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Treatment Effectiveness and Side Effects: A Model of Physician Learning

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In this paper we study how treatment effectiveness and side effects impact the prescription decision of a risk-averse physician, and how detailing and patient feedback help reduce the physician's uncertainty in these two attributes in the erectile dysfunction category. To separately identify the impacts of effectiveness and side effects, we augment the observed prescription choices with unique data on self-reported reasons for switching in our estimation. Results show that the two new drugs Levitra and Cialis have higher mean effectiveness than the existing drug Viagra, but physicians have large uncertainty regarding the effectiveness for Levitra and side effects for Cialis. Detailing is effective in reducing the uncertainty for effectiveness but much less so for side effects. Based on the results, we investigate the roles of effectiveness and side effects in physicians' prescription choices, and the importance of detailing for new entrants in competing with incumbent drugs.

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1. Introduction

Consumer learning is a topic widely studied in the economics and marketing literature. A risk-averse consumer is less likely to choose a product with large uncertainty. To reduce this uncertainty, he relies on a variety of informational sources such as advertising and/or his own consumption experience. Prior research (for example, Erdem and Keane 1996) has typically focused on the uncertainty and consumer learning of overall product quality. However, products can be differentiated along many dimensions, and consumers routinely evaluate multiple attributes when making purchase decisions. Although this characteristics-based approach has been well established in the choice modeling literature (see Train 2003 for an overview of the different discrete-choice models developed in the literature), consumer learning on multiple product attributes has rarely been studied. For new products, a better understanding of such a consumer learning process can provide important policy and managerial implications on issues such as new product diffusion and firm competition.

The importance of learning on multiple product attributes certainly applies to the choice of prescription drugs. Drugs can be effective in curing an illness or relieving a symptom but can also have harmful side effects. The value of a drug, among others, depends on the trade-off between treatment effectiveness and side effects. Recognizing this, firms conduct clinical trials to compare drugs even after their drugs are introduced. Although the goal of clinical trials is to objectively measure the effectiveness and side effects, it is also important for firms to understand how these attributes are evaluated by patients and physicians. Studying the willingness to trade off between effectiveness and side effects is complicated by the fact that when new drugs are introduced into the market, physicians and patients usually have limited information on the attributes. Because information available on public domains, such as clinical trial reports, may be insufficient, physicians use other information including detailing,[1] feedback from patients, medical journals, and word of mouth from other physicians to learn about these attributes. Suppose there is a large uncertainty associated with the side effects of a new drug. The pharmaceutical firm has to find an effective marketing channel to reduce such uncertainty. Given that drugs may have different profiles in effectiveness and side effects, and hence the types and amount of uncertainty associated with each drug may also differ, effective channels for past drugs may not work for a new drug. It is crucial from the managerial perspective to understand the efficiency of different information sources in reducing different types of physician uncertainties.

[1] Detailing refers to the marketing practice that pharmaceutical firms send sales representatives to directly talk to physicians.

The objectives of our study are to address the previously mentioned issues and extend our understanding on consumer learning of multiple product attributes of new products. In particular, we examine the impact of different product attributes on physicians' prescription decisions and the effectiveness of various information sources in reducing physicians' uncertainties associated with these attributes. To achieve our research objective, we construct a structural model to study how a risk-averse physician evaluates treatment effectiveness and side effects in his prescription decision, and how learning from detailing versus patient feedback helps reduce his uncertainty in these two attributes. To control for other confounding explanations about physicians' prescription choices, we also allow for switching costs and persuasive detailing in our model. We apply our model to a unique physician panel data set from the erectile dysfunction (ED) category. We choose this category because this is one of the few categories with significant drug entries; hence it provides an appropriate context to study physician learning. The proposed empirical framework, however, can be used to model consumer learning of multiple product attributes beyond the pharmaceutical market.

The key methodological challenge we face in this study is to separately identify the learning of treatment effectiveness and side effects and its impacts on the prescription choice. A typical identification strategy in the empirical literature is to use observed treatment outcomes data (e.g., Crawford and Shum 2005, Chan and Hamilton 2006). However, for those drugs that only relieve symptoms (e.g., ED drugs in our study), treatment outcomes are not observed by researchers. A different identification strategy is therefore required. We use an additional data source, self-reported reasons for switching drugs, as well as the observed treatment choice by each physician–patient pair to achieve our research objective. Whereas observed treatment choices allow us to infer the overall quality evaluation of drugs from physicians and patients, self-reported reasons for switching help us identify effectiveness separately from side effects as well as their impacts on prescription choices. To understand consumer satisfaction or dissatisfaction level regarding various product and service attributes, firms (e.g., hotels, investment banks, and online retailers) have routinely conducted surveys after consumers purchased their products or decided to leave. Therefore, our methodology can be applied to a general context where researchers can combine survey data with consumer choice data.

Our estimation results show that the two new drugs Levitra and Cialis have significantly higher mean patient evaluation in effectiveness than the existing drug Viagra. However, physicians have a higher degree of uncertainty regarding the effectiveness of Levitra and side effects of Cialis, suggesting a potentially large entry cost for the new drugs. Informative detailing plays a significant role in reducing physicians' uncertainties and increasing the adoption; however, its informational value for effectiveness is different from that for side effects. Detailing is more efficient in reducing the uncertainty of effectiveness than reducing the uncertainty of side effects—one detailing visit would almost eliminate all physician uncertainty in effectiveness and increase the market share considerably for both new drugs. However, there is still significant uncertainty among physicians regarding their side effects. Subsequent detailing visits help Cialis gain more market share because these visits continue to provide physicians important information on side effects. We also illustrate the importance of detailing in helping new improved drugs compete with incumbent drugs and hence improving the patient welfare.

1.1. Literature Review

The paper by Erdem and Keane (1996) is an influential paper that structurally estimates a learning model where consumers use past experience and advertising signals to update their expectations of quality. Since then, there has been a growing body of literature that studies consumer learning, including a few recent papers in the pharmaceutical market. For example, Ching (2010) considered a model where physicians learn about the quality of a generic drug through patients' feedback. Narayanan and Manchanda (2009) focused on physicians' heterogeneous learning about the quality of new drugs. Chintagunta et al. (2009) considered both cross-patient learning of a drug's overall efficacy and within-patient learning of the patient–drug match. Ching and Ishihara (2010) allowed firms to learn about the true quality of their drugs over time and linked the effectiveness of detailing to the current information sets and the size of well-informed physicians. Unlike these previous studies that assume learning about an overall drug "attribute" or "quality," we study how physicians evaluate and learn about two drug attributes, treatment effectiveness and side effects, separately. Furthermore, we model learning of these two attributes through two different channels: detailing and feedback from patients. We allow for the informational content of these two channels to differ across effectiveness and side effects.

To separately identify the learning of treatment effectiveness and side effects and the impact on choice, a typical identification strategy in the empirical literature is to use observed treatment outcome data. For example, Crawford and Shum (2005) estimated a demand model under uncertainty in the

antiulcer category. They used the treatment length of individual patients to separate the curative effects of drugs from the symptomatic effects. Their patient-level panel data, including treatment choice and drug switching in each period, also helped them identify the patient learning about specific drug–patient matches in both effects. In another study, Chan and Hamilton (2006) investigated how patients evaluate treatment effectiveness and side effects using clinical trial data of AIDS patients. They use an objective measurement of effectiveness (CD4 counts) and patients' noncompliance decisions in data to infer patients' learning of the two attributes within each treatment arm.

Our paper uses a different identification strategy because the treatment outcome data are not available to us. In particular, we rely on an additional data source, self-reported reasons for switching drugs, as well as the observed treatment choice for each physician–patient pair to achieve such a research objective. Our approach is closely related to the literature that combines stated preference data with revealed preference data. For instance, Harris and Keane (1999) used survey data on consumer attitudes toward different product attributes to help identify consumer preference for different dimensions of health plans. Previous studies in economics have also used similar data sources to identify model parameters that cannot be inferred from choices alone. For example, a self-reported consumer survey was used by Manski (2004) to help understand the extent of consumer uncertainty. Berry et al. (2004) used data on consumers' reported secondary choices in the automobile market to identify the correlation between consumers' preferences for product attributes. Our approach in this paper is similar to Harris and Keane (1999), Manski (2004), and Berry et al. (2004).[2]

Finally, our paper is also related to the literature that studies the informative versus persuasive role of detailing. Leffler (1981) and Hurwitz and Caves (1988) found that advertising contributes to expanding the entrants' market share. They used reduced-form regressions to show that persuasive and informative functions both exist in drug advertising. Ching and Ishihara (2012) used data from a comarketing agreement between pharmaceutical firms to separately identify the informative role from the persuasive role of detailing. Consistent with this literature, our model also allows for both the persuasive and the informative functions from detailing.

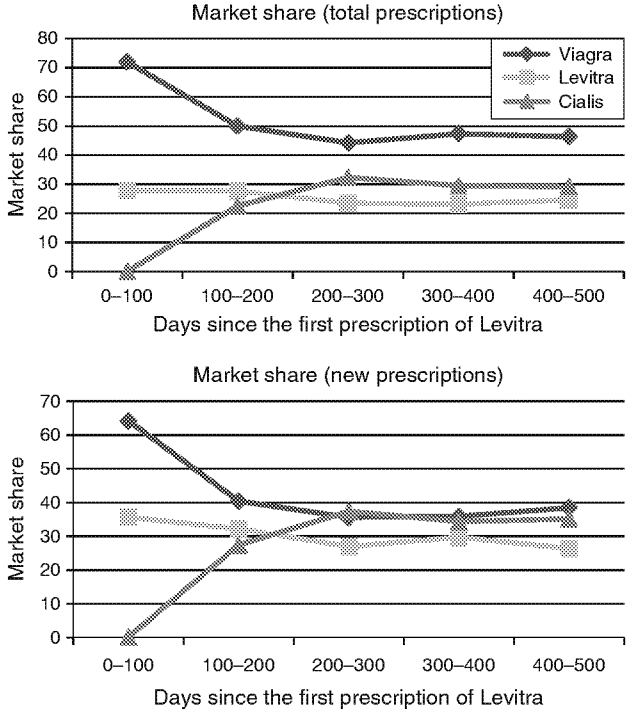
[2] In a recent paper, Dickstein (2011) studied the physician learning of the quality of match between a particular patient and a drug in the antidepressant category. In his model, a physician updates a vector of coefficients on the drug's characteristics, and the process permits correlated learning across drugs that is similar to that in our setting. However, his identification strategy is different from ours.

