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# An Empirical Model of Drug Detailing: Dynamic Competition and Policy Implications

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The practice of detailing in the marketing of prescription drugs is undergoing significant changes. For instance, in September 2013, the Physician Payment Sunshine Act went into full effect. The accompanying transparency requirements have prompted physician practices and hospitals to severely restrict pharmaceutical sales representatives' direct access to their physicians. Despite all the attention in the popular press, scant scholarly research has investigated how these restrictions on physician access impact physician prescription behavior and competitive detailing to physicians. To analyze the impact of these restrictions, we develop a structural model of how pharmaceutical firms compete dynamically to schedule detailing to physicians. Detailing activities are known to have significant carryover effects that are captured in a first-stage model of physicians' demand for prescription drugs. We also specify detailing policy functions that describe each firm's observed detailing actions. In a second stage, we estimate a model that describes costs of detailing, assuming that the observed detailing levels are consistent with a Markov perfect Nash equilibrium. The estimated structural model is used to examine the implications of restrictions on the amount of detailing via counterfactual simulations. We find that restriction policies would increase the market share of a nondrug-treatment-only option but impact firms asymmetrically; firms that are strong in detailing and/or rely more on detailing would be hurt more. Unexpectedly, a policy that imposes a ceiling on detailing frequency could significantly reduce detailing of all firms in the market, including those firms with average detailing levels below the ceiling, and effectively would soften competition between firms and enhance their profits.

*Keywords*: pharmaceutical marketing; detailing competition; dynamic oligopoly game; dynamic programming; detailing cost; restrictions on detailing; regulation
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## 1. Introduction

Although the pharmaceutical industry is mainly driven by innovation, it spends an enormous amount of money on marketing. Among various marketing resources expended, detailing—personal selling through representatives—together with related sampling, is the single largest expenditure. In 2011, the U.S. pharmaceutical industry spent $6.5 billion on detailing, which accounted for more than 60% of the total promotional budget (IMS Health 2011).

The vast amount of detailing expenditure in the pharmaceutical industry has drawn the attention of the public and of policy makers. In some instances, critics have accused pharmaceutical representatives of promising more from a drug than they should, and physicians of having been pressured into prescribing certain drugs. Additionally, concerns about health cost and safety have surged since some heavily marketed drugs were revealed to pose public health risks (Waxman 2005). This has prompted wide-ranging legislative proposals in different countries to regulate and limit detailing activities as well as stepped up efforts at self-regulation by the pharmaceutical industry and the medical profession. For example, the United Kingdom limits pharmaceutical firms' sales promotion expenditure to a proportion of their overall profits (Stremersch and Lemmens 2009). Spain prohibits pharmaceutical firms from providing more than 10 sample packages to a physician within one year (Llopart et al. 2012). In 2009, Pharmaceutical Research and Manufacturers of America issued new guidelines on marketing to physicians that prohibit noneducational and practice-related gifts such as pens.

In the United States, sales representatives' access to physicians has become increasingly difficult. In some specialties such as oncology, access restrictions placed by physicians are so widespread that pharmaceutical companies are tempted to secure more doctor visits by sending several different representatives to promote the same drug (ZS Associates 2012). In September 2013, the Physician Payment Sunshine Act went into full effect in the United States. The act's transparency requirements have prompted physician practices and hospitals to severely restrict pharmaceutical sales representatives' direct access to their physicians. For example, in 2013, 45% of the prescribers placed significant restrictions on detailing representatives' access, compared to 35% in 2012 and 23% in 2008 (Rockoff 2014). Despite all the attention these industry trends have received in the popular press, scant scholarly research investigates how these restrictions on physician access impact physician prescription behavior and competitive detailing to physicians.

Set against this backdrop, our research is motivated by two opportunities to make a contribution. Our primary motivation is substantive. Specifically, as greater access restrictions are imposed on the detailing activities of pharmaceutical firms, either via government regulation, or by physicians and their practices, or by pharmaceutical industry associations, what are the implications for strategic behaviors of competing firms that are vying for the limited number of slots for meeting physicians? In equilibrium, which firms gain and which firms lose in terms of revenues and profits? What are the implications of these emerging restrictions on the practice and use of detailing for the pharmaceutical industry as well as for public policy?

To address these substantive research questions we make a few methodological advancements as well. Thus far, the empirical research on detailing decisions has been largely silent on the question of optimal detailing behaviors in a dynamic setting. Previous studies (Gönül et al. 2001, Mizik and Jacobson 2004, Liu et al. 2015) have shown a positive effect of detailing on physicians' prescription behavior. Further, similar to the effect of advertising, it has been found that the effect of drug detailing can last for more than one period. This carryover effect implies that the decision of how much to detail needs to be studied using a dynamic model rather than a static model. Even though researchers have recognized this carryover effect, previous studies on firms' detailing behavior have assumed that firms are myopic decision makers in that they only optimize their current profits (Dong et al. 2009). By contrast, forward-looking firms should measure the carryover effect of detailing and take it into account in making optimal detailing decisions. However, this is a challenging problem from a computational and analytical perspective because information has to be incorporated from a dynamic equilibrium into a structural parameter (marginal cost of detailing) estimation algorithm. This difficulty may have prohibited researchers from pursuing this problem in the past.[1]

We attempt to make a methodological contribution in this domain by specifying and estimating a dynamic structural model of oligopoly competition at the individual physician level. The model explains the scheduling of detailing for competing drugs and backs out the detailing cost structure consistent with such scheduling. To overcome the computational challenge, we adopt a two-stage approach (Hotz and Miller 1993, Hotz et al. 1994, Bajari et al. 2007) to estimate supply side structural parameters of the proposed framework. The estimated detailing costs, combined with the proposed dynamic structural model of oligopoly competition, provide the perfect vehicle to learn via counterfactual analysis the equilibrium impact of an expected change in the environment, namely, greater access restrictions. Importantly, we do not have to rely on accounting cost information to conduct these analyses. Potential endogeneity of detailing is a concern with our empirical analysis for which we apply reasonable controls. However, the unavailability of good instrumental variables limits our ability to fully eliminate this concern.

Our empirical analysis is applied to the statin drugs market. Several of our findings are consistent with prior research. For example, consistent with previous demand-side results, we too find evidence of positive and persistent effects of detailing (Gönül et al. 2001, Mizik and Jacobson 2004, Liu et al. 2015). On the supply side, our analysis reveals that firms direct less detailing to a physician if they already have a high detailing stock at that physician. This result is consistent with the finding of Dubé et al. (2005) that the dynamic optimal advertising level decreases with own goodwill. We also find that a firm's detailing decreases in its competitors' detailing stock. This is consistent with a previous theoretical finding by Villas-Boas (1993) that oligopolists should advertise in alternating periods. Taken together, these results provide strong economic support for the need to account for demand-side detailing carryovers while setting optimal competitive detailing levels on the supply side, as we do in this study.

Beyond these results that confirm previous empirical or theoretical findings, our empirical analysis

[1] For example, the computational burden of solving for the Markov perfect equilibrium makes the nested fixed-point estimator of Rust (1987) impractical for empirical work in dynamic models.

also provides new substantive insights for marketers and policy makers. These substantive findings are derived from our novel econometric modeling approach, which enables us to recover both the constant marginal cost of detailing and the distribution of private shocks to detailing costs, both of which are allowed to vary across brands. This specification implies that our estimates of the cost of detailing account for all economically relevant information from the observed decisions of firms to detail, as well as not to detail in certain periods. As a consequence, our estimates are particularly valuable for conducting counterfactual analyses of how competing firms will respond to restrictions on physician access. Importantly, accounting-based estimates of detailing costs are insufficient for this purpose.

Using the demand model and detailing cost estimates, we compute equilibrium detailing policies and profits under multiple hypothetical restricted detailing scenarios and obtain several useful and interesting results:

1. Alternative restriction policies that lead to similarly reduced detailing levels may have very different profit consequences for firms. Policies that raise the marginal cost of detailing are injurious to industry profits, but policies that simply limit the number of detailing visits might have the unintended effect of softening competition and increasing industry profits. Given that restricting detailing levels could increase industry profits, the industry may want to think twice before it lobbies against such a policy.

2. Imposing a ceiling on detailing frequencies leads to significant reduction in detailing across the board, including by firms whose average unrestricted optimal detailing is less than the ceiling. Although a firm is able to move some detailing visits to months in which detailing levels were previously not hitting the ceiling, the effective marginal cost goes up as it does so, reducing firms' incentives to reallocate more detailing visits to those months.

3. Restriction policies have asymmetric effects on firms' market shares and profits. They benefit firms that have the weakest detailing effects, while hurting firms with the strongest detailing effects. The deleterious effect of restriction policies is especially pronounced on new drugs that need to build up their goodwill stocks and often have larger detailing effects. This may be an undesirable consequence when new drugs are significantly better from a therapeutic viewpoint.

4. A self-imposed ceiling policy by an individual firm is not likely to succeed in reducing detailing levels across the board. It is also less effective in expanding outside the share of nondrug treatments and leads to less favorable changes to industry total profits than an industry-wide ceiling policy.

5. With firms' detailing levels reduced by a detailing restriction policy, the share of prescription options that do not rely on detailing, such as nondrug treatment or generic drugs, expands. Depending on the effectiveness of the outside option, this may help or hurt public health.

The rest of this paper is organized as follows: In §2, we present a brief review of the extant literature. We describe the data in §3. We specify the model in §4, and discuss the estimation strategy in §5. Empirical results are presented and discussed in §6, followed by several counterfactual simulation studies in §7. We conclude and present a discussion of the limitations of our study in §8.

## 2. Literature Review

Because few studies have been conducted on the dynamics of detailing, and detailing is akin to advertising and other marketing communication instruments, we first review a broader field, the dynamics of marketing communication. The effects of marketing communication have been characterized as persuasive effects and informative effects (Ackerberg 2003, Narayanan and Manchanda 2009, Ching and Ishihara 2012, Chan et al. 2013). Both kinds of effects spill over to more than one period and therefore introduce dynamics into the analysis of competition in marketing communication. Using a theoretical model where advertising increases consumers' consideration, Villas-Boas (1993) shows that out-of-phase pulsing advertising maximizes long-term profits in an oligopoly. Chintagunta and Vilcassim (1992) and Erickson (1995) study the dynamics of competitive advertising using differential games in which analytic solutions of equilibrium advertising strategies are obtained. By setting up a dynamic game and solving for a Markov perfect equilibrium, Dubé et al. (2005) empirically investigate how competing firms should optimally allocate their advertising over time, where the advertising effect is modeled using an augmented goodwill stock function. Sriram and Kalwani (2007) study the optimal levels of advertising and promotion budgets in dynamic markets with brand equity as a mediating variable. Using a Kalman filter, they specify and estimate a flexible demand system and then solve for the dynamic optimal advertising strategy.

