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Abstract

We develop a structural model of detailing and prescribing decisions under an environment where detailing helps physicians obtain the current information sets about drug qualities. Our model assumes that a representative opinion leader is responsible for updating the prior belief about the quality of drugs via patients' experiences, and manufacturers use detailing as a means to build/maintain the measure of physicians who are informed of the current information sets. We estimate our model using data on sales, prices, and detailing minutes at the product level for ACE-inhibitor with diuretic in Canada. We quantify the marginal impact of detailing on current demand at different points in time, and demonstrate how it depends on the measure of well-informed physicians and the information sets. Furthermore, we conduct a policy experiment to examine how a public awareness campaign, which encourages physicians/patients to report their drug experiences, would affect managerial incentives to detail.

Keywords: Detailing, Prescription Drugs, Decisions Under Uncertainty, Representative Opinion Leader, Diffusion

JEL: D83, I11, I18, M31, M37, M38

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1 Introduction

> Many serious Adverse Drug Reactions (ADRs) are discovered only after a drug has been on the market for years. Only half of newly discovered serious ADRs are detected and documented in the Physicians' Desk Reference within 7 years after drug approval.
>
> *Lasser et al. (2002), Journal of American Medical Association*

A major tool of marketing communication in the prescription drug market is detailing, in which drug manufacturers send sales representatives to visit physicians. This type of personal selling activities allows sales representatives to directly discuss compliance information, side-effects, and clinical studies of the drugs. One challenge in managing detailing activities throughout a drug's product lifecycle is that even manufacturers may be uncertain about the product attributes of their own drugs. Although some information on product attributes is established from clinical trials when a drug gains approval from the public health agency, many side-effects are not revealed until a large number of patients have tried the drug (Lasser et al. 2002).

One implication from this observation is that the information set about the quality of drugs is changing over time. As a result, detailing may only help physicians to obtain the current information about drugs. This is different from the conventional view of informative detailing under which manufacturers know the true quality of their product from the beginning of the product lifecycle, and use detailing to convey noisy signals about the true quality of their drugs to physicians (e.g., Narayanan et al. 2005). Under the conventional framework, the effectiveness of informative detailing will depend mainly on the true quality of the drugs and how much information physicians have learned. However, when detailing helps physicians obtain the most updated information about drugs, the effectiveness of detailing should directly depend on the current information set.

The goal of this paper is to provide a structural model that captures this alternative view of informative detailing, and to quantify how the effectiveness of detailing changes when additional information on drugs is revealed via patients' experiences during the product lifecycle. Our model can be estimated using standard *product level* panel data on sales volume, prices, and detailing efforts. To demonstrate the usefulness of our model, we apply it to the ACE-inhibitor with diuretic market in Canada.

In our model, detailing serves as a means to build/maintain the measure of physicians who are informed of the most updated information. For each drug, physicians are either informed of the most updated information or uninformed. We assume that the measure of physicians who are informed about a particular drug to depend on its cumulative detailing efforts. We also assume that the most updated information is maintained by a representative opinion leader. This is to capture the idea that opinion leaders play an important role in disseminating new information about drugs, and are often considered as an important source of the most up-to-date information about the drug categories in which they specialize (e.g., Haug 1997, Thompson 1997). Furthermore, we model physicians' forgetting by allowing the measure of well-informed physicians to depreciate over time.[1] One important implication of our framework is that informative detailing will continue to affect physicians' prescribing decisions even after the uncertainty about drugs' efficacies and side-effects is completely resolved, as long as the depreciation rate for the measure of well-informed physicians is strictly positive. In other words, our way of modeling informative detailing captures the role of reminding physicians of the most updated information about drugs.

This paper also deals with the potential endogeneity problem of detailing. Conceivably, when the prior belief about the quality of a drug is updated favorably, its manufacturer may react to it by increasing his detailing efforts so as to bring this information to physicians.[2] Ignoring this endogeneity problem would potentially result in biased estimates of the parameters associated with detailing. Nonetheless, the structural modeling literature in pharmaceutical demand

[1] We provide a formal definition of forgetting in our context in Section 3.2.

[2] Azoulay (2002) finds evidence that drug companies change their detailing efforts when new information about their drugs becomes available in the U.S. anti-ulcer drugs market.

that uses product level data has so far neglected to take this endogeneity problem into account.[3] To take the potential endogeneity problem of detailing into account, we extend the estimation method proposed by Ching (2000; 2008b), which does not require solving manufacturers' (dynamic or static) optimization problem. This method uses a reduced form approach to model detailing as a function of observed and unobserved state variables that determine demand, and then jointly estimate this pseudo-detailing policy function with the demand side model.

There has been a growing literature in economics and marketing that studies the demand for pharmaceuticals using product level data.[4] Most of these studies (e.g., Leffler 1981, Hurwitz and Caves 1988, Berndt et al. 1997, Rizzo 1999, Narayanan et al. 2004, Osinga et al. 2007) use a reduced-form approach to provide evidence that cumulative detailing can influence the demand for drugs. Another set of studies takes a structural modeling approach to study how uncertainty about drug qualities affects demand (e.g., Ching 2000; 2008a; 2008b, Narayanan et al. 2005, Mukherji 2002). In particular, Narayanan et al. (2005) and Mukherji (2002) use the framework of Erdem and Keane (1996) to investigate the effects of detailing on demand, in which they assume manufacturers use detailing to convey noisy signals about the true quality of their products to physicians. These studies provide a useful framework for quantifying the impact of aggregate learning on demand and how detailing affects the rate of learning when manufacturers have complete information about the quality of their drugs from the beginning of the product lifecycle. However, to our knowledge, the existing structural modeling literature has not studied the situation that detailing helps physicians to obtain the most updated information about drug qualities.

[3] As far as we know, there is only one recent structural modeling paper by Dong et al. (2006), which endogenizes detailing at the individual level. The endogeneity problem that they focus on is different from ours. In their case, the endogeneity problem is due to the unobserved physician level heterogeneity. In our case, it is due to the unobserved product characteristics because we use product level data. Another difference is that Dong et al. (2006) do not model consumer/physician learning.

[4] The majority of the studies in this industry use product level data because they are the least expensive data that could be purchased from IMS. Recently, there are a few studies which use proprietary individual level data to study the demand for prescription drugs (e.g., Gonul et al. 2001, Wosinska 2002, Manchanda et al. 2004, Crawford and Shum 2005, Dong et al. 2006, Narayanan and Manchanda 2006). In particular, Crawford and Shum (2005) and Narayanan and Manchanda (2006) model how an individual physician/patient learns his/her own match with different drugs. Unfortunately, individual level data in this market is very hard to obtain.

Our paper is also related to the consumer learning literature. In addition to Erdem and Keane (1996), the following papers are particularly relevant. Mullainathan (2002) studies learning and forgetting in a theoretical model. Mehta et al. (2004) develop and estimate a structural model of learning with forgetting using individual level scanner data instead of product level data. Both Mullainathan (2002) and Mehta et al. (2004) do not model the effect of marketing communication mix. Ackerberg (2003) estimates a model in which a consumer infers the value of the product to him/her from the advertising intensity (implicitly through the signaling equilibrium). He does not allow for consumer forgetting. Moreover, similar to Erdem and Keane (1996), he assumes manufacturers know the true mean quality of their products. Ching (2000; 2008a; 2008b) estimates a structural learning model to examine the equilibrium pricing strategies and diffusion pattern empirically in the U.S. prescription drug market after patent expiration. However, since brand-name firms usually cut their detailing efforts dramatically after patent expiration, he does not model detailing.

As far as we know, this is the first paper that develops an empirical structural model to study the effects of detailing on demand, under the environment that detailing can help physicians obtain the most updated information about drugs. Our main findings can be summarized as follows: First, we quantify the marginal impact of detailing on current demand at different points in time and show how it depends on the measure of well-informed physicians and the information sets; Second, we find evidence that the endogeneity problem biases the estimates of the coefficients associated with detailing; Third, using our parameter estimates, we conduct a policy experiment to evaluate how a public awareness campaign, which encourages physicians/patients to report their drug experiences, would affect managerial incentives to detail. Given our parameter estimates, we find that the marginal return of detailing has increased under this campaign, suggesting that managers should increase their detailing efforts.

The rest of the paper is organized as follows. Section 2 provides some background of the prescription drug market. Section 3 describes the demand model. Section 4 describes data and the estimation strategy. Section 5 discusses the results. Section 6 is the conclusion.

2 Background

Why would the information about drugs' efficacies and side-effects change over time? To understand this, it is important for us to give some background information about the approval process of new drugs. Most countries, including the U.S. and Canada, have a similar approval process. Drug manufacturers are required to prove that a new drug is safe and effective before marketing it. The proof involves a series of clinical trials, which are divided into three phases. Phase I and II studies provide basic evidence that the drug works in a small sample of patients. Phase III studies require a relatively larger sample of patients, which ranges from hundreds to several thousands. These studies are designed to evaluate the safety and effectiveness of the drug, wherein manufacturers need to demonstrate that the drug works better than a placebo. Nevertheless, manufacturers are not required to show that the new drug performs better than existing drugs that treat the same problem. Moreover, although most public health agencies set high standards for phase III clinical studies, it is not uncommon that they do not reveal all the side-effects, as documented by Lasser et al. (2002).

Physicians are supposed to keep themselves updated of the latest information for drugs. However, with many new drugs entering the market each year, it is difficult for general physicians to keep up with the enormous amount of information that changes regularly.[5] Most primary care physicians therefore rely on three external sources of information: (1) sales representatives (Coleman et al. 2004, p.179, Greider 2003, p.67); (2) peers who are opinion leaders (Haug 1997, Thompson 1997); (3) medical journals. Among these three external sources, sales representatives are the most time-saving source of information because they visit primary care physicians, compile information on clinical studies for them, and remind them of drug information. Given that primary care physicians are usually occupied with seeing patients, without detailing, it is plausible that they may forget the information about a drug's attributes (e.g., side-effects and efficacy profile) over time, and they may become reluctant to prescribe the drug. There is indirect evidence that supports this hypothesis: Caves et al. (1991) find that most drug manufacturers

[5]For example, the number of active drugs in the cardiovascular drug category increased from 215 in March 1993 to 294 in February 1999 in Canada.

during the 80s dramatically reduces their detailing efforts for drugs whose patents are about to expire, and the total demand for those drugs typically declines over time after patent expiration.