The rest of this paper is organized as follows. We describe our data in §2 and discuss the model and details of model identification and limitations in §3. In §4 we report the results, and in §5 we conclude our paper, pointing out future directions in this research stream.

2. Data Description

Our data were made available to us by ImpactRX, a pharmaceutical consulting firm, with sample period from May 2003 to October 2004. For model estimation we use the data starting from August 2003 when Levitra first entered the market. During the first three months, only Viagra and Levitra existed, and for the remainder of the data period, all three drugs were in the market. Our data consist of 828 primary care physicians and, for each physician, the history of prescriptions and detailing visits from pharmaceutical firms. Of the 13,619 prescriptions in total, about 54% were for returning patients (i.e., patients who had been prescribed a drug in the ED category before), and the rest were for new patients. The prescription trends of the three drugs are plotted in Figure 1. The market share of Cialis grew steadily in the first six months after its introduction and then stabilized. Similar penetration was also observed for Levitra at a faster rate. At the end of the sample period, Viagra still had the largest market share, but Cialis had caught up in terms of the share of new patients. The gradual growth of Cialis after its introduction may

Figure 1 Prescription Trends of the ED Drugs in Sample Period



imply that physicians have more prior uncertainty associated with new drugs. The fact that Viagra has a larger share among returning patients indicates that physicians are less likely to switch to new drugs (most returning patients were prescribed Viagra before), implying that there are other switching costs among returning patients.

Unlike clinical studies, we do not have any objective measurement of effectiveness or side effects in data. To infer patient evaluations of these two treatment outcomes, our strategy is to use the data of self-reported reasons for switching drugs from returning patients. Among those patients, 77.4% were prescribed the same drug as before, and the others (a total of 1,652) were switched to a different drug. Physicians are required to report the reason for switching; however, we still observe about one-third of switches without stated reasons. Panels (A) and (B) in Table 1 show the number of switches from one drug to another due to "ineffectiveness" and "side effects." Approximately 90% of switchers are from Viagra. Only a few switches from Levitra and Cialis are due to severe side effects. Panel (C) reports the ratios of switching because of "ineffectiveness" to switching because of "side effects." The ratios of those switching to Viagra and Levitra (4.0 and 4.4, respectively) are far lower than the ratio of switching to Cialis (9.6), indicating that physicians perceive Cialis as a more effective drug than Viagra or Levitra.[3]

Table 1 Switchings Among Drugs Due to Ineffectiveness and Side Effects

(A) Switching due to ineffectiveness

	To			
From	Viagra	Levitra	Cialis	Total
Viagra	—	446	337	783
Levitra	25	—	85	110
Cialis	15	16	—	31
Total	40	462	422	924

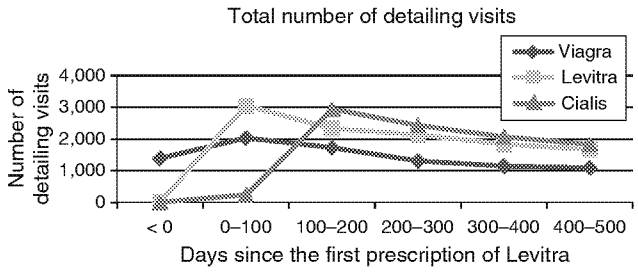
(B) Switching due to side effects

	To			
From	Viagra	Levitra	Cialis	Total
Viagra	—	93	32	125
Levitra	5	—	12	17
Cialis	5	12	—	17
Total	10	105	44	159

(C) Ineffectiveness/side effects ratio

Overall	5.81			
	Switched from			
Switched to	Both drugs	Viagra	Levitra	Cialis
Viagra	4.00	—	5.00	3.00
Levitra	4.40	4.80	—	1.33
Cialis	9.59	10.53	7.08	—

Figure 2 Detailing Trends of the ED Drugs in Sample Period



We also have detailing data for the physician panel. There are a total of 26,509 detailing visits, about 17.5% accompanied by meals. The total numbers of detailing visits for the three drugs are plotted in Figure 2. Levitra and Cialis were both promoted heavily immediately following their market entry. As a response, Viagra also increased detailing efforts. The number of visits decreased in later periods, and Cialis still remained at the top. There is a large variation of detailing visits across physicians. Some physicians had no visits at all in one month, and some had multiple visits. The highest number of monthly visits a physician received from a firm was 11. Both Levitra and Cialis started detailing one month before they were introduced. One month after Levitra was introduced, 29% of physicians in our data were visited twice or more, 32% once, and 39% were not detailed. For Cialis, one month after its introduction, the proportions were 32%, 26%, and 42%, respectively. To further examine the targeting strategy of detailing, we run a simple reduced-form regression for Levitra and Cialis separately, using $\ln(detailing\_visits + 1)$ for each physician during the period from one month before to one month after the new drug's launch as the dependent variable, and their competitors' total detailing visits and the physician's total prescriptions of ED drugs from May 2003 until one month before the new drug's launch as independent variables. Results are reported in Table 2. Both new drugs seemed to follow their competitors' targeting strategy, as the coefficients for $\ln(number\_of\_competitors'\_detailing\_visits + 1)$ are significantly positive. For Levitra, the coefficient for $\ln(total\_number\_of\_previous\_prescriptions + 1)$ is also significantly positive, consistent with findings in previous studies (e.g., Manchanda et al. 2004, 2008). The coefficient for Cialis is positive but insignificant, probably because competitors' detailing visits and physicians' previous prescriptions are highly collinear.

[3] The reason that there were more switches from Viagra to Levitra than to Cialis is because the former entered the market three months earlier. The comparison here has not taken account of the timing issue.

Table 2 Reduced-Form Regressions of Detailing Targets

	Levitra's detailing		Cialis's detailing	
	Estimate	Std. error	Estimate	Std. error
Intercept	0.37	0.03	0.61	0.09
ln(*competitors'_detailing* + 1)	0.26	0.03	0.7	0.04
ln(*total_previous_prescriptions* + 1)	0.07	0.02	0.01	0.04
R^2	0.13		0.32	

Table 3 Reduced-Form Regressions of Effect of Detailing on Prescription Choice

	Model 1 (days 1–90)		Model 2 (days 91–180)	
	Estimate	Std. error	Estimate	Std. error
Levitra	−1.74	0.09	−1.05	0.11
Cialis	—	—	−1.98	0.11
ln(*Viagra_detailing_visit* + 1)	0.27	0.06	0.35	0.05
ln(*Levitra_detailing_visit* + 1)	1.01	0.07	0.64	0.06
ln(*Cialis_detailing_visit* + 1)	—	—	1.46	0.07

We use a reduced-form multinomial logit model of physician's prescription choice to examine the evidence of detailing effects. Two separate regressions are run. The first uses observations from days 1 to 90 in the data, and the second from days 91 to 180 (before and after Cialis entered, respectively). We use brand indicators and a variable, ln(*number_of_detailing_visits* + 1), as covariates. We also allow the effect of detailing to be brand specific. Estimation results in Table 3 show that Viagra has the highest intercept parameter (normalized to zero), indicating that without detailing, Viagra would dominate the market. The drug may be the most effective treatment or have the fewest side effects, but the market dominance may also imply the presence of switching costs and physicians' uncertainty of the value of the new drugs. Several results of the detailing effect are noteworthy. First, among the three drugs, the detailing effect for Viagra is the smallest but still significant. Because it had been in the market for five years before our sample period starts, physician uncertainty regarding its effectiveness and side effects should be very small. The detailing effect for Viagra therefore is mostly due to the persuasive function.[4] Coefficients for detailing of Levitra and Cialis represent the combined effect of the persuasive and informative functions. The coefficient for Levitra's detailing declined from 1.01 in the first model to 0.64 in the second, implying a decreasing marginal effect over time. Assuming the persuasive effect remains stable, this implies that the longer a drug is in the market, the smaller the informative effect of detailing. Finally, the coefficient for Cialis's detailing in Model 2 is higher than that for Levitra's in both models, most likely due to the difference in the informative function between detailing of the two drugs. A structural explanation for the differential results will be offered in §4.

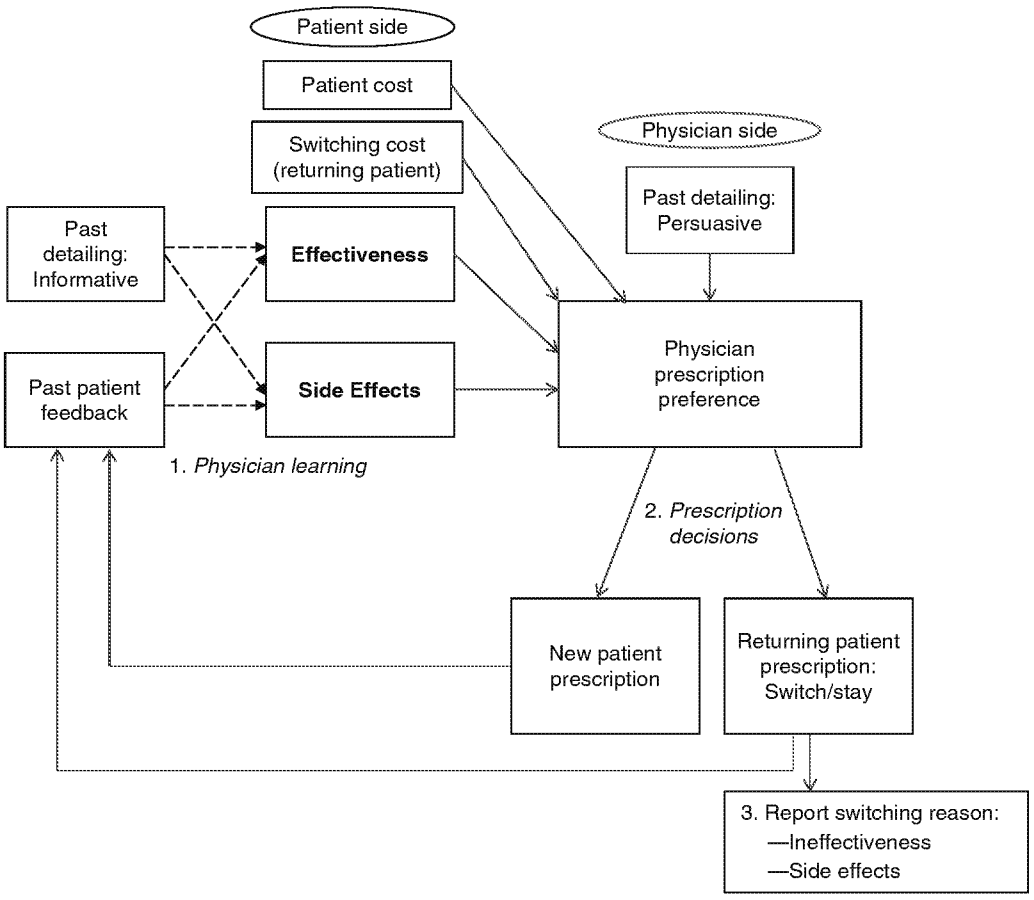
Patient characteristics, such as age, ethnicity, insurance coverage, and severity status of disease are also provided in the data. These characteristics may shift physician prescription decisions. For example, if one insurance plan covers the cost of prescribing one drug but not the others, we may observe that patients covered by the plan are more likely to be prescribed the drug due to lower out-of-pocket cost. Most of the patients are Caucasians in the age range of 41–70. Health maintenance organizations (HMO), preferred provider organizations, and point of service plans are the main insurance coverage plans followed by Medicare. Most patients in the data are moderate disease status (73%), whereas very few are severe. For our model estimation purpose, we group patients of moderate and severe status together as "moderate" patients versus "mild" patients in data.[5]

