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

Xiaojing Dong¹

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¹ Xiaojing Dong is doctoral candidate at Northwestern University. This paper represents Essay 1 of her dissertation. Her dissertation is co-chaired by Pradeep K. Chintagunta, Robert Law Professor of Marketing, and Puneet Manchanda, Associate Professor of Marketing, both at the Graduate School of Business at the University of Chicago. She would like to thank Frank Koppelman, Sridhar Narayanan, Gary Russell, Ying Xie, Harikesh Nair, Vaneet Sethi from ZS Associates, seminar participants at the University of Chicago and participants at the 2005 Marketing Science conference in Atlanta for valuable feedback. All correspondence may be addressed to her at xjdong@northwestern.edu. 1915 Maple Ave. 1003, Evanston, IL 60201.
Abstract

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. Typically, these approaches calibrate a response model and use the variation in response parameter estimates to compare the firm’s profits under various targeting schemes – at the individual customer level, at the segment level, or via mass marketing (i.e., no targeting). Implicit in this approach to quantifying the benefits of targeting is the assumption that the data being used to estimate the response parameters do not reflect any strategic behavior that the firm may be engaged in vis-à-vis the marketing variables whose responsiveness is being estimated. Specifically, this assumption implies that the firm is currently not using any information about its customers to set marketing policy.

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). Relative to previous approaches, our approach allows for data available for estimation to reflect firms’ strategic behavior (i.e., the firm is already engaged in targeting its marketing activities to its customers).

We focus on detailing – the most important marketing in pharmaceutical industry. The pharmaceutical firm’s decision is the allocation of detailing visits across individual physicians. In this industry, firms already use the information on how detailing affects individual physician behavior in setting their detailing allocation. Thus, the standard approach to developing and quantifying the value of targeting mentioned is inappropriate.

For our analysis, we develop a model of prescriptions and a model of detailing. Our model of prescriptions is an individual level heterogeneous response model that relates the level of detailing to the number of prescriptions written. Our model of detailing is based on the assumption that firms are profit maximizing. Using this and the parameters from the response model, we then specify a model of detailing at the individual physician level. We estimate our model on a novel physician panel dataset from the Proton Pump Inhibitor 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.

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.

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) and Kim et al. (2005)), Internet marketing (Montgomery (2000), Ansari and Mela (2003) and Murthi and Sarkar (2003)) and couponing (Rossi et al 1996). Typically, these approaches 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).

Implicit in the above approach to quantifying the benefits of targeting is the assumption that the data being used to estimate the response parameters do not reflect any strategic behavior that the firm may be engaged in vis-à-vis the marketing variables whose responsiveness is being estimated. Specifically, this assumption implies that the firm is currently not using any information about its customers to set marketing policy. This assumption may not be valid in many industries where the firm already has a targeting strategy in place i.e., the firm behaves strategically. Consequently, the data available for estimation reflect such strategic firm behavior as well as customers’ responses to such behavior. If this strategic behavior of firms is present but 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). The main difference between our proposed approach and the traditional approach described above that has been used in prior targeting research is that when we quantify the improvement in firm profits, we explicitly account for the possibility that the firm is already using some knowledge about its customers to set its marketing policy. In other words, our approach allows for the data available for estimation to reflect firms’ strategic behavior (i.e., the firm is already engaged in targeting its marketing activities to its customers).

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 in setting their detailing allocation. Thus, the traditional approach to develop and quantify the value of targeting mentioned earlier will bias the estimates of physicians’ responses and hence the benefits of targeting.

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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.

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. Note that we will discuss various targeting scenarios in detail in the subsequent sections.
Given that pharmaceutical firms are already engaged in physician level targeting, the question then arises – how can we quantify the benefits of targeting in such an industry context? Specifically, how much does the firm’s profits change when it goes from a situation of individual physician level targeting (i.e., the current policy) to one in which the resource allocation decision happens at a more aggregate (in this case, segment level)? 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 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 observed in the data are outcomes of firms acting to maximize their profits from each individual physician given the response model previously assumed. Using the profit maximization assumption and the prescription model, we then specify a model of detailing at the individual physician level. This structure allows us to incorporate a firm’s strategic behavior with respect to detailing explicitly in the analysis.5

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 context, we would need instruments that vary across physicians and time periods. It is not clear whether such valid instruments exist.
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. Note that individual level estimation is 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. 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. 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 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. Finally, we estimate a series of alternative models to ensure that our results are robust to model specification and estimation.