It is possible that the presentations given by sales representatives are biased towards the drugs they promote. This possibility appears to be well-recognized by health care professionals (e.g., Cooper et al. 2003, Ziegler et al. 1995), and physicians are usually cautious when listening to the sales representatives' claims. It is common that during their visits, sales representatives hand out printed documents related to efficacies and side-effects of the drugs being promoted (e.g., published academic articles about clinical trials). Although the printed documents may not be complete, more likely than not it saves physicians' time in gathering the related literature. Most importantly, the favorable picture of the drug presented by them may trigger physicians' interests to learn the latest information of the drug being promoted. They may then be more likely to read the related medical literature, or contact peers who are opinion leaders in the related field for more information. One implication of this hypothesis is that the impact of detailing on demand would depend on the actual effectiveness and side-effects of the drug. A recent study by Venkataraman and Stremersch (2006) finds evidence that supports this hypothesis in three therapeutic classes: anti-cholesterol drugs (statins), gastrointestinal drugs and erectile dysfunctions drugs. Our way of modeling detailing will be consistent with this hypothesis.

It should also be emphasized that opinion leaders play an important role in disseminating the most current information about drugs in this industry. The medical continuing education literature find that opinion leaders is an important source of information for general physicians (e.g., Haug 1997, Thompson 1997). In Medicine, opinion leaders are physicians who specialize in doing research in a particular field (e.g., cardiovascular). The research focus of their career allows them to be much more updated about the current evidence about the drugs used in the field. In our model, we introduce a representative opinion leader to capture their role.

3 Model

We now turn to discuss our model of detailing and prescribing decisions. Our framework here extends Ching (2000; 2008b). In our model, there are three types of agents: physicians, manufacturers, and a representative opinion leader. There are two types of products: inside goods which represent the products that use similar chemical compounds (so-called "me-too" drugs), and an outside good that represents their substitutes (0). Product characteristics can be distinguished as p_j and q_j, $j = 1, ..., J$, where p_j is the price of product j, and q_j is the mean quality level of product j. All agents in the model are perfectly informed about p_j, but are imperfectly informed about the drug's mean quality level, q_j.

To capture the idea that there are opinion leaders who gather the most recent information about drug qualities, we introduce a *representative opinion leader* in our model. The representative opinion leader maintains a vector of public information sets, $I(t) = (I_1(t), ..., I_J(t))$, which describes the most updated belief about $q = (q_1, \ldots, q_J)$ at time t based on past patients' experiences available to the public. For each drug j, a physician either knows $I_j(t)$, or $\underline{I}_j^p$, which is the initial prior that physicians have when drug j is first introduced. Let M_{jt} be the measure of physicians who know $I_j(t)$. We assume that M_{jt} depends on the cumulative detailing efforts at time t. There are two stages in each period. In the first stage, manufacturers choose the amount of detailing, D_{jt}. Given D_{jt}, M_{jt} is determined. Each physician makes his/her prescribing decision based on his/her information about the drugs. In the second stage, patients consume the prescribed drugs and some of their experience signals are revealed to the public. The representative opinion leader then uses these signals to update $I(t+1)$ in a Bayesian fashion. We will describe these two stages backward.

3.1 Updating of the Information Set

A drug is an experienced good. Consumption of a drug provides information about its quality. It is assumed that physicians and patients in the model can measure drug qualities according to a fixed scale. For example, a patient can measure quality in terms of how long he/she needs to wait before the drug becomes effective to relieve his/her symptoms, how long his/her symptoms would be suppressed after taking the drug, or how long the side-effects would last.[6]

[6]Obviously, drug qualities are multi-dimensional. Implicitly, we assume patients are able to use a scoring rule to map all measurable qualities to a one-dimensional index. It is the value of this one-dimensional index that enters the utility function.

Each patient i's experience with the quality of drug j at time t ($\tilde{q}_{ijt}$) may differ from its mean quality level q_j. As argued in Ching (2000), the difference between $\tilde{q}_{ijt}$ and q_j could be due to the idiosyncratic differences of human bodies in reacting to drugs. An experience signal may be expressed as,

$$\tilde{q}_{ijt} = q_j + \delta_{ijt}, \tag{1}$$

where δ_{ijt} is the signal noise. We assume that δ_{ijt} is an *i.i.d.* normally distributed random variable with zero mean:

$$\delta_{ijt} \sim N(0, \sigma_\delta^2), \tag{2}$$

and the representative opinion leader's initial prior on q_j ($\underline{I}_j^o$) is also normally distributed:

$$q_j \sim N(\underline{q}_j^o, \underline{\sigma}_j^{o2}). \tag{3}$$

The representative opinion leader updates the public information set at the end of each period using the experience signals that are revealed to the public. The updating is done in a Bayesian fashion. In each period, we assume that the number of experience signals revealed is a random subsample of the entire set of experience signals. This captures the idea that not every patient revisits and discusses his/her experiences with physicians, and not every physician shares his/her patients' experiences with others.

According to the Bayesian rule (DeGroot 1970), the expected quality is updated as follows:

$$E[q_j|I(t+1)] = E[q_j|I(t)] + \iota_j(t)(\bar{q}_{jt} - E[q_j|I(t)]), \tag{4}$$

where $\bar{q}_{jt}$ is the sample mean of all the experience signals that are revealed in period t.[7] $\iota_j(t)$ is a Kalman gain coefficient, which is a function of the variance of the signal noise (σ_δ^2), perceived variance ($\sigma_j^2(t)$), the quantity sold at time t (n_{jt}), and the proportion of experience signals revealed to the public (κ), and it can be expressed as:

$$\iota_j(t) = \frac{\sigma_j^2(t)}{\sigma_j^2(t) + \frac{\sigma_\delta^2}{\kappa n_{jt}}}. \tag{5}$$

[7]Let q_j be the true mean quality level of drug j. Then, $\bar{q}_{jt}|(\kappa n_{jt}, I(t)) \sim N(q_j, \frac{\sigma_\delta^2}{\kappa n_{jt}})$.

ι_j can be interpreted as the weights that the representative opinion leader attaches to the information source in updating its expectation about the level of q_j. In particular, $\iota_j(t)$ increases with $\sigma_j^2(t)$.

The perception variance at the beginning of time $t+1$ is given by (DeGroot 1970):

$$\sigma_j^2(t+1) = \frac{1}{\frac{1}{\sigma_j^2(0)} + \frac{\kappa N_{jt}}{\sigma_\delta^2}}, \tag{6}$$

where $N_{jt}(= \sum_{\tau=1}^{t} n_{j\tau})$ is the cumulative consumption of drug j, or,

$$\sigma_j^2(t+1) = \frac{1}{\frac{1}{\sigma_j^2(t)} + \frac{\kappa n_{jt}}{\sigma_\delta^2}}. \tag{7}$$

Equation (6) implies that, after observing a sufficiently large number of experience signals for a product, the representative opinion leader will learn about q_j, at any arbitrarily precise way (i.e., $\sigma_j(t) \to 0$ and $E[q_j|I(t)] \to q_j$ as the number of signals received grows large). We will next turn to discuss the physicians' choice problem and how detailing influences their choices.

3.2 Detailing and Measure of Well-Informed Physicians

There is a continuum of physicians with measure one. They are heterogeneous in their information sets. A physician is either well-informed or uninformed about drug j. A well-informed physician knows the current information set maintained by the representative opinion leader, i.e., $I_j(t)$. An uninformed physician only knows the initial prior, i.e., $\underline{I}_j^p = N(\underline{q}_j^p, \underline{\sigma}_j^{p2})$. This implies that the number of physician types is 2^J. Note that physicians' initial prior $\underline{I}_j^p$ could differ from the initial prior of the representative opinion leader, $\underline{I}_j^o$.

We assume that manufacturers observe $I(t)$ when they decide the amount of detailing, $D_{1t}, ..., D_{Jt}$. In general, the measure of well-informed physicians for drug j at time t, M_{jt}, is a function of M_{jt-1} and $D_{1t}, ..., D_{Jt}$. For simplicity, we assume that this function only depends on M_{jt-1} and D_{jt}, i.e., $M_{jt} = f(M_{jt-1}, D_{jt})$. We assume that $f(M_{jt-1}, .)$ is monotonically increasing in D_{jt}. To capture the idea that physicians may forget, we assume that $f(M, 0) \leq M, \forall M$.

Two remarks should be made regarding the way we model the relationship between detailing and the measure of well-informed physicians. First, similar to Mullainathan (2002), we do not allow uninformed physicians for drug j at time t to possess any $I_j(t')$ for $t' < t$, but $\underline{I}_j^p$. As we mentioned above, even with our current setup, the number of types increases exponentially in J. Although allowing physicians who "partially" forget may seem more appealing, it will dramatically increase the size of the state space – we would need to keep track of the measure of physicians who know $I_j(t')$, for all j and $t' < t$. The number of types will increase to t^J in time t. Such a modification will make the model computationally infeasible to estimate using product level data.[8] On the other hand, our assumption is not as restrictive as it may seem. One interpretation is that we approximate the aggregate demand from t^J types of physicians by randomizing the demand of 2^J types.

Second, we assume that M_{jt} depends on D_{jt} partly because the main job of sales representatives is to give physicians documented information about side-effects and efficacies of the drug that they are promoting. We do not mean that physicians simply believe what sales representatives claim during their conversations. Rather, we try to capture the intuition that detailing would increase the chances that physicians obtain the most recent information about the drug (by consulting their peers, reading the medical literature, etc.). This could be because the visits stimulate their interests, increase their awareness of existing or new clinical studies, and make it easier for them to access the relevant journal articles.

