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The authors study physicians' prescription choices when uncertainty about drug efficacy is resolved through two channels: firms' marketing activities (e.g., detailing) and patients' experiences with the drugs. They first provide empirical evidence that suggests that the well-understood information incentive for physicians to experiment with new drugs is reduced when physicians anticipate future detailing. Therefore, increased detailing activity triggers opposing forces: Adoption is hastened as physicians become informed (assuming prior knowledge is initially low) and slows as they reduce experimentation and instead obtain information from detailing at no cost. The authors then estimate a dynamic Bayesian learning model that embodies these trade-offs using physician-level data on prescription choices and detailing received in the months surrounding the introduction of two erectile dysfunction drugs, Levitra and Cialis. Detailing elasticities are lower when physicians anticipate changes in detailing activity than when such changes are unexpected. Accordingly, the authors conclude that to maximize the effect of detailing, firms should avoid announcing increases in detailing activities.

Keywords: uncertainty, learning, dynamic discrete choice, new drug diffusion

New Drug Diffusion When Forward-Looking Physicians Learn from Patient Feedback and Detailing

Researchers in marketing and economics have studied the impact of firms' marketing activities (e.g., detailing) and feedback from patients on the diffusion of new drugs within and across physicians (see Manchanda et al. 2005). Given the possibility that physicians might be uncertain about the quality of the new drug, researchers have typically assumed physicians learn about drug quality in a Bayesian way, with detailing and patient feedback providing the information for such learning (e.g., Chan, Narasimhan, and Xie 2007; Currie and Park 2002; Narayanan and Manchanda 2009). Various researchers have demonstrated that physicians learn from multiple sources of information (e.g., Ching 2010a, b; Ching and Ishihara 2010, 2012; Coscelli and Shum 2004; Narayanan and Manchanda 2009; Narayanan, Manchanda, and Chintagunta 2005) and that physicians are willing to sacrifice current utility by experimenting with a new drug to obtain information that enables them to make better future decisions (e.g., Crawford and Shum 2005; Ferreyra and Kosenok 2011). However, researchers have yet to combine multiple information sources with physicians' forward-looking behavior. We address this gap in the literature and assess the managerial implications of both current and expected future detailing on forward-looking physicians' choices.

Why is it important to account for these two aspects when studying new drug diffusion? Forward-looking physicians have a greater incentive to act strategically because of the feedback mechanism. By experimenting early, forward-looking physicians can learn the effectiveness and side effects of new drugs more quickly, knowledge they can apply to other patients. For most ethical drugs (e.g., those used in the majority of the previous literature that has focused on myopic physician behavior), experimentation

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seems unlikely given the potentially severe consequences the physician could face—namely, malpractice lawsuits. However, this concern is mitigated in the case of lifestyle drugs such as the one we consider in the current study. In our setting, a forward-looking physician trades off lower current utility from prescribing a new drug of uncertain quality with the future option value from having more information about the new drug's true quality.

Narayanan, Manchanda, and Chintagunta (2005) and Narayanan and Manchanda (2009) establish that multiple sources of information influence drug diffusion. Although physicians typically do not choose whether they receive detailing visits, they do choose whether to experiment with a new drug to obtain patient feedback. Therefore, physicians may strategically substitute between sources of information: Experimentation is costly, so a physician will be less likely to experiment if he or she expects to obtain free information through detailing. Indeed, in our data, physicians who had yet to receive detailing were less likely to adopt with early patients when they expected a greater level of future detailing. Such behavior is consistent with both strategic substitution of feedback information with detailing information and physicians possibly waiting to receive free samples from sales representatives. By modeling physicians as forward looking, we can investigate the implications of strategic substitution between information sources. Although detailing tends to increase adoption (assuming the information is favorable), an increase in expected detailing can delay adoption by physicians who were initially planning to obtain information through experimentation. For physicians unlikely to experiment, this substitution effect of expected detailing is reduced. Thus, detailing has a greater impact on physicians who are less likely to obtain information through experimentation. Without capturing this intertemporal behavior of physicians, a myopic model will likely provide incorrect inferences regarding the effects of detailing, just as previous studies have shown that inferences regarding price effects are incorrect when forward-looking behavior is ignored (e.g., Erdem, Imai, and Keane 2003).

In this study, we investigate the diffusion of Levitra and Cialis, two drugs that were launched in the erectile dysfunction (ED) category, in which the incumbent Viagra had enjoyed monopoly status for more than five years. For our empirical analysis, we use data on physicians' prescription writing and detailing received over ten months, from August 2003 to May 2004. The data provide evidence consistent with physicians being forward-looking and substituting feedback information with detailing information when expected detailing is high. Accordingly, in formulating our model of physicians' learning behavior, we assume physicians are forward looking and use information from detailing visits as well as from patient feedback to learn about the quality of Cialis and Levitra.

Building on the Bayesian learning framework (Eckstein, Horsky, and Raban 1988; Erdem and Keane 1996; Miller 1984; Narayanan and Manchanda 2009), we incorporate into a dynamic discrete-choice model the evolution of physicians' beliefs regarding the eficacies of new drugs. With each patient visit, a forward-looking physician decides which drug to prescribe given his or her current beliefs about the drug's average efficacy across his or her patient base.[1] If a new drug is prescribed, patient feedback provides information for updating beliefs. Physicians also update beliefs with information from firms' detailing activities. This informative effect of detailing is absent for the incumbent Viagra because its efficacy is already known, given its launch five years earlier. Therefore, detailing by Viagra separately identifies its persuasive role. We assume that physicians have rational expectations regarding firms' detailing activities: Those who receive frequent detailing expect frequent detailing. We accommodate heterogeneous priors and true efficacies across physicians and use the nested fixed-point approach of Rust (1987) to estimate the model.[2]

Our results indicate that most physicians initially perceive the new drugs as inferior to Viagra and increase their beliefs as they learn the drugs' true efficacies from detailing and patient feedback. The average true efficacies of the drugs are similar, with Cialis having the highest and Levitra the lowest. We also find that if physicians expect a high level of detailing, it slows their adoption of the new drug in that expected detailing induces forward-looking physicians to wait for free information or free samples from detailing.

We compute detailing elasticities for the new drugs under three scenarios: with myopic physicians and with forward-looking physicians who either do or do not anticipate the new detailing levels. Elasticities with myopic physicians are more than twice as high as those with forward-looking physicians because myopic physicians with low initial beliefs rarely prescribe the drugs and remain in the low-belief state until detailing informs them. In contrast, forward-looking physicians are more likely to experiment with a drug to obtain information about its efficacy, which enables them to escape the low-belief state without detailing information. We also find that the effect of increased detailing to forward-looking physicians depends on whether they anticipate the change. Detailing elasticities are lower when physicians anticipate changes in detailing because they reduce experimentation in response to higher expected detailing.

Finally, we evaluate the optimality of the level of detailing by Levitra and Cialis in the postlaunch months of our data, holding other firms' detailing activity fixed. We find that Levitra's observed detailing level maximizes its expected discounted profits if each Levitra prescription during the postlaunch period translates into 32 future prescriptions. For Cialis, observed detailing levels are optimal if each prescription results in 24 future prescriptions.

INDUSTRY AND DATA OVERVIEW

Erectile dysfunction is the inability to achieve or sustain an adequate erection for sexual activity. The first oral ED treatment the U.S. Food and Drug Administration approved was Pfizer's Viagra, on March 27, 1998, followed by Bayer

[1]Crawford and Shum (2005) observe the sequence of each patient's visits and therefore focus on learning patient-specific match values. We do not observe patient identities and therefore restrict our model to prescriptions for new ED patients; moreover, we focus on learning about a drug's physician-specific average efficacy. Efficacy varies across physicians because of differences in patient-base characteristics.

[2]Narayanan and Manchanda (2009) are able to estimate a richer heterogeneity structure given their static setting.

and GlaxoSmithKline's Levitra on August 19, 2003, and Eli Lilly's Cialis on November 21, 2003. All three of these drugs are phosphodiesterase inhibitors, which enable erections by enhancing the effects of nitric oxide, a chemical the body produces during sexual stimulation to increase blood flow. Although the basic mechanism is the same, the drugs differ in their chemical makeup. Patients may therefore experience different outcomes across the drugs, such as how quickly they take effect and wear off, how they interact with other medications, and side effects. Notably, Cialis works for 36 hours, whereas Levitra and Viagra last up to four hours. As such, Cialis is the only drug offered as a once-daily medication.

Various medical journals report that Viagra, Levitra, and Cialis do not usually cause severe side effects but that some people experience headache, flushing, indigestion, and a runny nose after taking these drugs. A small number of men taking ED drugs have reportedly suffered vision loss or sudden hearing loss. Physicians do not recommend ED drugs to patients who have high or low blood pressure, diabetes, high cholesterol, eye problems, heart pain, or a history of stroke or life-threatening arrhythmia within the past six months. Given these possible complications, all existing drugs in the ED category require a doctor's prescription.

Since the successful launch of Viagra in April 1998, growing public awareness of ED problems has rapidly expanded the ED drug market. Viagra sales in 1998 were $788 million worldwide, with $656 million in the United States. In 2006, global ED drug sales exceeded $3 billion.