Relative to the existing literature on targeting, as noted previously, a major departure of this study is that we account for the strategic behavior of firms. This holds another key benefit when attempting to quantify the benefits of targeting which is that the analysis can explicitly account for competitive interactions among firms when evaluating the various alternative targeting scenarios. Consider again the situation in which we do not account for firms’ strategic behavior when evaluating the profits of firms under targeting. When calculating profits, we need to make an assumption of what rival firms will be doing when the focal firm sets its detailing levels to maximize individual profits. The usual default is a *ceteris paribus* condition that assumes that competitors’ do not react when one firm targets. In the proposed approach, on the other hand, prescription and detailing levels are obtained by solving the system of prescription and detailing levels across all products in the category for each individual physician. As such this explicitly takes into account the competitive interactions among firms. The same will be true when evaluating each of the alternative scenarios. In this way, our proposed approach addresses another potential shortcoming of the existing approach to targeting. At the same time, it is consistent with the theoretical literature on targeting (e.g., Shaffer and Zhang (1995)).

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
the first to estimate 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.

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.\(^6\) Conditional on detailing, the number of prescriptions by each physician in each quarter, \(rx_{pb,t}\), is assumed to follow a Poisson distribution, with parameter \(\lambda_{pb,t}\) for physician \(p\), brand \(b\) and quarter \(t\)

\[
prob(rx_{pb,t} = y) = \frac{\exp(-\lambda_{pb,t}) \times \lambda_{pb,t}^y}{y!}
\]

(1)

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

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

(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 \(b\). \(f(dtl_{pb,t})\) is a transformation of own detailing, capturing potentially nonlinear effects (typically, diminishing returns) of

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\(^6\) A plausible alternative specification would be a discrete choice model to characterize the individual patient’s prescription decision. With quarterly data such as those available to us, this would amount to an aggregate version of the model, e.g., an aggregate 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.
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, \( \exp\left(\beta_{pb,b} f\left(dtl_{pb,t}\right)\right) \), is that, with respect to \( dtl_{pb,t} \), it should allow prescriptions to increase with diminishing returns. Given that the function \( \exp(x) \) increases exponentially in \( x \), it turns out that a function with \( dtl_{pb,t} \)'s negative power is preferable to a function with a positive power (see Appendix A). For the sake of parsimony, we choose the log-reciprocal transformation (Lilien, Kotler and Moorthy (1992)), that is, \( f\left(dtl_{pb,t}\right) = \frac{1}{1 + dtl_{pb,t}} \) or \( \exp\left(\beta_{pb,b} f\left(dtl_{pb,t}\right)\right) = \exp\left(\frac{\beta_{pb,b}}{1 + dtl_{pb,t}}\right) \). Detailing in the data, \( dtl_{pb,t} \), 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 \( dtl_{pb,t} \). 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 total 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). In a typical share model (e.g., one that uses a logit form), only one detailing parameter for each brand is estimated. In that case, the competitive effects are driven largely by variation in shares across brands. Therefore, our model is more flexible by virtue of using more parameters to uncover competitive effects (than a share model where the identification of competitive effects relies heavily on the model structure).

\[
\log\left( r_{pb,t-1} + 1 \right)
\]

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 either unobserved or not measurable by the researcher. 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 are expected to affect physician \(p’\)’s prescription of brand \(b\), and vary across time. 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 \(d_{tb}\) (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 \(\forall b\), then \(\xi_{pt} \sim N(0, \Sigma_{\xi})\).

Given the assumptions on \(r_{pb,t}\) 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 to specify prescription behavior of physicians. 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 each firm sets detailing levels strategically at the individual physician level under the following assumptions:

1. Firms have full information, including physicians’ response to detailing, competitors’ decision rule as well as the demand side random shocks $\xi_{pbt}$. As a result, firm’s decision on detailing level is a function of the unobserved component $\xi_{pbt}$, thereby allowing for the detailing levels that are observed by researchers to be correlated with the random error terms $\xi_{pbt}$ that are not observed by researchers.⁷

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 this analysis and industry managers’ claim that they decide detailing efforts at each quarter. 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

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⁷ While consistent with previous studies that have allowed for firms’ strategic behavior (see for example, Yang, Chen and Allenby 2003), the full information assumption is nevertheless an extreme assumption regarding the information set. We plan on checking the robustness of our results to a variety of alternative information assumptions in a future study.
generating process, we chose the assumption that is most consistent with industry practice for the particular category we analyze.

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 my 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 effect 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.