Montoya et al. (2010) use a nonhomogeneous hidden Markov model (HMM) to account for the long-term effects of marketing activities (detailing and sampling) by allowing them to affect how physicians transition between a set of latent prescription-behavior states, and then implement a partially observable Markov decision process to dynamically allocate pharmaceutical marketing resources across physicians. They demonstrate that ignoring the dynamics in physician prescription behavior leads to

a suboptimal allocation of marketing interventions. Similar to studies of advertising dynamics we previously reviewed, Montoya et al. (2010) follows a two-step approach, i.e., a demand model is estimated first and then the estimated demand parameters are plugged into a supply structure. Taking exogenous cost information from industry reports, a dynamic optimization problem is then solved. An important benefit of the approach is that it does not require the assumption that observed behaviors of firms are optimal. However, a concern with this approach is the assumption that researchers have access to the correct marketing communication costs. Although this assumption is not as problematic to study advertising, since advertising costs are often public, costs of detailing are often largely private to each firm, and are challenging if not impossible for researchers to obtain. An equally important concern is that cost information from industry reports, even when available, often only represents accounting data that do not capture all economically relevant information that affects agents' behaviors. For instance, it is not clear at all if accounting data measure marginal costs of detailing, or simply total costs. Using a structural model to estimate the marginal costs would at least provide another benchmark, although in our case it relies on the assumption of profit-maximization and Markov-perfect Nash equilibrium.

Other marketing scholars have used structural modeling approaches to recover firms' supply side parameters based on physicians' observed prescription writing behaviors and pharmaceutical firms' decisions. Using Bayesian methods, Dong et al. (2009) estimate a prescription response model and a strategic profit-maximizing detailing equation at the physician level. The structural parameter, namely, the marginal cost of detailing, is estimated based on an optimality condition. Our study is similar to Dong et al. (2009) in that both studies investigate firms' strategic behavior at the physician level and recover firms' detailing costs. Our study complements Dong et al. (2009) in that we account for the carryover effects of detailing in forward-looking firms' detailing decisions. With this in mind, we adopt a dynamic oligopoly competition model to analyze the scheduling of detailing. Similarly, Ching (2010b) developed and estimated a dynamic oligopoly structural model for a prescription drug market after patent expiration. The focus of Ching's study is firms' dynamic pricing decisions and generic firms' market entry decisions when learning about the quality of generics is important.

Although the pharmaceutical industry is heavily regulated, the effects of regulation have not been extensively analyzed in the marketing literature. Stremersch and Lemmens (2009) study the role of regulatory regimes in explaining the international sales growth of new products by using a regression model with time-varying coefficients. They investigate regulatory constraints such as manufacturer price controls, restrictions of physician prescription budgets, and the prohibition of direct-to-consumer advertising. Using a learning model, Ching and Ishihara (2010) study a public policy of encouraging physicians to share their patients' experiences with the public health agency. With an empirical dynamic oligopoly model, Ching (2010b) examines the impact of a policy that speeds up generic drugs' approval process via counterfactual policy simulations. He reports an interesting finding that shortening the expected approval time brings generics to the market sooner, but lowers generic firms' expected return from entering the market, thereby reducing the total number of generic entrants and consumer welfare.

Our research examines the implications of a newly emerging but rapidly growing phenomenon—restrictions on the amount of detailing-based promotions. Our study, therefore, adds to the literature on advertising restrictions. In the context of alcohol and tobacco consumption, a substantial literature examines the impacts and policy implications of advertising restrictions or bans. The traditional econometric approach to measuring the impacts of advertising restrictions or bans used the natural experiment available in cross section or panel data wherein some states or countries had implemented an advertising ban while others had not (Nelson 2001). By contrast, more recent work, including our paper, relies on counterfactual simulations based on a structural model to predict the effects of advertising restrictions that may or may not have been seen in the data. Tan (2006), for instance, modifies the advertising response parameter in a policy simulation of the tobacco market, whereas we place ceilings on the level of detailing in a simulation of prescription drug markets. Qi (2013) uses a dynamic oligopoly model of advertising to explain the impact of the 1971 TV/radio advertising ban on the cigarette industry.

## 3. Data

The data used for the empirical analysis in this study are from a group of prescription drugs known as statins (or HMG-CoA reductase inhibitors). Statins are used to lower cholesterol levels in people at risk for cardiovascular disease because of hypercholesterolemia. These drugs work in patients' livers to block a substance needed to make cholesterol, and also to help the body reabsorb cholesterol that has accumulated as plaque on their arterial walls. Statins sales surpassed $16 billion in 2005, making them the biggest-selling drugs in the United States (Consumer Reports 2007). Our data contain three major

statins: Lipitor produced by Pfizer, Zocor by Merck, and Crestor by AstraZeneca.[2] In addition to these three drugs, our data include an alternative prescription option, "nondrug-treatment-only," that is commonly written by physicians. For simplicity, henceforth, we refer to this option as nondrug treatment. Nondrug treatment methods include eating healthy, quitting smoking, increasing physical activity, moderating alcohol intake, and maintaining an ideal body weight.

The data were collected by a market research firm from a panel of physicians in the United States. The panel consists of a representative sample of the universe of physicians, balanced across geographic regions, and prescription volumes. Each physician reports the number of detailing calls received and prescriptions written for each drug. We have access to monthly data for the period from June 2002 to May 2004. Since Crestor was introduced in August 2003, we only observe details and prescriptions of Crestor for 10 months. Our sample consists of physicians who wrote at least one new prescription[3] of each of the prescription options in this category during the last 20 months of the 24-month period,[4] and who are active throughout the study period (i.e., have at least one prescription or detailing record for the first six-month period and the last six-month period each). This results in a sample of 448 physicians who wrote 14,995 prescriptions and received 26,278 detailing visits.

We report descriptive statistics of the prescriptions per physician-month and the market share for each prescription option in Table 1. As seen in the table, even though Crestor is a new drug, it gained a large prescription share quickly upon entry in August 2003. Zocor appears to suffer the most from Crestor's entry with its market share reduced from 27.54% to 16.10%, a drop of 41.54%. Lipitor's market share was reduced from 40.14% to 29.91%, a drop of 25.49%, and the nondrug treatment's market share was reduced from 32.28% to 22.91%, a drop of 29.03%. We report descriptive statistics of the number of detailing visits per physician-month for each brand in Table 2. Because only a very small number of physician-months witness more than four detailing visits from a brand, we group those occasions along with the frequency of 4. For all three brands, the most frequently observed outcome is no detailing, followed by one detailing, two, and so on. Crestor delivers the most frequent visits to physicians on average (1.379), followed by Zocor (1.054), and Lipitor (0.816).

**Table 1 Prescriptions per Physician-Month and Market Shares**

| | | | Market share % | |
|---|---|---|---|---|
| Drug | Mean | Variance | Before 08/03 | After 08/03 |
| Lipitor | 0.575 | 1.148 | 40.14 | 29.91 |
| Zocor | 0.352 | 0.714 | 27.54 | 16.10 |
| Crestor | 0.591 | 1.391 | — | 31.08 |
| Nondrug treatment | 0.451 | 1.117 | 32.28 | 22.91 |

**Table 2 Frequency Distribution of Detailing Visits per Physician-Month**

| | 0 | 1 | 2 | 3 | ≥4 | Mean frequency |
|---|---|---|---|---|---|---|
| Lipitor | 5,448 | 3,061 | 1,358 | 546 | 339 | 0.816 |
| Zocor | 4,637 | 3,013 | 1,643 | 806 | 653 | 1.054 |
| Crestor | 1,379 | 1,336 | 893 | 432 | 440 | 1.379 |

We analyze firms' detailing decisions at the physician level to assess whether there is preliminary evidence in the data that firms act dynamically and strategically. In this analysis, we focus on the last nine months (from September 2003 to May 2004) of the two-year window to avoid the complications caused by Crestor's entry in August 2003. For each physician and firm, we compute for each of the nine months the total number of detailing visits made to the physician by the firm in the past 12 months. For instance, for September 2003 we consider the 12-month period from September 2002 to August 2003, and for October 2003 we consider the 12-month period from October 2002 to September 2003, and so forth. We then rank order the nine months based on descending value of this measure of past detailing and split the months into two groups: group 1 contains the top five months with more detailing visits in the past and group 2 contains the bottom four months with fewer past detailing visits. Next we take the average of current (not past) detailing frequencies across the top five months for each physician-firm as an observation in group 1 and the average across the bottom four months for each physician-firm as an observation for group 2. By comparing the 1,344 pairs of underlying observations from the two groups, we find that firms on average make 13.6% more detailing visits ($t = 4.007$, $p < 0.01$) per physician and month in group 2 (mean = 1.170, SD = 0.924) than in group 1 (mean = 1.030, SD = 0.887). This suggests that a firm delivers more detailing to a physician who has received fewer detailing visits from the firm in the past. Intuitively, it is less profitable to detail a physician if a firm already delivered a lot of detailing to the physician in the past because of the diminishing marginal return to detailing. This effect will be incorporated

[2] The three major statin brands account for more than 80% of new statin prescriptions. The other three statins with smaller market shares are Lescol, Pravachol, and Mevacor/Lovastatin.

[3] Throughout this paper, the term prescriptions refers only to new prescriptions written by the physician, excluding refills.

[4] As explained later, we use the first four months to calibrate the detailing stock.

into our subsequent structural model. Similarly, for each physician and firm, we rank order and split the nine months into another two groups based on the total number of detailing visits made to the physician by its competitors in the past 12 months. We find that the average current monthly detailing per physician is 1.145 (SD = 0.937) for group 2 and 1.050 (SD = 0.880) for group 1, a difference of 9.1% ($t = 2.715$, $p < 0.01$). This result indicates that firms also take into consideration their competitors' past detailing behavior when making detailing decisions. In particular, a firm delivers more detailing in physician-months that have received fewer detailing visits from competitors in the past. In summary, the data pattern is consistent with firms making dynamic and strategic detailing decisions.[5]

## 4. Model

On the demand side of the market, we specify a model of prescriptions written by physicians. In the model, detailing increases the value of a drug via a "detailing stock" that depreciates over time but is replenished by further detailing visits. On the supply side, we consider $J$ pharmaceutical firms, each of which produces one statin drug brand. The $J$ firms employ detailing as an instrument to compete for a share of each physician's prescriptions over an infinite time horizon. All economically relevant conditions for each firm to decide how much to detail in month $t$ to physician $p$ are summarized by a vector of state variables, $S_{pt} \in \mathcal{S}$. Given the state $S_{pt}$, firms behave strategically and make detailing decisions simultaneously in each period. Equilibrium is reached when each firm maximizes its expected present discounted value, given expectations about the evolution of competition. Similar to Dong et al. (2009), we assume that both demand and competition are independent across physicians.