Data

We obtained physician-level data from ImpactRx, a consulting firm specializing in the pharmaceutical industry. Our panel data set covers 9900 prescription records written by 957 physicians over the ten-month period from August 2003 to May 2004. The data set also contains daily detailing records for 4819, 6936, and 4874 sales force visits from Viagra, Levitra, and Cialis, respectively. All physicians in our sample are primary-care physicians. We only consider physicians who prescribed Viagra at least once before the launch of the new drugs because we assumed that all physicians know Viagra's efficacy.

Similar to Narayanan and Manchanda (2009), we focus our attention on new prescriptions. Although we observe returning patients and their prior prescription, we do not observe their full prescription history. Thus, we do not model prescription choice for returning patients. However, we do account for feedback information obtained by a physician who switches a consumer from one drug to another. That is, we include such signals in the updating of physicians' beliefs even though we do not include prescription outcomes for such switchers in the likelihood function. We assume that physicians obtain no additional feedback information from renewal prescriptions.[3]

In Figure 1, we report the number of new prescriptions each week for each drug by the 957 physicians in our sample, along with new prescriptions for the category. The decline in Viagra prescriptions and increase in ED drug prescriptions when the new drugs enter reflect business stealing and ED drug market expansion, respectively. Cialis takes the lead in new prescriptions a few months after its launch, and the market shares of the three drugs stabilize around April 2004. The adjustment to the new steady state takes several months as physicians learn the efficacies of Cialis and Levitra. Such patterns from our micro-level sample are consistent with aggregate patterns in the IMS Health's New Product Spectra data.

Figure 2 shows firms' detailing activities by week. Both new entrants aggressively detail physicians shortly after launch and moderately reduce detailing during the final months of our sample. Incumbent Viagra increases its detailing activities in response to the new competition. The midsample dip in both new prescriptions and detailing activities reflect the end-of-year holiday period.

Figure 3 provides information regarding the reach of detailing and the extent of adoption across physicians. As Panels A and B show, pharmaceutical firms do not contact all the physicians at the beginning, though both firms concentrate a significant amount of financial resources on the early phase of drug release. By the end of the sample, 89% of physicians have been detailed regarding Levitra and 80% have been detailed regarding Cialis. Panels C and D reveal that the number of physicians adopting the new drugs mirrors, with a slight lag, the detailing coverage in Panels A and B. Although these aggregate patterns suggest that detailing fosters adoption, we base our identification of the effectiveness of detailing on the relationship between detailing and adoption at the individual physician level. For example, the prescription rate for Levitra is 46% for a physician's first postlaunch patient if the physician had been detailed, compared with 14% if not.

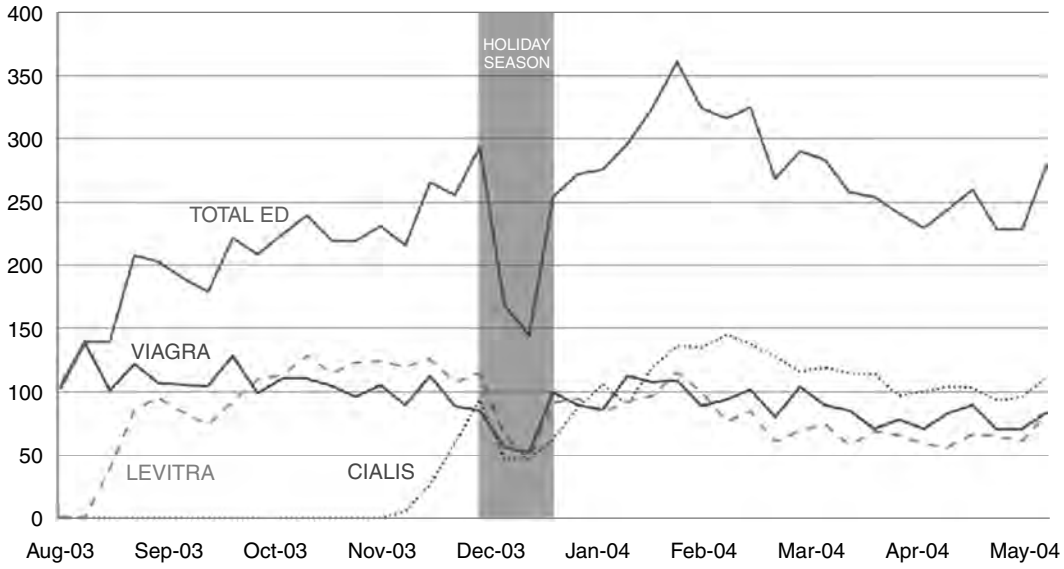
Because firms choose their detailing strategies, it is reasonable to be concerned about endogeneity. For example, firms might target physicians who have yet to adopt, which could lead to a bias in detailing effectiveness. Our data do not reflect such a strategy. Instead, the firms appear to be following the standard practice of sorting physicians by prescriptions written in the category and using decile-based rules to allocate detailing resources (Manchanda and Chintagunta 2004). In Figure 4, we present the average monthly number of each firm's detailing visits during the sample period, broken down by physician segments based on the number of new prescriptions written during the ten months after Levitra's launch. We compute Cialis's monthly average using only the seven months after its launch. For each drug, detailing frequency monotonically increases with the size of the physician's patient base. Among the new drugs, Levitra details physicians more heavily than Cialis. Moreover, even if the total amount of detailing to a physician is endogenous, the timing of the detailing visits is influenced by random components such as the availability of the physician and the sales representative's calling plan, which reflects travel cost considerations.

Suggestive Evidence of Strategic Physician Behavior

Next, we provide empirical evidence that suggests that physicians adapt their behavior to their expectations of future detailing. In particular, reduced-form regressions,

[3]To be consistent with renewal prescriptions not providing patient feedback, a patient who switches back to a previously prescribed drug should also provide no information. Although our data do not reveal whether switches are switchbacks, we suspect that switchbacks are rare and therefore assume that all switches provide patient-feedback information.

Figure 1
NEW PRESCRIPTIONS IN THE SAMPLE, BY WEEK



reported in Table 1, indicate that physicians who have yet to be visited by a sales representative are less likely to adopt a new drug if they have a greater expectancy of future detailing activity.

In the first row of regressions, the dependent variable is a dummy variable for whether the physician adopts the new drug (Levitra or Cialis) for the first new ED patient. The other regressions modify the dependent variable to consider adoption by the second, third, or fourth new ED patient arrivals. The dummy variable Levitra accounts for the generally faster adoption of Levitra than Cialis, probably due to the greater similarity of Levitra to the incumbent Viagra.

The regressions are conditional on physicians not yet having been visited by a Levitra sales representative, for observations pertaining to the adoption of Levitra, and likewise for observations pertaining to the adoption of Cialis. That is, we include in the regressions only physicians who