5. Only one drug is detailed at each visit.

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. The firm’s objective is to find the optimal detailing level for that physician in that quarter:

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

(3)

8 In this empirical analysis, each firm markets only one brand, therefore we refer to the firm that markets brand b as firm b.
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 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 comparing to detailing cost). We use price to approximate $markup_{pbt}$ with the assumption that prices are constant across physicians and across time, that is $price_{pbt} = price_b, \forall b$.

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 (albeit production costs), we use a linear specification for $mc_{pbt}$ as follows.

$$mc_{pbt} = \alpha_b + X_p \alpha + s_b + \eta_{pbt}$$  \hspace{1cm} (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 physician. $\alpha$ is the parameter associated with these exogenous variables. $s_b$ accounts for the systematic deviation during a holiday season, and $\eta_{pbt}$ 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 $t$. The vectors (with dimension $B$, the number of brands in the same category) of

$$\eta_{pt} = \{\eta_{p1t}, \eta_{p2t}, ..., \eta_{pBt}\}$$

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 $\eta_{pt} \sim N(0, \Sigma_{\eta})$. 

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Linking the prescription and detailing models

In the above, we have set up the prescription and the detailing models. In the following, we show how to link these two models into a joint system. To solve the profit maximization in (3), we need to compute the first order conditions (FOC) as follows:

\[
\text{markup}_{pbt} \times \frac{\partial E \left( r_{x_{pbt}} \mid \xi_{pbt} \right)}{\partial dtl_{pbt}} = \text{mc}_{pbt} \tag{5}
\]

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

\[
\frac{\partial E \left( r_{x_{pbt}} \mid \xi_{pbt} \right)}{\partial dtl_{pbt}} = \exp(u_{pbt}) \times \frac{-\beta_{ph,b}}{(dtl_{pbt} + 1)^2} \tag{6}
\]

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

\[
\text{markup}_{pbt} \times \exp(u_{pbt}) \times \frac{-\beta_{ph,b}}{(dtl_{pbt} + 1)^2} = \alpha_{b} + X_{p}\alpha + s_{b} + \eta_{pbt} \tag{7}
\]

The above equation can be re-written as

\[
(dt_{pbt} + 1)^2 = \text{markup}_{pbt} \times \exp(u_{pbt}) \times \frac{-\beta_{ph,b}}{(\alpha_{b} + X_{p}\alpha + s_{b} + \eta_{pbt})}
\]

In general, the above is an implicit equation in detailing, \( dt_{pbt} \), since the function \( u_{pbt} \) is a function of \( dt_{pbt} \). Nevertheless, we can use the above expression to understand its properties. First, note that since \( \beta_{ph,b} < 0 \) (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 $u_{pbt}$, which contains all the demand parameters $(\beta_{pbt,0}, \ldots, \beta_{pbt,l})$ appears in both the prescription model (equation (1)) through $\lambda_{pbt} = \exp(u_{pbt})$, 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 $dl_{pbt}$, is a function of the prescription equation error, $\xi_{pbt}$ . 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 significantly 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 $\beta_{pbdtl}$, we obtain the SOC:

$$\text{markup}_b \times \exp(u_{pbdtl}) \times \left( \frac{2\beta_{pbdtl}}{(dtl_{pbdtl} + 1)^3} + \left( \frac{\beta_{pbdtl}}{(dtl_{pbdtl} + 1)^2} \right)^2 \right) < 0$$ (8)

Solving this inequality, we get, $dtl_{pbdtl} > -\frac{\beta_{pbdtl}}{2} - 1$. That is, if physician $p$’s response parameter to brand $b$’s detailing $\beta_{pbd}$ satisfies the condition, $-2 < \beta_{pbd} \leq 0$, it is guaranteed that the detailing levels, $dtl_{pbd} \geq 0$, 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.

**Bayesian estimation**

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

$$f \left( \{\beta_{pbd}\}, \{\xi_{pbd}\}, \{\alpha, s_b\}, \{\alpha\}, \Sigma_{\xi}, \Sigma_m | \{rx_{pbd}\}, \{dtl_{pbd}\} \right)$$

$$\propto \prod_{p, b, t} \text{prob} \left( rx_{pbd}, dtl_{pbd}, \beta_{pbd}, \xi_{pbd} \right)$$

$$\times \pi_1 \left( dtl_{pbd}, \beta_{pbd}, \xi_{pbd}, \alpha, s_b, \alpha, \Sigma_m \right)$$