In our econometric model, we capture the relationship between M_t and (M_{t-1}, D_t) by introducing a detailing goodwill stock, G^I_{jt}, which accumulates as follows:

$$G^I_{jt} = (1 - \phi_I)G^I_{jt-1} + D_{jt}, \tag{8}$$

where D_{jt} is manufacturer j's detailing efforts in time t, and $\phi_I \in [0, 1]$ is the corresponding depreciation rate. We specify the relationship between M_{jt} and G^I_{jt} as:

$$M_{jt} = \frac{exp(\beta_0 + \beta_1 G^I_{jt})}{1 + exp(\beta_0 + \beta_1 G^I_{jt})}. \tag{9}$$

Define the average rate of forgetting, $\phi_M \equiv (M - f(M, 0))/M$. Although ϕ_I is a constant, G^I_{jt} affects M_{jt} nonlinearly. In particular, the implied average forgetting rate, ϕ_M, will exhibit

[8]However, with individual level data, it is feasible to estimate a model of learning with partial forgetting (Mehta et al. 2004).

an inverted-U shape. This might first appear to be restrictive, but it is consistent with the following intuition. It is likely that individual physicians are heterogeneous in terms of their rate of forgetting. Some physicians who are more willing to spend time to keep up with the most recent medical literature themselves are likely to have a lower rate of forgetting. Other physicians who prefer to spend most of their time seeing patients, are likely to have a higher rate of forgetting – they probably will rely more on sales representatives to help them get the most updated information. When M is small, we expect that most of the well-informed physicians would be those who have a lower rate of forgetting. As M increases, we expect that the proportion of well-informed physicians who have a higher forgetting rate would increase. On the other hand, we expect that the number of interactions among well-informed physicians would also increase with M. They might remind each other about how this drug works, which helps reduce the average rate of forgetting (i.e., the network effect). These two forces work against each other. In particular, it is likely that the latter dominates the former when M is large, and vice versa. We therefore expect that when M is small, ϕ_M will first increase with M at a diminishing rate. After M has passed a certain threshold, ϕ_M will eventually decrease with M.

3.3 Prescribing Decisions

Now we turn to discuss how physicians make their prescribing decisions. Each physician takes the current expected utility of his/her patients into account when making prescribing decisions. Physician h's objective is to choose $d_{hij}(t)$ to maximize the current period expected utility for his/her patients:

$$E[\sum_{j\in\{0,1,\ldots,J\}} u_{ijt}\cdot d_{hij}(t)|I^h(t)], \tag{10}$$

where $d_{hij}(t)=1$ indicates that alternative j is chosen by physician h for patient i at time t, and $d_{hij}(t)=0$ indicates otherwise. We assume that $\sum_j d_{hij}(t)=1$. The demand system is obtained by aggregating this discrete choice model of an individual physician's behavior.

We assume that a patient's utility of consuming a drug can be adequately approximated by a quasilinear utility specification, additively separable in a concave subutility function of drug return, and a linear term in price. The utility of patient i who consumes drug j at time t is given by the following expression:

$$u_{ijt} = \alpha - \exp(-r\tilde{q}_{ijt}) - \pi_p p_{jt} + \zeta_{ikt} + e_{ijt}, \tag{11}$$

where p_{jt} is the price for product j at time t; r is the risk aversion parameter; α is the common intercept across drugs; π_p is the utility weight for price; $(\zeta_{ikt} + e_{ijt})$ represents the distribution of patient heterogeneity; k indexes nest (i.e., inside good or outside good).[9] ζ_{ikt} and e_{ijt} are unobserved to the econometrician but observed to the physicians when they make their prescribing decisions. We assume that ζ_{ikt} and e_{ijt} are *i.i.d.* extreme value distributed. The exponential specification of the subutility function of drug return is known as the Constant Absolute Risk Aversion (CARA) utility. In this specification, r represents the coefficient of absolute risk aversion.

Note that $\tilde{q}_{ijt}$ is observed neither by physicians nor patients when prescribing decisions are made. It is observed by physicians/patients only after patients have consumed the drug, but it remains unobserved by the econometrician. Physicians make their decisions based on the expected utility of their patients. Let $I(t)$ and $I^h(t)$ denote the representative opinion leader's information set and physician h's information set at time t, respectively. If physician h is well-informed about drug j at time t, his/her expected utility will be:

$$\begin{aligned} E[u_{ijt}|I^h(t)] &= E[u_{ijt}|I_j(t)] \\ &= \alpha - exp(-rE[q_j|I(t)] + \frac{1}{2}r^2(\sigma_j^2(t) + \sigma_\delta^2)) - \pi_p p_{jt} \\ &\quad +\zeta_{ikt} + e_{ijt}. \end{aligned} \tag{12}$$

If physician h is uninformed about drug j at time t, his/her expected utility of choosing drug j becomes:

$$\begin{aligned} E[u_{ijt}|I^h(t)] &= E[u_{ijt}|\underline{I}_j^p] \\ &= \alpha - exp(-r\underline{q}_j^p + \frac{1}{2}r^2(\underline{\sigma}_j^{p2} + \sigma_\delta^2)) - \pi_p p_{jt} + \zeta_{ikt} + e_{ijt}. \end{aligned} \tag{13}$$

[9] This is equivalent to modeling physicians' choice as a two-stage nested process, where they choose between the inside goods and the outside good in the first stage, and then choose an alternative among the inside goods in the second stage.

It should be noted that patient heterogeneity components of the utility function (ζ_{ikt}, e_{ijt}) reappear in the expected utility equation because they are stochastic only from the econometrician's point of view.

Equations (11)-(13) apply only to the inside alternatives. In each period, physicians may also choose an outside alternative that is not included in our analysis (i.e., other non-bioequivalent drugs). We assume the expected utility associated with the outside alternative takes the following functional form:

$$E[u_{i0t}|I^h(t)] = \alpha_0 + \pi_t t + \zeta_{i0t} + e_{i0t}. \tag{14}$$

The time trend of the outside alternative allows the model to explain why the total demand for inside goods may increase or decrease over time.

The quantity demand, n_{jt}, can be expressed as,

$$n_{jt} = Size_t \cdot S(j|D_t, (E[q_j|I(t)], \sigma_j(t), M_{jt-1})_{j=1}^2; \theta_d) + \epsilon_{jt}, \tag{15}$$

where $Size_t$ is the size of the market, $S(j|\cdot)$ is the market share of drug j, ϵ_{jt} represents a measurement error, and θ_d is a set of demand side parameters.

3.4 Empirical Implications and Identification

To illustrate some empirical implications of our model for the effectiveness of detailing, we consider the case of two products. In this case, there are four types of physicians (2^2) who differ in their information sets. Let $s_{jt}(I_j, I_k)$ be the probability of choosing drug j at time t by physicians who have the information sets I_j and I_k for drugs j and k, respectively ($j \neq k$). Then the market share for drug j at time t is given by,

$$\begin{aligned} S_{jt} &= M_{jt}M_{kt}s_{jt}(I_j(t), I_k(t)) + M_{jt}(1 - M_{kt})s_{jt}(I_j(t), \underline{I}_k^p) \\ &\quad +(1 - M_{jt})M_{kt}s_{jt}(\underline{I}_j^p, I_k(t)) + (1 - M_{jt})(1 - M_{kt})s_{jt}(\underline{I}_j^p, \underline{I}_k^p), \end{aligned} \tag{16}$$

where $s_{jt}(I_j, I_k)$ has a closed form expression given that we use the nested logit framework. It follows that the marginal return of detailing on current market share for drug j is,

$$\frac{\partial S_{jt}}{\partial D_{jt}} = \frac{\partial M_{jt}}{\partial D_{jt}} \times \{M_{kt}\Delta s_{jt}(I_k(t)) + (1 - M_{kt})\Delta s_{jt}(\underline{I}_k^p)\}, \tag{17}$$

where $\Delta s_{jt}(I_k) \equiv s_{jt}(I_j(t), I_k) - s_{jt}(\underline{I}_j^p, I_k)$. Intuitively, $\Delta s_{jt}(I_k)$ is the change in the probability of choosing j when a physician switches his/her information set for drug j from $\underline{I}_j^p$ to $I_j(t)$, conditional on his/her information set for drug k being I_k. Equation (17) shows that the marginal return of detailing depends on $\Delta s_{jt}(I_k(t))$ and $\Delta s_{jt}(\underline{I}_k^p)$, which are weighted by M_{kt} and $1-M_{kt}$, respectively. This weighted average is further adjusted by $\partial M_{jt}/\partial D_{jt}$. It is worth noting that $\partial S_{jt}/\partial D_{jt}$ increases (decreases) with M_{kt} if $(\Delta s_{jt}(I_k(t)) - \Delta s_{jt}(\underline{I}_k^p))$ is positive (negative).

Consider a situation where a new drug enters a market with a matured incumbent (in the sense that the representative opinion leader has learnt the true quality of the incumbent, i.e., $I_k(t) \to I_k(\infty)$). Conditional on M, equations (16) and (17) imply that the entrant's marginal return of detailing will increase with its market share. Moreover, the detailing elasticity of demand in our model could **increase** or **decrease** over time partly depending on how $I(t)$ evolves. In particular, even after the uncertainty about the drug quality is completely resolved, detailing still affects demand as long as $\phi_I > 0$, and its effect depends on $I(t), \underline{I}^p$ and M_{jt-1} (i.e., G_{jt-1}^I). On the contrary, previous models of learning and informative detailing/advertising, which follow the framework of Erdem and Keane (1996), imply that the detailing/advertising elasticity of demand **diminishes** over time as uncertainty about product quality is slowly resolved. This demonstrates that the empirical implications from our model are quite different from those from the previous models.

A new feature in our model is the way detailing builds/maintains the measure of well-informed physicians. It is worth discussing the identification of β_1 and ϕ_I. It may first appear that it is hard to separately identify them, because intuitively the effect on M due to an increase in β_1 (which captures the role of building up M) could be canceled by increasing ϕ_I (which captures the depreciation rate of M) appropriately. However, a more careful examination of equations (8) and (9) reveals that there are subtle differences in terms of how M is generated by β_1 and ϕ_I . In particular, equation (8) implies that a change in ϕ_I has a multiplier effect on M (and it translates to a multiplier effect on demand), while equation (8) implies that a change in β_1 does not has such a multiplier effect.[10]

[10]For the identification of learning parameters, please refer to Ching (2008b).

4 Estimation

4.1 Overview of the Data

Having described our model, we now turn to an application. We estimate our model using Canadian data for ACE-inhibitor with diuretic, which treats hypertension. ACE-inhibitor (Angiotensin Converting Enzyme Inhibitor) works by limiting the production of a substance that promotes salt and water retention in the body. Diuretic induces the production and elimination of urine, which helps in lowering blood pressure. This class of combination drugs is usually not prescribed until therapy is under way.