Figure 2
NUMBER OF DETAILING VISITS, BY WEEK

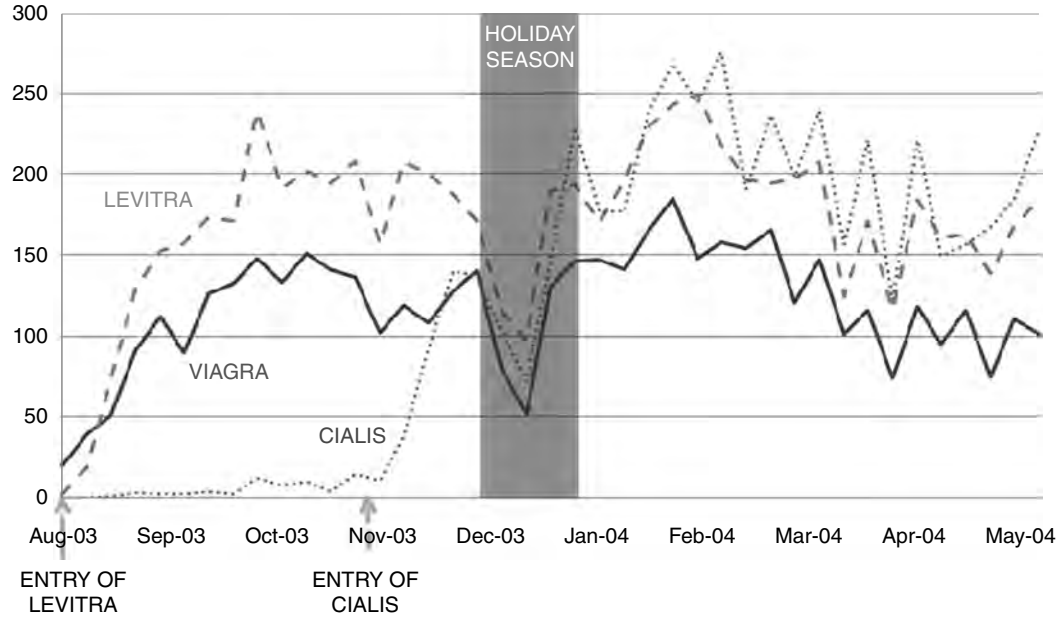
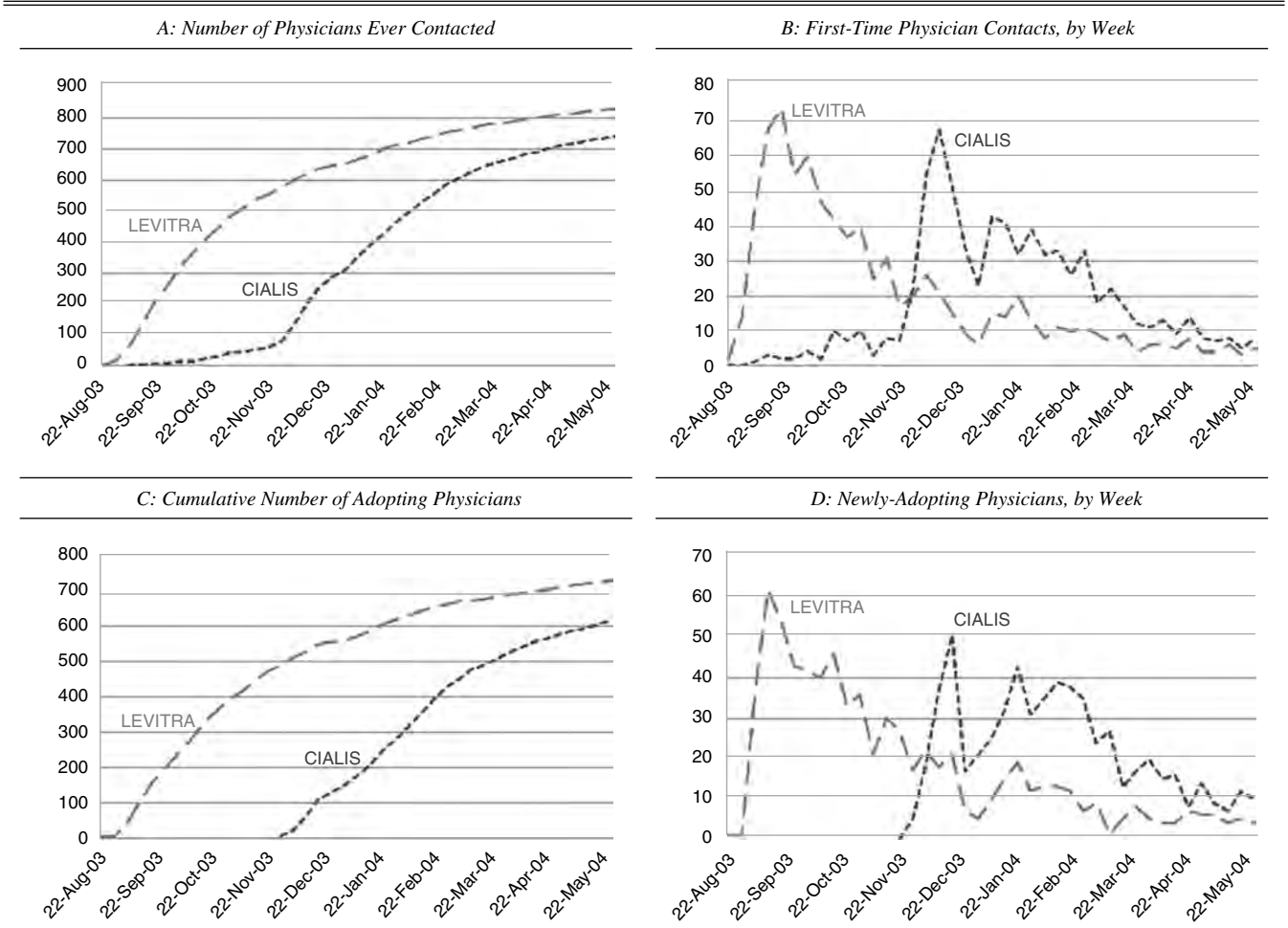


Figure 3
FIRMS' OF DETAILING AND NEW DRUG ADOPTION ACROSS PHYSICIANS



have not received a detail visit from the relevant firm (Levitra or Cialis) before the arrival of the Xth patient.

We report results both with and without conditioning on the arrival date of the Xth patient. Excluding the calendar date could lead to a negative coefficient on the future detailing variable because physicians with high detailing tend to have many patients and therefore will encounter their first patient sooner. Patients arriving shortly after launch may be less likely to receive a new drug because other information transmission mechanisms, such as word of mouth, will not have had as much time to boost demand. However, we find that "days to Xth patient" affects the coefficient on future detailing only in the first regression and the coefficient remains marginally significant. In the other three regressions, the coefficient on this control variable is precisely estimated to be zero, and the coefficient on future detailing is significantly negative. The range of the log(1+future detailing) variable is 3.9, which implies that its effect is also economically significant.

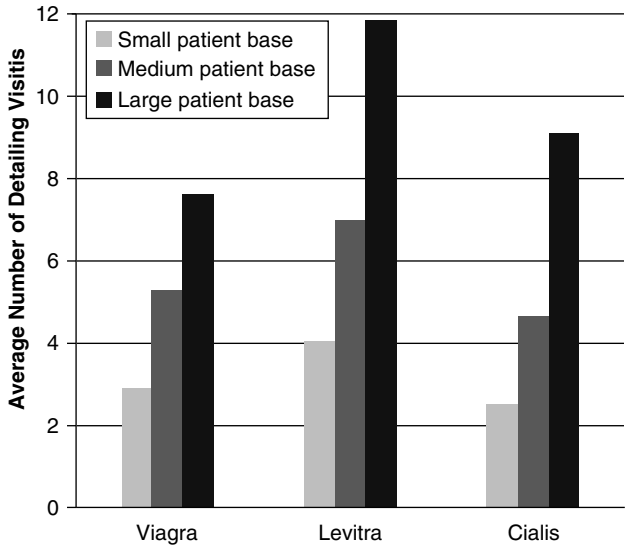
The lower adoption by physicians expecting high future detailing reflects their willingness to wait for information from detailing or the possible free samples rather than incur costly experimentation to obtain patient feedback or require their patients to pay for the prescriptions. In our dynamic model, we capture this substitution behavior by accounting for physicians' expectations regarding firms' detailing activities.

A MODEL OF PHYSICIAN BEHAVIOR

Consistent with evidence presented in the "Data" section, we assume that physicians are forward looking and update their initially uncertain beliefs about the quality (i.e., true mean efficacy) of Levitra and Cialis for their patient base using information obtained from detailing visits and patient feedback on prior prescriptions.[4] With each patient visit, physicians whose beliefs suggest that the best drug for the patient is the incumbent Viagra face the following trade-off: They can obtain the higher utility from prescribing Viagra, or they can obtain a lower expected utility from one of the new drugs while gaining information that will enable them to make better decisions with future patients. The valuation of these two options depends on the rate at which

[4] "True mean efficacy" refers to a physician's ultimate perception of a drug's average efficacy across his or her patients. This measure of mean utility need not match objective measures of efficacy from medical studies.

Figure 4
AVERAGE MONTHLY NUMBER OF EACH FIRM'S DETAILING VISITS



the physician discounts future utility (which depends on his or her patient-base size) and on his or her expectations of future detailing about the new drugs. Being forward-looking, physicians choose their prescription-writing policy to maximize the expected discounted flow of utilities from their current and future patients. The discount factor depends on the time between patient arrivals, which in turn is driven by the physician's patient-base size.

Table 1
REGRESSIONS RELATING ADOPTION RATES TO EXPECTED DETAILING

	Model 1		*Model 2*	
	Estimate	*SE*	*Estimate*	*SE*
Dependent Variable: Adopt by First Patient				
Constant	.0333	.0111	.0026	.0140
Levitra	.1332	.0129	.1337	.0128
Log(1+ future detailing)	−.0172	.0061	−.0093	.0064
(Days to first patient)/100			.0507	.0142
Dependent Variable: Adopt by Second Patient				
Constant	.0716	.0160	.0658	.0186
Levitra	.2628	.0209	.2646	.0211
Log(1+future detailing)	−.0289	.0089	−.0271	.0094
(Days to second patient)/100			.0029	.0048
Dependent Variable: Adopt by Third Patient				
Constant	.0953	.0198	.0937	.0238
Levitra	.3901	.0282	.3908	.0288
Log(1+ future detailing)	−.0347	.0111	−.0342	.0117
(Days to third patient)/100			.0005	.0046
Dependent Variable: Adopt by Fourth Patient				
Constant	.1293	.0235	.1156	.0299
Levitra	.4553	.0349	.4620	.0361
Log(1+future detailing)	−.0456	.0132	−.0413	.0144
(Days to fourth patient)/100			.0037	.0050

Our assumption that physicians derive utility from patients' outcomes is consistent with evidence that physicians' careers and reputations depend on patients' health outcomes (Applegate 1986; Gallagher et al. 2003; Lopez et al. 2009). We follow Crawford and Shum (2005) and Narayanan and Manchanda (2009) by assuming agency issues involving third parties—for example, insurance and pharmaceutical companies do not affect physicians' choices.

In our model, physicians are risk neutral. As Coscelli and Shum (2004) discuss, risk aversion is not identified when agents' prior means are estimated separately from products' true mean utilities, because resistance to adoption may reflect either risk aversion or low prior means. Because we estimate prior means separately from true efficacies (i.e., mean utilities), we assume risk neutrality. If we could elicit prior means directly from physicians, we could estimate their degree of risk aversion; however, our data do not provide this option.