One major data limitation is that we do not observe those patients who seek treatment but decide not to use any existing drug. Our analysis is restricted to those who received treatments during the sample period. We also do not know whether a new patient in the data has sought treatment in the past but chosen not to use any drugs. By ignoring those "nonprescription" incidences, our study may be subject to the standard selection issue. This may not be a problem in our data because we do not find significant changes in the number of new patient visits. For example, compared with the average monthly visits when there were only Viagra and Levitra, the number of new patients in the month after Cialis was introduced increased by only 5%, and in the last three months of data, the number virtually remained the same. If selection bias comes from patients not choosing a treatment because existing drugs do not work for them, there should be a more significant increase in the number of patients after Cialis entered. Finally, because we only have physician panel but not patient panel data, we cannot match repeated visits in the data with every returning patient. Therefore, we have to make some assumptions on the information content of patient visits in our model, which we will discuss in the next section.

[4] This argument is similar to the identification strategy of Ackerberg (2001), who separated the informative and prestige effects of advertising based on differences between inexperienced and experienced consumers' responses to advertising.

[5] More detailed descriptive statistics of the patient characteristics are available in the online appendix at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2134084.

Figure 3 **Diagram of Physician Learning and Prescription Decision**



3. The Model

Our model specifies how a physician updates his beliefs of the effectiveness and side effects of a drug, and how he uses the beliefs to make prescription decisions for either new or returning patients. Figure 3 provides a graphical illustration of the process. A physician uses information from two channels to update his beliefs. First, salespeople would discuss both attributes during detailing visits. Second, returning patients would report their evaluation of both attributes for the drug they took. When a new or returning patient seeks treatment, the physician makes the prescription decision. His decision depends, among other things, on (i) his updated beliefs of the effectiveness and side effects of available drugs on the patient, (ii) patient characteristics, (iii) the switching cost for a returning patient if switching drugs, and (iv) the persuasive function of the past detailing visits. The physician will choose the drug that maximizes a preference function that captures the effects (i)–(iv). If he switches the prescription for a returning patient, he will report the switching reason (due to ineffectiveness or severe side effects). After receiving the prescription, the patient, when they visit next time, will report the effectiveness and side effects of the drug. This information, together with new detailing visits, will be used to further update the physician's beliefs and influence his future prescriptions.

To identify the informative and persuasive functions of detailing, we assume that the intensity of detailing and what is discussed (effectiveness versus side effects) during detailing visits are exogenous to the unobservables (researchers) in the physician's preference function. This implies that the endogeneity of detailing decisions that can be potentially important (Villas-Boas and Winer 1999, Manchanda et al. 2004) is not considered in this study. We also assume that after a new drug is introduced it will be considered by the physician in his prescription choice, even though he has not received any detailing. More details regarding the identification will be discussed later in §3.4.

3.1. Physician's Prescription Decision

We specify a utility function of physician i prescribing drug j for patient h on occasion t as follows:

$$U^j_{ih,t} = f(e^j_h, s^j_h) + X^j_{ih,t}\beta + \varepsilon^j_{ih,t}. \quad (1)$$

The function $f(\cdot)$ represents the physician's preference based on the patient evaluation of the effectiveness

and side effects of drug j, e_h^j, and s_h^j,[6] respectively. The vector $X_{ih,t}^j$ contains patient characteristics such as age and race, and an interaction between insurance and drug identity that captures the out-of-pocket cost for the patient. It also accounts for persuasive detailing that could shift the physician's preference but not the patient's. Finally, $\varepsilon_{ih,t}^j$ is a random component, independent and identically distributed (i.i.d.) across physician, patient, drug, and time in the prescription decision but unobserved to researchers.

When seeking treatment, we assume that a returning patient h will reveal information on his evaluation of e_h^j and s_h^j if drug j was prescribed to him on his last visit, and his evaluation remains the same over time. We also assume that the physician has complete information about $X_{ih,t}^j$ and $\varepsilon_{ih,t}^j$; therefore, he can evaluate $U_{ih,t}^j$ in (1) without uncertainty. For other drugs that patient h has not used before, however, the physician has to form an expectation on the patient's e_h^j and s_h^j based on the information available at the time. Because we do not observe prescription history for the returning patient before their last visit, we assume that they have no knowledge about other drugs that were not prescribed on this last visit. This assumption may not be unreasonable because Levitra and Cialis had not existed very long during our sample period, therefore multiple switches between drugs are rare in our data. Let Ω_{it} be the physician's information set at time t that includes his knowledge of the treatment effectiveness and side effects of all available drugs. Note for the returning patient, Ω_{it} also consists of the patient's evaluation of the previously prescribed drug, e_h^j and s_h^j. The expected utility of the physician in prescribing another drug j' to the patient is represented as follows:

$$E[U_{ih,t}^{j'} \mid \Omega_{it}] = E[f(e_h^{j'}, s_h^{j'}) \mid \Omega_{it}] + X_{ih,t}^{j'}\beta + \varepsilon_{ih,t}^{j'}. \quad (1')$$

In the ED category, a returning patient may only need to call his physician to refill the prescription, thus saving a trip to visit the physician and the associated copayment (if there is any).[7] However, he has to visit the physician if he switches to other drugs. It may also take time for the patient to adjust to using the new drug (e.g., whether or not he can have alcoholic drinks before taking the drug). There may also be psychological costs involved for both the physician and the patient. For the ease of discussion we refer to these as "switching costs" (Klemperer 1995). Also, for simplicity we assume that the costs are the same for all patients and all switches. Based on the previous discussion, we assume that the same drug j will be prescribed to the returning patient if the following condition is satisfied:

$$U_{ih,t}^j \geq E[U_{ih,t}^{j'} \mid \Omega_{it}] - SC, \quad \forall j' \neq j, \quad (2)$$

where SC is the switching cost. Otherwise the physician will switch to a new drug j' that provides the highest expected utility.

For a new patient, the physician will form expectations for the patient's effectiveness and side effects with the same representation as (1'). Evaluations of effectiveness and side effects of any drugs for this particular patient are not included in the physician's information set Ω_{it}. The physician will prescribe drug j if the following condition is satisfied:

$$E[U_{ih,t}^j \mid \Omega_{it}] \geq E[U_{ih,t}^{j'} \mid \Omega_{it}], \quad \forall j' \neq j. \quad (3)$$

Given that we do not observe any objective measures of treatment outcomes, all we can identify in the model are the patient's evaluations of the three drugs relative to each other. We use a parsimonious specification for f that captures the following two features. First, trade-offs between effectiveness and side effects should be allowed. Second, if uncertain about treatment effectiveness and side effects of a new drug, the physician may not prescribe the drug even if its expected effectiveness is high and side effects are low. Therefore, we propose to use the following specification:

$$f(e_h^j, s_h^j) = -\exp[-(e_h^j + s_h^j)]. \quad (4)$$

This specification implies constant absolute risk aversion, where the Arrow–Pratt coefficient of absolute risk aversion $r_A(x_h^j) = -f''(x_h^j)/f'(x_h^j)$ is constant.

Let J be the total number of drugs in the market. We denote $\bar{E}$ as a $J \times 1$ vector of average effectiveness and $\bar{S}$ as a $J \times 1$ vector of average side effects across patients of all drugs. We specify that

$$e_h = \bar{E} + \xi_h^E, \quad (5)$$

where e_h is a $J \times 1$ vector of effectiveness for patient h, and

$$s_h = \bar{S} + \xi_h^S \quad (6)$$

is similarly defined for side effects. We assume that $\xi_h^E \sim N(0, \Sigma_\xi^E)$ and $\xi_h^S \sim N(0, \Sigma_\xi^S)$, where Σ_ξ^E and Σ_ξ^S are $J \times J$ variance–covariance matrices representing the extent of heterogeneity across patients and will be estimated from the model. Nonzero covariances imply that e_h or s_h are correlated across drugs—a patient experiencing more side effects with a drug may also experience more side effects with another.

[6] The evaluations e_h^j and s_h^j are the product of the treatment outcomes and the patient preferences for the outcomes. For simplification we will refer to the patient evaluations as "effectiveness" and "side effects" hereafter in this paper as long as there is no confusion.

[7] For simplification we assume that the physician learns e_h^j and s_h^j even when the patient only calls for a refill. A call-in may reveal information of drug attributes because the patient will be asked to describe treatment outcomes of the drug, though the discussion may be briefer than a personal visit.