We choose Canada and ACE-inhibitor with diuretic for three reasons. First, most of the patients who have high blood pressure are elderly, and their prescription drugs are covered by the Canadian government. Moreover, Canada has price regulations on brand-name drugs. The Patented Medicine Price Review Board restricts Canadian prices of patented drugs to be below the median prices of G7 countries. There is evidence which suggests that this constraint is binding on average (Elgie 2001). These institutional details, which suggest that price does not play an important role in determining demand, allow us to treat prices as exogenous and focus on modeling the effects of detailing. Second, the market of ACE-inhibitor with diuretic does not have direct-to-consumer (DTC) advertising. DTC advertising has increased dramatically in the U.S. since 1997. It is believed that it plays an important role in the demand for prescription drugs. However, the way that DTC advertising influences physicians' choice is likely to be different from detailing. Modeling the effects of DTC advertising is beyond the scope of this paper. Third, the market of ACE-inhibitor with diuretic only has two dominant drugs. We feel that it is sensible to first apply our framework to this simple market before tackling markets with more competitors.

Data sources for this study come from IMS Canada, a firm that specializes in collecting sales and advertising data for the Canadian pharmaceutical industry. The revenue data is drawn from their Canadian Drugstore and Hospital Audit (D&H); the number of prescriptions is drawn from their Canadian Compuscript Audit (CCA); the number of detailing minutes is drawn from their Canadian Promotion Audit (CPA). Although D&H does not include purchases made by the government, mail order pharmacies, and nursing homes or clinics, IMS believes that it covers about 90% of total sales. The price is obtained by dividing the revenue by the number of prescriptions. We deflated the prices using the consumer price index in the Canadian pharmaceutical industry. We note that on average less than one percent of sales is from hospital purchases. Due to its dominance, we only model the segment of the drugstore market and ignore how hospitals reach their purchase decisions.

The data set contains monthly data from March 1993 to February 1999. There are two main brand-name drugs in the market – Vaseretic and Zestoretic. Vaseretic is marketed by Merck; its generic ingredients are enalapril and hydrochlorothiazide. It was approved by Health Canada in September 1990. Zestoretic is marketed by AstraZeneca; its generic ingredients are lisinopril and hydrochlorothiazide. It was approved in October 1992. Both of them are present throughout the sample period, and they capture more than 80% of sales of the ACE-inhibitor with diuretic category. We therefore focus our analysis on these two drugs. Treating product/month as one observation, the total sample size is 144. We report the summary statistics in Table 1.

For an overview of the data, we plot the number of prescriptions filled for Vaseretic and Zestoretic in Figure 1. The sales of both drugs increase over time. The monthly sales of Vaseretic grow slowly and steadily from 2,500 prescriptions to 4,500 prescriptions, while Zestoretic's monthly sales grow at a much faster rate from around 300 prescriptions to more than 14,000 prescriptions. Being the incumbent of the ACE-inhibitor with diuretic, the sales of Vaseretic is about eight times that of Zestoretic at the beginning of the sample period (March 1993). It took Zestoretic more than two years to overtake Vaseretic's sales. By the end of the sample period (February 1999), the sales of Zestoretic is more than three times that of Vaseretic. The sales trend of Zestoretic is remarkable, and illustrates the slow diffusion of new drugs well documented in this industry. The potential size of the market is defined as the total number of prescriptions for drugs that belong to ACE-inhibitor, Thiazide Diuretic, and ACE-inhibitor with diuretic. It increases from 655,000 to 860,000 during the sample period.

We also plot detailing minutes in Figure 2. The average detailing minutes of Zestoretic are about the same as those of Vaseretic before $t = 30$. But after $t = 30$, about the time when

Zestoretic overtakes Vaseretic, the average detailing minutes of Zestoretic becomes higher than Vaseretic. It should also be noted that detailing minutes fluctuates a lot. The fluctuation should help us identify the parameters of that determine the measure of well-informed physicians (i.e., β_0, β_1, and ϕ_I).

4.2 Simultaneity Problem

If prices and detailing are exogenous, then we can form a likelihood function simply based on demand equations (i.e., equation (15)), and choose parameters to maximize the likelihood. However, as we argued above, although we are willing to assume price is exogenous, we feel that detailing could be potentially endogenous. It is plausible that manufacturers observe $I(t)$ before detailing takes place in each period. If this is true, detailing could be a function of $I(t)$. In particular, we expect that D_{jt} may be correlated with $E[q_j|I(t)]$ and $\sigma_j(t)$. For instance, if $E[q_j|I(t)]$ is higher than $E[q_k|I(t)]$, manufacturer j may have an incentive to increase D_{jt} so as to disseminate the information. If we ignore this correlation, the parameters for building up the measure of well-informed physicians will likely be biased upward. In other words, maximizing the likelihood function simply based on equation (15) might give us biased estimates.

A popular method to estimate this class of model using product level data is developed by Berry et al. (1995) (BLP). They show that there is a one-to-one mapping between the mean utility levels and the observed market shares, conditional on a parameter vector. As a result, it is possible to construct a GMM objective function based on the mean utility function without explicitly solving the supply side model. However, as pointed out by Chernozhukov and Hong (2003), BLP's GMM objective function is highly nonconvex with many local optima. This poses a formidable challenge when minimizing it in practice. Another way to handle this endogeneity problem is to explicitly model manufacturers' decision on detailing, and incorporate their detailing policy functions in a full-information maximum likelihood procedure. Since detailing has a long-lived effect, this would involve developing a forward-looking dynamic oligopoly structural model. Unfortunately, estimating this type of dynamic oligopoly model using a full-solution method has proved to be infeasible given today's computational power.

In this paper, we estimate our model using the approach developed by Ching (2000; 2008b). Similar to BLP, this method does not require solving the dynamic oligopolistic supply side model. To take the endogeneity of detailing into account, he proposes to approximate manufacturers' policy functions by expressing it as a polynomial of the state variables (both observed and unobserved), and then jointly estimate this pseudo-policy function and the demand model.[11]

This approach does not require us to make any strong assumptions about the equilibrium solution, and whether drug manufacturers maximize their total discounted profits or current profits. So we can avoid some risks of misspecifying the supply side, which may result in biased estimates. More importantly, it allows us to avoid the computational burden of solving a dynamic oligopoly model when estimating the demand model. However, there are two drawbacks in this approach: (i) It increases the number of parameters to estimate due to the pseudo-detailing policy functions; (ii) The estimates are not as efficient as full-information maximum likelihood because the supply side model is not explicitly modeled in the estimation.

Regardless of whether manufacturers are forward-looking or myopic, the state variables of our model consist of $(E[q_j|I(t)], \sigma_j^2(t), M_{jt-1})_{j=1}^2$. We therefore assume that the detailing policy function depends on these variables. The detailing policy function may also depend on variables that we do not explicitly model. For instance, the total detailing minutes by manufacturer j in the cardiovascular drug category could affect D_j. It is possible that a manufacturer sets its detailing budget for the entire cardiovascular drug category first, and then determines the detailing for individual drugs in the category. We therefore include the total detailing minutes by manufacturer j in the cardiovascular drug category net D_j in the pseudo-detailing policy function.[12] This variable is useful in identifying the parameters associated with detailing in the demand model (i.e., β_0, β_1, and ϕ_I) because it plays the role of exclusion restriction, and essentially serves as an instrumental variable for D_{jt}. Berndt et al. (2003) use this variable as the instrument for detailing in their reduced form model.

[11]This method can also be applied to address price endogeneity. See Ching (2008b) for further details.

[12]Cardiovascular drug category includes ACE-Inhibitor, Antihypertensive, Beta-Blocker, Calcium Channel Blocker, Diuretic, etc.

When specifying the pseudo-detailing policy function, ideally one would use a flexible high order polynomial to do the approximation if the sample is large. In practice, however, one may need to make some trade-offs between flexibility and the number of parameters by choosing a functional form carefully. After experimenting with a number of functional forms, we specify the detailing policy function as follows: For $j, k = 1, 2$, and $j \neq k$,

$$\begin{aligned} log(D_{jt}) &= \lambda_{j0} + (\lambda_{j1} + \lambda_{j2} * M_{kt-1}) * (1 - M_{jt-1}) * |\Delta u^q_{jkt}| * \mathbb{I}(\Delta u^q_{jkt} > 0) \\ &\quad + (\lambda_{j3} + \lambda_{j4} * M_{kt-1}) * M_{jt-1} * |\Delta u^q_{jkt}| * \mathbb{I}(\Delta u^q_{jkt} < 0) \\ &\quad + \lambda_{j5} * IV_{jt} + \nu_{jt}, \end{aligned} \tag{18}$$

where

$$\Delta u^q_{jkt} = E[u^q_{jt}|I(t)] - E[u^q_{kt}|I(t)], \tag{19}$$

$$E[u^q_{jt}|I(t)] = -exp(-rE[q_j|I(t)] + \frac{1}{2}r^2(\sigma^2_j(t) + \sigma^2_\delta)), \tag{20}$$

ν_{jt} is the prediction error, $\mathbb{I}(\cdot)$ is an indicator function, and IV_{jt} is the instrumental variable described above. Note that $E[u^q_{jt}|I(t)]$ is part of the expected utility that depends on $E[q_j|I(t)]$ and $\sigma^2_j(t)$. Δu^q_{jkt} is difference between this partial expected utility from choosing drug j and k.

Our model suggests that manufacturer j has an incentive to increase detailing if $\Delta u^q_{jkt} > 0$. Such an incentive is stronger if M_{jt-1} is small because of the diminishing return of $\partial M_j / \partial D_j$. We therefore interact $(1 - M_{jt-1})$ with $|\Delta u^q_{jkt}|$ when $\Delta u^q_{jkt} > 0$. We expect the coefficient associated with the interaction term to be positive (i.e., $\lambda_{j1} > 0$). Similarly, when $\Delta u^q_{jkt} < 0$, we interact M_{jt-1} with $|\Delta u^q_{jkt}|$. We expect that manufacturer j would have less incentives to detail when M_{jt-1} is large. However, when M_{jt-1} is small, manufacturer j, if forward-looking, may still detail more in order to build up M_j earlier even though $\Delta u^q_{jkt} < 0$. This is because manufacturer j may take into consideration the stochastic nature of Δu^q_{jkt}, which could become positive later. The sign of the coefficient for the interaction term (i.e., λ_{j3}) is therefore ambiguous.