Let Q_{pj} denote the true quality of drug j for the patient base of physician p. The expected flow utility of physician p who prescribes drug j at time t is

$$(1) \qquad u_{pjt} = \bar{Q}_{pjt} + s(n_{jpt}; \alpha_p) + \varepsilon_{pjt} \quad \text{for } j \in \{v, l, c\},$$

where $\bar{Q}_{pjt} \equiv E(Q_{pj} | I_{pt})$ is the expected quality of drug j for physician p given information I_{pt}; $s(n_{jpt}; \alpha_p)$ is the persuasive effect from n_{jpt} detailing visits since physician p's previous patient visit; ε_{pjt} is an i.i.d. idiosyncratic preference shock; and v, l, and c refer to Viagra, Levitra, and Cialis, respectively. We assume that price does not affect physicians' decisions, as Hellerstein (1998), Gonul et al. (2001), and Campo et al. (2005) demonstrate. Moreover, Reichert, Simon, and Halm (2000) find that physicians are largely unaware of patients' out-of-pocket expenditures.

In static models of physician behavior, researchers typically include patient characteristics, such as race and age, in the utility function. In principle, it is possible to do the same in dynamic models. However, such characteristics affect not only current utility but also future utility, thereby requiring physicians to form expectations regarding the distribution of patient characteristics they will encounter later. Because patient characteristics are not central to our research question, we omit them, essentially treating them as components of ε.

Because Viagra had been on the market for five years before the beginning of our analysis, we assume that its quality is known, which implies that $\bar{Q}_{pvt} = Q_{pv}$ for all p and t. Moreover, we measure the qualities of Levitra and Cialis relative to Viagra's quality by normalizing $Q_{pv} = 0$ for each physician. We also assume physicians' beliefs about the new drugs' qualities are distributed normally: $N(\bar{Q}_{pjt}, \sigma^2_{Q_{pjt}})$, where $\sigma^2_{Q_{pjt}}$ is the variance of *p*'s belief at time t. Exploiting conjugate distributions (DeGroot 1970), we adopt a Bayesian learning process in which physicians resolve their uncertainty regarding the new drug over time. The physician potentially receives signals from two sources: patient feedback after prescribing the drug and informative detailing from sales representatives. We assume

that both sources provide unbiased information that is distributed normally.[5] Accordingly, let $F_{p,j,t+1} \sim N(Q_{pj}, \sigma^2_{Rj})$ and $D_{p,j,t+1} \sim N(Q_{pj}, \sigma^2_{Dj}/n_{p,j,t+1})$ denote realizations of the feedback and average detailing signals between periods t and t + 1. A physician choosing action $a_{pt} \in \{v, l, c\}$ at time t will then update his or her mean beliefs by averaging the realized signals in with his or her prior mean beliefs:

$$\bar{Q}_{p,j,t+1} = \frac{\dfrac{\bar{Q}_{pjt}}{\sigma^2_{Q_{pjt}}} + \dfrac{\mathcal{I}(a_{pt} = j)F_{p,j,t+1}}{\sigma^2_{Rj}} + \dfrac{n_{p,j,t+\ ,1}D_{p,j,t+1}}{\sigma^2_{Dj}}}{1/\sigma^2_{Q_{pjt}} + \mathcal{I}(a_{pt} = j)/\sigma^2_{Rj} + n_{p,j,t+1}/\sigma^2_{Dj}}, \tag{2}$$

where $\mathcal{I}(\cdot)$ is an indicator function. The variance of physicians' beliefs shrinks to

$$\sigma^2_{Q_{p,j,t+1}} = \frac{1}{1/\sigma^2_{Q_{pjt}} + \mathcal{I}(a_{pt} = j)/\sigma^2_{Rj} + n_{p,j,t+1}/\sigma^2_{Dj}}. \tag{3}$$

Conveniently, the posterior variance depends only on the precision of the signals, not on their realized values. A physician's beliefs regarding the new drugs' qualities at time t are fully characterized by the 4-tuple $x_{pt} \equiv (\bar{Q}_{plt}, \sigma^2_{Q_{plt}}, \bar{Q}_{pct}, \sigma^2_{Q_{pct}})$.

In our model, social interactions do not influence physicians' learning. Our data do not permit such interactions, nor are they likely to be significant among primary care physicians for whom ED drugs are a small fraction of overall prescriptions. For an analysis of prescription decisions with social interactions, see Nair, Manchanda, and Bhatia (2010).

A unique aspect of our model is that physicians' beliefs regarding firms' future detailing affect current prescription choices because future detailing affects future utilities, beliefs, and choices and physicians are forward looking. Consistent with Manchanda and Chintagunta (2004), we assume that firms' detailing policies are functions of physician characteristics z_p, such as patient-base size. Let $d^v(z_p)$, $d^l(z_p)$, and $d^c(z_p)$ denote the detailing policies for Viagra, Levitra, and Cialis, respectively.[6] We also assume physicians have rational expectations regarding future detailing, which implies they know the detailing policy functions.

Given expectations of drug qualities and future detailing and realizations of persuasive detailing $n_{pt} = (n_{pvt}, n_{plt}, n_{pct})$ and ε_p, a physician chooses an action $a_{pt} \in \{v, l, c\}$ to maximize expected discounted utility from the current and future patients. The physician's decision rule is therefore a mapping $d^p : X \times Z \times \mathcal{N}_0^3 \times \mathcal{R}^3 \to \{v, l, c\}$, $a_{pt} = d^p(x_{pt}, z_p, n_{pt}, \varepsilon_{pt})$. With the finite action space, an optimal decision rule exists and maximizes

$$\max_{\{a_{p\tau} = d^p(x_{p\tau}, z_p, n_{p\tau}, \varepsilon_{p\tau}, I_{p\tau})\}_{\tau=t}^{\infty}} E\left\{\sum_{\tau=t}^{\infty} \exp[-\delta\Delta_p(\tau - t)] \times u_{p,a_{p\tau},\tau}(\varepsilon_{p\tau}) \mid I_{pt}\right\}, \tag{4}$$

where δ is the daily discount rate and Δ_p is the number of days between patients for physician p, yielding a discount factor of $\beta_p = \exp(-\delta\Delta_p)$. The higher discount factor of physicians with more patients (i.e., lower Δ_p) provides a greater incentive for them to experiment with new drugs to obtain information relevant for future patients. We assume an infinite horizon because no deterministic final period exists (Ackerberg 2003).

The Bellman equation for the recursive formulation of physician p's dynamic optimization is

$$\begin{aligned} V^p(x, z, n, \varepsilon) &= \max_{a \in \{v,l,c\}} u_a(x, n, \varepsilon) + \beta_p E[V^p(x', z', n', \varepsilon') \mid x, z, n, \varepsilon, a] \\ &= \max_{a \in \{v,l,c\}} u_a(x, n, \varepsilon) \\ &\quad + \beta_p \int V^p(x', z, n', \varepsilon') f(dx' \mid x, z, a) h(dn' \mid z) g(d\varepsilon'), \end{aligned} \tag{5}$$

where t and p subscripts have been omitted and the prime symbol ($'$) denotes next-period values.The second line in the Bellman equation reflects several specifics regarding the transition of state variables, as governed by f, h, and g. First, $z' = z$ because z is constant over time. Second, the transition of beliefs to x' is independent of ε, ε', n, and n'_v because they are uninformative about drug efficacies themselves and influence neither the detailing of the new drugs nor the patient feedback. Finally, the transition to n' depends on firms' detailing policies, which we assume are functions of z only. The transition to n' is therefore independent of current and continuation values of the other state variables.

Following Rust (1987), we integrate over ε in the Bellman equation to obtain the *integrated* value function, which represents the physician's expected discounted utility before observing the current period's ε. Given the similarity of Levitra to Viagra, we expect their ε to be correlated, and therefore we assume that ε follows a generalized extreme value distribution (shifted to have a mean zero). That is, we specify a nested logit model with Viagra and Levitra in one nest and Cialis in another:

$$\begin{aligned} EV^p(x, z, n) &= \ln\left\{\exp\left[\rho \ln\left(\sum_{j \in \{v,l\}} \exp\left\{\left[\bar{Q}_j + s(n_j; \alpha_p) + \beta_p \int EV^p(x', z, n') f(dx' \mid x, z, j) h(dn' \mid z)\right] \Big/ \rho\right\}\right)\right] \right. \\ &\quad \left. + \exp\left[\bar{Q}_c + s(n_c; \alpha_p) + \beta_p \int EV^p(x', z, n') \times f(dx' \mid x, z, c) h(dn' \mid z)\right]\right\}, \end{aligned} \tag{6}$$

where $\rho = 1$ yields the standard logit with independent utilities. (Note that $\bar{Q}_j$ is $\bar{Q}_{pjt}$ after omitting the p and t subscripts.)

Three random components drive the transition to x'. First, n'_l and n'_c determine the number of informative detailing signals. Second, detailing signals D'_l and D'_c are realized, with precision governed by n'_l and n'_c. These signals are then combined with the patient feedback signal F'_l or

[5] The model permits sales agents to provide biased information if physicians know the level of bias and can therefore filter it out. With our data, the model with unbiased signals is observationally equivalent to the model with filtered-out biases. Therefore, we refer to the signals as being unbiased.

[6] In principle, firms' detailing policies could be functions of time-varying characteristics or of past detailing. Neither extension is empirically relevant for our application, so we use the simpler formulation with constant detailing intensities.