3.2. Physician Uncertainty and Learning

We model the physician learning similar to the previous literature with the key difference that effectiveness and side effects are separately learned. We assume that all physicians have the same prior beliefs about the effectiveness and side effects of a new drug. We further assume that physicians have rational expectations[8] so that the mean effectiveness and mean side effects in physicians' prior beliefs are consistent with the true values $\bar{E}$ and $\bar{S}$. For simplification we also assume that physicians know the heterogeneity matrices Σ_ξ^E and Σ_ξ^S. However, physicians are uncertain of the true means of effectiveness and side effects. Consistent with the Bayesian learning framework, physicians' prior beliefs in period 0 are specified as follows:

$$\bar{E}^0 \sim N(\bar{E}, \Sigma_{v,0}^E), \quad \text{and} \quad \bar{S}^0 \sim N(\bar{S}, \Sigma_{v,0}^S), \tag{7}$$

where the superscript "0" denotes physicians' prior beliefs of the mean values in period 0. To reduce the parameter space, we assume that the variance–covariance matrices $\Sigma_{v,0}^E$ and $\Sigma_{v,0}^S$ are diagonal matrices of which the jth diagonal elements are $\sigma_{E,j}^{v,2}$ and $\sigma_{S,j}^{v,2}$, respectively.

Detailing can be persuasive and informative. Persuasive detailing may change the preference of physicians unrelated to the consideration of effectiveness and side effects, and hence "distort" physician's prescription decisions and exacerbate the principal–agent problem. The informative function of detailing is modeled as providing information about the true effectiveness and side effects of a drug. Following Erdem and Keane (1996), we assume that there may be noise regarding effectiveness and side effects associated with each detailing message. The larger the magnitude of the noise, the lower the informational value of detailing. For simplicity we assume that detailing provides information only for the firm's own drug. On each occasion t, the physician receives detailing messages as follows:

$$D_{it}^E = 1_{it}^D \cdot (\bar{E} + \zeta_{it}^E), \quad \text{and} \quad D_{it}^S = 1_{it}^D \cdot (\bar{S} + \zeta_{it}^S), \tag{8}$$

where D_{it}^E and D_{it}^S are $J \times 1$ vectors of detailing messages regarding effectiveness and side effects, respectively; 1_{it}^D is a $J \times 1$ indicator of which the jth element is equal to one if detailing for drug j happened at t and zero otherwise; and the operator "$\cdot$" is an element-by-element multiplication. The variables ζ_{it}^E and ζ_{it}^S are detailing noises, which are assumed to be i.i.d. over time and across drugs and are normally distributed as follows:

$$\zeta_{it}^E \sim N(0, \sigma_{E,\zeta}^2 \cdot I_J), \quad \zeta_{it}^S \sim N(0, \sigma_{S,\zeta}^2 \cdot I_J),$$

where I_J is a $J \times J$ identity matrix. We assume in the model that physicians know the distributions of ζ_{it}^E and ζ_{it}^S.

Feedback from returning patients also provides information regarding the effectiveness and side effects of drugs. Once a returning patient h has used drug j, we assume that the physician will fully observe the effectiveness e_h^j and side effects s_h^j on that particular patient, and update his beliefs regarding $e_{h'}^j$ and $s_{h'}^j$ on other patients h'. If effectiveness and side effects across drugs are correlated (when off-diagonal elements in Σ_ξ^E and Σ_ξ^S in Equations (5) and (6) are nonzero), the physician can also use this information to form expectations for the effectiveness and side effects of other drugs on the same patient.

We model physician learning using a Bayesian framework. Given the information set $\Omega_{i,t}$, let Z be the true mean effectiveness and side effects evaluation across patients, i.e., $Z = \{\bar{E}, \bar{S}\}$. On each occasion t the physician receives either reports from a returning patient h regarding the pair of reported treatment outcomes $R_{ih,t}^j = \{e_h^j, s_h^j\}$ or a detailing message D_{it}^Z from sales representatives. He will update his beliefs according to the Bayesian rule (DeGroot 1970) as follows:

$$\begin{aligned} E[Z \mid \Omega_{i,t}] = E[Z \mid \Omega_{i,t-1}] &+ 1_{iht}^P \cdot \Gamma_{1,it}(R_{ih,t}^j - E[Z \mid \Omega_{i,t-1}]) \\ &+ 1_{it}^D \cdot \Gamma_{2,it}(D_{it}^Z - E[Z \mid \Omega_{i,t-1}]), \end{aligned} \tag{9}$$

where 1_{iht}^P is a $J \times 1$ vector of which the jth diagonal element is equal to one if a returning patient h used drug j in the previous period and zero otherwise. Deviations of the realized treatment outcome and detailing message from the previously expected value of treatment outcome are measured by $R_{ij,t}^j - E[Z \mid \Omega_{i,t-1}]$ and $D_{it}^Z - E[Z \mid \Omega_{i,t-1}]$, respectively. The Kalman gain coefficients Γ's in (9) are defined as

$$\begin{aligned} \Gamma_{1,it} &= \Sigma_{v,t}^Z \cdot (\Sigma_{v,t}^Z + \Sigma_\xi^Z)^{-1} \quad \text{and} \\ \Gamma_{2,it} &= \Sigma_{v,t}^Z \cdot (\Sigma_{v,t}^Z + \sigma_{Z,\zeta}^2 \cdot I_J)^{-1}, \end{aligned} \tag{10}$$

where $\Sigma_{v,t}^Z$ is the updated variance of the physician's beliefs of mean effectiveness or side effects on occasion t, Σ_ξ^Z is the variance–covariance matrix for ξ_h^E and ξ_h^S (see Equations (5) and (6)), and $\sigma_{Z,\zeta}^2 \cdot I_J$ is the variance for effectiveness or side effects associated with detailing noise. According to the Bayesian rule, the variance $\Sigma_{v,t}^Z$ is updated as

$$\Sigma_{v,t}^Z = \left[(\Sigma_{v,0}^Z)^{-1} + (\Sigma_\xi^Z)^{-1} \cdot \sum_{s=0}^{t} I_{ihs}^P + (\sigma_{Z,\zeta}^2 \cdot I_J)^{-1} \cdot \sum_{s=0}^{t} I_{is}^D \right]^{-1}, \tag{11}$$

[8] This is a somewhat strong assumption. However, the prior beliefs are very difficult to infer from the prescription choices alone. Similar assumptions are made in many other learning papers, including those by Erdem and Keane (1996), Crawford and Shum (2005), and Chan and Hamilton (2006).

where $\Sigma^Z_{v,0}$ is the period 0 prior beliefs defined in Equation (7).

The updating rule based on patient reports $R^j_{ih,t}$ in Equations (10) and (11), assuming every returning patient brings unique information to the physician, may be restrictive. Supposing the patient has been repeatedly using the same treatment in our data, the information value of his later visits regarding effectiveness and side effects may be much lower than for his first revisit. Because Viagra has existed in the market for more than five years, we assume that physicians have no prior uncertainty regarding its effectiveness and side effects. Reports from patients who used Viagra before account for 80% of returning patients in data, and therefore do not directly impact physicians' learning. For the remaining 20% of returning visits, very few occurred during the first 100 days after either Levitra or Cialis was launched, a period when intensive learning was taking place. In later periods, the information value of patient feedback from returning patients becomes smaller. Therefore, whether or not those patients have used Levitra or Cialis more than once should have little bearing on our estimation results.

3.3. Modeling Reasons to Switch

To separately identify e^j and s^j, we model the switching reasons for returning patients together with the prescription choice. Suppose the prescription for a returning patient h switches from drug j to drug k. We assume that the expected utility associated with drug k, $E[U^k_{ih,t} \mid \Omega_{it}] - SC$, is the highest among all alternatives including drug j (Equation (2)). Moreover, if "side effects" was stated as the switching reason, the following two conditions have to be satisfied:

$$\text{(i) } s^j_h < E[s^k_h \mid \Omega_{it}] \quad \text{and} \quad \text{(ii) } s^j_h < e^j_h.$$

Condition (i) states that if switching is due to side effects, the expected side effects of drug k must be less severe than the current prescription.[9] Condition (ii) states that side effects are of greater concern than effectiveness, otherwise ineffectiveness of drug j would be indicated as the switching reason. Similarly, if "ineffectiveness" was stated as the switching reason, the following two conditions have to be satisfied:

$$\text{(iii) } e^j_h < E[e^k_h \mid \Omega_{it}] \quad \text{and} \quad \text{(iv) } e^j_h < s^j_h.$$

For those switching either without reasons provided or due to other reasons, we group them into "other reasons." Patients may be affected by direct-to-consumer promotions and request switches. However, the underlying switching reasons may still be the concerns of effectiveness or side effects. Another possibility is that the conditions listed above are not satisfied. Finally it is possible that physicians are just too busy to fill in reports. Because we do not want to impose any further restrictions on switching reasons for these cases, we assume that s^j_h and e^j_h of the previously prescribed drug are generated from the estimated distribution of effectiveness and side effects of drug j, conditional on the realized utility of using j being lower than the expected utility of using k plus the switching cost, i.e., $U^j_{ih,t} < E[U^k_{ih,t} \mid \Omega_{it}] - SC$.

3.3.1. Alternative Models. To test the robustness of our results, we also estimate two alternative models under different behavioral specifications. First, we explicitly test the assumption of switching costs by estimating another model assuming that $SC = 0$ in Equation (2).[10] Second, instead of Equation (2), we make an alternative assumption that physicians will not switch drugs for patients, even when the expected utility of the new drug is higher than the current one, as long as either the complement of the set defined by conditions (i) and (ii) or the complement of the set defined by conditions (iii) and (iv) is satisfied. Suppose for a patient, side effects of current drug j is the major concern (i.e., $s^j_h < e^j_h$ in condition (ii)). The physician will not prescribe him a new drug k if its expected side effects are worse than those of drug j (i.e., $s^j_h < E[s^k_h \mid \Omega_{it}]$ in condition (i) is violated). Such an assumption applies to a very risk averse type of prescription choice. Given that the probability of no switching is larger under this alternative assumption, we also assume $SC = 0$ for returning patients. For cases of no reported switching reasons, they are assigned probabilities for "side effects" and "ineffectiveness" based on model parameters. We call this model the "alternative model" to distinguish from the previous "proposed model."

We estimate the prescription choice and switching probabilities using the likelihood approach. The major difficulty in evaluating the likelihoods is that we as researchers do not observe detailing messages and treatment outcomes, $\{D^E_{i,t}, D^S_{i,t}, e^j_h, s^j_h\}$, which are used in the physician learning. We use numerical simulations to integrate out these stochastic variables in the likelihood functions.[11]

3.4. Model Identification

3.4.1. Identifying Effectiveness, Side Effects, and Their Variances. Because there is no outside option in our data, we normalize the mean effectiveness and

[9] A higher value of s^j implies lower side effects from drug j.