$$\times \pi_2 \left( \beta_{pbd}, \beta, \xi_{pbd}, \alpha, s_b, \alpha, \Sigma_m \right)$$

$$\times \pi_3 \left( \beta, \Sigma_{\beta}, \Sigma_{\xi}, \alpha, s_b, \alpha, \Sigma_m \right)$$

$$\times \pi_4 \left( \beta, \Sigma_{\beta}, \Sigma_{\xi}, \alpha, s_b, \alpha, \Sigma_m \right)$$ (9)
Where \( \text{prob}(rx_{pbt} \mid dtl_{pbt}, \{\beta_{pb}\}, \xi_{pbt}) \) 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 \( \lambda_{pbt} = \exp(u_{pbt}) \) and \( u_{pbt} \) defined in equation (2) with \( f(dtl_{pbt}) = \frac{1}{dtl_{pbt} + 1} \).

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 sequence of draws from the full conditional distribution for each group of the parameters conditional on all the other parameters. By iterating over all groups of parameters, we can obtain 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 (9)), including individual level parameters, i.e. the \( \{\beta_{pb}\} \)’s. Data augmentation techniques allow us to draw the random component \( \xi_{pbt} \) 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 Appendix B. 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, \( \eta_{pbt} \sim N(0, \Sigma_{\eta}) \) 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 actual 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). 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 brand) 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.

Table 1 Summary statistics of the data

<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>

One of the challenges in this analysis is to find some reasonable cost shifters that varies 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 our estimation parameters. 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 \( y = \exp \left( \frac{\bar{\beta}_{h,b}}{dtl + 1} \right) \) in Figure 1, using the four parameter values of \( \bar{\beta}_{h,b} \) for the population level estimates, as those listed in the diagonal. Interestingly, the mean detailing effects are similar across these four brands. Note however that this is not necessarily true for a given physician.

Table 2 Population level mean estimates for the prescription model

<table>
<thead>
<tr>
<th></th>
<th>Constant</th>
<th>Nexium</th>
<th>Prevacid</th>
<th>Aciphex</th>
<th>Protonix</th>
<th>( \ln(1 + R_{x-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>

Figure 1 Nonlinear transformation of detailing in the demand model

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, 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 exactly the factor that leads to targeting benefits.

Figure 2 Response curves for two individual physicians

![Response curves for two individual physicians](image)

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, except the competitive detailing effects of Aciphex on Protonix, which contains zero in the 95% probability interval.

Figure 3 Competitive detailing effects on Nexium’s prescription

![Competitive detailing effects on Nexium’s prescription](image)

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.

### 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>

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 data in terms of market share for each brand, and that Aciphex and Protonix are 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 with the smallest daily dosage are listed in Table 4. The table also shows the ratio of all the prices relative to the price of Protonix, which is the brand with the lowest price. Based on the discussion in the previous section, only these ratios are relevant to characterize $\text{markup}_b$ term in equation (7). Using ratios instead of actual prices only changes the explanation of the marginal cost to “the ratio of the marginal cost of detailing relative to the price of Protonix”.

**Table 4 Prices of the four brands**

<table>
<thead>
<tr>
<th>Brands</th>
<th>Prices for 90 days ($)</th>
<th>Ratio over price of Protonix</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nexium</td>
<td>362</td>
<td>1.29</td>
</tr>
<tr>
<td>Prevacid</td>
<td>351</td>
<td>1.25</td>
</tr>
<tr>
<td>Aciphex</td>
<td>345</td>
<td>1.23</td>
</tr>
<tr>
<td>Protonix</td>
<td>280</td>
<td>1</td>
</tr>
</tbody>
</table>

**Table 5 Parameter Estimates for the Detailing Model**

<table>
<thead>
<tr>
<th></th>
<th>Constant</th>
<th>Holiday</th>
<th>Population Density</th>
<th>Number of PCPs</th>
<th>Number of GEs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1/1000)</td>
<td>(1/100)</td>
<td>(-1/1000)</td>
<td>(-1/100)</td>
<td>(-1/10)</td>
</tr>
<tr>
<td>Nexium</td>
<td>0.47</td>
<td>0.15</td>
<td>-0.53</td>
<td>-0.06</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>(0.41, 0.52)</td>
<td>(0.10, 0.19)</td>
<td>(-1.34, 0.31)</td>
<td>(-0.27, 0.14)</td>
<td>(-0.12, 0.17)</td>
</tr>
<tr>
<td>Prevacid</td>
<td>0.44</td>
<td>0.18</td>
<td>0.32</td>
<td>-0.24</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>(0.38, 0.50)</td>
<td>(0.14, 0.22)</td>
<td>(-0.62, 1.27)</td>
<td>(-0.46, -0.02)</td>
<td>(-0.05, 0.26)</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</td>
</tr>
<tr>
<td></td>
<td>(0.42, 0.53)</td>
<td>(0.01, 0.09)</td>
<td>(-1.16, 0.66)</td>
<td>(-0.40, 0.06)</td>
<td>(-0.10, 0.22)</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>
</tr>
</tbody>
</table>
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 bolded.