### 4.1. Model of Prescriptions

Prescription decision variable $y_{pjk} = 1$ if physician $p$ chooses prescription alternative $j$ for patient $k$; $y_{pjk} = 0$ otherwise. We also include the prescription of nondrug treatment only as an outside option ($y_{p0k}$). We assume that physicians write prescriptions exclusively to maximize the utility of their patients based on their professional judgments. Physicians' preferences for maximizing patients' utility are due to a sense of professional integrity and obligation, a desire to maintain their reputation, and a fear of malpractice suits. Specifically, when patient $k$ visits physician $p$, the physician chooses the prescription alternative $j$ (i.e., $y_{pjk} = 1$) that provides the greatest utility for her patient, with the latent utility defined as

$$\begin{aligned} \tilde{U}_{pjk} &= \alpha_{pj} + \sum_{t=1}^{T} \gamma_{jt} X_t + \beta_j \log(1 + G_{pjt(k)}) + \varepsilon_{pjk}, \\ &\quad p = 1, \ldots, P,\ j = 1, 2, 3,\ k = 1, \ldots, K, \\ f(\varepsilon_{pjk}) &\sim \exp(-\varepsilon_{pjk}) \exp(-\exp(-\varepsilon_{pjk})), \end{aligned} \tag{1}$$

where $\alpha_{pj}$ is physician $p$'s intrinsic utility from prescribing drug $j$, and this intrinsic utility is related to physician $p$'s propensity to favor a certain set of drug features (e.g., drug efficacy, lack of side effects) and is related to the particular characteristics of her pool of patients. The intrinsic utility parameter also absorbs physicians' long-term habits of prescribing particular drugs. To capture various drug-time-specific influences on physicians' prescription decisions at the market level, we include $X_t$, a time-specific dummy variable, along with a drug-time-specific coefficient. The time-specific dummy variable $X_t = 1$ if $t = t(k)$ and $t \neq T$, 0 otherwise, where $t(k)$ represents the month in which patient $k$ visits physician $p$. Impacts captured by the time-specific dummy variable effects include, but are not limited to the following: (i) other pharmaceutical promotional tools that potentially affect physicians' prescription decisions, such as direct-to-consumer advertising (DTCA) and journal advertising; (ii) partial availability of Crestor in August 2003. Since Crestor was introduced in August 2003, it may or may not have been available for prescription decisions in that month depending on the particular date of the patient visit. Because we do not observe the exact date of each prescription decision, the month-fixed effect can capture the effect of nonavailability of Crestor for some prescriptions in August 2003; (iii) medical news about statins that can potentially influence physicians' prescription decisions. For example, in March 2004, soon after Crestor entered the market, Public Citizen's Health Research Group filed a petition with the U.S. Food and Drug Administration (FDA) asking for removal of Crestor from the market because there were some cases of serious side effects. As discussed subsequently, $G_{pjt}$ is the detailing stock built by firm $j$ at physician $p$ through detailing. We use a log transformation to allow for diminishing marginal effect of detailing stock on physicians' prescription decisions. Physicians' responsiveness to detailing stock of firm $j$ is measured by $\beta_j$.[6]

[5] Graphic plots of the average detailing visits for the rank ordered nine months (omitted for space reasons) confirm the patterns we describe in the above tests of differences.

[6] It would be ideal to be able to estimate demand functions for each physician separately and get a physician-drug-specific responsiveness to detailing stock. However, this approach is not feasible because we only have a limited number of observations for each physician (maximum of 24 months).

The utility of the outside option (nondrug treatment) is specified as $\tilde{U}_{p0k} = \varepsilon_{p0k}$. Let $U_{pjk}$ be the deterministic part of $\tilde{U}_{pjk}$. Given that $\varepsilon_{pjk}$ follows a type-I extreme-value distribution, the choice probability can be written as

$$P(y_{pjk} = 1) = \frac{\exp(U_{pjk})}{1 + \sum_l \exp(U_{plk})}. \quad (2)$$

Note that we do not include drug prices in our demand model. The reasons are the following: First, much of the drug cost is not paid by patients because over 98% of patients in our data are covered by insurance.[7] Second, previous research suggests that physicians have limited price sensitivity (Gönül et al. 2001) or lack accurate knowledge about actual patient costs and insurance coverage of drugs (Reichert et al. 2000). Finally, the prices of statin drugs are stable for the time period our data cover (Consumer Reports 2006) and price effects, if they exist, can be absorbed by the drug intercepts. Demand models based on longer time periods and across-markets price variation might be in a better position to capture the price effects of prescription drugs (e.g., Chintagunta and Desiraju 2005).

Previous studies have found that detailing visits by pharmaceutical sales representatives influence physicians' prescription decisions not only in the current period but also in future periods. We model this carryover effect of detailing on demand via a detailing stock that results from the current detailing and depreciated detailing stock from the previous period. Following the standard Nerlove–Arrow form (Nerlove and Arrow 1965), we assume an exponential decay process as follows:

$$G_{pjt} = d_{pjt} + \lambda G_{pjt-1} \quad (0 < \lambda < 1), \quad (3)$$

where $d_{pjt}$ is the number of detailing visits by firm $j$ to physician $p$ at time $t$,[8] and $\lambda$ is a retention rate that captures the detailing stock carried over from the previous period.

As modeled in Equation (1), the deterministic utility of prescribing a drug for all patients visiting a given physician in a given month is the same since we do not observe patient history and patient characteristics. Therefore, we can compute the demand for drug $j$ (i.e., number of new prescriptions written) generated by physician $p$ in month $t$, $Y_{pj}(G_{pt})$, as follows:

$$Y_{pj}(G_{pt}) = M_p P(y_{pjk} = 1), \quad (4)$$

where $k$ is any patient with high cholesterol visiting physician $p$ in month $t$; and $M_p$ is the expected number of patients with high cholesterol who visit physician $p$ within a month, i.e, the size of the market firms face at physician $p$.

### 4.2. Model of Detailing Decisions

On the supply side, we define firm $j$'s per month \$-contribution from the prescriptions written by physician $p$ as $\pi_{pj}(S_{pt}, d_{pt}) = Y_{pj} m_j$, where $m_j$ is the dollar-contribution margin per prescription of drug $j$; state variables $S_{pt}$ summarize economically relevant conditions facing all firms and include each firm's detailing stock, and exogenous state variables. We assume a constant margin because, as noted previously, the prices of statin drugs are stable for the study period. Therefore, firm $j$'s per month profit from physician $p$ is given as

$$\tilde{\pi}_{pj}(d_{pt}, S_{pt}, \omega_{pjt}; c_{pj}, \varsigma_{pj}) = \pi_{pj}(S_{pt}, d_{pt}) - d_{pjt}(c_j + \omega_{pjt}), \quad (5)$$

where $c_j$ is firm $j$'s constant marginal cost of detailing to physicians that is known to all firms. Although detailing cost is mainly determined by how much the firm pays its sales force, the cost could vary across physicians because some physicians are harder to access and some are easier. Ideally, we should be able to estimate the detailing cost structure with reasonable accuracy for each physician if we observe the physician for a large number of time periods. However, the relatively small number of time periods (24 months for Lipitor and Zocor, 10 months for Crestor) in our data prevents us from accomplishing this. Instead, we specify and estimate a common detailing cost structure across all physicians. We also specify $\omega_{pjt}$ as a private shock that is drawn independently from a normal distribution with mean 0 and standard deviation $\varsigma_j$. Note that with our specification in Equation (5), a nonzero mean of $\omega_{pjt}$ is not identified because of the presence of $c_j$. We assume that although firm $j$ itself can observe $\omega_{pjt}$ before choosing its detailing action, competitors cannot observe the realization of this shock, but only have knowledge of the distribution of $\omega_{pjt}$. Here, the private shock mainly accounts for variations in the marginal cost of detailing that are not captured by $c_j$. The variations may arise from changes in a firm's sales force in the field, due to, for instance, sales representatives quitting the company or being on leave or out for

[7] In our data, 29% of patients are covered by Medicare. Even though Medicare did not cover drug expenditures before 2006, more than 90% of Medicare beneficiaries have supplemental insurance coverage (source: MedPAC analysis of 2000 Medicare Current Beneficiary Survey, Cost and Use file, https://www.cms.gov/Research-Statistics-Data-and-Systems/Research/MCBS/index.html?redirect=/mcbs, accessed November 4, 2015).

[8] The approach we use here assumes that prescription decisions in month $t$ are affected by all detailing visits in the same month. Alternatively, we can use the number of detailing visits in month $t-1$ in Equation (3). The alternative approach, however, assumes that detailing visits in month $t$ do not affect prescription decisions in the same month even if the prescription is written after the detailing visit event. Empirically, we find that the alternative approach yields similar estimates of the effect of detailing.

training. These temporary changes make it more difficult to detail physicians in affected areas and increase the company's cost of detailing. Finally, $d_{pt}$ is a vector including each firm's detailing variable, $d_{pjt}$.

We model the $J$ firms' competition in detailing to physician $p$ as an infinite horizon game played each month. To analyze the equilibrium, we follow the standard practice in the dynamic oligopoly literature and focus on a Markov perfect Nash equilibrium (MPNE) in pure strategies. At the beginning of each month, firms observe the state variables $S_{pt}$ and realizations of their private shocks, and then make simultaneous detailing decisions. Firm $j$'s optimal detailing decision is made by maximizing its expected discounted profits over the entire horizon:

$$\max_{d_{pj}} E\left[\sum_{\tau=t}^{\infty} \rho^{\tau-t}\tilde{\pi}_{pj}(d_{p\tau}, S_{p\tau}, \omega_{pj\tau}) \mid S_{pt}\right], \tag{6}$$

where $\rho$ is the monthly discount rate assumed to be common across firms.

As demand and competition are both assumed to be independent across physicians, we drop the physician subscript to simplify notation in this subsection. A Markov strategy for firm $j$ is a mapping from state and private shock spaces into an action space $\sigma_j$: $\mathcal{S} \times \otimes_j \to \mathcal{D}_j$ and a strategy profile is a vector $\sigma = (\sigma_1, \ldots, \sigma_J)$. Here, $S_t \in \mathcal{S}$ and $\omega_{jt} \in \otimes_j$. Suppose the maximum number of details a firm can deliver to a physician in a month is $D$. Firm $j$'s strategy profile essentially includes the probability of visiting the physician $d$ times in a month for all $0 \le d \le D$. If all firms' behavior is given by a Markov strategy profile $\sigma$, firm $j$'s expected long-term profits given a state $S$ (before the realization of its private shock) can be written in recursive form as

$$V_j(S \mid \sigma) = E_{\omega}\Big[\tilde{\pi}_j(\sigma(S,\omega), S, \omega_j) + \rho \int V_j(S' \mid \sigma)\, dP(S' \mid \sigma(S,\omega), S) \mid S\Big]. \tag{7}$$

Here, $V_j(S \mid \sigma)$ is the expected profits at the beginning of a period before the realization of private shocks, and $P(S' \mid \sigma(S,\nu), S)$ is a transition probability function of state variables. It governs the evolution of state variables from time $t$ to $t+1$ because of firms' actions at time $t$. In our model, the detailing-stock building function in (3) determines the change in state variables and plays the role of a deterministic state transition function.

For a strategy profile $\sigma$ to be a MPNE, each firm $j$ must prefer strategy $\sigma_j$ to all other Markov strategies $\sigma_j'$, given its opponents' strategy profile $\sigma_{-j}$. Specifically, $\sigma$ is a MPNE if

$$V_j(S \mid \sigma_j, \sigma_{-j}) \ge V_j(S \mid \sigma_j', \sigma_{-j}) \tag{8}$$

for all $j$, $S$, and any alternative Markov strategy $\sigma'$.

If firm $j$ chooses to visit the physician $d$ times in a month, the alternative specific value function is given by

$$v_j^d(S, \omega_j) = E_{\omega_{-j}}[\pi_j(S, d_j = d)] + \rho E_{\omega_{-j}}[V_j(S') \mid S, d_j = d] - d \times c_j - d \times \omega_j. \tag{9}$$

For the purpose of simplifying notation, we define

$$\bar{V}_j^d = E_{\omega_{-j}}[\pi_j(S, d_j = d)] + \rho E_{\omega_{-j}}[V_j(S') \mid S, d_j = d]. \tag{10}$$

We assume that the number of details has a diminishing marginal effect on $\bar{V}_j^d$. So we have

$$\bar{V}_j^{d+1} - \bar{V}_j^d \le \bar{V}_j^d - \bar{V}_j^{d-1} \tag{11}$$

for any $d \in \mathcal{D}$ and $0 < d < D$.

As noted previously in Equation (1), we use a log transformation to capture the diminishing marginal effect of detailing stock on physicians' prescription choices. Dubé et al. (2005) show that a logit transformation does not change the concavity of a log transformed variable as long as the coefficient of the variable is less than 1 in the logit demand model.[9] Therefore, the specified per period revenue function is concave, which is consistent with our assumption here.