As shown in equation (17), the static marginal return of detailing depends on the measure of well-informed physicians for a competing drug as well. This implies that the dynamic marginal return of detailing for drug j will also depend on M_{kt}, $j \neq k$. Therefore, we also allow M_{kt-1} to interact with M_{jt-1} and Δu^q_{jkt}. Following from equation (17), if manufacturers are myopic, the sign of λ_{j2} and λ_{j4} would be positive if $\Delta s_{jt}(I_k(t)) > \Delta s_{jt}(\underline{I}^p_k)$, and vice versa. If manufacturers are forward-looking, they will take the future stochastic evolution of $I(t)$ into account, and the sign of λ_{j2} and λ_{j4} would be ambiguous.

The following two subsections describe the likelihood function and the initial conditions problem. Readers who are not interested in details may skip to Section 5 directly.

4.3 The Likelihood Function

Assuming that the prediction error, ν_{jt}, in equation (18) is normally distributed, we obtain the conditional likelihood of observing D_t,

$$f_d(D_t|(E[q_j|I(t)], \sigma_j(t), M_{jt-1})_{j=1}^2; \theta_s), \tag{21}$$

where θ_s is the vector of parameters.

Assuming that the measurement error, ϵ_{jt}, in equation (15) is normally distributed, and denote $f_n(n_t|D_t, (E[q_j|I(t)], \sigma_j(t), M_{jt-1})_{j=1}^2,\ Size_t; \theta_d)$ as the likelihood of observing n_t conditional on $(D_t, (E[q_j|I(t)], \sigma_j(t), M_{jt-1})_{j=1}^2, Size_t)$. The joint likelihood of observing (n_t, D_t) is simply the product of $f_n(n_t|D_t, .)$ and $f_d(D_t|.)$:

$$\begin{aligned} &l(n_t, D_t|(E[q_j|I(t)], \sigma_j(t), M_{jt-1})_{j=1}^2, Size_t; \theta_d, \theta_s) = \\ &\quad f_n(n_t|D_t, (E[q_j|I(t)], \sigma_j(t), M_{jt-1})_{j=1}^2, Size_t; \theta_d) f_d(D_t|(E[q_j|I(t)], \sigma_j(t), M_{jt-1})_{j=1}^2; \theta_s). \end{aligned} \tag{22}$$

Now note that $\sigma_j(t)$ is a function of $\{n_{j\tau}\}_{\tau=1}^{t-1}$ (see (7)). Therefore, one can rewrite (22) as,

$$\begin{aligned} &l(n_t, D_t|(E[q_j|I(t)], \sigma_j(t), M_{jt-1})_{j=1}^2, Size_t; \theta_d, \theta_s) = \\ &\quad l(n_t, D_t|(E[q_j|I(t)], \{n_{j\tau}\}_{\tau=1}^{t-1}, M_{jt-1})_{j=1}^2, Size_t; \theta_d, \theta_s). \end{aligned} \tag{23}$$

The likelihood of observing $n = \{n_t\}_{t=1}^T$ and $D = \{D_t\}_{t=1}^T$ is,

$$\begin{aligned} &L(n, D|\{E[q|I(\tau)], M_{\tau-1}, Size_\tau\}_{\tau=1}^T; \theta_d, \theta_s) = \\ &\quad \prod_{t=1}^T l(n_t, D_t|E[q|I(t)], \{n_\tau\}_{\tau=1}^{t-1}, M_{t-1}, Size_t; \theta_d, \theta_s). \end{aligned} \tag{24}$$

But $E[q|I(t)]$ is unobserved to the econometrician and therefore must be integrated over to form the unconditional sample likelihood for (n, D). Evaluating such an integral numerically is very difficult. It involves high order integrals because $E[q|I(t)]$ is autocorrelated. We resolve this problem by using the method of simulated maximum likelihood. The details of the simulation procedures are similar to Ching (2008b).

4.4 Initial Conditions Problem

Notice that both Vaseretic and Zestoretic were introduced before March 1993, the first period of our data set. Therefore, we do not observe the initial values of the state variables at $t = 1$: $G^I_{j0}, E[q_j|I(1)]$ and $\sigma_j(1)$. Given this initial conditions problem, consistent estimation for fixed T requires integration over the joint unconditional distribution of the state variables at $t = 1$. As discussed in Heckman (1981), this integration is extremely difficult. It requires us to explicitly incorporate complete dynamic equilibrium since the inception of both drugs into the estimation procedure. As discussed above, this approach is not computationally feasible at this point.

We therefore adopt a middle-ground approach. We set $(D_{jt^I_j}, ..., D_{j0})$ equal to the average D_{jt} for the first 30 observations, where t^I_j is the period that drug j is introduced. In other words, for $t = t^I_j, ..., 0$, we set $D_{jt} = \bar{D}_j$, where $\bar{D}_j = \frac{\sum_{t=1}^{30} D_{jt}}{30}$. Also, for $t = t^I_j, ..., 0$, we set p_{jt} at the average observed values. For the size of market, we first run a linear regression of the size of market on a constant and time trend and then use the predicted values to fill in $Size_t$, for $t = t^I_j, ..., 0$. Given the imputed values of $(D_{jt^I_j}, ..., D_{j0})$, $(p_{jt^I_j}, ..., p_{j0})$, and $(Size_{t^I_j}, ..., Size_0)$, we use our physician's choice model to simulate the unconditional joint distribution of $(G^I_{j0}, E[q_j|I(1)], \sigma_j(1))$, which is then incorporated in our likelihood function.

5 Results

5.1 Parameter Estimates

We now discuss the parameter estimates. The total number of structural demand parameters is 14. Recall that we treat Vaseretic and Zestoretic as inside goods because they compose more than 80% of the demand for the ACE-inhibitor with diuretic. We combine all other drugs that belong to ACE-inhibitor with diuretic, ACE-inhibitor, and Thiazide Diuretic as the outside good. For identification reasons, we need to normalize the scaling parameter for the number of consumption experience signals, κ, the intercept term for the utility of the outside good, α_0, and the true mean quality of Vaseretic, q_1. We set $\kappa = 1/30000$, and $\alpha_0 = q_1 = 0$. We also restrict $\underline{I}_j^o = \underline{I}_j^p \equiv \underline{I}_j$ and $\underline{\sigma}_j^o = \underline{\sigma}_j^p \equiv \underline{\sigma}, \forall j$ because we do not observe the data during the initial part of the product lifecycle, which is important in identifying their difference. We refer to $\underline{I}$ as the market initial prior.

Table 2 shows the parameter estimates. Model 1 refers to the model presented above. Drug 1 is Vaseretic (incumbent) and drug 2 is Zestoretic (entrant). The time trend of the outside good (π_t) is negative and significant, indicating that the value of the outside good relative to inside goods is declining over time. This is consistent with the continuous expansion of demand for both Vaseretic and Zestoretic, as shown in Figure 1. The parameter estimates for the true mean quality and the initial priors are all statistically significant. The true mean quality of Zestoretic (q_2) is 29.04, which is higher than that of Vaseretic (q_1). The initial prior mean qualities of Vaseretic and Zestoretic are -10.24 and -18.92, respectively, which are lower than their true mean qualities. This indicates that the market has pessimistic priors about both drugs when they are first introduced into the market. It should also be noted that the initial prior mean quality for Vaseretic is better than that for Zestoretic.

All of the preference parameter estimates are statistically significant. The price coefficient is not significant. This is not surprising because, as mentioned before, Canada provides prescription drug coverage to patients who are 60 or older, and most of the patients who have hypertension are elderly. The risk coefficient (r) is positive and significant, indicating risk-averse behavior. In other words, an increase in the perceived variance of a product will lower the expected utility of choosing it. However, the estimate for r is 0.05, which is quite small. Given the functional form of the utility function, this implies that $E[q_j|I(t)]$ carries significantly more weight than $\sigma_j(t)$ in physicians' choice.

The parameters associated with the measure of well-informed physicians are all statistically significant. The estimate for β_0 is -1.42, which implies that nearly 20 percent of physicians will be well-informed about $I_j(t)$ (i.e., $M_j = 0.2$) when $G_j^I = 0$. This represents the percentage of physicians who keep up with the most updated information about ACE-inhibitor with diuretic themselves even without any help from detailing. The estimate of ϕ_I is close to 3%. The implied average rate of forgetting is shown in Figure 3. As we discussed before, it exhibits an inverted-U shape. The average rate of forgetting starts from 0% at around $M_{jt-1} = 0.2$. It increases and reaches the maximum of 2.1% at around $M_{jt-1} = 0.6$, and then declines. The estimate of β_1 is 5.80e-05. To get a sense of the economic significance of β_1, in Figure 4 we plot its implied rate of building M_{jt} without forgetting (i.e., $\phi_I = 0$), conditioning on M_{jt-1} and $D_{jt} = 1300$, which is the average per period detailing for both Vaseretic and Zestoretic in our sample. The rate of building M_{jt} starts off at slightly above 6% when M_{jt-1} is around 0.2 (i.e., $G_I = 0$). Then it declines almost linearly at the rate of 0.775% per 0.1 increase in M_{jt-1}.