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 are listed in Table 6.

Table 6 Average marginal cost of detailing

<table>
<thead>
<tr>
<th></th>
<th>Estimated marginal cost of detailing ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nexium</td>
<td>121</td>
</tr>
<tr>
<td>Prevacid</td>
<td>108</td>
</tr>
</tbody>
</table>
To apprehend these estimated values, we need to first understand the meaning of the marginal cost of detailing. We think that the marginal cost of detailing reflects the economic opportunity cost of visiting a physician, which is defined as the largest possible revenue that could have been brought in if a different physician was visited during the same time period. The estimation results show that Protonix has a lower value of marginal cost of detailing comparing to the other three brands. This can be explained by the fact that Protonix is the weakest brand (lowest market share and lowest detailing efforts) in this competition extensive category. In the reality, Wyeth’s (the manufacturer of Protonix) strategy is actually not going after the top physicians. In this case, if a sales rep for Protonix did visit a top physician, given the vigorous competitors’ in this category, Protonix would still not have got revenue as high as the other brands. Therefore, the marginal cost of detailing for Protonix is lower than the other three brands.

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 $dtl_{pla}$ 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.

4. 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). The two targeting strategies that we compare in this analysis are: individual level and segment level targeting. In reality, firms set detailing at the physician decile or segment level, where they group physicians into 10 groups based on physicians’ total category prescription volumes, and set identical detailing levels as the segment level detailing to be implemented. The segment level planning needs to be translated into a specific “calling” plan for each physician. This is accomplished by local managers and sales persons who deal detailing with the physicians and can make adjustments to the decile plans to tailor the detailing to each physician. Given the “hybrid” nature of the true detailing plan, in this section we compare the profitability under the two “extreme” cases: individual level detailing and segment level detailing\(^9\). We conduct the comparisons using estimation results from the following two approaches, the first one is the proposed approach presented in section 3; the second one is the traditional approach which ignores firms’ strategic behaviors. The estimation results for both models are obtained using data from the first 11 quarters (12 quarters altogether in the data). Using each set of the estimated model parameters, we compare the profitability of individual verses segment level targeting.

When computing each of the four\(^{10}\) profit values, we follow three steps. First, predict the optimal detailing level for each individual physician for each brand in the final quarter, by solving the system of four FOCs simultaneously (equation (7)). Second, compute the predicted prescriptions for the final quarter based on the predicted optimal detailing for each physician and each brand. This can be achieved using the following equation

\[
E \left[ E \left( r_{xbt} \mid \xi_{pbt} \right) \right] = E \left[ \exp \left( \tilde{u}_{pbc} + \xi_{pbt} \right) \right] = \exp \left( \tilde{u}_{pbc} + 0.5 \times \text{diag} \left( \Sigma_{\xi} \right) \right)
\]

\(^9\) Since we impose physician level detailing in the estimation, this suggests that we need to check for robustness of our results when estimation is carried out and under the other extreme.

\(^{10}\) Two profit values (individual and segment level) for each of the two approaches (the proposed approach and the traditional approach).
Where $\tilde{u}_{p_{hx}}$ is part of the $u_{p_{hx}}$ defined in equation (2), without the random shock $\xi_{p_{bt}}$. That is, equation (2) can be also written as $u_{p_{hx}} = \tilde{u}_{p_{hx}} + \xi_{p_{bt}}$. The second equation above is because of the assumption that $\xi_{p_{bt}} \sim N(0, \Sigma_{\xi})$.

Finally, we can obtain the profits for each physician using the predicted detailing levels, the computed prescriptions and the estimated individual physician level marginal cost of detailing.