With the diminishing marginal return assumption applied iteratively, we have

$$\begin{aligned} & k(\bar{V}_j^d - \bar{V}_j^{d-1}) \\ &= (\bar{V}_j^d - \bar{V}_j^{d-1}) + (\bar{V}_j^d - \bar{V}_j^{d-1}) + \cdots + (\bar{V}_j^d - \bar{V}_j^{d-1}) \\ &\le \bar{V}_j^d - \bar{V}_j^{d-1} + (\bar{V}_j^{d-1} - \bar{V}_j^{d-2}) + \cdots + (\bar{V}_j^{d-1} - \bar{V}_j^{d-2}) \\ &\quad \vdots \\ &\le \bar{V}_j^d - \bar{V}_j^{d-1} + (\bar{V}_j^{d-1} - \bar{V}_j^{d-2}) + \cdots + (\bar{V}_j^{d-k+1} - \bar{V}_j^{d-k}) \\ &= \bar{V}_j^d - \bar{V}_j^{d-k}. \end{aligned}$$

This leads to $\bar{V}_j^d - \bar{V}_j^{d-1} \le (\bar{V}_j^d - \bar{V}_j^{d-k})/k$ for any $k = 2, \ldots, d$. Similarly, we find $\bar{V}_j^{d+1} - \bar{V}_j^d \ge (\bar{V}_j^{d+k} - \bar{V}_j^d)/k$ for any $k = 2, \ldots, D-d$.

The probability of detailing $d$ times ($0 < d < D$) in a month given its state variable $S$ can be written as

$$\begin{aligned} P_j^d(S) &= P(v_j^d(S, \omega_j) > v_j^k(S, \omega_j), \forall k \in \mathcal{D}_j \text{ and } k \ne d) \\ &= P\left(\left[\omega_j > \frac{\bar{V}_j^{d+l} - \bar{V}_j^d}{l} - c_j, \forall l = 1, \ldots, D-d\right] \text{ and } \left[\omega_j < \frac{\bar{V}_j^d - \bar{V}_j^{d-k}}{k} - c_j, \forall k = 1, \ldots, d\right]\right). \end{aligned} \tag{12}$$

Note that $\bar{V}_j^{d+1} - \bar{V}_j^d \ge (\bar{V}_j^{d+l} - \bar{V}_j^d)/l$ for any $l = 2, \ldots, D-d$. That is, as long as $\omega_j > \bar{V}_j^{d+1} - \bar{V}_j^d$, the condition of $\omega_j > (\bar{V}_j^{d+l} - \bar{V}_j^d)/l$ is satisfied for any $l = 2, \ldots, D-d$. Similarly, as long as $\omega_j < \bar{V}_j^d - \bar{V}_j^{d-1}$,

[9] Empirical estimates of our model show that the coefficients of detailing stock are all less than 1.

the condition of $\omega_j < (\bar{V}_j^d - \bar{V}_j^{d-k})/k$ is satisfied for any $k = 2, \ldots, d$. With these results, the probability in Equation (12) collapses into

$$P_j^d(S) = P(\bar{V}_j^{d+1} - \bar{V}_j^d - c_j < \omega_j < \bar{V}_j^d - \bar{V}_j^{d-1} - c_j) = \Phi\left(\frac{\bar{V}_j^d - \bar{V}_j^{d-1} - c_j}{\varsigma_j}\right) - \Phi\left(\frac{\bar{V}_j^{d+1} - \bar{V}_j^d - c_j}{\varsigma_j}\right). \quad (13)$$

Note that $\Phi(\cdot)$ is the cumulative distribution function for the standard normal distribution. Similarly, we can find that

$$P_j^0(S) = P\left(\left[\omega_j > \frac{\bar{V}_j^{0+l} - \bar{V}_j^0}{l} - c_j, \forall l = 1, \ldots, D\right]\right) = P(\bar{V}_j^1 - \bar{V}_j^0 - c_j < \omega_j) = 1 - \Phi\left(\frac{\bar{V}_j^1 - \bar{V}_j^0 - c_j}{\varsigma_j}\right) \quad (14)$$

and

$$P_j^D(S) = P\left(\left[\omega_j < \frac{\bar{V}_j^D - \bar{V}_j^{D-k}}{k} - c_j, \forall k = 1, \ldots, D\right]\right) = P(\omega_j < \bar{V}_j^D - \bar{V}_j^{D-1} - c_j) = \Phi\left(\frac{\bar{V}_j^D - \bar{V}_j^{D-1} - c_j}{\varsigma_j}\right). \quad (15)$$

Now we integrate out the private shock $\omega$ and obtain the expected value function

$$\begin{aligned}
V_j(S) &= E_\omega[\max\{v_j^0, v_j^1, \ldots, v_j^D\}] \\
&= P_j^0 E_{\omega_j}[\bar{V}_j^0 \mid v_j^1 < v_j^0] \\
&\quad + P_j^D E_{\omega_j}[\bar{V}_j^D - D(c_j + \omega_j) \mid v_j^D > v_j^{D-1}] \\
&\quad + \sum_{0<d<D} P_j^d E_{\omega_j}[\bar{V}_j^d - d(c_j + \omega_j) \mid (v_j^d > v_j^{d-1}) \text{ and } (v_j^d > v_j^{d+1})] \\
&= \sum_{0\le d\le D} P_j^d(\bar{V}_j^d - d \times c_j) \\
&\quad - DP_j^D E_{\omega_j}[\omega_j \mid \omega_j < \bar{V}_j^D - \bar{V}_j^{D-1} - c_j] \\
&\quad - \sum_{0<d<D} dP_j^d E_{\omega_j}[\omega_j \mid \bar{V}_j^{d+1} - \bar{V}_j^d - c_j < \omega_j < \bar{V}_j^d - \bar{V}_j^{d-1} - c_j] \\
&= \sum_{0\le d\le D} P_j^d(\bar{V}_j^d - d \times c_j) + D\varsigma_j \phi\left(\frac{\bar{V}_j^D - \bar{V}_j^{D-1} - c_j}{\varsigma_j}\right) \\
&\quad + \sum_{0<d<D} d\varsigma_j \left[\phi\left(\frac{\bar{V}_j^d - \bar{V}_j^{d-1} - c_j}{\varsigma_j}\right) - \phi\left(\frac{\bar{V}_j^{d+1} - \bar{V}_j^d - c_j}{\varsigma_j}\right)\right]. \quad (16)
\end{aligned}$$

Here $\phi(\cdot)$ is the probability density function for the standard normal distribution. Conditional on other firms' policy function $P_{-j}(S)$ and expected value function $V_{-j}(S)$, we can compute firm $j$'s policy function $P_j$ and expected value function $V_j(S)$ when we solve the game for counterfactual simulations. In equilibrium, firms' detailing policies should be mutually consistent.

## 5. Estimation Strategy

Two-stage estimation for dynamic models stemmed from work by Hotz and Miller (1993) and Hotz et al. (1994), who proposed this approach for a single-agent, discrete-choice dynamic problem. Since then, two-stage estimation has been extended to multiagent discrete choice and continuous action dynamic problems in work by Aguirregabiria and Mira (2007), Pakes et al. (2007), and Bajari et al. (2007). The basic idea of two-stage estimation is described by Bajari et al. (2007) as follows: First, in an equilibrium model, firms are assumed to have correct beliefs about their economic environment and the actions of other agents. As a result, we can empirically recover the firms' equilibrium beliefs by estimating the probability distribution for their observed actions.[10] Second, in an equilibrium model, firms are assumed to maximize expected discounted profits given their beliefs. The conditions for optimality can be represented as a system of inequalities that require that each firm's observed decisions at each state be weakly preferred to any feasible alternatives. The dynamic model's structural parameters are estimated as the solution to this system of inequalities.

Following this approach, in the first stage we estimate firms' demand functions, policy functions governing firms' detailing behavior, and state transition functions by pooling the data across physicians. In the second stage, we estimate the marginal cost of detailing ($c_j$) and standard deviation of the private shock distribution ($\varsigma_j$) by simulating the behavior of firms, given the first-stage estimates and imposing the equilibrium conditions of the MPNE embodied in Equation (8).

### 5.1. First-Stage Estimation

We use detailing data of the first 4 months (from June 2002 to September 2002) to initialize detailing stock for Lipitor and Zocor,[11] and the remaining 20 months (from October 2002 to May 2004) to estimate demand.

[10] Ching (2010a) develops another approach that is closely related to Bajari et al. (2007). He estimates a pseudo-pricing policy function jointly with a model of dynamic demand for prescription drugs after patent expiration. This allows him to recover the firms' pricing policy functions. Ching and Ishihara (2010) use his approach to recover firms' detailing policy functions.

[11] An average of preliminary detailing stock levels over the first 12 months (from June 2002 to May 2003) is used for approximating detailing stock in the month ahead of the four-month period (Lipitor and Zocor). To calculate the preliminary detailing-stock levels,

Note that the transitions of state variables are known once we have estimates of the detailing retention rate from the demand estimation.

Identification of detailing effects in our model is based on both across-physician and across-time variability. Since we pool data across physicians, on the cross-physician side, concern about a spurious detailing effect may arise if a firm allocates more detailing visits to physicians who have stronger preference for the drug. It is well known that a homogeneous demand model (i.e., not controlling for physicians' heterogeneous brand preferences) may overestimate detailing effects. Chamberlain (1980) has also shown that there can be asymptotic bias in random coefficient demand models estimated with only a conditional likelihood function when random intercepts are correlated with independent variables. However, our inclusion of fixed physician brand intercepts precludes such a concern and allows us to get unbiased estimates even if detailing levels are correlated with brand intercepts. It is also worth noting that previous studies such as Manchanda et al. (2004) modeled the number of category prescriptions, which is susceptible to being a driver of the number of details (i.e., firms detail more to physicians who write many category prescriptions). By contrast, we model physicians' choice probabilities of different drugs to prescribe, hence our model is less susceptible to this particular simultaneity/endogeneity concern even if we do not use fixed physician brand intercepts.

In relying on the variation over time, we carefully control for the partial availability of Crestor in August 2003 (the month of Crestor introduction), medical news, and other time-specific factors by using time fixed effects in the proposed demand model. Failure to control for such factors can seriously bias the estimates of detailing effects. Further, our demand model omits one important element of the pharmaceutical promotional mix, DTCA. In general, DTCA has been found to affect patient visits to physicians (Liu and Gupta 2011) or influence patients to request advertised drugs from physicians. The role of DTCA varies across therapeutic categories. If DTCA has significant effects on drug requests in the hyperlipidemia category and if firms' DTCA expenditures are positively correlated with detailing schedules, we may overestimate detailing effects because of the failure to control for the effects of DTCA in our demand model. This, however, might not be a grave concern in our case because (i) statin drugs spend more than 90% of DTCA budgets on national media (Stremersch et al. 2013). As a consequence, the time fixed effects can absorb these effects on demand; (ii) Stremersch et al. (2013) find that DTCA does not impact patient requests for statin drugs. The time fixed effects can also help to control for the national publicity that has been found to influence prescription drug demand (Ching et al. 2016). Despite these controls, we cannot rule out the possibility of detailing endogeneity in our brand choice model because of unobserved demand effects (Villas-Boas and Winer 1999), e.g., DTCA and publicity in local media. Given the difficulty of finding a good instrument for detailing and the goals of this study, we leave a full test and remedy of detailing endogeneity to future research. While noting the difficulty of a completely clear interpretation of the estimated detailing effect, we take it as unbiased for the subsequent analysis of detailing policies.

we use a monthly detailing stock retention rate of 0.86 reported by Narayanan et al. (2004). Our estimates are insensitive to this approximation because of significant decay after four months.