F'_c if Levitra or Cialis is chosen. Being explicit about these components, the continuation values in Equation 6 become

$$(7)\quad \beta_p \int EV^p\big[\bar{Q}'_l(\bar{Q}_l, \sigma^2_{Q_l}, F'_l, j, D'_l, n_l), \sigma^{2'}_{Q_l}(\sigma^2_{Q_l}, j, n_l), \bar{Q}'_c(\bar{Q}_c, \sigma^2_{Q_c}, F'_c, j, D'_c, n_c), \sigma^{2'}_{Q_c}(\sigma^2_{Q_c}, j, n_c), z, n'\big] \phi_{F_l}(dF'_l|\bar{Q}_l, \sigma^2_{Q_l})\phi_{F_c}(dF'_c|\bar{Q}_c, \sigma^2_{Q_c}) \phi_{D_l}(dD'_l|\bar{Q}_l, \sigma^2_{Q_l}, n'_l)h_l(dn'_l|z)\phi_{D_c}(dD'_c|\bar{Q}_c, \sigma^2_{Q_c}, n'_c) h_c(dn'_c|z)h_v(dn'_v|z),$$

where $\bar{Q}'_l(\cdot)$, $\bar{Q}'_c(\cdot)$, $\sigma^{2'}_{Q_l}(\cdot)$, and $\sigma^{2'}_{Q_c}(\cdot)$ are the posterior mean and posterior variance functions in Equations 2 and 3, $h_j(\cdot)$ is the probability of n_j details for $j \in \{v, l, c\}$, ϕ_{F_l} and ϕ_{F_c} are the normal densities for the feedback signals, and ϕ_{D_l} and ϕ_{D_c} are the normal densities for the average detailing signals. Because the physician does not yet know Q_l and Q_c, these densities have means equal to current beliefs ($\bar{Q}_l$ or $\bar{Q}_c$) and variances that reflect both the noise in the signal and the uncertainty in current beliefs of quality. For example, the perceived distribution for the feedback signal F_l is normal with mean $\bar{Q}_l$ and variance $\sigma^2_{R_l} + \sigma^2_{Q_l}$. We do not include variance $\sigma^2_{R_l}$ and $\sigma^2_{R_c}$ in Equation 7, because these variances are known parameters that are fixed over time.

In the data, detailing counts between patient visits have means that match their variances. Therefore, we model detailing expectations using the Poisson distribution. We estimate these densities in a first stage, as we discuss in the next section. To evaluate the integral in the continuation value of Equation 7, we consider $n_j \in \{0, 1, 2, E(n_j|n_j \geq 3)\}$ for each drug's detailing levels.[7] For each set of (n_v, n_l, n_c), we use the tensor product of five Gauss-Hermite nodes to integrate over the signals D_l, D_c, and either F_l or F_c if $j \in \{l, c\}$ (Judd 1998).

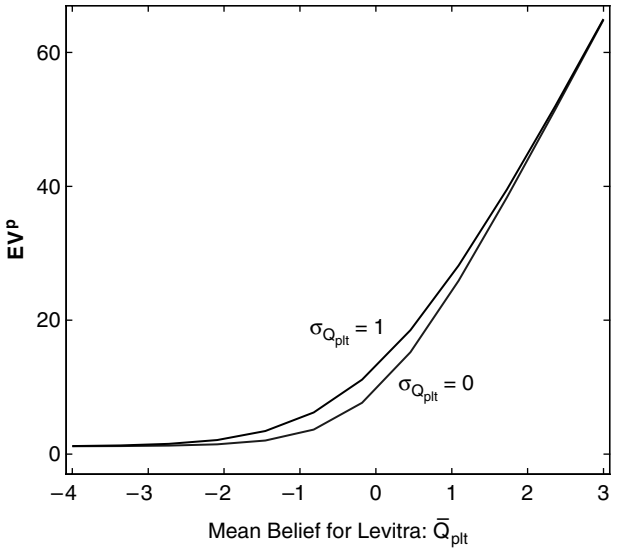
We assume that the persuasive effect of detailing depends only on whether $n_j > 0$, which implies $s(n_{jpt}; \alpha_p) = \alpha_p \mathcal{I}(n_{jpt} > 0)$.[8] We can then replace the 3-tuple (n_v, n_l, n_c) in the state-space with the 3-tuple $n^{>0} = [\mathcal{I}(n_v > 0), \mathcal{I}(n_l > 0), \mathcal{I}(n_c > 0)]$, which takes one of eight values.

We compute EV^p using value function iteration with multidimensional linear interpolation to evaluate points not on our discretized grid for the four continuous state variables $(\bar{Q}_l, \sigma^2_{Q_l}, \bar{Q}_c, \sigma^2_{Q_c})$. Figure 5 depicts the monotonic relationship between EV^p and mean beliefs, both with and without uncertainty. The figure depicts the relationship for Levitra, holding fixed p's beliefs for Cialis (at $\bar{Q}_{pct} = -4$ and $\sigma_{Q_{pct}} = 0$) and levels of detailing (at $n_{pt} = 0$). Uncertainty has a negligible effect on the value function when beliefs are sufficiently low or high that the choice probability is nearly 0 or 1 for all probable realizations of true quality. The option value of uncertainty, represented by the difference in the value functions with and without uncertainty, is maximized at a moderate level of mean beliefs near zero. Without uncertainty, the choice probability is essentially .5 when $\bar{Q}_{plt} = 0$ (given $Q_{pvt} = 0$ and $\bar{Q}_{pct} = -4$). Therefore, with uncertainty, the realized true quality will have the greatest expected impact on choice probabilities when the expected distribution of true quality is centered on zero.

[7]The set of detailing outcomes can be refined to explicitly integrate over three visits, four visits, and so on at additional computational costs.

[8]This specification fits the data as well as using $a(n_{jpt}; \alpha_p) = \alpha_p n_{jpt}$ in the static model and yields a smaller state space for the dynamic model.

Figure 5
SLICES OF THE VALUE FUNCTION



Notes: To illustrate the effect of Levitra's mean belief and uncertainty on the value function, we plot EV^p holding fixed $\bar{Q}_{pct} = -4$, $\sigma_{Q_{pct}} = 0$, and $n_{vpt} = n_{lpt} = n_{cpt} = 0$. Other detailing levels and values for Cialis's beliefs yield similar plots.

ESTIMATION

We estimate the model in two stages. In the first stage, we estimate firms' detailing policies toward physicians using a Poisson model that is conditional on z_p. We then estimate the remaining parameters, denoted θ, using the nested fixed-point approach of Rust (1987). For patient visits that precede the launch of Cialis, we assume that physicians do not anticipate the entry of Cialis. That is, for these patients, physicians' policy functions maximize the expected discounted value from prescribing either Viagra or Levitra through perpetuity.[9]

We account for heterogeneity across physicians using observable characteristics z_j and the unobserved true efficacies Q_{pl} and Q_{pc}, which we assume are distributed normally: $N(Q_l, \sigma^2_{Q_l})$ and $N(Q_c, \sigma^2_{Q_c})$, respectively.[10] We allow physicians' initial beliefs to be incorrect by specifying initial beliefs as $\bar{Q}_{pj0} \sim N(Q_{pj} + \bar{Q}_{j0}, \sigma^2_{j0})$ for $j \in \{l, c\}$. This specification allows physicians to initially be wrong, on average, by $\bar{Q}_{j0}$ while also allowing physicians with higher true efficacies Q_{pj} to have, on average, higher initial beliefs. We follow Narayanan, Chintagunta, and Miravete (2007) by fixing σ^2_{l0} and σ^2_{c0} to 1. Estimating the initial variance without directly soliciting beliefs or observing additional choices that reveal initial beliefs is difficult. Goet-

[9]If physicians anticipate Cialis's entry, the time until its entry becomes an additional state variable, and a finite-horizon solution method must be used with continuation values in the final period before Cialis's entry is derived from the value function in Equation 6.

[10]Allowing the persuasive effect of detailing to vary across physicians did not yield a statistically significant improvement in the fit of the myopic model, so we assume homogeneous persuasive effects in the dynamic model.

tler and Clay (2011) observe initial tariff choices in addition to usage choices and can therefore estimate initial prior variances.

We construct z_j to account for two physician characteristics: patient-base size (PB_j) and detailing frequency for each drug (DF_{pj}). The term PB_p is the number of ED patient visits to physician p during our estimation sample, and DF_{pj} is the average number of drug j detailings between patient visits for physician p. In the absence of computational constraints, we would make physicians' expectations regarding future patient visits and detailing conditional directly on PB_p and DF_{pj}. However, computing EV^p for each combination of $(PB_p, DF_{pv}, DF_{pl}, DF_{pc})$ is prohibitive. Therefore, we segment physicians according to three levels of PB_j and three levels of $DF_{pv}+DF_{pl}+DF_{pc}$, yielding nine observable physician segments.[11]

We first segment consumers according to whether they have three or fewer new patient visits, four to eight new patient visits, or more than eight new patient visits during the estimation period. We define a vector of patient-base-size dummy variables $PB_p = (PB_{small,\,p}, PB_{medium,\,p}, PB_{large,\,p})$ to capture this physician characteristic. Then,we characterize each physician according to whether $DF_{pv}+DF_{pl}+DF_{pc}$ is in the low, middle, or top third among physicians with the same patient-base size. Let the vector of dummy variables $D_p = (D_{low,\,p}, D_{middle,\,p}, D_{high,\,p})$ reflect physician p's detailing segment.