Measures of well-informed physicians, expected qualities and perceived variances play crucial roles in our model. They are also potentially important for marketing managers, who need to make strategic decisions on how to allocate their sales forces. Although these variables are not directly observed in the data, having explicitly modeled how these elements influence physicians' choice, we are able to recover them from the evolution of market shares and detailing data. Figure 5 shows the evolution of the measures of well-informed physicians during the sample period. For Vaseretic, the measure of well-informed physicians starts off at around 0.57. It increases to 0.7 after 30 months, and then gradually reduces to around 0.55 at the end of the sample period. For Zestoretic, the measure of well-informed physicians increases from 0.3 to around 0.85. Figure 6 shows how $E[q_j|I(t)]$ evolves during the sample period. For Vaseretic, it increases slowly from around -5 to -2. For Zestoretic, it increases at a much faster rate from -18 to 23.[13]

As for the pseudo-detailing policy functions, most of the parameters are statistically significant except $\lambda_{13}, \lambda_{14}, \lambda_{15}$, and λ_{22}. The instrumental variable for Zestoretic (λ_{25}) is positive and significant while the instrumental variable for Vaseretic (λ_{15}) is not significant. Both λ_{11} and λ_{21} are positive, suggesting that manufacturers respond to favorable information about their own drugs by increasing the amount of detailing. λ_{23} is positive, indicating that the incentive to detail in order to build up M is stronger than the disincentive to detail due to $\Delta u^q_{21t} < 0$. This is

[13]Since our estimate of r implies that $\sigma_j^2(t)$ does not play an important role in physicians' choice, we do not report the evolution of $\sigma_j^2(t)$ in the interest of space. It is available upon request.

possible given that Zestoretic is a new entrant. Even though Zestoretic's partial expected utility, $E[u^q_{2t}|I(t)]$, is lower than the incumbent's, its manufacturer may be forward-looking and tries to build up M earlier in anticipating that its $E[u^q_{2t}|I(t)]$ might become higher than its rivals' later. In fact, given our parameter estimates, Δu^q_{21t} changes from negative to positive over time.

Also, both λ_{j2} and λ_{j4} are negative for $j = 1, 2$, implying that D_{jt} decreases as M_{kt-1} increases. This suggests that the marginal return of detailing would decrease as M_{kt-1} increases. Interestingly, using our parameter estimates, we simulate sequences of $(\Delta s_{jt}(\underline{I}^p_k), \Delta s_{jt}(I_k(t)))$, and find that $\Delta s_{jt}(\underline{I}^p_k) > \Delta s_{jt}(I_k(t))$ for all j, k and t. It follows from equation (17) that the implied static marginal return of detailing indeed decreases as M_{kt-1} increases. Although this does not mean the dynamic marginal return of detailing would necessarily decrease, it is likely that they would move in the same direction. Overall, our results suggest that the endogeneity problem of detailing is present in this market.

5.2 Goodness-of-fit

Our estimated model provides a good fit to the data. To illustrate this, we simulate 5000 sequences of quantity demanded (expressed in terms of number of prescriptions) for both Vaseretic and Zestoretic using the demand model and the pseudo-detailing policy functions. We compute the average predicted quantity by averaging simulated quantities. Figures 7 and 8 plot the average predicted demand and the actual demand for Vaseretic and Zestoretic, respectively. In general, the model is able to fit the diffusion pattern of demand very well. This indicates that even though we only have four types of physicians in our model, it is flexible enough to fit the data. Figures 9 and 10 plot the average predicted detailing minutes and the actual ones for Vaseretic and Zestoretic, respectively. As we can see, the average predicted detailing minutes is able to capture the data trend reasonably well. In particular, the average predicted detailing minutes is able to mimic the observed fluctuation for Zestoretic. This is mainly due to the positive correlation between detailing for Zestoretic and its instrument (total detailing minutes by Zestoretic's manufacturer in the cardiovascular category net the detailing minutes for Zestoretic) used in the pseudo-detailing policy function.

5.3 Effectiveness of Detailing

5.3.1 The effect of a temporary increase in detailing

Measuring the effectiveness of detailing is important for managers because they often need to decide how to allocate their sales forces. In this subsection, we discuss the effectiveness of detailing using our parameter estimates. It is worth reiterating that M_{jt} and $E[q_j|I(t)]$ play important roles in determining the marginal return of detailing in our model. Although these variables are not directly observed in the data, we are able to use the estimates of our structural parameters to generate them. We will first illustrate how the marginal impact of detailing on current demand depends on them.

Notice that the marginal return of detailing for drug j not only depends on $I_j(t)$ and M_{jt}, but also $I_{-j}(t)$ and M_{-jt}. To simplify the illustration, we set $M_{1t} = M_{2t}$ for all t. In the baseline case, for $t \geq 1$, we simulate 5000 histories of demand and $I(t)$ by setting $D_{1t} = D_{2t} = 1300$, which is the average observed amount of detailing across both drugs. We also set p_{jt} at its average observed values for all t. Recall that Vaseretic and Zestoretic enter the market before $t = 1$ (when our sample begins). To ensure $M_{1t} = M_{2t}$ and obtain the initial value of the information sets at $t = 1$, we set $M_{1t} = M_{2t} = 0.5$ for $t < 1$ in our baseline simulation. For $t \geq 1$, M_{jt} is determined by D_{jt}. We evaluate the effects of a one-time increase in detailing at three different points in time, based on the average expected qualities in the baseline simulation: (i) $t = 1$ when the average expected quality for Vaseretic is higher; (ii) $t = 23$ when the average expected qualities are about the same for both drugs; (iii) $t = 60$ when the average expected quality for Zestoretic is higher. In each case, we increase the detailing amount by 50% for one of the drugs, holding the other one fixed, and examine its effect on current demand.

Panel 1 of Table 3 shows the results. For Vaseretic, the percentage changes in current demand are 0.348%, 0.417%, and 0.414% at $t = 1$, 23, and 60, respectively. The effect at $t = 23$ is higher than that at $t = 1$, mainly because $E[q_1|I(t)]$ increases from -5.52 to -3.68 during that period. However, the effect at $t = 60$ is about the same as that at $t = 23$ despite the fact that Vaseretic's average $E[q_1|I(t)]$ improves from -3.68 to -2.06. One reason is that Zestoretic's average $E[q_1|I(t)]$ improves even more from -3.11 to 19.79 during that period. This reduces the attractiveness of Vaseretic to physicians at $t = 60$. Another reason is that there is diminishing return in building up the measure of well-informed physicians. During that period, M_{1t} increases from 0.64 to 0.73. According to equation (17), a lower return in building up M results in a smaller effect of detailing on current demand.

We find a similar pattern for Zestoretic: The percentage changes in current demand are 0.283%, 0.996%, and 0.903% at t = 1, 23, and 60, respectively. The explanation is similar to the case for Vaseretic. It should be noted that at $t = 23$, the percentage change in current demand is much larger for Zestoretic (0.996%) than for Vaseretic (0.417%) although the average expected qualities of Vaseretic and Zestoretic are about the same. This is because the initial prior for Zestoretic's quality is lower than that for Vaseretic's. Consequently, it follows from equation (17) that the marginal impact of detailing is higher for Zestoretic.

The magnitudes of our detailing elasticities are consistent with Berndt et al. (1997). According to their estimates, the upper bound of the elasticity of demand with respect to cumulative detailing minutes ranges from 0.67 to 0.92.[14] In our simulation above, a 50% increase in detailing corresponds to increases of 2.6%, 1.9%, and 1.6% in cumulative detailing minutes at $t = 1, 23$, and 60, respectively. Thus our elasticity of demand with respect to cumulative detailing minutes falls in a range between 0.1 and 0.6.[15]

[14]Berndt et al. (1997) estimates the following equation using the data on anti-ulcer drugs in the U.S.:

$$log\left(\frac{n_{jt}}{n_{1t}}\right) = \beta \cdot log\left(\frac{G^I_{jt}}{G^I_{1t}}\right) + \cdots, \tag{25}$$

where n_{jt} is the sales of drug j at time t, G^I_{jt} is the cumulative detailing minutes of drug j at time t, and drug 1 is the first entrant in this market. This equation implies that

$$\varepsilon_{jj} = \beta + \varepsilon_{1j}, \tag{26}$$

where ε_{jk} is the elasticity of demand for drug j with respect to cumulative detailing minutes of drug k. If $\varepsilon_{jk} < 0$ for $j \neq k$, β is the upper bound of ε_{jj}.

[15]We do not compare our detailing elasticity with those implied by Narayanan et al. (2005) and Mukherji (2002) because they use detailing expenditures instead of detailing minutes, which is used in our paper.

5.3.2 The Importance of Endogeneity of Detailing

Our estimates in the pseudo-detailing policy function suggest that detailing is endogenous. However, it is hard to assess the economic significance of the endogeneity problem from the estimates. To investigate the extent of the parameter bias if one fails to take the endogeneity problem of detailing into account, we re-estimate the demand model without using the pseudo-detailing policy functions. The parameter estimates are reported in Table 2, under Model 2 (demand only model). The estimate for β_1 is 6.74e-05. This is higher than the estimate from the base model (i.e., Model 1), which is 5.80e-05. The depreciation rate of the detailing stock, ϕ_I, is 0.022. This is lower than the estimate 0.029 in the base model. A likelihood ratio test rejects the hypothesis that the estimates of $(\beta_0, \beta_1, \phi_I)$ in the base model are the same as those in Model 2 at 5% significance level. This suggests that the estimated marginal return of detailing is biased upward if we do not take the endogeneity problem into account. To show the extent of the bias, we plot the implied average rate of forgetting from the demand only model in Figure 3, and the implied rate of building M in Figure 4. The average rate of forgetting is biased downward, with its peak at 1.5% instead of 2.1%; the rate of building M is biased upward, starting at around 7% instead of 6%.

To understand how the bias would affect the estimates of the effectiveness of detailing, we repeat the exercise in Section 5.3.1 by using the parameter estimates from Model 2. We use the same simulated values of $I(t)$ and M_{jt-1} at $t = 1$, 23, and 60 from the baseline simulation in Panel 1 of Table 3. Conditional on these simulated $I(t)$ and M_{jt-1}, we use the parameter estimates from Model 2 to simulate the effect of the one-time temporary increase in detailing. The results are reported in Panel 2 of Table 3. The percentage change of the current demand are 0.412%, 0.510% and 0.509% for Vaseretic, and 0.381%, 1.214% and 1.057% for Zestoretic, at $t = 1, 23$, and 60, respectively. Compared with the baseline case (Model 1, Panel 1 of Table 3), this confirms that the effectiveness of detailing would be biased upward if we do not take the endogeneity into account.