We turn next to the estimation of the detailing policy function. For two-stage estimation to work, the state space needs to be stationary over time, so that observed detailing decisions for different months can be pooled to recover a detailing policy function. The entry of Crestor midway through our data periods, however, invalidates the stationarity assumption. After the entry of Crestor, incumbent firms may opt to play a qualitatively different equilibrium than they did before. More importantly, forward-looking incumbents should anticipate the entry of Crestor and change their detailing policies in the months ahead of Crestor's entry. This poses a challenge for the estimation of the detailing policy. Although the state space is not stationary over the entire study period, one can reasonably assume that the state space is stationary over the time period after Crestor's entry, namely, the last nine months. Therefore, we bypass the aforementioned problem by only using the observed detailing actions from the last nine months to recover firms' optimal detailing strategies. The month fixed effects captured by $X_t$ in the last nine months are assumed to be random events that firms cannot foresee.

Detailing policy function estimation aims to empirically recover the optimal strategies, $\sigma_j$: $\mathcal{S} \times \otimes_j \rightarrow \mathcal{D}_j$ from the observed data. Estimation of policy functions is challenging because these functions are equilibrium outcomes and any particular parametric form assumed for the policy functions would be unlikely to be consistent with the primitives of the underlying dynamic game. In other words, a flexible estimation approach is preferred where the functional relationship between ($d_{pjt}$) and ($S_{pt}$, $\omega_{pjt}$) is mainly determined by the observed data.

Firms' decision variable at each physician—the number of details per month—is ordered discrete data in nature, which suggests the use of an ordered discrete model. By examining the optimal probabilities derived in Equation (13), we see that an ordered

probit model structure fits the derived optimal policies well. Given the continuous nature of state variables, we adopt an ordered probit regression model to approximate the distribution of detailing actions at each state.

If one had access to large amounts of data for each physician and firm, one could estimate the detailing policy functions separately at each physician for each firm and then impose MPNE conditions in the second stage. This estimation strategy would allow firms to play a different equilibrium at each physician. However, because of our data limitation, we pool data across physicians to recover firms' optimal detailing strategies by assuming that the same equilibrium is played at all physicians. Consistent with this pooling strategy, the common state variable $S_t$ consists of (i) each firms' detailing stock at time $t-1$, $G_{pjt-1}$; (ii) an exogenous time varying state variable to capture the effect of December holidays; (iii) a vector of exogenous physician-specific characteristics (e.g., patient size $M_p$). Since we do not observe all physician-specific characteristics, we use physician-specific fixed effects to capture their effects. Additionally, we include brand-specific fixed effects to capture the base difference in detailing between brands.[12] A similar strategy of pooling data across markets or/and firms and then controlling for market or/and firm fixed effects in the policy estimation has been used in the literature on two-stage dynamic game estimation (Yao and Mela 2011, Ryan 2012, Suzuki 2013).

Specifically, we define firm $j$'s latent value of detailing to physician $p$ at time $t$, $W_{pjt}$, as

$$\begin{aligned} W_{pjt} &= \vartheta_p + \eta_j + \zeta\Gamma_t + \theta_{1j}' bs_{1j}(G_{pjt-1}) \\ &\quad + \theta_{2j}' bs_{2j}(sumG_{p-jt-1}) + \epsilon_{pjt}, \\ \epsilon_{pjt} &\sim N(0,1) \quad p=1,\dots P; t=1,\dots,T, \\ d_{pjt} &= d \quad \text{if } \tau_d \le W_{pjt} < \tau_{d+1} \ d=0,1,2,3,4, \end{aligned} \tag{17}$$

where $\vartheta_p$ is the intrinsic value of detailing to physician $p$; $\eta_j$ is a brand-specific fixed effect that captures the difference in the value of detailing between brands; $\Gamma_t$ is an exogenous state variable to capture the effect of December holidays; $\tau_d$ is a latent "cutoff point" that satisfies $\tau_d < \tau_{d+1}$, $\tau_0 = -\infty$, $\tau_5 = \infty$, and we fix $\vartheta_P = 0$ and $\eta_J = 0$ for identification. Here, we set four as the maximum detailing level per physician-month given that most physician-months witness no more than four detailing visits from a brand in our data. Following a similar approach invoked in previous research (Yao and Mela 2011, Ryan 2012), we use a summary measure of firm $j$'s competitive detailing stock, $sumG_{p-jt-1}$, to approximate the competing states in a limited information context. Since we want to be as flexible as possible in recovering a firm's detailing behavior as a function of the state variables, we use the method of sieves in the detailing policy estimation. In particular, we use cubic b-splines as the basis functions of own detailing-stock and sum competitive detailing stock for firm $j$, denoted by $bs_{1j}(\cdot)$ and $bs_{2j}(\cdot)$, respectively. Although we pool data across all brands to estimate physician fixed effects, we allow for a different optimal detailing strategy for each brand by specifying brand-specific basis functions and brand-specific coefficients for detailing-stock splines in Equation (17).

[12] Ideally, we would like to include a dummy variable for each physician-firm combination. Given that we use only nine months of data for each firm at each physician, we are not able to allow for physician-firm fixed effects.

### 5.2. Second-Stage Estimates

The first stage provides estimates of demand functions and firms' equilibrium policy functions. The second-stage estimation is concerned with finding supply side structural parameters $\phi_j = (c_j, \varsigma_j)$ that can rationalize these observed policy functions. In other words, the goal is to estimate costs that are consistent with the observed profit-maximizing detailing decisions.

Once again, we drop the physician subscript to simplify notation in this subsection. Suppose that firm $j$ and its competitors follow a Markov strategy profile $\sigma$, and the value function of firm $j$ at state $S$ is given as

$$\begin{aligned} &V_j(S \mid \sigma; \phi_j) \\ &\quad = E\left[\sum_{t=0}^{\infty} \rho^t \tilde{\pi}_j(\sigma(S_t, \omega_t), S_t, \omega_{jt}; \phi_j) \mid S_0 = S; \phi_j\right]. \end{aligned} \tag{18}$$

Notice from profit function (5) that the profit $\tilde{\pi}_j$ is linear in the supply side parameters $c_j$ and $\varsigma_j$ if we define $\omega_j = \varsigma_j \nu_j$, where $\nu_j \sim N(0,1)$. As a consequence, firm $j$'s value function $V_j$ can be further expressed as a linear function of $\phi_j$:

$$V_j(S \mid \sigma; \phi_j) = M_j(S \mid \sigma) + N_j(S \mid \sigma) \cdot \phi_j', \tag{19}$$

where

$$M_j(S \mid \sigma) = E\left[\sum_{t=0}^{\infty} \rho^t \pi_{jt}(S_t, \sigma_j(S_t, \omega)) \mid S_0 = S\right], \tag{20}$$

$$\begin{aligned} N_j(S \mid \sigma) = \Bigg(&E\left[\sum_{t=0}^{\infty} \rho^t \sigma_j(S_t, \omega) \mid S_0 = S\right], \\ &E\left[\sum_{t=0}^{\infty} \rho^t \sigma_j(S_t, \omega)\nu_j \mid S_0 = S\right]\Bigg). \end{aligned} \tag{21}$$

The linearity of the unknown parameters significantly reduces the computation burden in the second-stage estimation because we do not have to simulate separate value function paths for each set of parameters.

With the linearity, the optimality conditions (8) can be written as

$$M_j(S \mid \sigma_j, \sigma_{-j}) + N_j(S \mid \sigma_j, \sigma_{-j}) \cdot \phi_j \geq M_j(S \mid \sigma_j', \sigma_{-j}) + N_j(S \mid \sigma_j', \sigma_{-j}) \cdot \phi_j. \quad (22)$$

Let $X \in \chi$ index the equilibrium conditions, so that each $X$ denotes a particular deviation $(S, \sigma_j')$ combination. Define a new function $g(X; \phi_j)$ as

$$g(X, \phi_j) = M_j(S \mid \sigma_j', \sigma_{-j}) - M_j(S \mid \sigma_j, \sigma_{-j}) + [N_j(S \mid \sigma_j', \sigma_{-j}) - N_j(S \mid \sigma_j, \sigma_{-j})] \cdot \phi_j. \quad (23)$$

Here $g(X, \phi_j) \geq 0$ means that strategy $\sigma_j'$ is a profitable deviation from the optimal policy. On the other hand, the optimality condition (22) is satisfied if and only if $g(X, \phi_j) \leq 0$. As a consequence, if the observed detailing policy is the firm's optimal policy, upon plugging the true detailing cost parameters into the profit function, the calculated function value of $g(X, \phi_j)$ should be less than or equal to zero. The intuition for second-stage estimation therefore comes from this assertion: if we can find value of parameters such that chances of profitable deviations from the optimal policies are minimized, those parameters then will be as close as possible to the true cost of detailing.

Formally, suppose $H$ is a distribution over the set $\chi$ of inequalities that is chosen by the researcher. We define the function

$$Q(\phi_j) = \int 1(g(X; \phi_j) > 0) \cdot g(X; \phi_j)\, dH(X). \quad (24)$$

The true parameters, $\phi_j^0$, satisfy

$$Q(\phi_j^0) = 0 = \min_{\phi_j \in \oplus} Q(\phi_j). \quad (25)$$

Therefore, the estimator of $\phi_j$ is formed by minimizing the sample analog of $Q(\phi_j)$. Specifically, the estimation proceeds in two steps. In the first step, we construct the sample analog of $Q(\phi_j)$. Let $\{x_k\}_{k=1,\ldots,n_I}$ be a set of inequalities from $\chi$ randomly drawn from the distribution $H$. These independent and identically distributed draws are created by drawing states at random and adding normally distributed noise to the estimated optimal policy. The resulting alternative policies $\sigma_j'$ represent slight perturbation of the estimated optimal policy. For each chosen inequality, $x_k$, we use a forward simulation procedure to construct empirical analogues of $N_j$ and $M_j$. We denote the resulting empirical counterpart to $g(X, \phi_j)$ by $\tilde{g}(x, \phi_j)$. The sample analog of $Q(\phi_j)$ is then given by

$$Q_n(\phi_j) = \frac{1}{n_I} \sum_{k=1}^{n_I} [1(\tilde{g}(x_k; \phi_j) > 0) \cdot \tilde{g}(x_k; \phi_j)]. \quad (26)$$

In the second step, we use an optimization procedure to minimize this objective function and get the estimator

$$\hat{\phi}_j = \arg\min_{\phi_j \in \oplus} Q_n(\phi_j). \quad (27)$$

## 6. Results and Discussion

### 6.1. Demand Model

We report the estimation results of the demand model specified in Equation (1) in column II of Table 3. For all three brands, the estimates of detailing-stock effects are positive and significant, confirming results from previous studies. Crestor has the largest detailing-stock effect (0.533), followed by Zocor (0.225), and Lipitor (0.218). We believe the higher detailing-stock effect of Crestor is because (i) it is a new drug, hence physicians are more receptive to its messaging; and (ii) sales representatives of AstraZeneca (manufacturer of Crestor) are more effective. Evidence from the industry indicates that AstraZeneca leads in detail minutes per call and percent of calls rated excellent or good.[13] The estimate of the detailing-stock retention rate is 0.878, indicating strong carryover effects. This is consistent with previous findings and justifies the need for the dynamic framework we use for firms' detailing decisions.