For each segment (PB, D), we estimate drug j's Poisson parameter $\lambda_j(PB, D)$ as the average DF_{pj} among physicians in segment (PB, D):

$$\lambda_j(PB, D) = \frac{\sum_p DF_{pj}\mathcal{I}(PB_p == PB)\mathcal{I}(D_p == D)}{\sum_p \mathcal{I}(PB_p == PB)\mathcal{I}(D_p == D)}. \tag{8}$$

By assuming that each physician knows the segment to which he or she belongs and knows that segment's λ_j for each drug, we impose the assumption that physicians have rational expectations regarding future detailing.

We report characteristics of each segment and the λ_j estimates, along with standard errors, in Table 2. The λ_j estimates range from .104 to 4.221, revealing substantial variation across physicians in actual and expected detailing. The λ_j estimates are precise, as revealed by the standard errors being low relative to the λ_j estimates themselves. We also report the variance of DF_j across physicians within each segment. These variances are remarkably close to the λ_j estimates, which supports our choice of the Poisson distribution to model detailing expectations. The reported discount factors β_p, which range from .9413 to .9934, are defined as $\exp(-\delta\Delta_p)$ using a daily discount rate of $\delta = .2/365$ and the Δ_p reported in column 3 of Table 2.[12]

Given EV^p, the probability that physician p chooses drug j at time t conditional on his or her state $(x_{pt}, z_p, n_{pt}^{>0})$ is as follows:

$$P_{pjt}[x_{pt}, z_p, n_{pt}^{>0}; \theta, \lambda(PB_p, D_p)] = \frac{\exp\{V_j^p[x_{pt}, z_p, n_{pt}^{>0}; \theta, \lambda(PB_p, D_p)]\}}{\sum_{k\in\{v,l,c\}} \exp\{V_k^p[x_{pt}, z_p, n_{pt}^{>0}; \theta, \lambda(PB_p, D_p)]\}}, \tag{9}$$

where

$$\begin{aligned} V_j^p(\cdot) \equiv{}& \bar{Q}_{pjt} + \alpha_p n_{jpt}^{>0} + \beta_p \int EV^p(x_{p,t+1}, z_p, n_{p,v,t+1}^{>0}) \\ &\times f[dx_{p,t+1} | x_{pt}, z_p, \mathcal{I}(a_{pt} = j), n_{p,v,t+1}] \\ &\times h(dn_{p,v,t+1} | z_p) \end{aligned} \tag{10}$$

is the conditional value function—the expected discounted utility, net of ε_{pjt}, if j is chosen (i.e., $a_{pt} = j$). For each candidate θ, we compute EV^p assuming physicians' detailing beliefs are accurately represented by the estimated count models. To efficiently compute the choice probability in Equation 9, for each $(z_p, n_{pt}^{>0})$, we compute P_{pjt} at each point in the four-dimensional grid discretizing beliefs x_{pt}, and use cubic interpolation to approximate P_{pjt} at states not on the grid.

Beliefs x_{pt} and true efficacies (Q_{pl}, Q_{pc}) are unobserved to the econometrician. Accordingly, we use Monte Carlo simulation to numerically integrate over their possible values. Using R = 1000 draws of p's efficacies $\{Q_{pl}^r, Q_{pc}^r\}_{r=1}^R$ and history of beliefs $\{x_{p,0}^r, \ldots, x_{p,T_p}^r\}_{r=1}^R$, the simulated likelihood for his T_p patient visits is as follows:

$$L_p(\theta) = \frac{1}{R}\sum_{r=1}^{R}\prod_{t=1}^{T_p} P_{p,a_{pt},t}[x_{pt}^r, z_p, n_{pt}; \theta, \lambda(PB_p, D_p)], \tag{11}$$

where $a_{pt} \in \{v, l, c\}$ is p's choice in period t. We do not face an initial conditions problem regarding physicians' beliefs, because our panel begins before the launches of Levitra and Cialis and the efficacy of the incumbent Viagra is known.

We use the simulated maximum likelihood estimator defined by

$$\hat{\theta} = \text{argmax} \prod_{p=1}^{N} L_p(\theta). \tag{12}$$

Narayanan and Manchanda (2009) provide a detailed discussion of the parameters of the myopic version of a similar model using the same data we do. For a description of the features of our data that facilitate identification, see Narayanan and Manchanda's study.

RESULTS

Given the discount factors β_p and the detailing expectations λ_j in Table 2, we estimate the model using 621 randomly selected physicians from among the 957 available. The log-likelihood of the dynamic model with forward-looking consumers is −4567.45, compared with −4581.63 when we assume physicians are myopic with $\beta_p = 0$ for all p. Because the data reject the myopic model, we only present and discuss estimates of the dynamic model with forward-looking physicians.

[11] The DF_{pj} levels are highly correlated across drugs, which prompts us to segment physicians according to $DF_{pv}+DF_{pl}+DF_{pc}$. Segmenting physicians according to detailing for each drug individually expands the state space with little benefit because few physicians would be in segments characterized by low detailing in one drug and high detailing in the others.

[12] In an unreported specification, we estimate the daily discount rate δ to be .157/365. The estimates and model fit are relatively insensitive to variations in δ from $\delta = .15/365$ to $\delta = .4/365$. We choose $\delta = .2/365$ because the counterfactual simulations are easier to compute when the discount factors are further below 1.

Table 2
CHARACTERISTICS AND DETAILING PROCESSES OF PHYSICIAN (PB_P, D_P) TYPES

	Number of Physicians	Δ_p	β_p	λ_j	*var*(DF_{pj})	*SE* λ_j
Type 1: PB_{small}, D_{low}	119	87.985	.9529			
Viagra				.192	.195	.0274
Levitra				.273	.276	.0326
Cialis				.246	.240	.0304
Type 2: PB_{small}, D_{middle}	127	93.461	.950			
Viagra				.764	.837	.0564
Levitra				1.000	.893	.0583
Cialis				1.209	1.074	.0639
Type 3: PB_{small}, D_{high}	124	11.378	.9413			
Viagra				2.272	2.347	.1040
Levitra				3.161	2.858	.1148
Cialis				4.221	4.127	.1379
Type 4: PB_{medium}, D_{low}	103	31.954	.9826			
Viagra				.138	.132	.0146
Levitra				.153	.172	.0166
Cialis				.200	.196	.0177
Type 5: PB_{medium}, D_{middle}	102	32.549	.9823			
Viagra				.455	.447	.0274
Levitra				.604	.626	.0324
Cialis				.792	.827	.0373
Type 6: PB_{medium}, D_{high}	107	34.066	.9815			
Viagra				1.021	1.004	.0407
Levitra				1.430	1.285	.0460
Cialis				1.582	1.455	.0490
Type 7: PB_{large}, D_{low}	91	12.100	.9934			
Viagra				.104	.104	.0084
Levitra				.174	.171	.0108
Cialis				.213	.200	.0117
Type 8: PB_{large}, D_{middle}	91	12.695	.9931			
Viagra				.261	.303	.0150
Levitra				.410	.472	.0187
Cialis				.517	.629	.0216
Type 9: PB_{large}, D_{high}	93	15.035	.9918			
Viagra				.499	.444	.0193
Levitra				.781	.755	.0251
Cialis				.989	.943	.0281

Notes: $\beta_p = \exp(-\delta\Delta p)$, where δ is assumed to be .2/365 and Δ_p is days between patient visits. DF_{pj} is the detailing frequency between a physician's patient visits for drug j. λ_j is the average DF_{pj}, as defined in Equation 8. SE λ_j is its standard error.

Parameter Estimates

In Table 3, we provide the estimates and standard errors of the structural parameters. The estimated biases in initial priors, $\bar{Q}_{l0} = -1.61$ and $\bar{Q}_{c0} = -2.99$, indicate that physicians were initially pessimistic about both new drugs' true efficacies. These low initial beliefs are consistent with the low initial sales for both Levitra and Cialis.

Levitra's estimated average efficacy Q_l is slightly below Viagra's normalized value of zero, whereas the average efficacy of Cialis Q_c is higher than zero. These quality rankings accord with the firms' long-term market shares: Cialis became the leader, with Viagra retaining the number-two position.[13] The dispersion in efficacy across physicians is greater for Cialis ($\sigma_{Q_c} = .86$) than for Levitra ($\sigma_{Q_l} = .49$). This result is consistent with Levitra and Viagra being chemically more similar than Cialis and Viagra because Q_{lp} and Q_{cp} are measured relative to Viagra for each physician.

As physicians gained information from detailing and patient feedback, they revised their beliefs upward and began prescribing Cialis and Levitra more often. The precision of the information signals govern the rate at which physicians modify their beliefs and consequent behavior. Detailing signals from Levitra are more informative than detailing signals from Cialis: $\sigma_{D_l} = .5$ compared with $\sigma_{D_c} = .97$. This finding perhaps reflects the relative ease of informing a physician that Levitra is similar to the incumbent Viagra, compared with the challenge of explaining differences between Cialis and Viagra. However, the patient feedback signal for Cialis is more precise than for Levitra: $\sigma_{R_c} = .42$ versus $\sigma_{R_l} = .62$.

We estimate the persuasive effect of detailing to be .22, which exceeds the average quality difference between Cialis and Viagra and is nearly as large as the average quality difference between Cialis and Levitra. To assess

[13] According to Narayanan and Manchanda (2009), industry reports also claim Cialis is the most effective ED drug.