[10] Parameter estimates of this model are very similar to those for our proposed model, but the model is rejected using either the Akaike information criterion or the Bayesian information criterion, implying the importance of having switching costs in our model for better data fit. Results are available from the authors upon request.

[11] The details of model estimation are available in the online appendix.

side effects of Viagra to zero. We also normalize the standard deviation in the distribution of effectiveness of Viagra to one. With such normalization, the interpretation of the mean effectiveness and side effects of Levitra and Cialis in our model should always be relative to that of Viagra. The identification of $\bar{E}$ and $\bar{S}$ comes from the proportion of switches among the three drugs that are due to ineffectiveness relative to side effects. Panel (C) in Table 1 shows that switching to Cialis from other drugs due to the effectiveness concern is far higher than due to side effects (at a ratio of 9.6). In contrast, the ratio of switching to Viagra from other drugs due to ineffectiveness relative to that due to side effects is much lower (at a ratio of 4.0). This implies that the difference $\bar{E}^C - \bar{S}^C$ should be larger than $\bar{E}^V - \bar{S}^V$, which is normalized to zero. Because the market share of Viagra and Cialis have identified the overall quality of Cialis, $\bar{Q}^C$, we can now separate $\bar{E}^C$ from $\bar{S}^C$ in our model. The same argument can be applied to identifying $\bar{E}^L$ and $\bar{S}^L$ for Levitra.

To identify the variance–covariance parameters, suppose there are zero correlations between drugs. New information (e_h^j, s_h^j) from drug j will not change the expected utility of prescribing drug k for a returning patient h. According to the model, the ratio of the probability of switching to drug k versus that of switching to another drug k', $r_{k,k'} \equiv P_{ih,t}^k / P_{ih,t}^{k'} = \exp(E[U_{ih,t}^k \mid \Omega_{it}] - E[U_{ih,t}^{k'} \mid \Omega_{it}])$, for returning patients who were previously prescribed j and complained of side effects will be the same as for new patients. If this ratio is systematically different between types of patients in data, this indicates that e_h^j and s_h^j have changed the expected utility of prescribing other drugs, implying nonzero correlations of effectiveness and side effects among drugs. Some evidence of nonzero correlations of effectiveness and side effects among drugs can be found from Table 1. For example, conditional on switching away from Viagra due to "ineffectiveness," the ratio of switching to Levitra relative to switching to Cialis is 1.3. Yet, conditional on switching away from Viagra due to "side effects," the ratio of switching to Levitra relative to switching to Cialis is 2.9. These suggest that physicians who found Viagra ineffective or with severe side effects for a patient adjusted their expectations of Levitra and Cialis in a different way. Similar asymmetric switching patterns are also observed for those patients switching away from Levitra and from Cialis.

3.4.2. Identifying the Informative and Persuasive Functions of Detailing. As discussed earlier, we do not consider the endogeneity issue of detailing in our model. The estimated informative and persuasive functions of detailing may be biased if endogeneity exists. For example, our reduced-form regressions in Table 2 show that Levitra and Cialis followed competitors' detailing targets. If these physicians have a higher switching cost, we may have underestimated the persuasive function of detailing. Table 2 also shows that salespeople from Levitra are more likely to visit physicians with more prescriptions in the previous months. If these physicians are also more informed, we may have overestimated the informative function of detailing.[12] We also assume that when making prescription decisions physicians will consider all drugs available in the market. If detailing of new drugs influences the likelihood of including the new drugs in the consideration set, we may have overestimated the informative and persuasive functions of detailing in the model.

Based on model assumptions, physicians' prior uncertainties of mean effectiveness and side effects, $\sigma_{E,j}^{v,2}$ and $\sigma_{S,j}^{v,2}$ (Equation (7)), are inferred from the time-varying tendency of prescribing a new drug j. If the uncertainty is large, physicians will be less likely to prescribe j to their patients when the drug was just introduced. The difference in the probability of prescribing Levitra and Cialis to those patients who switched from Viagra due to ineffectiveness and due to side effects in the early periods will identify the difference in prior uncertainties of these two drugs. The identification of the noise in detailing message, $\sigma_{E,\xi}^2$ and $\sigma_{S,\xi}^2$, comes from the change in the probability of switching from an incumbent drug to a new drug and the associated reported switching reasons, as a physician is exposed to an increasing level of detailing from the new drug. Suppose $\sigma_{E,\xi}^2$ is small; a physician who receives a few detailing visits from the maker of j will resolve his uncertainty of effectiveness and is more likely to switch patients to j. In addition, the likelihood of reporting ineffectiveness as the switching reason should quickly converge to the steady state. Otherwise we will observe continuous adjustment in reported switching reasons as the physician receives more information from detailing. For example, 98 physicians received at least one detailing visit from Levitra during the first two weeks after the drug was launched. The market share of Levitra during the subsequent month for this group of physicians was 33%, higher than its market share of 21% among physicians who did not receive any detailing visits. Furthermore, when switching from Viagra to Levitra, the physicians reported ineffectiveness as the reason approximately 80% of the time, close to the fraction that we observe in the later period. This implies that

[12] Physicians with more prescriptions in the previous months are more informed about competitors' drugs. The new drug's firm tends to detail these physicians more to inform them that its effectiveness/side effects are better than those of its competitor's drug. This results in a positive correlation between detailing intensity and unobserved effectiveness/side effects.

switching due to drug ineffectiveness has quickly converged to the steady state.

Conditional on the Bayesian updating framework we impose in the model, uncertainties of a physician are reduced in a deterministic way following patient feedback and detailing visits. This has a direct impact on physicians' prescription choices. Suppose a detailing visit induces an increase in the prescription choice above the impact of the calculated informativeness of detailing. Our model will attribute such an additional effect to the persuasive function of detailing.

3.4.3. Identifying Switching Costs of Returning Patients. Our data contain prescription data for new patients as well as returning patients whenever a different drug is prescribed. The difference in prescribing a new drug to new patients versus to returning patients helps separate SC for returning patients in our model from the unobserved patient heterogeneity in effectiveness and side effects. Figure 1 shows that the market share of Viagra among returning patients (whose previously prescribed drug is mostly Viagra) is consistently higher than that among new patients, even in the last 200 days of our sample period, when most physicians have learned much about Levitra and Cialis.

We conducted a Monte Carlo simulation study to further examine the identification issue. We used the same patient and detailing records from our data (13,619 patient visits and 26,509 detailing visits, in total) and assumed model parameters to simulate the prescription outcomes and reported reasons for switching.[13] Results show that our interested parameters can be reasonably recovered from the simulated data. One concern we have is that because we observe few switches from Levitra and Cialis to Viagra because of side effects (see Table 1), the variance–covariance matrix for side effects Σ_ξ^S may not be well identified. In our simulated study, all of the estimated variance–covariance parameters have the right signs, and most estimates are close to the "true" parameters. For example, cov(*Viagra, Levitra*) and cov(*Viagra, Cialis*) for effectiveness are reasonably recovered even though there are very few switches from Levitra and Cialis to Viagra because of ineffectiveness in the simulated data. These results provide evidence that model parameters can be reasonably recovered from a data set with a similar magnitude of switching among drugs.

3.5. Some Details in Estimation Models

Because Viagra has existed for a long time, we assume that there are no prior uncertainties of effectiveness and side effects among physicians, i.e., $\Sigma_{v,0}^E$ and $\Sigma_{v,0}^S$ (Equation (7)) are zero. We use several demographic variables in data for $X_{ih,t}^j$ (Equation (1)), including age (ln(*age*)), race indicators (*Black* and *White*, with other races as the normalized variable), and type of insurance (*HMO, Indemnity, Medicaid, Medicare*, with no coverage as the normalized variable). Parameters of these variables for Viagra are normalized to zero, and those for Levitra and Cialis are estimated separately.

To allow for the persuasive function of detailing, we include the number of detailing visits in $X_{ih,t}^j$. To distinguish the long-run and short-run persuasive effects of detailing and the differential impacts of detailing with and without a meal, we break down this variable into (i) ln(*number_of_detailings_with_or_without_meals_in_the_past_30_days*); (ii) ln(*number_of_detailings_with_or_without_meals_more_than_30_days_ago*); (iii) ln(*number_of_detailings_with_meals_in_the_past_30_days*); (iv) ln(*number_of_detailings_with_meals_more_than_30_days_ago*). Negative difference between estimated coefficients for (ii) and (iv) and those for (i) and (iii) would imply the depreciation of the persuasive effect. Coefficients for (iii) and (iv) represent the additional impacts of detailing when meals are offered. Finally, we estimate $\bar{E}^j$, $j =$ Levitra or Cialis, separately for the groups of patients with "mild" and "moderate" statuses of illness. Such differentiation implies that different drugs may work differently for patients depending on the severity of their condition. For simplicity of analysis we do not differentiate the side effects $\bar{S}^j$ based on the severity, but this seems to be a reasonable assumption in our empirical context. We also assume that the heterogeneities in effectiveness and side effects are the same for the two types.

In summary, our parameter set includes $\bar{E}^{\text{mild}}$, $\bar{E}^{\text{mod}}$, $\bar{S}$, Σ_ξ^E, Σ_ξ^S, SC, $\Sigma_{v,0}^E$, $\Sigma_{v,0}^S$, $\sigma_{E,\varsigma}$, $\sigma_{S,\varsigma}$, and β, where $\bar{E}^{\text{mild}}$ is a 2×1 vector of mean effectiveness of Levitra and Cialis for patients with a mild condition, and $\bar{E}^{\text{mod}}$ is that for patients with a moderate condition. Other parameters are defined as before.

4. Results

Because the "proposed model" and "alternative model" are based on different behavioral assumptions, it is difficult to judge which one is a better model. Instead, we choose to report estimation results from both models in Tables 4–6. Table 4 provides estimates of the mean effectiveness and side effects and their correlation coefficients among the three drugs, as well as the switching costs ($\bar{E}^{\text{mild}}$, $\bar{E}^{\text{mod}}$, $\bar{S}$, Σ_ξ^E, Σ_ξ^S, and SC in the parameter set). In terms of mean effectiveness (for both mild and moderate conditions), both models estimate that Cialis ranks the best and Levitra second, all significantly better than Viagra (for which the mean effectiveness is normalized to zero). Our result is consistent with the evidence from Phase III

[13] A detailed description of the Monte Carlo simulation study is available in the online appendix.