5.3.3 Policy Experiment: A campaign that encourages sharing drug experiences

We now turn to discuss a policy experiment. In order to enhance the speediness of updating the safety profile of drugs, public health agencies have been considering various measures to encourage health care professionals and patients to share their drug experiences with them. For example, Health Canada set up a program called MEDEffect to promote awareness about the importance of filing reports using their on-line report system for the general public. It is likely that such a program would increase the portion of experience signals revealed to the public (correspond to an increase in κ in our model). How should marketing managers respond to this kind of campaign? We will use our structural model to address this question. To illustrate this, we re-simulate the effects of detailing in our model using the procedure above by doubling the value of κ. Panel 3 of Table 3 shows the results. Compared with the baseline case in Panel 1 of Table 3, the information set, $I(t)$, has improved much quicker, and the percentage changes of current demand are also higher at $t = 1, 23$, and 60. In particular, the increases in the effectiveness of detailing are much higher in the earlier part of the product lifecycle. Given these results, marketing managers should consider *increasing* the amount of detailing in this market if this campaign is carried out, in particular, at the beginning stage of the product lifecycle.

It is important to understand the intuition behind these results. They are mainly driven by the pessimistic initial prior in this market. As more experience signals are revealed in each period under this campaign, the expected qualities are revised upward more quickly over time. Consequently, this shifts up the effectiveness of detailing. Following this argument, it should be emphasized that the effectiveness of detailing could very well shift down under this campaign if the market has optimistic initial prior about drug qualities. In that case, the expected qualities will be revised downward more quickly over time, and the implications would be that marketing managers should reduce their detailing efforts under such a campaign.

The discussion above again highlights the difference between our model and the traditional learning models pioneered by Erdem and Keane (1996), which assume that advertising/detailing signals and consumption experience signals are substitutes for each other in updating the prior belief about product qualities. In those models, increasing the value of κ will necessarily cause the marginal return of advertising/detailing to decrease, which suggests that managers should reduce their advertising/detailing efforts. This is just the opposite of what our model suggests, given our parameter estimates.

We should emphasize that this does not mean that our model is necessarily better than the previous learning models. Clearly, if we consider a market where manufacturers indeed have complete information about their products throughout the product lifecycle, using our model to conduct policy experiments may generate misleading managerial implications. Rather, our results point out that it is crucial for researchers to investigate the mechanisms of how advertising/detailing convey information in the market that they study, and incorporate its main features into their model. Here, we demonstrate that different ways to model informative detailing could generate very different managerial implications.

6 Conclusion

In this paper, we develop a new structural model of physicians' prescribing decisions and detailing under quality uncertainty. We introduce a representative opinion leader, whose role is to update the most current information about drug qualities based on past consumption experiences. Unlike the previous literature which assumes detailing is a way to convey noisy signals about the true quality of the drug to physicians, we assume that detailing changes the measure of physicians who are informed of the current public information sets maintained by the representative opinion leader. This allows our model to directly link the marginal return of detailing to the measure of well-informed physicians and current information sets. We also explicitly model physician forgetting by allowing the measure of well-informed physicians to decrease if current detailing efforts are too low.

We estimate our model using product level data on the ACE-inhibitor with diuretic market in Canada. Our estimation approach, which makes use of a pseudo-detailing policy function, allows us to control for the potential endogeneity of detailing. The results show that our model is able to fit the diffusion pattern well. We also demonstrate that the effectiveness of detailing depends on the current information set and the measure of well-informed physicians. We examine how a public awareness campaign, which encourages physicians/patients to report their drug experiences, would affect managerial incentives to detail. Given our parameter estimates, our model suggests that managers should increase the detailing efforts. The implications are diametrically different from the previous learning models, which implies that managers should reduce the detailing efforts under such a campaign. We emphasize that this does not mean that our model is necessarily better than the previous learning models. Rather, our results point out the importance of using an appropriate structural model of detailing that would better describe the institutional details of the market under study.

One limitation of this paper is that we do not explicitly incorporate data from clinical trials outcomes and side-effect information. Conceivably, such data will be very valuable for analyzing the effects of detailing. Also, we do not model how direct-to-consumer advertising, journal advertising, free samples, and educational meetings or conferences sponsored by drug companies may affect pharmaceutical demand. We leave modeling the role of these marketing communication mix in the environment we consider here for future research.

Another limitation is that we do not allow for heterogeneous opinion leaders in our model. Some opinion leaders may obtain more past patients' experiences than others, (perhaps some work for larger hospitals and therefore are able to collect more patients' experiences) and as a result, they may possess different public information sets representing their various levels of learning. Physicians may receive more influence from opinion leaders who are located in their neighborhoods. Although these are attractive features, unfortunately, incorporating them will dramatically complicate the model. One would also need a richer data set to estimate such a model. Instead, our approach of using a representative opinion leader leads to a tractable model which can be estimated simply using product level data, which is the most commonly used data in this market. We hope future research will extend our framework to allow for multiple representative opinion leaders. Another interesting research direction is to use individual level data to examine the role of opinion leaders. A recent study by Bhatia, Manchanda and Nair (2006) is taking this important step to examine the effects of heterogeneous opinion leaders on physician decisions.

The third limitation is that our model does not take into account the "bribery" effect. Sales representatives often give away gifts during their visits. Critics argue that these gifts may affect physicians' prescribing behavior. The main difficulty of incorporating the bribery effect is that there is no data on the amount of gifts given by sales representatives. The traditional approach to handle this is to allow a detailing goodwill stock to enter the utility function directly (e.g., Anand and Shachar 2005, Narayanan et al. 2005). Unfortunately, given the data that we have, it is not clear how we can separately identify the bribery effect and the informative effect that we model here (other than relying on the functional form assumptions). If the bribery effect is important, we would overestimate the informative role of detailing in this paper. We therefore emphasize that the empirical exercise conducted here is mainly for illustrating the empirical implications of our model. Disentangling between the bribery and the informative effects of detailing will be an important topic for future research.

Our model can potentially help a marketing manager evaluate the future return of alternative long-term detailing strategies. Conditional on his/her own future detailing strategies and his/her rivals' future detailing strategies, we can take the uncertainty about true quality into account by integrating out the prior distributions of q. However, when the marketing manager changes his/her own detailing strategies, it is likely that his/her rivals will react and change theirs as well. Although our pseudo-detailing policy function approach allows us to correct the endogeneity problem, it does not allow us to predict how rivals react when one changes his/her own detailing strategy due to its reduced form nature. In order to utilize our demand model to evaluate alternative future detailing strategies, we would need to combine it with a supply side model explicitly. By developing a tractable demand side model, we hope that our framework has laid some groundwork for this challenging research direction.

Finally, although we present our model in the context of pharmaceutical demand, it could also be applied to other markets such as movies, video games, softwares, restaurants, etc., where both sides of the market are uncertain about how new products will perform, and opinion leaders (e.g., professional critics) may play an important role in influencing consumer purchase decisions. Given that data on reviews and critics are typically available in the public domain, it is surprising that structural modeling of opinion leaders is relatively scarce. Our model could be served as a starting point to analyze their roles and potentially improve our understanding about how information is transmitted in markets other than prescription drugs.

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Table 1: Summary statistics

	Brand	Mean	Standard deviation	Max	Min
Number of prescriptions	Vaseretic	4,007.63	676.80	5,446	2,429
	Zestoretic	6,388.75	4,900.28	16,330	322
Detailing Minutes	Vaseretic	1,032.63	689.11	3,240	97
	Zestoretic	1,627.08	828.67	4,203	93
Price	Vaseretic	40.54	8.76	69.21	24.45
	Zestoretic	34.29	8.65	61.48	15.74

Table 2: Parameter estimates

1 - Vaseretic (incumbent)
2 - Zestoretic (entrant)

	Model 1 (base)		Model 2 (demand only)	
	estimates	standard errors	estimates	standard errors
Learning parameters				
σ_δ^2	**8.410**	0.566	**7.560**	0.122
$\underline{q}_1$	**-10.237**	0.888	**-12.153**	2.302
$\underline{q}_2$	**-18.916**	0.418	**-19.542**	2.534
$\underline{\sigma}^2$	**3.479**	0.262	**3.654**	0.093
q_1	0		0	
q_2	**29.038**	1.529	**20.106**	3.618
κ	1/30000		1/30000	
Preference parameters				
α	**-3.893**	0.063	**-3.864**	0.040
r	**0.049**	4.17E-04	**0.046**	0.006
π_p	4.98E-04	5.12E-04	5.72E-04	4.04E-04
π_t	**-0.005**	6.51E-04	**-0.006**	3.31E-04
Detailing stock parameters				
Φ_I	**0.029**	0.003	**0.022**	0.006
β_0	**-1.420**	0.183	**-1.360**	0.095
β_1	**5.80E-05**	9.79E-06	**6.74E-05**	1.06E-05
Other parameters for error terms				
s.d.(ε)	**180.673**	11.272	**171.320**	7.452
s.d.(ζ)	1		1	
s.d.(e)	**0.729**	0.021	**0.621**	0.036
Pseudo-detailing policy functions				
λ_{10}	**7.777**	1.324		
λ_{11}	**2.811**	0.995		
λ_{12}	**-6.166**	1.127		
λ_{13}	0.708	1.512		
λ_{14}	-2.831	1.701		
λ_{15}	-0.085	0.145		
λ_{20}	**0.173**	1.669		
λ_{21}	**19.195**	7.463		
λ_{22}	-18.698	10.946		
λ_{23}	**16.370**	4.031		
λ_{24}	**-22.477**	6.040		
λ_{25}	**0.690**	0.186		
s.d.(ν)	**0.643**	0.029		
log likelihood	-2110.439		-962.275	

* Estimates shown in bold are significant at 5% level .

