Rx</th>
<th>Mean Detailing</th>
<th>Sd. Detailing</th>
<th>Launch time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nexium</td>
<td>Astra Zeneca</td>
<td>11.7</td>
<td>(12.7)</td>
<td>3.8</td>
<td>(3.1)</td>
<td>Feb. 2001</td>
</tr>
<tr>
<td>Prevacid</td>
<td>TAP</td>
<td>8.5</td>
<td>(9.7)</td>
<td>3.5</td>
<td>(3.3)</td>
<td>May 1995</td>
</tr>
<tr>
<td>Aciphex</td>
<td>Janssens &amp; Eisai</td>
<td>6.5</td>
<td>(8.3)</td>
<td>2.8</td>
<td>(2.7)</td>
<td>Aug. 1999</td>
</tr>
<tr>
<td>Protonix</td>
<td>Wyeth</td>
<td>5.9</td>
<td>(7.4)</td>
<td>2.8</td>
<td>(3.3)</td>
<td>Feb. 2000</td>
</tr>
</tbody>
</table>

Table 2: Population level mean estimates for the prescription model

<table>
<thead>
<tr>
<th></th>
<th>Constant</th>
<th>(\frac{1}{1+dtl_{\text{Nexium}}})</th>
<th>(\frac{1}{1+dtl_{\text{Prevacid}}})</th>
<th>(\frac{1}{1+dtl_{\text{Aciphex}}})</th>
<th>(\frac{1}{1+dtl_{\text{Protonix}}})</th>
<th>(\ln (1 + Rx_{t-1}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nexium</td>
<td>1.52</td>
<td>-0.99</td>
<td>0.09</td>
<td>0.26</td>
<td>0.22</td>
<td>0.16</td>
</tr>
<tr>
<td></td>
<td>(1.42, 1.63)</td>
<td>(-1.11, -0.87)</td>
<td>(0.01, 0.17)</td>
<td>(0.17, 0.35)</td>
<td>(0.10, 0.34)</td>
<td>(0.11, 0.21)</td>
</tr>
<tr>
<td>Prevacid</td>
<td>1.37</td>
<td>0.38</td>
<td>-1.12</td>
<td>0.15</td>
<td>0.12</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>(1.26, 1.49)</td>
<td>(0.29, 0.47)</td>
<td>(-1.25, -0.98)</td>
<td>(0.05, 0.25)</td>
<td>(0.00, 0.22)</td>
<td>(0.06, 0.15)</td>
</tr>
<tr>
<td>Aciphex</td>
<td>1.12</td>
<td>0.10</td>
<td>0.28</td>
<td>-1.19</td>
<td>0.41</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>(1.01, 1.24)</td>
<td>(0.00, 0.20)</td>
<td>(0.17, 0.39)</td>
<td>(-1.33, -1.06)</td>
<td>(0.31, 0.51)</td>
<td>(0.06, 0.15)</td>
</tr>
<tr>
<td>Protonix</td>
<td>1.17</td>
<td>0.13</td>
<td>0.29</td>
<td>-0.04</td>
<td>-1.10</td>
<td>0.14</td>
</tr>
<tr>
<td></td>
<td>(1.08, 1.26)</td>
<td>(0.02, 0.24)</td>
<td>(0.18, 0.40)</td>
<td>(-0.18, 0.10)</td>
<td>(-1.25, -0.96)</td>
<td>(0.09, 0.18)</td>
</tr>
</tbody>
</table>

Table 3: Mean elasticities

<table>
<thead>
<tr>
<th></th>
<th>Nexium</th>
<th>Prevacid</th>
<th>Aciphex</th>
<th>Protonix</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nexium</td>
<td>0.140</td>
<td>-0.014</td>
<td>-0.041</td>
<td>-0.031</td>
</tr>
<tr>
<td></td>
<td>(0.134, 0.147)</td>
<td>(-0.018, -0.010)</td>
<td>(-0.048, -0.035)</td>
<td>(-0.042, -0.022)</td>
</tr>
<tr>
<td>Prevacid</td>
<td>-0.060</td>
<td>0.154</td>
<td>-0.024</td>
<td>-0.017</td>
</tr>
<tr>
<td></td>
<td>(-0.068, -0.055)</td>
<td>(0.149, 0.160)</td>
<td>(-0.033, -0.016)</td>
<td>(-0.024, -0.005)</td>
</tr>
<tr>
<td>Aciphex</td>
<td>-0.012</td>
<td>-0.042</td>
<td>0.177</td>
<td>-0.057</td>
</tr>
<tr>
<td></td>
<td>(-0.017, -0.007)</td>
<td>(-0.048, -0.037)</td>
<td>(0.171, 0.182)</td>
<td>(-0.063, -0.050)</td>
</tr>
<tr>
<td>Protonix</td>
<td>-0.020</td>
<td>-0.040</td>
<td>0.006</td>
<td>0.150</td>
</tr>
<tr>
<td></td>
<td>(-0.026, -0.016)</td>
<td>(-0.046, -0.033)</td>
<td>(-0.012, 0.024)</td>
<td>(0.144, 0.161)</td>
</tr>
</tbody>
</table>
Table 4: Prices of the four brands