Table 4 Estimates (Standard Error) of Mean Effectiveness and Side Effects, Their Correlation Coefficients, and Switching Cost

	Proposed model	Alternative model
Mean effectiveness and side effects		
Mean effectiveness of Levitra (mild)	0.693 (0.015)	1.289 (0.003)
Mean effectiveness of Levitra (moderate)	0.721 (0.009)	1.301 (1.7E–4)
Mean side effects of Levitra	0.003 (0.001)	0.0002 (0.001)
Mean effectiveness of Cialis (mild)	1.900 (0.017)	2.065 (0.011)
Mean effectiveness of Cialis (moderate)	1.947 (0.010)	2.087 (0.004)
Mean side effects of Cialis	0.071 (0.009)	−0.194 (0.003)
Variance–covariance of effectiveness		
Covariance (Viagra, Levitra)	0.689 (2.2E–4)	0.476 (9.1E–5)
Variance (Levitra)	3.043 (0.001)	5.508 (0.001)
Covariance (Viagra, Cialis)	0.555 (6.8E–5)	0.665 (1.8E–5)
Covariance (Levitra, Cialis)	−0.414 (1.7E–4)	−0.707 (7.0E–5)
Variance (Cialis)	0.555 (1.1E–4)	0.641 (2.7E–5)
Variance–covariance of side effects		
Variance (Viagra)	0.016 (6.2E–5)	0.013 (0.007)
Covariance (Viagra, Levitra)	0.016 (6.2E–5)	0.013 (0.001)
Variance (Levitra)	0.701 (0.015)	0.781 (0.001)
Covariance (Viagra, Cialis)	0.016 (0.002)	−0.00022 (0.015)
Covariance (Levitra, Cialis)	0.333 (0.088)	0.534 (0.062)
Variance (Cialis)	5.731 (0.018)	6.573 (0.005)
Switching cost	1.658 (0.033)	—

clinical trials (Goldstein et al. 1998, Brock et al. 2002, Hellstrom et al. 2002), that Cialis has a longer half-life and works faster (15 minutes) than the other two drugs (30 minutes for both). In terms of mean side effects, Cialis is also the best in the proposed model, but it is the worst in the alternative model. This is the major difference in the results of the two models. Still, because the magnitudes of mean effectiveness are much larger than the mean side effects in both models, such difference should have no significant bearing on prescription choices. This is also consistent with clinical trial results finding that the side effect profiles are similar among the three drugs, and that most of the side effects are rather mild.[14]

The two models generate consistent estimates for patient heterogeneity in treatment effectiveness and side effects. The variance of Cialis's effectiveness is significantly smaller than that of the others. Whereas Viagra is positively correlated with Levitra as well as with Cialis, the covariance is negative between Levitra and Cialis. The implication is that, everything else being equal, a patient is more likely to find Cialis, not Viagra, effective to him if Levitra is ineffective for him.

[14] Vasodilatory side effects (headaches, nasal congestion, flushing) are common with all three drugs but are mild, as they rarely cause men to drop out of clinical trials (2%–3% quit rate). The side effect of blue discoloration of vision is seen only with Viagra, and muscle aches only with Cialis, however, the incidence of these two side effects is very low (<0.5% for the former case and approximately 5% for the latter case).

Table 5 Estimates (Standard Error) of Prior Uncertainties and Detailing Noises

	Proposed model	Alternative model
Prior uncertainty (variance)		
Effectiveness of Levitra	0.750 (0.031)	0.552 (0.017)
Effectiveness of Cialis	0.277 (0.079)	0.342 (0.132)
Side effects of Levitra	0.274 (0.016)	0.002 (0.311)
Side effects of Cialis	0.894 (0.024)	0.620 (0.211)
Detailing noise (variance)		
Effectiveness (without meal)	0.029 (0.019)	0.031 (0.014)
Side effects (without meal)	1.201 (0.075)	0.171 (0.195)
Effectiveness (with meal)	0.0002 (0.021)	0.0001 (0.010)
Side effects (with meal)	0.648 (0.032)	0.216 (1.107)

The estimated variances in side effects of the three drugs suggest that the heterogeneity in side effects of Levitra and especially Cialis is much larger than that of Viagra. With the smallest heterogeneity in side effects, Viagra might be a "safe" drug for a risk-averse physician. This is consistent with Viagra's recent promotional message emphasizing its safety profile. The covariances between three drugs on side effects are mostly positive. Finally, we find large switching costs for returning patients in the proposed model. This rationalizes the difference in prescription choice for new and returning patients. As new drugs, Levitra and Cialis already have the disadvantage that physicians have uncertainties. This is an additional obstacle for physicians to switch prescription from Viagra to the new drugs for returning patients.

We report in Table 5 the estimates of prior uncertainty associated with the two new drugs in effectiveness and side effects, and the extent of noise

Table 6 Estimates (Standard Error) of the Effects of Demographic Variables and Persuasive Detailing Effects

	Proposed model	Alternative model
Demographic variables		
$\ln(age+1) * Levitra$	0.269 (0.006)	0.887 (0.001)
$Black * Levitra$	−0.009 (0.059)	0.016 (0.027)
$White * Levitra$	0.070 (0.028)	0.449 (0.006)
$HMO * Levitra$	0.108 (0.029)	0.287 (0.007)
$Indemnity * Levitra$	0.201 (0.076)	0.090 (0.066)
$Medicaid * Levitra$	−0.152 (0.152)	−0.582 (0.127)
$Medicare * Levitra$	0.154 (0.052)	−0.108 (0.022)
$\ln(age+1) * Cialis$	0.379 (0.007)	0.956 (0.012)
$Black * Cialis$	−0.103 (0.074)	−0.197 (0.187)
$White * Cialis$	0.071 (0.032)	−0.196 (0.092)
$HMO * Cialis$	0.094 (0.034)	−0.066 (0.148)
$Indemnity * Cialis$	0.252 (0.088)	0.641 (0.350)
$Medicaid * Cialis$	−0.521 (0.216)	−2.780 (1.073)
$Medicare * Cialis$	−0.155 (0.065)	0.268 (0.091)
Persuasive detailing effects		
$\ln(total\_detailing > 30\ days+1)$	0.193 (0.022)	0.310 (0.044)
$\ln(total\_detailing < 30\ days+1)$	0.402 (0.029)	0.308 (0.019)
$\ln(detailing\_with\_meal > 30\ days+1)$	−0.070 (0.033)	−0.110 (0.480)
$\ln(detailing\_with\_meal < 30\ days+1)$	0.087 (0.049)	0.091 (0.122)

in the detailing signal for effectiveness and side effects ($\Sigma^E_{v,0}$, $\Sigma^S_{v,0}$, $\sigma_{E,s}$, and $\sigma_{S,s}$ in the parameter set). Again, results from the two models are quite consistent. Physicians were more uncertain about the effectiveness of Levitra than Cialis when they were introduced, but the uncertainty of the side effects of Cialis was significantly higher than that for Levitra. These differences are probably driven by results from clinical trials as well as the promotion strategy of the firms during the prelaunch period. Detailing can be used to reduce these uncertainties. Because the magnitude of noise in detailing message regarding effectiveness is very small, detailing is informative about the effectiveness of a drug. Specifically, the standard deviation of the noise of detailing with meals is close to zero. However, the noise of detailing message regarding side effects is much larger in magnitude, implying that physicians still have large uncertainty regarding the side effects of new drugs after multiple detailing visits. In summary, our results show that the informational value of detailing is not homogeneous across product attributes.

Table 6 presents estimates of the effect of demographic variables and the persuasive detailing effect. Again, results from the two models are quite consistent. For example, the new drugs are more likely to be prescribed to older patients. Regarding persuasive detailing, we find a positive effect from detailing in either the short term (fewer than 30 days) or long term (more than 30 days). The proposed model also suggests the depreciation of such an effect, because the short-term effect is stronger than the long-term effect; however, there is no significant difference in the alternative model. Detailing with meal has an additional short-term effect in the proposed model, though it does not exist in the long term.

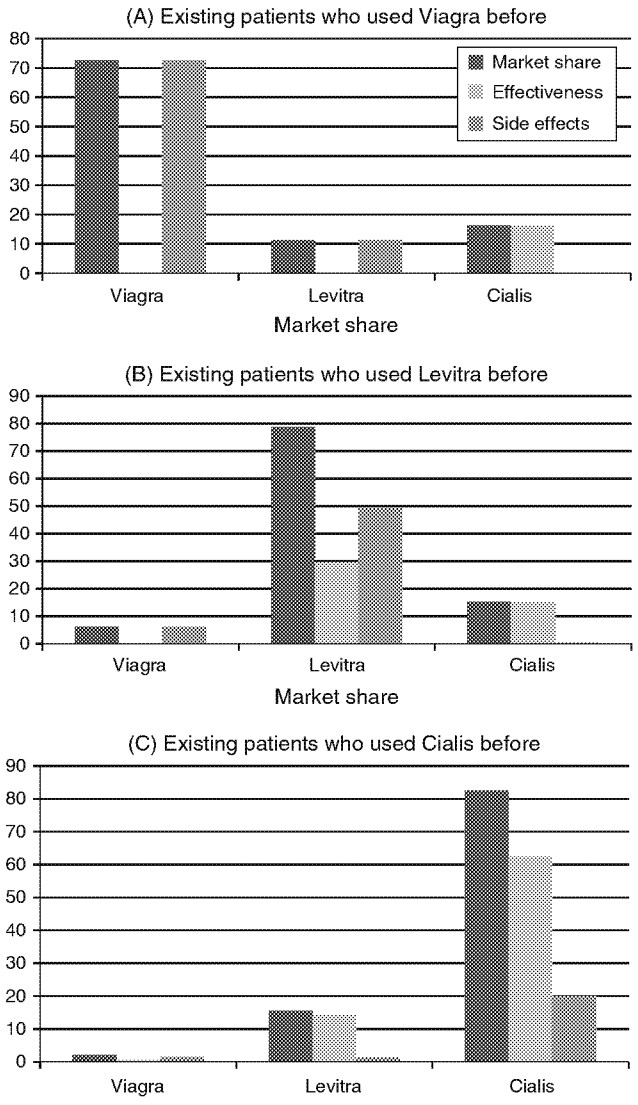
To better understand the impacts of effectiveness and side effects on prescription decisions and the informative role of detailing, we carry out a series of simulation exercises based on the estimation results from the proposed model.