In this process, the second and third steps are straightforward; following are more details regarding the first step. For the individual level targeting scenario, the optimal detailing of each individual physician is obtained by solving the system of the four FOCs simultaneously, substituting the individual level parameter estimates. For the segment level targeting scenario, however, the computation needs adjustment to reflect the assumption that detailing levels are obtained by maximizing segment level profits, and the 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 the 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:

$$\max_{dl_{s_{bt}}} \pi_{s_{bt}} = \sum_{p \in s} [markup_b \times E(rx_{p_{bt}} | \xi_{p_{bt}}) - mc_{p_{bt}} \times dtl_{s_{bt}}]$$

Where $s$ indexes for segment. The functional firm for $ln(E(rx_{p_{bt}} | \xi_{p_{bt}}))$ is the same as equation (2), except that the values of $dtl_{s_{bt}}$ 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.

The computations for both individual and segment level cases as mentioned above are applied using parameter estimates from both the proposed approach and the traditional approach. However, the latter doesn’t estimate the parameters related with the marginal cost of detailing. For the sake of consistency we use the estimates from the proposed approach.

This section is organized as follows; first we present the comparisons of profitability for the two targeting scenarios using the estimation results from the proposed approach. Then we provide the same profit comparison using the estimation obtained from the traditional approach in which firms’ decisions on detailing are not accounted for in the estimation process. Finally, we provide a comparison of the parameter estimates between the proposed approach and the traditional approach.

Comparisons of profitability for two targeting strategies


As mentioned above, using the parameter estimates from the proposed model, we can compute the optimal details at the individual physician level and hence the average profits for each physician in the final quarter for all four brands under the two targeting strategies¹¹. 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

¹¹ The profits are computed ignoring the switching or operation costs related to implementing the targeting strategies.
profits by targeting at the individual level is 38% across all four brands. This is a big increase in profit. 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 the 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.

Figure 4 Average profits for two targeting strategies, proposed model

Table 7 Average profits ($) for two targeting strategies, proposed model

<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 (25%)</td>
<td>2822 (47%)</td>
<td>1991 (39%)</td>
<td>1671 (40%)</td>
</tr>
</tbody>
</table>

Case (2): Parameters estimated without accounting for firms’ strategic behavior

We also conduct the profitability comparison using parameter estimates from the traditional 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
Using the estimates from the traditional 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 traditional approach obtain only a 5% increase in profits. This increase may not cover the costs related to implementing an individual level targeting strategy.

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

<table>
<thead>
<tr>
<th>Average Profit ($)</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 (0.2%)</td>
<td>2627 (5.8%)</td>
<td>2130 (5.3%)</td>
<td>1750 (7.3%)</td>
</tr>
</tbody>
</table>
Comparisons of the proposed approach and the traditional 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 literatures. 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 is 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 to those of Villas-Boas and Winer (1999).

Table 9 Comparison of mean own-elasticities from these 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 model</td>
<td>0.140</td>
<td>0.154</td>
<td>0.177</td>
<td>0.150</td>
</tr>
<tr>
<td>(0.134, 0.147)</td>
<td>(0.149, 0.160)</td>
<td>(0.171, 0.182)</td>
<td>(0.144, 0.161)</td>
<td></td>
</tr>
<tr>
<td>Traditional model</td>
<td>0.075</td>
<td>0.068</td>
<td>0.157</td>
<td>0.091</td>
</tr>
<tr>
<td>(0.060, 0.087)</td>
<td>(0.057, 0.080)</td>
<td>(0.143, 0.174)</td>
<td>(0.077, 0.100)</td>
<td></td>
</tr>
</tbody>
</table>
Both the proposed estimation approach and the traditional 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 traditional 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 heterogeneity. They documented that this result is 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 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

---

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 model</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 model</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>

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.
estimates for heterogeneity. Furthermore, both studies show evidence of influence between the estimated variance of the parameters and variance of the random shocks.

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 model</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>

In summary, the traditional approach, which ignores firm strategic behavior, underestimates a) elasticities, b) carry-over effects, and c) heterogeneity. Both a) and c) drive the finding that the traditional model underestimates the gains to targeting at the individual level vs. targeting at the segment level.

5. Interactive response of competitors

The above section shows the importance of incorporating firms’ strategic behaviors in the modeling process and how that impacts the analysis of the benefits of targeting. Another key benefit of this approach is that it can explicitly account for the competitive interactions among all competitors when evaluating alternative targeting strategies. Recall that in section 4, the detailing levels for all brands for each individual physician are obtained by solving the system of four FOCs simultaneously. The traditional approach, on the other hand, needs to make an assumption
regarding competitors’ strategies when computing the profits of different targeting scenarios for the focal brands. This section studies the implications of allowing for competitors’ interactive responses. One way to do this is to compare the profits obtained using the parameters from the traditional approach with the profits computed using the parameters from the proposed approach. Based on the analysis in section 4, the parameter estimates from these two approaches are quite different. Thus, this approach will have the difference in profits resulted from both the differences in parameter estimates and the differences in treating competitors’ response.