<table>
<thead>
<tr>
<th>Brands</th>
<th>Prices for 90 days ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nexium</td>
<td>362</td>
</tr>
<tr>
<td>Prevacid</td>
<td>351</td>
</tr>
<tr>
<td>Aciphex</td>
<td>345</td>
</tr>
<tr>
<td>Protonix</td>
<td>280</td>
</tr>
</tbody>
</table>

Table 5: Parameter Estimates for the Detailing Model

<table>
<thead>
<tr>
<th></th>
<th>Constant</th>
<th>Holiday</th>
<th>Season</th>
<th>Population Density (1/1000)</th>
<th>Number of PCPs (1/100)</th>
<th>Number of GEs (1/10)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nexium</td>
<td>0.47</td>
<td>0.15</td>
<td>-0.53</td>
<td>(-0.06, 0.03)</td>
<td>(-0.27, 0.17)</td>
<td>(-0.12, 0.17)</td>
</tr>
<tr>
<td></td>
<td>(0.41, 0.52)</td>
<td>(0.10, 0.19)</td>
<td>(-1.34, 0.31)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Prevacid</td>
<td>0.44</td>
<td>0.18</td>
<td>0.32</td>
<td>(-0.24, 0.11)</td>
<td>(-0.05, 0.26)</td>
<td>(-0.05, 0.26)</td>
</tr>
<tr>
<td></td>
<td>(0.38, 0.50)</td>
<td>(0.14, 0.22)</td>
<td>(-0.62, 1.27)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aciphex</td>
<td>0.47</td>
<td>0.05</td>
<td>-0.25</td>
<td>-0.16</td>
<td>-0.05, 0.22</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>(0.42, 0.53)</td>
<td>(0.01, 0.09)</td>
<td>(-1.16, 0.66)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Protonix</td>
<td>0.33</td>
<td>0.02</td>
<td>-0.27</td>
<td>0.03</td>
<td>0.00</td>
<td>-0.14, 0.14</td>
</tr>
<tr>
<td></td>
<td>(0.27, 0.38)</td>
<td>(-0.01, 0.06)</td>
<td>(-1.05, 0.52)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 6: Average estimated marginal cost of detailing

<table>
<thead>
<tr>
<th></th>
<th>($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nexium</td>
<td>121</td>
</tr>
<tr>
<td>Prevacid</td>
<td>108</td>
</tr>
<tr>
<td>Aciphex</td>
<td>123</td>
</tr>
<tr>
<td>Protonix</td>
<td>93</td>
</tr>
</tbody>
</table>
Table 7: Average profits ($) for two targeting strategies

(Proposed approach)

<table>
<thead>
<tr>
<th></th>
<th>Nexium</th>
<th>Prevacid</th>
<th>Aciphex</th>
<th>Protonix</th>
</tr>
</thead>
<tbody>
<tr>
<td>Segment level</td>
<td>2709</td>
<td>1914</td>
<td>1429</td>
<td>1193</td>
</tr>
<tr>
<td>Individual level</td>
<td>3381</td>
<td>2822</td>
<td>1991</td>
<td>1671</td>
</tr>
<tr>
<td></td>
<td>(25%)</td>
<td>(47%)</td>
<td>(39%)</td>
<td>(40%)</td>
</tr>
</tbody>
</table>

Table 8: Average profits ($) for two targeting strategies

(Standard approach)

<table>
<thead>
<tr>
<th></th>
<th>Nexium</th>
<th>Prevacid</th>
<th>Aciphex</th>
<th>Protonix</th>
</tr>
</thead>
<tbody>
<tr>
<td>Segment level</td>
<td>3194</td>
<td>2483</td>
<td>2022</td>
<td>1630</td>
</tr>
<tr>
<td>Individual level</td>
<td>3200</td>
<td>2627</td>
<td>2130</td>
<td>1750</td>
</tr>
<tr>
<td></td>
<td>(0.2%)</td>
<td>(5.8%)</td>
<td>(5.3%)</td>
<td>(7.3%)</td>
</tr>
</tbody>
</table>

Table 9: Comparison of mean own-elasticities from the two approaches

<table>
<thead>
<tr>
<th></th>
<th>Nexium</th>
<th>Prevacid</th>
<th>Aciphex</th>
<th>Protonix</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed approach</td>
<td>0.140</td>
<td>0.154</td>
<td>0.177</td>
<td>0.150</td>
</tr>
<tr>
<td></td>
<td>(0.134, 0.147)</td>
<td>(0.149, 0.160)</td>
<td>(0.171, 0.182)</td>
<td>(0.144, 0.161)</td>
</tr>
<tr>
<td>Standard approach</td>
<td>0.075</td>
<td>0.068</td>
<td>0.157</td>
<td>0.091</td>
</tr>
<tr>
<td></td>
<td>(0.060, 0.087)</td>
<td>(0.057, 0.080)</td>
<td>(0.143, 0.174)</td>
<td>(0.077, 0.100)</td>
</tr>
</tbody>
</table>