Table 3
PARAMETER ESTIMATES AND STANDARD ERRORS

Parameters		*Estimates*
Mean true efficacy: Levitra	Q_l	−.158
		.070
Mean true efficacy: Cialis	Q_c	.094
		.109
SD of true efficacy: Levitra	σ_{Q_l}	.488
		.070
SD of true efficacy: Cialis	σ_{Q_c}	.858
		.076
Initial bias: Levitra	$\bar{Q}_{l0}$	−1.615
		.161
Initial bias: Cialis	$\bar{Q}_{c0}$	−2.994
		.261
SD of detailing signal: Levitra	σ_{D_l}	.500
		.087
SD of feedback signal: Levitra	σ_{R_l}	.615
		.148
SD of detailing signal: Cialis	σ_{D_c}	.973
		.090
SD of feedback signal: Cialis	σ_{R_c}	.424
		.126
Persuasive effect	α	.220
		.044
Independence within nest	ρ	.556
		.071
Log-likelihood		-4567.449

Notes: The true efficacy of Viagra is normalized to zero. Standard errors are in the second line for each parameter.

whether detailing by Levitra and Cialis is indeed informative, we perform a likelihood ratio test of the restriction $\sigma_{D_l} = \sigma_{D_c} = \infty$. The −4681.07 log-likelihood of the restricted model yields a test statistic of $2 \times (4681.07 - 4567.45) = 227.23$, which exceeds the chi-square .01 critical value of 9.21. Therefore, we reject the model with uninformative detailing. Finally, the estimate of $\rho = .56$ implies that Viagra and Levitra indeed have correlated utilities and are appropriately modeled as being in the same nest.

Detailing Elasticities

To assess the managerial implications of differences between static and dynamic models and the role of detailing expectations, we determine how physician prescription behavior changes in response to changes in firms' detailing policies. We first simulate physicians' choices when each firm's detailing activities between patient visits are simulated using the Poisson model with mean counts given by the estimates of λ_j from Equation 8 and presented in Table 2. To compute the detailing elasticity for firm j, we inflate λ_i by 10% and resimulate physicians' choices with the higher simulated detailing activity of firm j.[14]

A natural question arises regarding whether physicians anticipate the new detailing policy of firm j. Firms could announce such a policy or, more likely, not announce such a policy and leave physicians to infer whether detailing intensities have changed. Rather than take a stand on how quickly physicians learn about any such changes, we compute elasticities under two scenarios: (1) Physicians do not anticipate the change and keep λ_j fixed, and (2) physicians anticipate the change and update λ_j accordingly. Under the second scenario, we recompute physicians' value functions, EV^p, before simulating choices with the higher detailing activity. These two scenarios bound the elasticities derived from a process in which physicians infer changes in detailing policies from observed activity.

We present the detailing elasticities for Levitra and Cialis in Table 4. The top half presents the effect of detailing on physician behavior with a physician's first patient after the respective drug's launch. We refer to this measure as the "short-term elasticity." The bottom half presents the long-term elasticity by measuring the effect of detailing on prescriptions written for all postlaunch patients in our sample.

For comparison, we also report elasticities if physicians were myopic, which we obtain by setting all β_p to zero. The myopic elasticities are more than twice as large as the elasticities with forward-looking physicians because initial beliefs are pessimistic and myopic consumers are not willing to sacriffice current utility to obtain information. Therefore, the information that myopic physicians receive has a larger effect on their choices: Without raising their pessimistic beliefs, the myopic physicians have low prescription rates.

As we report in the last column of Table 4, detailing elasticities are 8.6%–15.2% higher when $E(DF_{pj})$ are fixed. When physicians anticipate an increase in detailing, they lower their willingness to sacrifice current utility to obtain information through patient feedback because they expect an increased flow of free information from detailing. This substitution lowers the effect of detailing on prescription choices.

The short-term elasticities are higher than the long-term elasticities because in the short run, the informative effect of detailing is high because physicians initially have pessimistic beliefs. In the long run, physicians' beliefs are more accurate, which reduces the informative effect of detailing.

Table 4
ELASTICITY OF PRESCRIPTIONS WITH RESPECT TO DETAILING FREQUENCY

		Forward-Looking Physicians		
	Myopic Physicians	*Fixed* $E(DF_{pj})$	*Updated* $E(DF_{pj})$	*Column 2/ Column 3*
Short Run (First Postlaunch Patient)				
Levitra	.2231	.0930	.0807	1.1524
Cialis	.3574	.1564	.1393	1.1227
Long Run (All Postlaunch Patients)				
Levitra	.1426	.0654	.0596	1.0973
Cialis	.2016	.0923	.0850	1.0858

Notes: Elasticities are computed using the estimated dynamic model. The myopic case sets $\beta = 0$. We simulate baseline detailing activity using the λ_j values reported in Table 2. We simulate counterfactual detailing activity using λ_j values scaled by 1.1. With fixed detailing expectations (column 2), physicians' EV^p are unchanged. With updated detailing expectations (column 3), physicians' EV^p are recomputed using the higher λ_j.

[14]To reduce simulation error to negligible levels, we replicate the simulations 20,000 times and use the average.

The elasticities are higher for Cialis because the informative effect of detailing is greater for Cialis than for Levitra, given Cialis's greater degree of initial pessimism. Evidently, this more pronounced pessimism for Cialis swamps the lower precision of the drug's detailing signals.

Finally, we note that these elasticities ignore possible category expansion resulting from more detailing activity. Our model of prescription choice does not have an outside good because we do not observe the set of patients with ED-like conditions who choose alternative remedies. If many of these patients could be converted to Cialis or Levitra users, the elasticities could be substantially higher. The lack of over-the-counter treatments for ED, however, suggests that the set of ED patients who do not use one of these three drugs is small.

Conditional Choice Probabilities

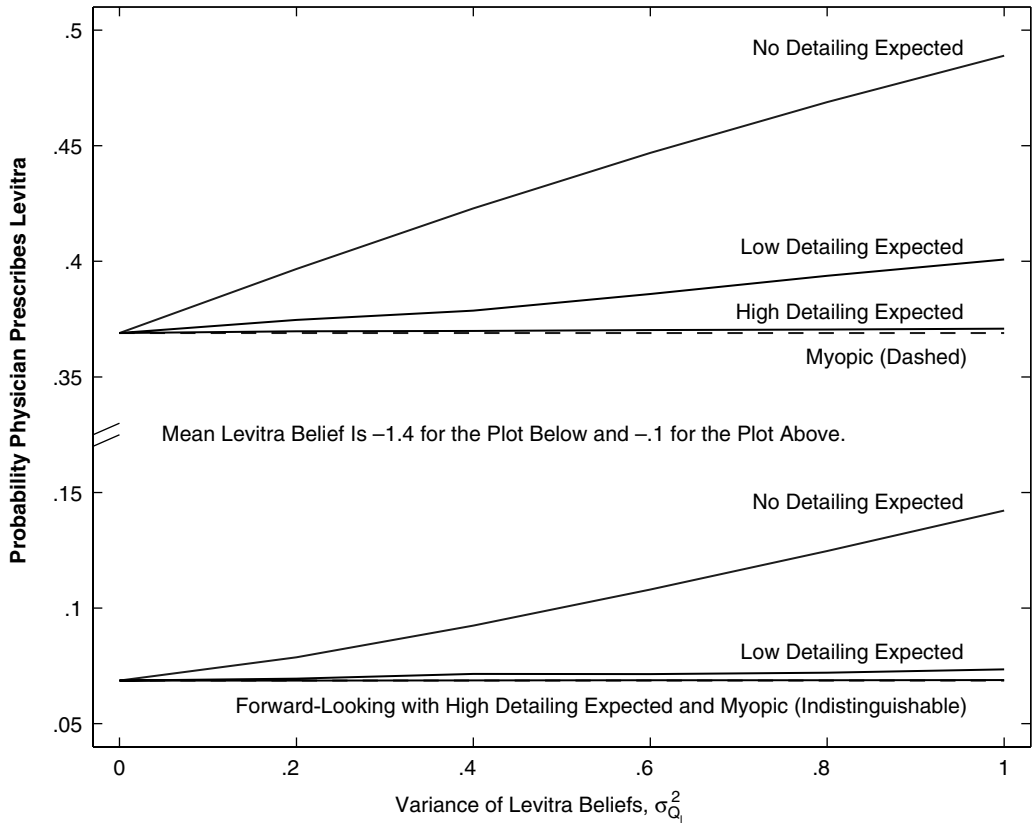
To assess the effect of forward-looking behavior and substitution of detailing information for patient feedback, we compute conditional choice probabilities at various states. Figure 6 presents the probability of prescribing Levitra as a function of uncertainty about its efficacy. The higher set of probabilities correspond to the physician having mean beliefs near Levitra's true efficacy, whereas the lower set assumes the physician's mean belief is lower, at −1.4. We fix beliefs about Cialis's efficacy at $\bar{Q}_{pc} = -3$ and $\sigma_{Q_{pc}} = 0$ and fix the persuasive effect state variables such that no firm has detailed the physician since the previous patient.