In Figure 1, we plot the monthly fixed effects estimates for the three brands. The figure shows that the entry of Crestor in August 2003 affects Zocor the most, with a large downward shift in its monthly fixed effects in the subsequent months. This suggests that upon Crestor's entry, physicians are more likely to switch to Crestor from Zocor than from Lipitor or the nondrug treatment. A large negative fixed effect in month August 2003 for Crestor captures the partial availability of Crestor in the month. The negative impact on Crestor in March 2004 of Public Citizen's petition to the FDA described previously is noticeable in the figure. Interestingly, the other two drugs also suffered a concurrent drop possibly due to a spillover effect of this negative news. By examining Figure 1, we can also see that no time trend can be detected from the monthly fixed effects for the last nine months for each of the three brands. Formally, we calculate the first order autocorrelation of the estimated monthly fixed effects from the last nine months for each of the three brands. We find that none of the coefficients is significant, which suggests that the estimated fixed effects can be treated as random events.

For comparison, we also estimate an alternative demand model with brand intercepts $\alpha_j$ set to be

[13] IMS Health Integrated Promotional Services, 12 months ending July 2003, cited in a presentation titled "AstraZeneca 2003 US Commercial Effectiveness" by Tony Zook, Senior VP Commercial Operations, AstraZeneca.

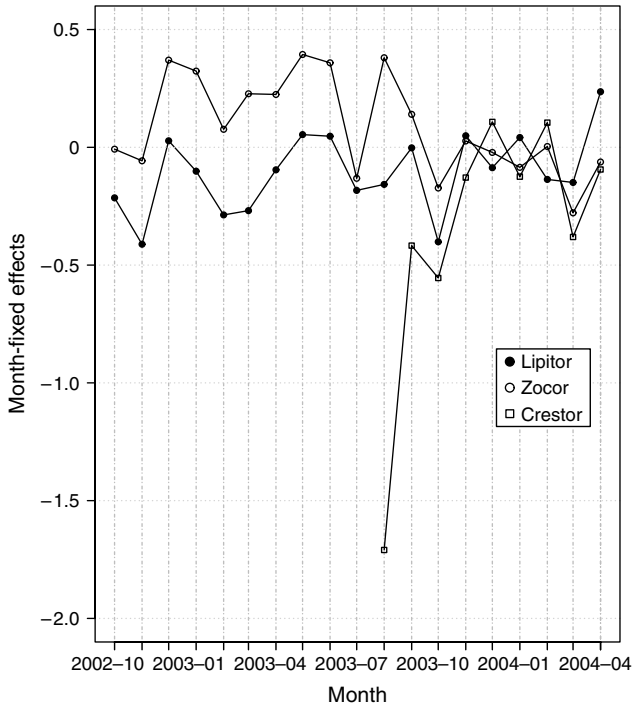
**Table 3 Prescription Drug Demand Estimates**

| | I | II[a] |
|---|---|---|
| Intrinsic utility[b] | | |
| Lipitor $\alpha_1$ | −0.260 | — |
| | (0.062) | |
| Zocor $\alpha_2$ | −0.943 | — |
| | (0.060) | |
| Crestor $\alpha_3$ | −0.748 | — |
| | (0.058) | |
| Detailing-stock effect | | |
| Lipitor $\beta_1$ | 0.236 | 0.218 |
| | (0.021) | (0.028) |
| Zocor $\beta_2$ | 0.222 | 0.225 |
| | (0.023) | (0.027) |
| Crestor $\beta_3$ | 0.528 | 0.533 |
| | (0.027) | (0.030) |
| Detailing-stock retention rate $\lambda$ | 0.884 | 0.878 |
| | (0.017) | (0.015) |
| Akaike information criterion | 36,788 | 31,795 |

[a]Estimates of $\alpha_{pj}$ and $\gamma_{jt}$ are not shown for reasons of space.
[b]Intrinsic utility of nondrug treatment is set to 0 for identification.

homogeneous across physicians. Results are shown in column I of Table 3. We see that Lipitor has the largest intrinsic utility among the three brands. As to the detailing effects, the homogeneous demand model gives similar estimates as the proposed model. However, according to the Akaike information criterion, the proposed demand specification greatly outperforms the homogeneous demand model in model fit.

**Figure 1 Estimated Monthly Fixed Effects in Demand Models**




## 6.2. Detailing Policy

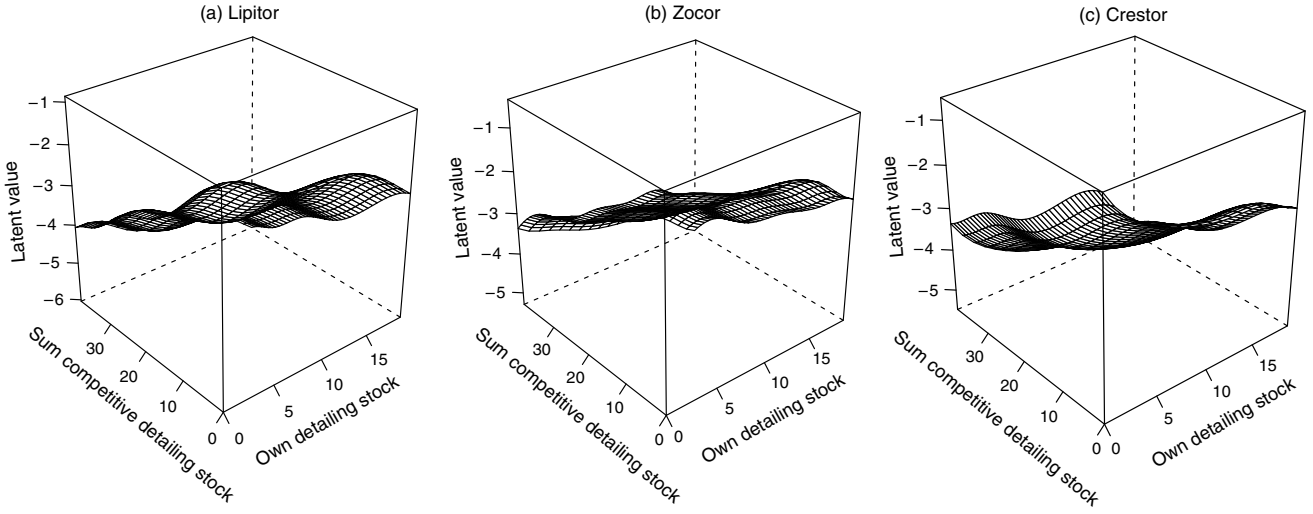
Table 4 reports detailing policy estimates based on the proposed specification and two alternative model specifications. Column III shows estimated coefficients of the proposed model—detailing policy specified in Equation (17)—for variables other than splines and physician-fixed effects. In the estimation, we use eight knots each for the own detailing stock and sum competitive detailing stock and strategic. We also tried alternative numbers of knots to check the robustness. The results turn out to be largely insensitive to the number of knots. The coefficient of holiday month (December) is negative, confirming that firms schedule fewer detailing visits in that month.

Because the relationship between the latent value of detailing and state variables (own detailing stocks and sum competitors' detailing stock) is a superposition of several piecewise polynomials, interpreting the b-spline coefficients is not insightful. Instead, to illustrate the dependence between detailing decisions and state variables captured by our ordered probit model with b-splines, we plot in Figure 2 for each of

**Table 4 Detailing Policy Estimates**

| | I | II | III |
|---|---|---|---|
| Own detailing stock | | | |
| Lipitor | — | −0.332 | See Figure 2 |
| | | (0.020) | |
| Zocor | — | −0.329 | —"— |
| | | (0.020) | |
| Crestor | — | −0.222 | —"— |
| | | (0.019) | |
| Sum competitive detailing stock | | | |
| Lipitor | — | −0.090 | See Figure 2 |
| | | (0.003) | |
| Zocor | — | −0.086 | —"— |
| | | (0.004) | |
| Crestor | — | −0.070 | —"— |
| | | (0.003) | |
| Brand effect | | | |
| Lipitor | −0.716 | −0.642 | −1.339 |
| | (0.026) | (0.049) | (0.639) |
| Zocor | −0.472 | −0.588 | −1.671 |
| | (0.025) | (0.048) | (0.817) |
| Holiday effect (December) | −0.219 | −0.187 | −0.212 |
| | (0.030) | (0.030) | (0.031) |
| Threshold | | | |
| $\tau_1$ | −1.317 | −2.730 | −5.125 |
| | (0.205) | (0.213) | (0.529) |
| $\tau_2$ | −0.371 | −1.702 | −4.082 |
| | (0.204) | (0.212) | (0.528) |
| $\tau_3$ | 0.372 | −0.886 | −3.528 |
| | (0.205) | (0.211) | (0.528) |
| $\tau_4$ | 0.973 | −0.227 | −2.595 |
| | (0.205) | (0.212) | (0.527) |
| Splines | No | No | Yes |
| Akaike information criterion | 29,378 | 27,817 | 27,656 |

**Figure 2 Detailing Policy as a Function of Own and Sum Competitive Detailing Stock**




the three drugs the predicted latent value of detailing with respect to its own detailing stock and sum competitive detailing stock.

As shown in Figure 2, the latent value of detailing decreases as a firm's own detailing stock increases. In other words, firms tend to direct less detailing to a physician if they already have a high detailing stock at that physician. This result is consistent with the preliminary model-free evidence discussed previously, and with the finding of Dubé et al. (2005) that the optimal advertising level decreases in own goodwill. Intuitively, because of the diminishing marginal returns to detailing, it is less profitable for a firm to detail a physician if there is already a high level of detailing stock at the physician. This intuitive explanation is also consistent with the implication suggested by Ching and Ishihara (2010) in a physician learning framework. A firm's detailing response to sum-competitive detailing stock shows a similar pattern, in that its latent value of detailing decreases in its competitors' detailing stock. The resulting detailing pattern is consistent with a previous finding by Villas-Boas (1993): oligopolists should advertise in alternating periods. It is more profitable for a firm to detail a physician when its competitors' detailing stock is low at that physician.

The alternative specification for which results are reported in Table 4, column I is an ordered probit model without any detailing-stock state variables. The alternative specification for which results are reported in column II is a parametric policy function in which own and sum-competitive detailing-stock state variables enter the latent value function linearly. Similar to the proposed specification, both alternative specifications include physician fixed effects.

To validate our proposed policy function specification, we compare fit statistics of the proposed model with the two alternative specifications in the last row of Table 4. The Akaike information criterion measures show that the parametric form (27,817) significantly underperforms the proposed specification (27,656). Further, inclusion of dynamic terms (own detailing stock and sum-competitive detailing stock) greatly improves the model fit relative to the model without these variables (29,378), which is consistent with our basic premise that firms are forward looking and strategic. We also find that although the parametric linear specification of detailing policy captures negative impacts of own detailing-stock and sum-competitive detailing-stock, the model is not sufficient to capture firms' complex strategic detailing behaviors, such as the nonlinearity shown in Figure 2.

In summary, the estimated policy functions show that firms are forward looking and their latent value of detailing is negatively impacted by their own detailing stock and sum-competitive detailing stock. A flexible approach, such as the method of sieves, is necessary to consistently capture firms' complex strategic behaviors.