Therefore, we use the same set of parameter estimates from the proposed approach and evaluate the profits under the two assumptions: one allows for interactive responses and the other one not. Solving the system of four FOCs simultaneously, as we did for filling Table 7, we can obtain the profits in the case of allowing for competitive interactions. The results are shown in the first line of Table 13, which are the same as those in the second row of Table 7. To obtain the profit values assuming no competitive interactions, we solve the FOCs one at a time, taking the detailing levels for the other three brands in the data as the competitive detailing values. This process reflects the assumption that when firms make targeting decisions, they take the competitors strategies as given. The computed profit values are listed in the second row of Table 13.

<table>
<thead>
<tr>
<th></th>
<th>Nexium</th>
<th>Prevacid</th>
<th>Aciphex</th>
<th>Protonix</th>
</tr>
</thead>
<tbody>
<tr>
<td>With interactive response</td>
<td>3381</td>
<td>2822</td>
<td>1991</td>
<td>1671</td>
</tr>
<tr>
<td>Without interactive response</td>
<td>3269</td>
<td>2548</td>
<td>1995</td>
<td>1745</td>
</tr>
</tbody>
</table>

Table 13 shows that when ignoring interactive response among competitors, the impact on profits is not very strong, and the impacts are different across the four brands.
6. Robustness checks

Section 4 shows 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 a key assumption in the proposed model that firms set detailing levels to maximize profit from each individual physician. We do this in two ways. First, we see if the gain of individual level targeting relative to segment level targeting remains large even if we assume that the details are generated from firms targeting at the segment level. Second, we compare the fit and predictive abilities of these two approaches (under two segment levels) and a heuristic approach to accounting for firms strategic behavior to see which of the three is more consistent with the data.

Robustness check I

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. In the first robustness check, 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.

Robustness check II

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 14, which shows that the proposed model (target at the individual level) predicts the best.

Table 14 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>
</tbody>
</table>

7. Conclusions

In this study, we develop a method to quantify the benefit of targeting at the individual level in the presence of firm strategic behavior. Our application domain is firms’ detailing decision 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 behaviors 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 interactive responses among competitors. Further, 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.

8. References:


Appendix A

A function with negative power of detailing is preferable to positive power.

If we define \( f(dt_{tbt}) = \frac{pbt}{dt_{tbt}} \) then \( \exp\left(\beta_{pbt,b} f(dt_{tbt})\right) = \exp\left(\beta_{pbt,b} \frac{dt_{tbt}^a}{pbt}\right) \), we want to show that if \( a < 0 \), the function shows diminishing returns for the range of detailing levels in the data, which is 0-33. To simplify the notation, in this demonstration, we use \( x \) for \( \frac{dt_{tbt}}{pbt} \), and \( \beta \) for \( \beta_{pbt,b} \). We want to show that when \( a < 0 \), the function \( \exp\left(\beta x^a\right) \) shows diminishing returns and also satisfies the second order condition for most of the data value of \( x \).

\[
y = \exp\left(\beta x^a\right) \Rightarrow \frac{\partial y}{\partial x} = \exp\left(\beta x^a\right) \times \beta ax^{a-1} \Rightarrow \frac{\partial^2 y}{\partial x^2} = \exp\left(\beta x^a\right) \times \left(\beta^2 a^2 x^{2a-2} + \beta a(a-1)x^{a-2}\right)
\]

In order for \( \frac{\partial^2 y}{\partial x^2} < 0 \), we need:

\[
\beta^2 a^2 x^{2a-2} + \beta a(a-1)x^{a-2} = \beta ax^{a-2}(\beta ax^{a} + (a-1)) < 0
\] (10)

When \( a < 0 \), we expect \( \beta < 0 \), in order for \( y \) to be an increasing function of \( x \). To satisfy equation (10), we need \( \beta ax^a + (a-1) < 0 \) \( \Rightarrow x^a < \frac{1-a}{\beta a} \Leftrightarrow x^{-a} > \frac{\beta a}{1-a} \Rightarrow x > \left(\frac{\beta a}{1-a}\right)^{-1-a} \)