Forward-looking physicians prescribe Levitra with a higher probability than myopic physicians because of the value of the patient feedback. However, this increase in prescription rates is nearly eliminated when physicians expect high detailing because physicians in the model substitute free information from future detailing for costly information from patient feedback. When low detailing is expected, the prescription rates are higher than when high detailing is expected but remain much lower than when no detailing is expected. This implication of the model is consistent with the empirical evidence of delayed adoption by physicians expecting high future detailing, as presented in Table 1.

PROFIT-MAXIMIZING DETAILING INTENSITY

Using the estimated dynamic model, we conduct a counterfactual analysis to assess the optimality of Levitra's and Cialis's detailing intensities. We unilaterally rescale λ_l and λ_c by factors ranging from .5 to 2.0 by .1 and plot in Figure 7 the implied profits for each detailing intensity, assuming competitors' detailing levels are fixed.

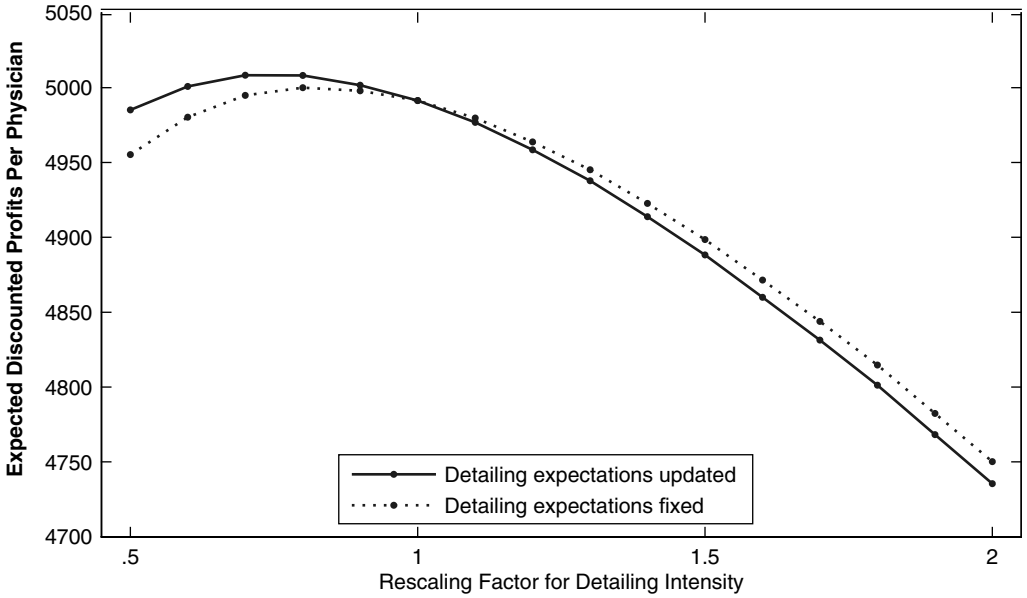
Figure 6
EFFECT OF EXPECTED DETAILING ON CONDITIONAL CHOICE PROBABILITIES



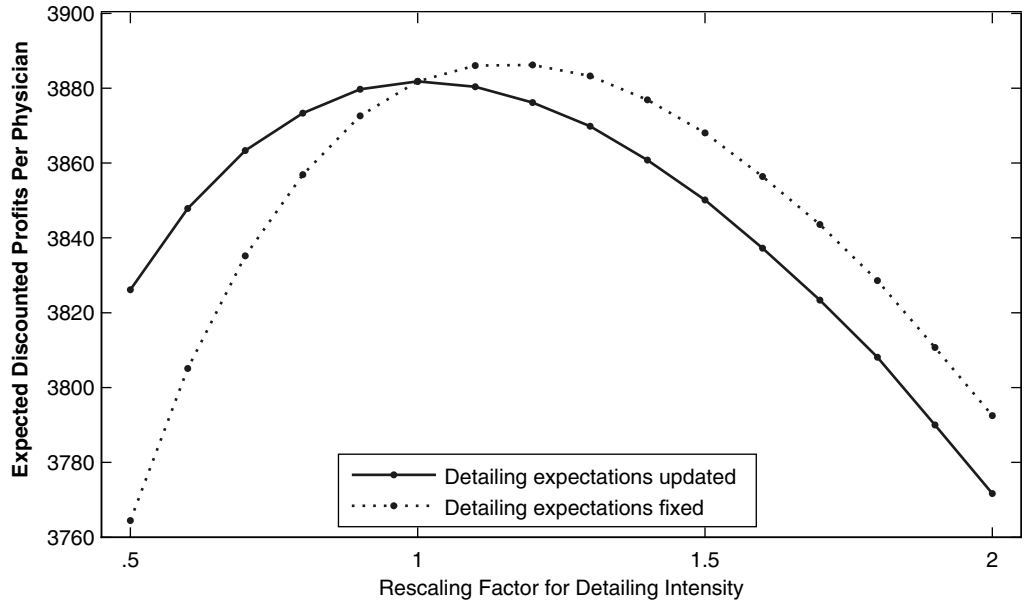
Notes: With forward-looking physicians, the model's implied probability of prescribing Levitra increases in the level of uncertainty $\sigma_{Q_{pl}}$ and mean beliefs $\bar{Q}_{pl}$. Expected detailing decreases the effect of uncertainty on the choice probability. For these plots, we fix beliefs about Cialis and assume the physician has not been detailed by any firm since the previous patient.

Figure 7
PROFIT AS FUNCTION OF DETAILING INTENSITY

A: Levitra Profit with Customer Lifetime Value Factor = 25



B: Cialis Profit with Customer Lifetime Value Factor = 25



Notes: We computed Levitra and Cialis profits assuming respective revenues per prescription of $76.16 and $98.74, respective detailing costs per visit of $97.07 and $118.20, and negligible manufacturing costs.

We assume that manufacturing costs are negligible and estimate revenues per prescription of $76.16 and $98.74, respectively, for Levitra and Cialis, using total revenues and total prescriptions, which we obtained from IMS Health's New Product Spectra data. These data also provide total detailing costs and detailing visits, which enables us to estimate detailing costs per visit of $97.07 and $118.20, respectively, for Levitra and Cialis. We compute profits for each detailing level under two scenarios: assuming physicians have rational expectations of detailing intensity and assuming physicians expect the detailing levels observed in the data.

Detailing is inherently an investment with payoffs that extend into the future. We simulate physicians' choices during our sample's postlaunch months for Levitra and Cialis and scale the sales by a customer lifetime value (LTV)

factor. That is, the LTV factor provides the number of prescriptions over the lifetime of each new patient acquired during these first several postlaunch months. As depicted by the solid line in the bottom panel of Figure 7, we find that an LTV factor of approximately 25 yields the actual detailing intensity of Cialis as profit maximizing when physicians anticipate changes to detailing levels. In the top panel, an LTV of 25 implies that Levitra provided too much detailing. An LTV of approximately 33 (not presented) yields a maximum profit for Levitra at its observed detailing levels.[15]

Comparing the solid lines with the dashed lines in Figure 7 reveals that the profit-maximizing level of detailing is lower when physicians have rational expectations regarding detailing than when expectations are fixed. The lower optimal detailing reflects the need for firms to account for the increased incentives for physicians to wait for free information (or samples) from detailing when such detailing is more frequent. This result succinctly illustrates the main point of our study.

CONCLUSION

In the current study, we investigate the role of physicians' forward-looking behavior and expectations of future detailing on the diffusion of two new prescription drugs in the ED category. We first provide empirical evidence that suggests that physicians delay adoption of the new drugs when they expect several visits from sales representatives in the future. Such delay may reflect strategic substitution between learning from detailing and learning from patient feedback or, alternatively, waiting for free samples from the sales representatives. We then estimate a dynamic Bayesian learning model that can replicate these features of the data.

We structurally estimate the true mean efficacies of the two new drugs, physicians' initial beliefs about these efficacies, the informative effect and the relative importance in physicians' learning of both patient feedback and each firm's detailing, and the persuasive impact of detailing. Estimation results from the dynamic model indicate that physicians initially view the new drugs as inferior to Viagra but revise their beliefs upward as they learn Cialis is the most effective ED drug and Levitra is nearly as effective as Viagra. The similarity in the chemical makeup of Levitra and Viagra imply that Levitra and Viagra are viewed as closer substitutes for each other than for Cialis. We estimate that learning from patient feedback and detailing are similarly effective for Levitra, whereas learning from feedback is more effective than detailing for Cialis.

Turning to managerial implications, we show that increased detailing sets two opposing forces in motion. First, physicians obtain information faster and therefore tend to adopt sooner, assuming the information is on average favorable, as in our case with priors below the true efficacies. Second, if physicians expect more future detailing, they are more likely to wait for free information from the expected detailing than to experiment with patients to obtain feedback. This latter effect, which the literature had not yet identified, can lower detailing elasticities by 8%–13%.

We also evaluate the optimality of Levitra's and Cialis's detailing intensities during the first several months following their respective launches. We find that the observed intensity for Cialis was optimal if each prescription written during our sample translates into approximately 24 additional prescriptions in the future. For Levitra, the observed detailing intensity maximizes profits if each prescription translates into 32 future prescriptions. A natural next step is to fully solve for firms' optimal detailing strategies given physician's forward-looking behavior and substitution across detailing and experimentation sources of information. We leave such an investigation to further study.

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[15]Levitra's profits per physician exceed those of Cialis primarily because Levitra launched two months prior to Cialis.

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