### 6.3. Detailing Costs

Analysis of detailing costs provides vital information for understanding and evaluating firms' detailing behaviors. The detailing cost structure specified in our framework includes a constant marginal cost of detailing, $c_j$, and a distribution of private shock on detailing cost, $N(0, \varsigma_j)$. We obtain the estimates of the detailing cost structure under the assumption that observed levels of detailing represent profit-maximizing behavior of competing firms. Thus, all relevant economic information is included in the estimates. Some questions are pertinent: How should our estimates be interpreted? What are the components of the marginal cost of a detailing visit estimated using our approach?

Consider a firm that can flexibly increase or decrease its total sales force effort, as well as the sales force effort allocated to any given drug and physician. Flexibility in overall sales force effort can be achieved, for example, by outsourcing (i.e., by employing a contract sales force). In determining the optimal sales force effort, the relevant question is what is the economic cost of one additional detailing visit? We believe the relevant cost for this firm is the allocated full cost of a sales representative's time. This includes salary, commissions, benefits, travel costs, and any other out-of-pocket costs incurred to visit the physician. It is important to note that although costs such as sales representatives' salary and benefits are ordinarily considered fixed and hence not part of marginal cost, the foregoing discussion implies that our estimates of the marginal cost of a detailing visit do include these components.

Note that our approach to estimating detailing costs takes into account both, periods when firms detail and periods when they choose to not undertake any detailing. In the latter periods, firms make the decision to not detail based on their prediction of the marginal cost of detailing and the return to detailing. The inclusion of a private shock in our detailing cost model allows the estimated marginal cost to be an average over the two kinds of periods and hence capture all economically relevant information from both, decisions to detail and decisions not to detail. We believe this makes our estimated cost suitable for counterfactual simulations.

As discussed previously, we estimate a common detailing cost structure by pooling the data across all physicians. We use physician-level point estimates of the demand model and detailing policy to conduct physician-level forward simulations of $[M_j(S\,|\,\sigma_j',\sigma_{-j}) - M_j(S\,|\,\sigma_j,\sigma_{-j})]$ and $[N_j(S\,|\,\sigma_j',\sigma_{-j}) - N_j(S\,|\,\sigma_j,\sigma_{-j})]$ in Equation (23) for all three brands over a lifetime of 100 months. For each physician, we use 100 simulation paths. Each simulation path has a unique deviation from the optimal policy and was replicated 50 times and averaged to obtain expected values. The estimate of the detailing cost structure of the "representative" physician is obtained using the approach laid out in §5.2 on forward simulations.

We need to determine the profit function for each drug in order to estimate the cost structure. We use the retail price and industry average manufacturer margin (53%) to approximate the firms' margin per prescription (Consumer Reports 2006, Coster 2000). To approximate the market size, we use the observed average number of patient visits per physician and month, 3.98,[14] and the mean number of months of continuous therapy, 21.[15] We also assume a common fill rate of 75% for written prescriptions for these three drugs.[16] The monthly discount factor is fixed at 0.99 in this study.

Note that the first-stage sampling instead of the second-stage simulation contributes to the asymptotic distribution of the estimators in the second stage. To obtain standard errors for the estimates of detailing cost, we use 25 subsamples of 224 physicians (50% of the full sample) and calculate the standard deviation of estimates in the second stage resulting from those 25 subsamples.

Although in Table 5 we see substantial differences in the estimated marginal detailing costs of Crestor, Lipitor and Zocor, the large estimated standard errors of marginal costs imply that these differences are not statistically significant. The average constant marginal cost of detailing across the three brands is \$153, which is similar to estimates based on industry accounting data. For example, Neslin (2001) reported that the average cost per detailing call in 1999 for office-based physicians was US\$138 and Lewis (2001) reported an approximate cost of US\$200 for a field representative's visit. Notably, these accounting measures of detailing costs do not differentiate between brands. We also want to emphasize here that accounting-based estimates of detailing cost only apply to the observed optimal detailing scenario, and cannot reflect the cost changes that originate from a change in detailing policy and therefore are not suitable to understand the implications of detailing restriction policies on competing firms.

With the estimated demand and detailing cost structures, we solve the dynamic competition game in detailing specified at the physician level. The solution algorithm involves iterating on the Bellman equation for all firms (see Equation (7)) and is similar to the modified policy iteration algorithm used by Dubé et al. (2005). In Table 6, we report the predicted market share and detailing frequency for each brand. These predications are based on a nine-month simulation in order to be comparable to the observed data. We note that the predictions are reasonably close to

[14] In ImpactRx data, physicians record prescriptions two days each week. So the mean number of patient visits per month is $2.5 \times 1.59 = 3.98$, where 1.59 is the mean number of patient visits per month from our sample, and 2.5 is the ratio of five working days per week and two prescription recording days.

[15] Here, we approximate the average renewal rate using the ratio of the volume of new written prescriptions to the volume of renewal written prescriptions. As a validation of this calculation, Howell et al. (2004) report a similar continuous therapy duration for statin users (23 months). The discounted value of continuous therapy is calculated by allocating renewal prescriptions according to a statin therapy duration curve provided by Cardinal et al. (2006).

[16] A study in general practice indicates that up to 25% of patients do not take statins as prescribed (Howell et al. 2004). A similar fill rate of statins is suggested by Benner et al. (2002).

**Table 5 Estimates of Detailing Costs ($)**

| | Marginal cost ($c_j$) | | SD of private shocks ($s_j$) | |
|---|---|---|---|---|
| Drug name | Mean | SE | Mean | SE |
| Lipitor | $150 | $44 | $36 | $13 |
| Zocor | 121 | 49 | 40 | 16 |
| Crestor | 187 | 42 | 39 | 14 |

**Table 6 Market Share and Detailing Frequency Prediction**

| | Market share (%) | | Detailing frequency per month | |
|---|---|---|---|---|
| Drug name | Observed | Predicted | Observed | Predicted |
| Lipitor | 29.51 | 29.23 | 0.822 | 0.806 |
| Zocor | 15.02 | 14.69 | 1.028 | 0.876 |
| Crestor | 32.99 | 33.18 | 1.425 | 1.515 |
| Nondrug | 22.48 | 22.90 | — | — |

the observed data, providing one measure of model validity.

## 7. Counterfactual Simulations

As discussed previously, with the estimates of the demand parameters and detailing cost structure, we can compute detailing equilibria and profit impacts under different hypothetical detailing regulation/access restriction scenarios.

In the first counterfactual study, we examine the effects of an event that limits the amount of sales promotion that a pharmaceutical firm can direct to physicians. Specifically, we assume that a ceiling is placed on the number of detailing visits for a drug that can be made to a physician within a certain time period. The precipitating event may be government regulation, or access restrictions placed by individual physicians, or the practice to which they belong. We consider two levels of ceilings: (1) each firm can make no more than one detailing visit to a given physician per month; and (2) each firm can make no more than one detailing visit to a given physician per quarter. We assume that the estimated demand and supply side parameters are invariant to this policy change, and hence we can solve the dynamic game using these parameters. We first simulate the market shares and optimal detailing frequencies for a benchmark scenario based on the solution of the original dynamic game as in Table 6, but for more time periods (24 months). We then solve the two dynamic games for ceiling 1 and ceiling 2 and simulate corresponding optimal detailing frequencies and market shares for 24 months. In both benchmark simulation and counterfactuals, Crestor starts as a new brand with zero detailing stock. We report results in Table 7.

A ceiling policy on monthly detailing frequency of no more than one per month reduces each drug's detailing frequency. Among the three brands, Zocor is affected the most with a 31.8% reduction in its detailing frequency (from 0.877 to 0.598), followed by Crestor (from 1.280 to 0.926), and Lipitor (from 0.818 to 0.602). For ceiling 2, the stricter policy (max one per quarter), we find that Crestor sets its optimal detailing frequency exactly at the ceiling, but Lipitor and Zocor set their optimal detailing slightly below the ceiling. It is straightforward that firms' detailing will be reduced in months in which detailing levels were previously above the ceiling because of the "mechanical" effect of the ceiling polices. However, it is worth noting that firms are able to move some of the reduced detailing to months in which detailing levels were previously not hitting the ceiling (i.e., the firm can reallocate detailing across months). Given the fact that Crestor's average detailing exceeded the ceiling but its competitors' average detailing levels were below the ceiling under the benchmark scenario, we may conjecture that Lipitor and Zocor will have more freedom to reallocate the chopped detailing to months in which detailing levels were below the ceiling, ceteris paribus. However, it is interesting that a comparable (even larger in the case of Zocor) reduction occurs under ceiling 1 for Lipitor and Zocor as well. We believe that the private shocks to detailing cost play an important role in reducing the overall detailing level for firms whose average unrestricted optimal detailing levels are below the ceiling when a ceiling policy is imposed. In the absence of a ceiling, firms were able to flexibly allocate their detailing across different months to exploit intertemporal variation in cost of detailing. Thus, they could allocate more than one visit to months with lower realized marginal costs ($c_j + \omega_{pjt}$) and make no visit in months with higher effective marginal costs. The ceilings on detailing visits, however, limit a firm's flexibility to do so. Although the firm is able to move some chopped

**Table 7 Counterfactual Simulations for 24 Months with a New Brand**

| Drug name | Benchmark | Ceiling 1 (Max 1/Month) | Ceiling 2 (Max 1/Quarter) | Double MC |
|---|---|---|---|---|
| | Detailing frequency per month | | | |
| Lipitor | 0.818 | 0.602 | 0.331 | 0.264 |
| Zocor | 0.877 | 0.598 | 0.328 | 0.326 |
| Crestor | 1.280 | 0.926 | 0.333 | 0.629 |
| | Market share (%) | | | |
| Lipitor | 28.25 | 29.32 | 31.75 | 29.13 |
| Zocor | 14.23 | 14.56 | 15.78 | 14.68 |
| Crestor | 35.93 | 33.35 | 27.69 | 32.12 |
| Nondrug | 21.59 | 22.77 | 24.78 | 24.07 |
| | Profit change relative to benchmark (%) | | | |
| Lipitor | — | 5.96 | 19.80 | 7.13 |
| Zocor | — | 4.29 | 18.02 | 5.13 |
| Crestor | — | −4.07 | −5.16 | −16.51 |
| Industry total | — | 1.55 | 9.29 | −2.88 |

detailing visits to other months with a ceiling policy imposed, the effective marginal cost goes up and reduces firms' incentive to reallocate more detailing visits to those months. We calculated each firm's realized marginal costs for detailing under the benchmark scenario and under ceiling 1. Consistent with the above explanation, we find that the realized marginal costs of detailing increases for all three brands under ceiling 1. Specifically, Zocor sees the largest increase by 36.1%, followed by Lipitor (22.9%) and Crestor (18.3%). The stronger "headwind" on marginal cost faced by Zocor is consistent with the fact that Zocor has a largest relative reduction in detailing under ceiling 1, even though the brand's average detailing level is below the ceiling under the benchmark scenario. Policy makers and drug companies might be surprised to learn that imposing a ceiling on detailing could limit their flexibility in reallocating detailing over time and lead to substantial reduction in detailing across the board including for firms that have average detailing levels well below the ceiling.