4.1. The Influence of Effectiveness and Side Effects on Prescription Choices

We simulate the prescription decisions for revisiting patients who used one drug previously and know exactly how this particular drug worked for them in both effectiveness and side effects. Conditional on this information, physicians form expectations on the effectiveness and side effects for the other two drugs.[15]

[15] A physician's prescription choice is based on the realized utility of the previously chosen drug versus the expected utilities for the other two drugs. In this exercise, we assume that there is no prior physician uncertainty in effectiveness and side effects. Our results can be treated as the long-run equilibrium outcomes after the three drugs entered the market.

Figure 4 A Simulation Study of Treatment Choices of Existing Patients



Because of the normalization we use in model estimation, all comparisons are relative to Viagra. Figure 4 plots the simulated market share for those revisiting patients who used Viagra, Levitra, and Cialis before, respectively. A general pattern we can immediately observe from the three graphs in Figure 4 is that the drug that patients start with has a significant "first-mover" advantage, because between 70% and 80% of patients would stay with their previously prescribed drug. This is due to three factors: the cost associated with switching to a different drug, the uncertainty of treatment outcomes for the other two drugs, and the risk aversion of patient–physician pair.

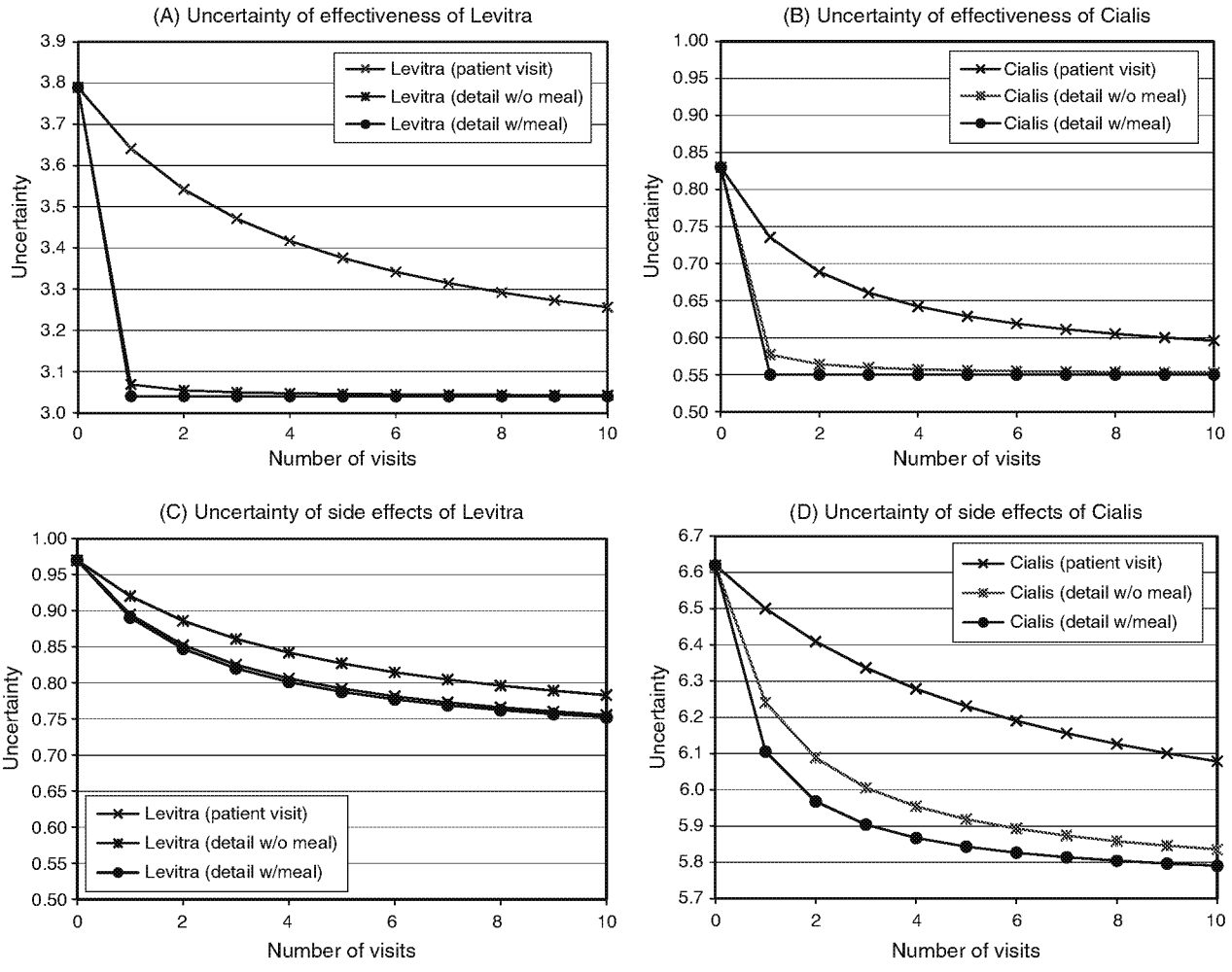
We also examine the reasons why a patient chooses either to stay with the previous drug or to switch to another drug. We assume that the reason for choosing (either staying with or switching to) a drug is "effectiveness" if the difference in effectiveness between the

chosen drug with the highest utility and the drug with the second highest utility is greater than the difference in side effects between these two drugs; otherwise, the reason of the choice is "side effects." Figure 4 shows an interesting substitution pattern among drugs: for patients who used Viagra before (panel (A)), if they decide to stay with Viagra or switch to Levitra, it is because of fewer side effects; if they decide to switch to Cialis, it is entirely due to higher expected effectiveness. For patients who used Levitra before (panel (B)), all will switch to Cialis if they find Levitra ineffective, but will switch to Viagra if Levitra has strong side effects. Finally, for patients who used Cialis before (panel (C)), most of them will stay because of its effectiveness, although a few will switch to either Viagra because of side effects or Levitra because of effectiveness. In summary, switching to Cialis from Viagra or Levitra is due to expected effectiveness, whereas switching to Viagra from the other two drugs is due to the expected side effects. This exercise illustrates the "competitive advantage" of the three drugs in the market place.

4.2. The Informative Role of Detailing

To understand the informative role of detailing in facilitating physician learning, panels in Figure 5 show the total uncertainty of a physician, which is the sum of the treatment heterogeneities across patients (i.e., variances in Table 4) and prior uncertainties (i.e., variances in Table 5) in effectiveness and side effects when the new drugs were introduced. We examine the change in a physician's uncertainty when his exposure to detailing (with a meal and without a meal) increases from 1 to 10, compared with when the number of patient feedback increases from 1 to 10. Note that the treatment heterogeneity across the patient population is the lower bound for the total uncertainty. Levitra has a larger heterogeneity in effectiveness than Cialis (the variances are 3.04 and 0.55 for Levitra and Cialis, respectively), whereas for side effects it is the opposite (the variances are 0.70 and 5.73 for Levitra and Cialis, respectively). Panels (A) and (B) in Figure 5 show that detailing especially accompanied by meals is much more informative than patient feedback in reducing the physician uncertainty of effectiveness.

Figure 5 Uncertainty Reduction Through Patient Feedback vs. Detailing



With one detailing visit with a meal, the total uncertainty in effectiveness is reduced from 3.79 to 3.04 for Levitra and from 0.83 to 0.55 for Cialis, virtually the lowest uncertainty levels that can be achieved. Consequently, subsequent detailing visits do not have any informative effect on the effectiveness of drugs. In contrast, panels (C) and (D) in Figure 5 show that detailing is less informative regarding side effects. With one detailing visit with a meal, the total uncertainty in side effects is reduced from 0.97 to 0.89 for Levitra, and from 6.62 to 6.11 for Cialis, much higher than the possible lower bounds. Patient feedback is comparable to detailing in terms of reducing the uncertainty of side effects. These results show that physicians still need information after the first detailing visit to further reduce uncertainty regarding side effects. For drugs such as Cialis that are associated with large uncertainty of side effects, subsequent visits will continue to provide significant informational value, but for Levitra, these visits are primarily persuasive.

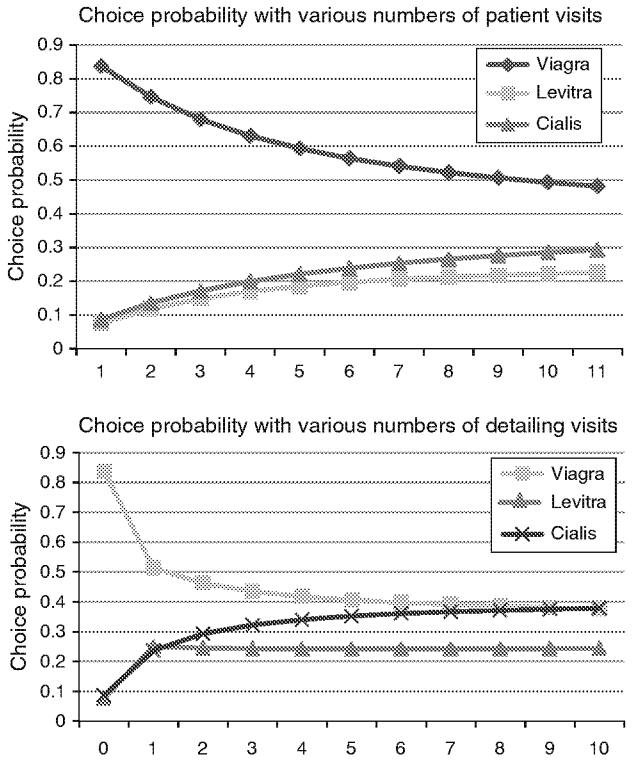
There can be multiple explanations for the difference in the informativeness of detailing visits, that we cannot identify in the model. Many types of side effects can be caused by ED drugs, so it may take multiple visits for physicians to learn. Another possibility is that these side effects may not be fully discovered until a drug has been marketed for years (Lasser et al. 2002); hence, salespeople cannot show physicians much evidence. It is also possible that side effects are not a big concern in the ED category; therefore salespeople would allocate less time and effort for their discussion. However, our next result shows that reducing the physician uncertainty in side effects is important for the adoption of Cialis.