Table 10: Comparison of parameter for lagged variables

<table>
<thead>
<tr>
<th></th>
<th>Nexium</th>
<th>Prevacid</th>
<th>Aciphex</th>
<th>Protonix</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed approach</td>
<td>0.159</td>
<td>0.105</td>
<td>0.106</td>
<td>0.137</td>
</tr>
<tr>
<td></td>
<td>(0.110, 0.206)</td>
<td>(0.057, 0.152)</td>
<td>(0.061, 0.150)</td>
<td>(0.089, 0.184)</td>
</tr>
<tr>
<td>Traditional approach</td>
<td>0.173</td>
<td>0.121</td>
<td>0.175</td>
<td>0.176</td>
</tr>
<tr>
<td></td>
<td>(0.123, 0.222)</td>
<td>(0.063, 0.177)</td>
<td>(0.112, 0.238)</td>
<td>(0.108, 0.243)</td>
</tr>
</tbody>
</table>
Table 11: Comparison of variance of own detailing parameter across individuals

<table>
<thead>
<tr>
<th></th>
<th>Nexium</th>
<th>Prevacid</th>
<th>Aciphex</th>
<th>Protonix</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed approach</td>
<td>1.093</td>
<td>1.366</td>
<td>1.464</td>
<td>1.598</td>
</tr>
<tr>
<td></td>
<td>(0.893, 1.312)</td>
<td>(1.142, 1.631)</td>
<td>(1.220, 1.751)</td>
<td>(1.330, 1.918)</td>
</tr>
<tr>
<td>Traditional model</td>
<td>0.877</td>
<td>0.696</td>
<td>1.414</td>
<td>0.940</td>
</tr>
<tr>
<td></td>
<td>(0.664, 1.076)</td>
<td>(0.556, 0.865)</td>
<td>(0.990, 2.049)</td>
<td>(0.717, 1.180)</td>
</tr>
</tbody>
</table>

Table 12: Variance of random shocks in the prescription model

<table>
<thead>
<tr>
<th></th>
<th>Nexium</th>
<th>Prevacid</th>
<th>Aciphex</th>
<th>Protonix</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed model</td>
<td>0.223</td>
<td>0.220</td>
<td>0.260</td>
<td>0.253</td>
</tr>
<tr>
<td></td>
<td>(0.207, 0.239)</td>
<td>(0.203, 0.237)</td>
<td>(0.243, 0.278)</td>
<td>(0.233, 0.273)</td>
</tr>
<tr>
<td>Traditional model</td>
<td>0.319</td>
<td>0.405</td>
<td>0.632</td>
<td>0.588</td>
</tr>
<tr>
<td></td>
<td>(0.291, 0.353)</td>
<td>(0.369, 0.445)</td>
<td>(0.565, 0.700)</td>
<td>(0.518, 0.674)</td>
</tr>
</tbody>
</table>

Table 13: RMSE for hold-out sample tests

<table>
<thead>
<tr>
<th>Assumptions of firm strategic behavior</th>
<th>RMSE of predicted and actual detailing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Target at the individual level</td>
<td>2.85</td>
</tr>
<tr>
<td>Target at the segment level</td>
<td>4.57</td>
</tr>
<tr>
<td>Heuristic</td>
<td>3.16</td>
</tr>
<tr>
<td>Sales Maximization</td>
<td>4.90</td>
</tr>
</tbody>
</table>

Table 14: Profit gains for both approaches using different cost values

<table>
<thead>
<tr>
<th>Cost values used ($)</th>
<th>Proposed approach (%)</th>
<th>Standard approach (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base model</td>
<td>38</td>
<td>5</td>
</tr>
<tr>
<td>Cost = $100</td>
<td>37</td>
<td>4</td>
</tr>
<tr>
<td>Cost = $123</td>
<td>41</td>
<td>5</td>
</tr>
<tr>
<td>Cost = $93</td>
<td>37</td>
<td>4</td>
</tr>
</tbody>
</table>
Figure 1: Nonlinear transformation of detailing in the demand model

\[ y = \exp\left( \frac{\beta_{h,b}}{d + 1} \right) \]

Figure 2: Response curves for two individual physicians

Figure 3: Competitive detailing effects on Nexium’s prescription
Figure 4: Average profits for two targeting strategies, proposed model

![Bar chart comparing average profits for different drugs at individual and segment levels.]

Figure 5: Average profits for two targeting strategies, model ignoring firm strategic behavior

![Bar chart comparing average profits for different drugs at individual and segment levels, with a different range.]

41
Figure 6: Comparison of the distribution of individual level parameters

From the Proposed Approach

From the Standard Approach