This condition can be easily satisfied for the range of \( x \) in the data. For example, if we define \( a=-1 \), the right hand side is equal to \( \frac{-\beta}{2} \). As \( \beta < 0 \), this is positive. Note that when \( a < 0 \), to accommodate \( dt_{tbt} = 0 \) in the data, we need to set \( x = \frac{dt_{tbt}}{pbt} + c \), where \( c \) is any constant, which is chosen to be 1 in our model. With this setup, we need \( x > \left(\frac{\beta a}{1-a}\right)^{-1-a} \Leftrightarrow dt_{tbt} > \left(\frac{\beta a}{1-a}\right)^{-1-a} - c \),

when \( a=-1 \), this requires \( dt_{tbt} > \frac{-\beta}{2} - c \). If \( c=1 \), when \( \beta > -2 \), the right hand side is negative, which allows all possible \( dt_{tbt} \) value to satisfy the SOC.

When \( a > 0 \), as we know that when \( a > 1 \), \( y = \exp\left(\beta x^a\right) \) will increase faster as \( x \) increases, which means it won’t satisfy the second order condition for any \( x \) value. Therefore, for the case of \( a > 0 \), we only consider \( 0 < a < 1 \).

In this case, in order for equation (10) to be satisfied, we need \( \beta ax^a + (a-1) < 0 \), that is \( \beta ax^a < 1-a \). Since \( a > 0 \), we should expect \( \beta > 0 \), so that the transformation is an increasing
function of x. Therefore, \( x < \left( \frac{1-a}{\beta a} \right)^{\alpha} \). In order for this condition to be satisfied by the value of x in the data, both a and \( \beta \) need to be very small. For example, if \( a = 0.5 \), the right hand side is \( x < \frac{1}{\beta^2} \). Given in the data, x could be as high as 33, this requires \( \beta \) to be really small. However, when a is small, we should expect \( \beta \) to be large enough to reflect how unit change in detailing impacts the number of prescriptions.

Comparing both the cases mentioned above, we realized that \( a < 0 \) is preferable, as it has more flexible requirement on the estimated value of \( \beta \), in order for the values of detailing in the data to satisfy the SOC, i.e. to be consistent with our assumption that the detailing levels observed in the data maximize their quarterly profit.

Appendix B

Gibbs sampler to draw all these parameters:

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

\[
\left[ \beta_p \ | \ * \right] \propto \prod_{t,b} \text{Poisson}\left( \lambda_{pbt} \right) \quad \text{Likelihood from prescription model}
\]

\[
\times \prod_{t,b} \left| \frac{\partial r}{\partial dtl_{pb}} \right| \left( \text{markup}_b \times \exp \left( u_{pte} \right) \times \frac{-\beta_{pb2}}{(dtl_{pb} + 1)^2} - (\alpha_b + \alpha_p + s_b) \right) \sim N\left( 0, \Sigma_q \right)
\]

Likelihood from detailing model

\[
\times \beta_p \sim N \left( \bar{\beta}, \Sigma_{\beta} \right) \quad \text{Prior}
\]

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

\[
r = \text{markup}_b \times \exp \left( u_{pte} \right) \times \frac{-\beta_{pb2}}{(dtl_{pb} + 1)^2}
\]

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

\[
\left[ \xi_{pt} \ | \ * \right] \propto \prod_{b} \text{Poisson}\left( \lambda_{pbt} \right) \quad \text{Likelihood from prescription model}
\]

\[
\times \prod_{b} \left| \frac{\partial r}{\partial dtl_{pb}} \right| \left( \text{markup}_b \times \exp \left( u_{pte} \right) \times \frac{-\beta_{pb2}}{(dtl_{pb} + 1)^2} - (\alpha_b + \alpha_p + s_b) \right) \sim N\left( 0, \Sigma_q \right)
\]

Likelihood from detailing model

\[
\times \xi_{pt} \sim N \left( 0, \Sigma_{\xi} \right) \quad \text{Prior}
\]
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 an Inverted Wishart conjugate prior, using the posterior draws of $\xi_{pt}$ as the data.
4. Draw $\bar{\beta}_b, \Sigma_\beta$ 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

Then $\alpha_b$ s and $s_b$ s are the parameters for this multivariate normal regression. That is $Y = X \begin{bmatrix} \text{diag}(\alpha_b) \\ \text{diag}(s_b) \end{bmatrix} + \eta$, where

$\eta \sim N(0, \Sigma_\eta)$ 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 $mc_{pb} - \alpha_p - s_b$ 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 $Y = X \alpha + \eta$, where $\eta \sim N(0, \Sigma_\eta)$, 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.