4.3. The Importance of Informative Detailing for New Entrants

For Levitra and Cialis, how important is the informative detailing in their competition with Viagra in the market? Suppose a physician treats a new patient with the following characteristics: Caucasian, age 40, with moderate severity and covered by an HMO. We set the total uncertainty of both effectiveness and side effects for Levitra and Cialis at the level of period 0 (i.e., variances at 4.8 and 7.5 for Levitra and Cialis, respectively), and simulate the choice probability for this new patient as the number of patient feedback or detailing visits simultaneously increases for all three drugs.[16] Suppose detailing was prohibited and patient feedback was the only information source for physicians to learn about the two drug attributes. The upper panel in Figure 6 shows that, with one patient

[16] For simplicity, we abstract away from the effect of persuasive detailing on prescription choice. We have also abstracted away from the additional switching costs when treating a returning patient.

Figure 6 Impact of Patient Feedback and Detailing on the Choice Probability of New Drugs



feedback, the choice probability increases from 7.6% to 11.8% for Levitra, and from 8.7% to 13.5% for Cialis. Both gain market share from Viagra. If the number of patient feedback increases to 10, their choice probabilities will further increase to 22.5% and 29.3% for Levitra and Cialis, respectively.

Now consider the opposite case that physicians are exposed to the same level of detailing from the three drugs, but suppose there is no patient feedback. The lower panel in Figure 6 shows that one detailing visit without a meal increases the choice probability from 7.6% to 25.0% for Levitra, and from 8.7% to 23.7% for Cialis. The increase in choice probability due to detailing is much greater than that due to patient feedback, indicating that for new drugs detailing is more efficient than patient feedback in reducing physician uncertainty. Detailing also helps to improve the patient welfare because physicians are more willing to prescribe improved drugs to new and returning patients.

Another interesting observation from Figure 6 is that subsequent detailing visits are also important for Cialis in gaining market share. As the number of detailing visits increases to 10, its choice probability further increases to 37.8%. Because the uncertainty of effectiveness has virtually been eliminated after the first visit, the additional gain comes from the fact that these visits continue to provide useful information regarding side effects, which is the biggest

concern of prescribing Cialis among physicians. By modeling the physician learning of effectiveness and side effects, our study offers a structural explanation for the differential marginal effects of detailing on prescription choice found from our reduced-form regressions, which are driven by the differential informational values of detailing. Without understanding such a difference, one may use the Levitra experience to conclude that there is little informational value from subsequent detailing visits and hence lead to misguided recommendations on detailing for Cialis, whose profile of effectiveness and side effects is different from Levitra's.

5. Conclusion and Future Research

In this paper, we develop a structural model to study how a risk-averse physician evaluates multiple drug attributes, i.e., treatment effectiveness and side effects, that are unobserved to researchers, and how detailing and patient feedback help to reduce the physician's uncertainty of these two attributes. We use a physician panel data set in the ED category to empirically estimate the model. To separately identify effectiveness and side effects, we combine the observed prescription choices with a unique data set of self-reported reasons for switching treatment and simultaneously model the prescription decisions and switching reasons. We find that the two new drugs, Levitra and Cialis, have significantly higher mean effectiveness than the existing drug, Viagra. However, large physician uncertainty in effectiveness for Levitra and in side effects for Cialis has prevented physicians from prescribing these two drugs. Detailing is more efficient than patient feedback in facilitating the physician's learning about the effectiveness of a drug, but much less so in reducing the uncertainty on side effects. One detailing visit would resolve almost all prior uncertainty in effectiveness and increase the market share considerably for both new drugs, but Cialis will further gain market share through subsequent detailing visits, as these visits continue to provide the physician important information on side effects. We show the importance of detailing in helping new drugs compete with incumbents and improving patient welfare.

There are several directions for future research. First, because of data limitation, we are unable to explore why there is a difference in the informational value of detailing regarding effectiveness and side effects. The intensity and content of detailing can be a salesperson's strategic choice. A better understanding of the detailing strategies of salespeople, as physicians' information evolves overtime, will provide us with a more complete picture of the physician learning process. Second, our results on how detailing helps new drugs compete with incumbents are only a partial analysis. It is important to study, under market equilibrium conditions, how pharmaceutical firms compete in detailing, and perhaps also in other policies such as pricing and direct-to-consumer advertising. Third, we applied our model to lifestyle drugs. It would be interesting to see how the results would be different in life-saving drugs such as cancer, diabetes, or AIDS drugs. Although we find that side effects are less important than effectiveness in prescription decisions in the ED category, it can be vastly different in these other categories. Fourth, in this paper we focus on modeling the demand side of the pharmaceutical market. Large uncertainty and other switching costs are found to influence physicians' prescription choices. A long stream of theoretical literature has discussed how consumer switching cost impacts competition between incumbents and new entrants (e.g., Klemperer 1987, 1988, 1992; Villas-Boas 2004, 2006; Doganoğlu 2010). We believe it is important for future research to model how pharmaceutical firms should compete in providing physicians information on drug effectiveness and side effects. Finally, we assume in our model that physicians maximize the joint utility during treatment. In reality, a physician can be forward looking and strategically experiment with new drugs to maximize the long-term utility. This assumption may be worth testing in the future research (for example, see Dickstein 2011).

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References

Ackerberg D (2001) Empirically distinguishing informative and prestige effects of advertising. *RAND J. Econom.* 32(2):316–333.

Berry S, Levinsohn J, Pakes A (2004) Differentiated products demand systems from a combination of micro and macro data: The new vehicle market. *J. Political Econom.* 112(1):68–104.

Brock GB, McMahon CG, Chen KK, Costigan T, Shen W, Watkins V, Anglin G, Whitaker S (2002) Efficacy and safety of Tadalafil for the treatment of erectile dysfunction: Results of integrated analysis. *J. Urology* 168(4):1332–1336.

Chan T, Hamilton B (2006) Learning, private information and the economic evaluation of randomized experiments. *J. Political Econom.* 115(6):997–1040.

Ching A (2010) Consumer learning and heterogeneity: Dynamics of demand for prescription drugs after patent expiration. *Internat. J. Indust. Organ.* 28(6):619–638.

Ching A, Ishihara M (2010) The effects of detailing on prescribing decisions under quality uncertainty. *Qualitative Marketing Econom.* 8(2):123–165.

Ching A, Ishihara M (2012) Measuring the informative and persuasive roles of detailing on prescribing decisions. *Management Sci.* 58(7):1374–1387.

Chintagunta PK, Renna J, Ginger ZJ (2009) Information, learning, and drug diffusion: The case of Cox-2 inhibitors. *Quant. Marketing Econom.* 7(4):399–443.

Crawford G, Shum M (2005) Uncertainty and learning in pharmaceutical demand. *Econometrica* 73(4):1137–1174.

DeGroot MH (1970) *Optimal Statistical Decisions* (McGraw-Hill, New York).

Dickstein MJ (2011) Efficient provision of experience goods: Evidence from antidepressant choice. Working paper, Stanford University, Stanford, CA.

Doganoğlu T (2010) Switching costs, experience goods and dynamic price competition. *Quant. Marketing Econom.* 8(2):167–205.

Erdem T, Keane M (1996) Decision-making under uncertainty: Capturing dynamic brand choice process in turbulent consumer goods markets. *Marketing Sci.* 15(1):1–20.

Goldstein I, Lue TF, Padma-Nathan H, Rosen RC, Steers WD, Wicker PA (1998) Oral Sildenafil in the treatment of erectile dysfunction. *New England J. Medicine* 338(20):1397–1404.

Harris K, Keane M (1999) A model of health plan choice: Inferring preferences and perceptions from a combination of revealed preference and attitudinal data. *J. Econometrics* 89(4):614–157.

Hellstrom WJG, Gittelman M, Karlin G, Segerson T, Thibonnier M, Taylor T, Padma-Nathan H (2002) Vardenafil for treatment of mean with erectile dysfunction: Efficacy and safety in a randomized, double-blind, placebo-controlled trial. *J. Andrology* 23(6):763–771.

Hurwitz MA, Caves RE (1988) Persuasion or information? Promotion and the shares of brand name and generic pharmaceuticals. *J. Law Econom.* 31(2):299–320.

Klemperer P (1987) Markets with consumer switching costs. *Quart. J. Econom.* 102(2):375–394.

Klemperer P (1988) Welfare effects of entry into market with switching costs. *J. Indust. Econom.* 37(2):159–165.

Klemperer P (1992) Multi-period competition with switching costs. *Econometrica* 60(3):651–666.

Klemperer P (1995) Competition when consumers have switching costs: An overview with applications to industrial organization, macroeconomics, and international trade. *Rev. Econom. Stud.* 62(4):515–539.

Lasser K, Allen P, Woolhandler S, Himmelstein D, Wolfe S, Bor D (2002) Timing of new black box warnings and withdrawals for prescription medications. *J. Amer. Medical Assoc.* 287(17):2215–2220.

Leffler KB (1981) Persuasion or information? The economics of prescription drug advertising. *J. Law Econom.* 24(1):45–74.

Manchanda P, Rossi PE, Chintagunta PK (2004) Response modeling with nonrandom marketing-mix variables. *J. Marketing Res.* 41(4):467–478.

Manchanda P, Xie Y, Youn N (2008) The role of targeted communication and contagion in product adoption. *Marketing Sci.* 27(6):961–976.

Manski C (2004) Measuring expectations. *Econometrica* 72(5): 1329–1376.

Narayanan S, Manchanda P (2009) Heterogeneous learning and the targeting of marketing communication for new products. *Marketing Sci.* 28(3):424–441.

Train K (2003) *Discrete Choice Methods with Simulation* (Cambridge University Press, Cambridge, UK).

Villas-Boas JM (2004) Consumer learning, brand loyalty, and competition. *Marketing Sci.* 23(1):134–145.

Villas-Boas JM (2006) Dynamic competition with experience goods. *J. Econom. Management Strategy* 15(1):37–66.

Villas-Boas JM, Winer RS (1999) Endogeneity in brand choice models. *Management Sci.* 45(10):1324–1338.