As expected, the nondrug treatment option benefits from each of the ceilings, with market share rising from 21.59% to 22.77% under ceiling 1 and to 24.78% under ceiling 2, respectively. The resulting welfare impact of this change is difficult to assess. On the one hand, the ceilings on detailing reduce the usage of prescription drugs and hence potentially cut the cost of healthcare. On the other hand, this shift may cause undertreatment and hurt patients' health outcomes. For instance, in studying the impact of physician-imposed restrictions on sales representative access, Chressanthis et al. (2012) find that physicians in more access-limited offices are not only less likely to adopt a first-in-class new drug, they also adopt at a slower speed than their counterpart physicians in more open-access offices. In cases where the outside option is generic drugs, the welfare benefit resulting from expanding the outside option is clearer, since health costs are lowered without too much adverse effect on treatments.

The counterfactuals also reveal that with ceiling policies, Crestor, the drug with the largest detailing stock effect and the highest detailing frequency, suffers the most, with its market share reduced from 35.93% to 33.35% and 27.69%, and profit decreased by 4.07% and 5.16%, respectively. It is interesting to note that the capping does not necessarily hurt all firms in this market. Both Lipitor and Zocor benefit from the capping policies and experience increased market shares and profits. By comparing the two ceiling policies, we find that the stricter the ceiling, the more the outside option expands, and the greater the benefits are to firms with weaker detailing effects.

In the second counterfactual study, we investigate exogenous changes, such as regulations that potentially raise pharmaceutical firms' cost of detailing. For example the District of Columbia in the United States passed legislation to require licensure of pharmaceutical sales representatives. The licensure standards mandate that pharmaceutical sales representatives adhere to a code of ethics and meet minimum educational requirements. Similarly, as noted previously, certain kinds of access limits on pharmaceutical representatives placed by physicians may also drive up the costs of detailing. For example, limits on the number of meetings with a particular sales representative may tempt some pharmaceutical firms to secure more office visits with physicians by sending several different representatives to promote the same drug. To understand the impact of increased detailing cost, we compute the equilibrium in a hypothetical case in which the constant marginal cost of detailing of all firms is doubled. The optimal detailing frequency and market shares are reported in the column labeled "double MC" in Table 7.

**Table 8 Counterfactual Simulations for 24 Months with Established Brands**

| Drug name | Benchmark | Ceiling 1 (Max 1/Month) | Ceiling 2 (Max 1/Quarter) | Double MC |
|---|---|---|---|---|
| | | Detailing frequency per month | | |
| Lipitor | 0.810 | 0.628 | 0.333 | 0.343 |
| Zocor | 0.868 | 0.618 | 0.333 | 0.405 |
| Crestor | 1.027 | 0.862 | 0.333 | 0.501 |
| | | Market share (%) | | |
| Lipitor | 27.60 | 27.76 | 29.44 | 28.20 |
| Zocor | 13.89 | 13.75 | 14.53 | 14.23 |
| Crestor | 37.26 | 36.53 | 31.55 | 33.54 |
| Nondrug | 21.25 | 22.01 | 23.98 | 24.03 |
| | | Profit change relative to benchmark (%) | | |
| Lipitor | — | 2.48 | 13.03 | 1.12 |
| Zocor | — | −0.71 | 11.30 | 0.21 |
| Crestor | — | −2.61 | −4.02 | −14.72 |
| Industry total | — | −0.89 | 5.05 | −5.66 |

The results indicate that, as expected, the share of the outside option is enhanced with higher detailing cost. All three drugs reduce their detailing frequencies significantly. In terms of profit, we find that Crestor suffers a significant reduction from the benchmark scenario, but both Lipitor and Zocor enjoy an increase even if in the face of doubled marginal costs. Lipitor and Zocor benefit in part because of their sharply reduced detailing frequencies as a result of reduced competition from Crestor. The gains may also arise from the fact that Lipitor and Zocor are well-established brands with larger detailing stocks relative to the new entrant Crestor.

To understand the extent to which Crestor is hurt because of being a new brand and hence having low detailing stock, we repeat ceiling 1, ceiling 2, and double MC counterfactuals but with one important difference: we treat Crestor as an established brand

instead of a new brand. To accomplish this, we simulate 48 months of data from the benchmark model and each of the three counterfactuals after the introduction of Crestor, thereby reaching a steady market share and goodwill stock for all brands. We then continue the benchmark and the three counterfactual simulations for another 24 months and discard the initial 48 months of data. Results for the 24-month simulations are in Table 8.

We see that similar to the result found in Table 7, even if Crestor is an established brand, it suffers the biggest profit losses in all three conditions. This suggests that part of the reason for the loss may be that its detailing effect is the strongest. By comparing Table 8 with Table 7, we see that there is a reduction in the asymmetry between brands in terms of the profit impact of the restrictions. For each of the policy changes, Lipitor's profit gains in Table 8 are smaller than those in Table 7, and Crestor's profit reductions in Table 8 are smaller than those in Table 7. The reduced asymmetry suggests that a new brand starting with zero detailing stock suffers more than incumbents because detailing restrictions limit its ability to catch up quickly via aggressive detailing.

We also show in Tables 7 and 8 the change in total industry profits in each of the counterfactual studies. The double marginal cost condition reduces industry profits because of the higher cost of detailing. Industry profits become higher under ceiling policy 1 (max one per month) in Table 7 but lower in Table 8. Industry profits become higher under ceiling policy 2 (max one per quarter) in both Tables 7 and 8. The negative impact of ceiling policies on industry profits probably arises because the ceiling reduces flexibility in allocating detailing resources over time. The positive impact of ceiling policies stems from the reduced detailing level and total detailing costs. In one sense, ceiling policies soften detailing competition. Although both ceiling policy 2 and the double marginal cost scenario cut firms' detailing frequencies to similar levels, their impacts on the industry's total profits are very different.

**Table 9 Counterfactual Simulations for Self-Regulation**

| Drug name | Benchmark | Ceiling on Lipitor (Max 1/Month) | Ceiling on Zocor (Max 1/Month) | Ceiling on Crestor (Max 1/Month) |
|---|---|---|---|---|
| | | Detailing frequency per month | | |
| Lipitor | 0.818 | 0.583 | 0.822 | 0.835 |
| Zocor | 0.877 | 0.884 | 0.569 | 0.897 |
| Crestor | 1.280 | 1.284 | 1.283 | 0.918 |
| | | Market share (%) | | |
| Lipitor | 28.25 | 27.59 | 28.48 | 27.59 |
| Zocor | 14.23 | 14.38 | 13.65 | 14.98 |
| Crestor | 35.93 | 36.26 | 36.16 | 32.82 |
| Nondrug | 21.59 | 21.77 | 21.71 | 22.43 |
| | | Profit change relative to benchmark (%) | | |
| Lipitor | — | −5.01 | 0.82 | 5.87 |
| Zocor | — | 1.01 | −9.66 | 5.73 |
| Crestor | — | 1.12 | 0.75 | −7.66 |
| Industry total | — | −1.33 | −1.26 | 0.34 |

Finally, one may wonder whether self-regulation by an individual firm in terms of limiting its own detailing levels will encourage its competitors to follow suit, thereby reducing industry-wide detailing levels. We answer this question in the counterfactuals by placing a ceiling (maximum one per month) on each of the competing firms' detailing levels in turn, allowing others to be free from restrictions. All other setups are the same as the first counterfactual simulation. We report results in Table 9. We find that competitors raise their detailing levels and do not imitate the firm that self-regulates. For example, the average optimal detailing is increased from 0.818 to 0.835 for Lipitor and from 0.877 to 0.897 for Zocor when Crestor implements self-regulation. In terms of profit change, the firm that self-regulates suffers a profit loss and the competitors enjoy a profit gain. By comparing the results in Table 7 in the column labeled "ceiling 1" with those in Table 9, we see that the nondrug treatment option is expanded less with self-regulation by individual firms than with an industry-wide ceiling policy. Also, self-regulation on detailing leads to either a net reduction in industry total profits or a smaller gain than occurs under the industry-wide ceiling policy. Our counterfactual simulation suggests that self-regulation by individual firms is not likely to succeed in reducing detailing levels across the board, but will in fact increase its competitors' average detailing levels. Notably, this is consistent with our empirical finding that a firm's optimal detailing level is inversely related to its competitors detailing stock.

In summary, our findings from counterfactual simulations provide rich implications for regulators and the pharmaceutical industry. Although restrictions on detailing can promote options such as nondrug treatment or generic drugs, policy makers should be sensitive to other consequences. For instance, a ceiling restriction policy could lead to reduction in detailing across the board. Further, alternative restriction policies that lead to similarly reduced detailing levels may have very different profit consequences for firms. As an industry that is already highly regulated, pharmaceutical firms certainly do not welcome further restrictions, and in fact actively resist them. For instance, in the United States, the pharmaceutical industry spent $2.56 billion on lobbying from 1998 to 2013, which is the largest among all industries.[17] Nevertheless, our analyses suggest that certain forms of regulation may benefit the industry

[17] Source: http://www.opensecrets.org.

as a whole because they soften competition. Further, when restrictions apply to all branded drugs' promotional detailing activities, brands with weaker detailing effectiveness tend to benefit in a competitive market. Restrictions hurt new brands more severely, an outcome that may be undesirable if the new drug offers significant therapeutic advantages. Finally, a self-imposed ceiling policy by individual firms is not likely to induce an industry-wide reduction in detailing. In the end, it is worth noting that our results hinge on our model of firms' dynamic detailing decisions and our estimates of the detailing costs.

## 8. Conclusion

This study introduces and estimates a dynamic structural model of oligopoly competition in detailing. First, we estimate a physicians' demand for prescription drugs. The demand estimates confirm that drug detailing has a positive effect on physicians' prescription choices and this positive effect spills over into future months. Second, we empirically estimate firms' detailing policies from the observed data using an ordered probit model with b-splines. The policy function estimates show that a firm tends to have more detailing when its own detailing stock is small and when its competitors' detailing stock is small. Third and most importantly, using the estimated demand and policy functions, and assuming firms are forward looking in their detailing decisions, we estimate firms' constant marginal costs of detailing and the distribution of private shocks in detailing costs. Our estimates of detailing costs provide information that is not publicly available but is essential to understand firms' detailing decision and to evaluate their profits in different policy scenarios.

To understand the impacts of different policies that restrict detailing activities of firms, we conduct counterfactual simulation studies using the estimated structural parameters. Our studies show that although detailing restriction policies leads to reduced levels of detailing and expands prescription options that do not rely on detailing, they have several effects that may be considered unanticipated and important for both public policy makers and the pharmaceutical industry.

We now discuss some of the limitations of our work and future research avenues. First, in the drug demand model, we do not distinguish between the persuasive and informative effects of detailing. An important area for future research is to model these two effects of detailing separately and assess how each affects the dynamic detailing competition between firms. Second, we do not model physicians' prescription habits in our demand system because we do not observe the exact time of prescription writing in our data. Future research with appropriate data can incorporate the dynamics that result from physician inertia into the dynamic competition framework. Third, our demand model does not incorporate changes in the number of patient visits (market size) over time. Future research can incorporate DTCA and other related factors to model the patient-level market size variation. Fourth, our counterfactual studies focus on detailing only and do not consider the possibility that firms reassign the reduced detailing budget (because of detailing regulation policies) to other promotional tools, such as direct-to-consumer advertising or price discounts. Future research can investigate how firms may reallocate their promotion budget in counterfactual policy environments. Fifth, the particular competitive detailing game we model assumes that firms can observe competitors' detailing activities in the past, which is the case for the sample of physicians included in the study. However, with different, presumably less, data available for the physicians not included in the sample, it is possible that a different game better describes firms' dynamic competition in detailing to those physicians. Finally, the framework developed in this study is not confined to detailing in the pharmaceutical industry. Future research can adapt this framework to marketing activities in other industries.

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