Table 3: Effect of a one-time increase in detailing by 50% on current demand

Panel 1 (Baseline, Model 1 estimates)

	Increase in detailing for Vaseretic		Increase in detailing for Zestoretic		Average I(t) $(E[q_j \mid I(t)], \sigma_j^2(t))$		Measure of well-informed physicians in the last period
	% change in demand		% change in demand				
time	Vaseretic	Zestoretic	Vaseretic	Zestoretic	Vaseretic	Zestoretic	
1 (Mar 93)	0.348	-0.097	-0.017	0.283	(-5.52, 1.87)	(-16.97, 3.34)	0.50
23 (Jan 95)	0.417	-0.070	-0.154	0.996	(-3.68, 1.24)	(-3.11, 2.33)	0.64
60 (Feb 98)	0.414	-0.035	-0.282	0.903	(-2.06, 0.70)	(19.79, 0.67)	0.73

Panel 2 (Without controlling for endogeneity of detailing, Model 2 estimates)

	Increase in detailing for Vaseretic		Increase in detailing for Zestoretic		Average I(t) $(E[q_j \mid I(t)], \sigma_j^2(t))$		Measure of well-informed physicians in the last period
	% change in demand		% change in demand				
time	Vaseretic	Zestoretic	Vaseretic	Zestoretic	Vaseretic	Zestoretic	
1 (Mar 93)	0.412	-0.194	-0.026	0.381	(-5.52, 1.87)	(-16.97, 3.34)	0.50
23 (Jan 95)	0.510	-0.130	-0.263	1.214	(-3.68, 1.24)	(-3.11, 2.33)	0.64
60 (Feb 98)	0.509	-0.056	-0.519	1.057	(-2.06, 0.70)	(19.79, 0.67)	0.73

Panel 3 (Policy experiment, Model 1 estimates with doubled kappa)

	Increase in detailing for Vaseretic		Increase in detailing for Zestoretic		Average I(t) $(E[q_j \mid I(t)], \sigma_j^2(t))$		Measure of well-informed physicians in the last period
	% change in demand		% change in demand				
time	Vaseretic	Zestoretic	Vaseretic	Zestoretic	Vaseretic	Zestoretic	
1 (Mar 93)	0.464	-0.126	-0.035	0.529	(-3.64, 1.23)	(-14.99, 3.19)	0.50
23 (Jan 95)	0.496	-0.051	-0.274	1.156	(-2.18, 0.73)	(11.39, 1.28)	0.64
60 (Feb 98)	0.445	-0.036	-0.295	0.912	(-1.12, 0.38)	(25.07, 0.29)	0.73

Figure 1: Total sales vs time

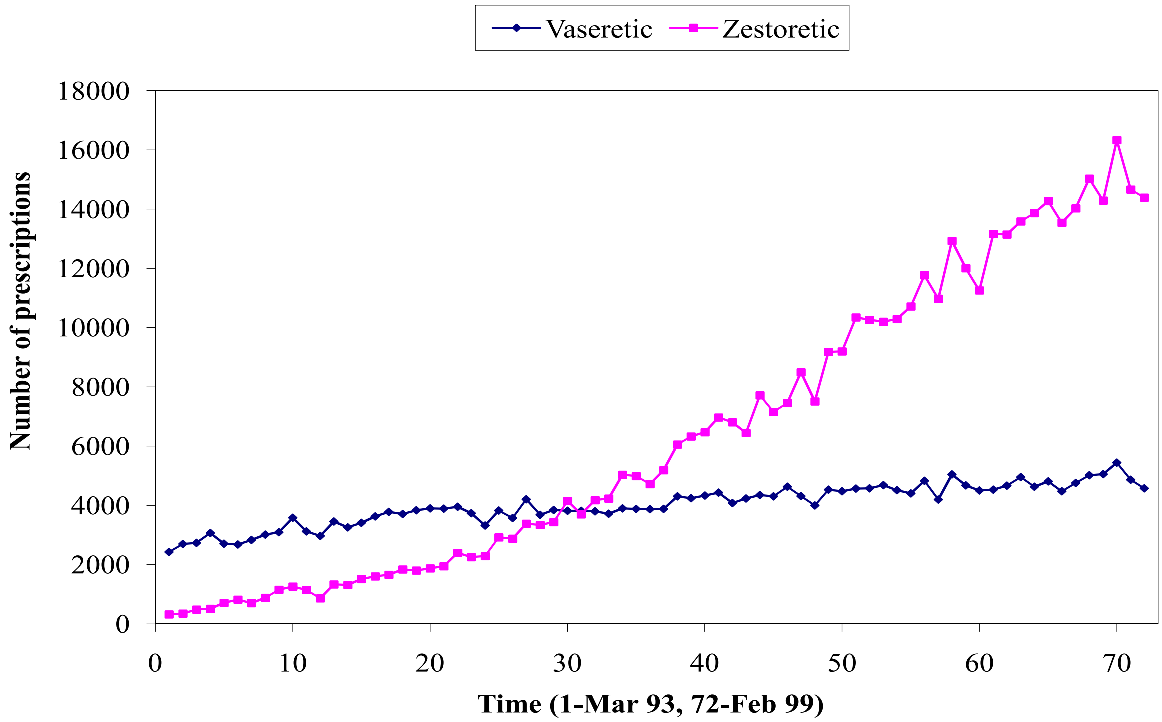

Figure 2: Detail minutes vs. time

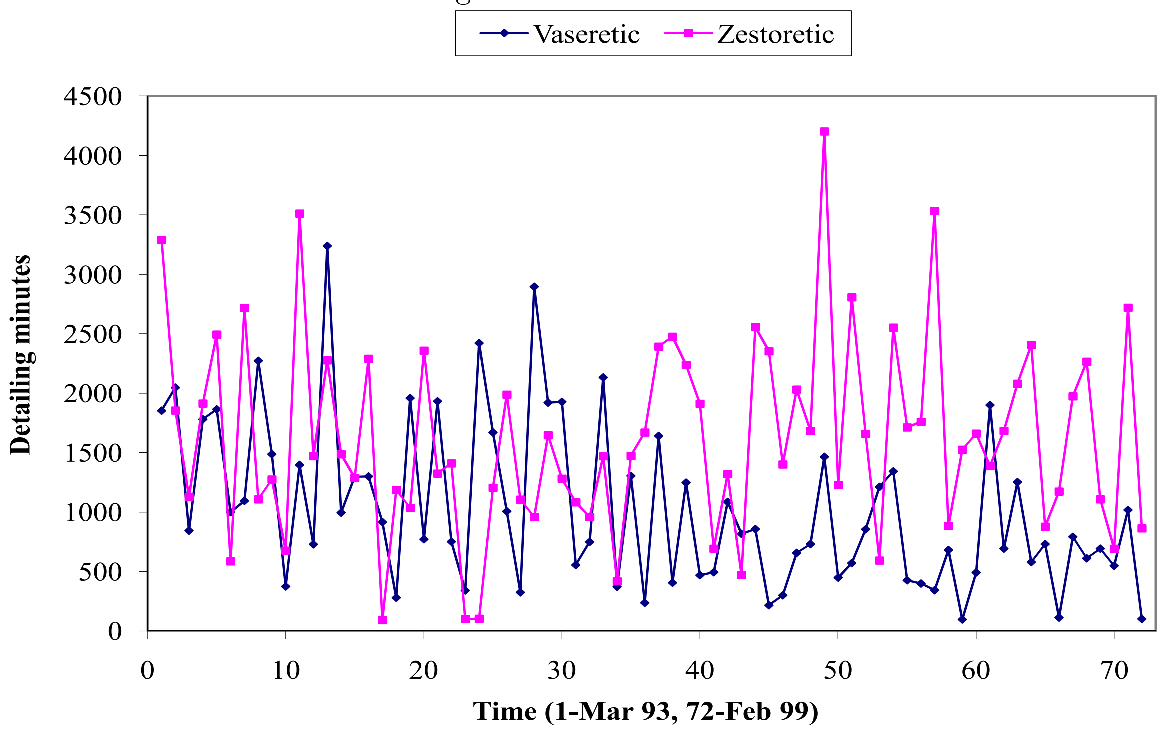

Figure 3: Rate of forgetting

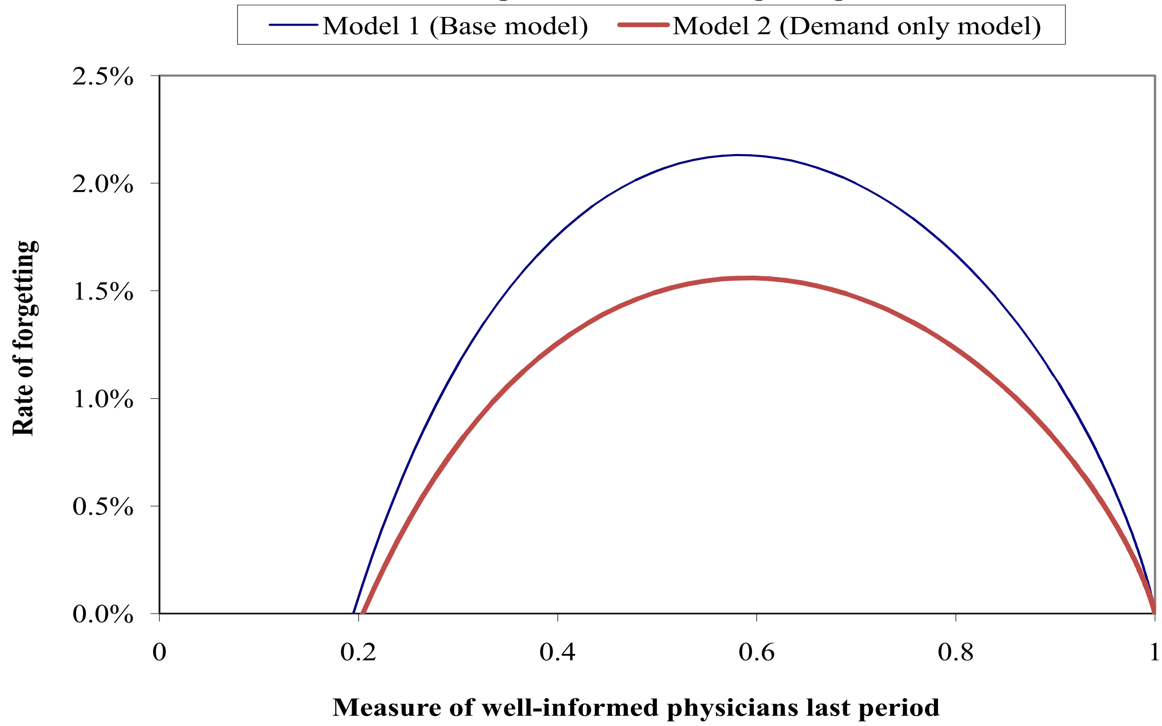

Figure 4: Rate of building the measure of well-informed physicians

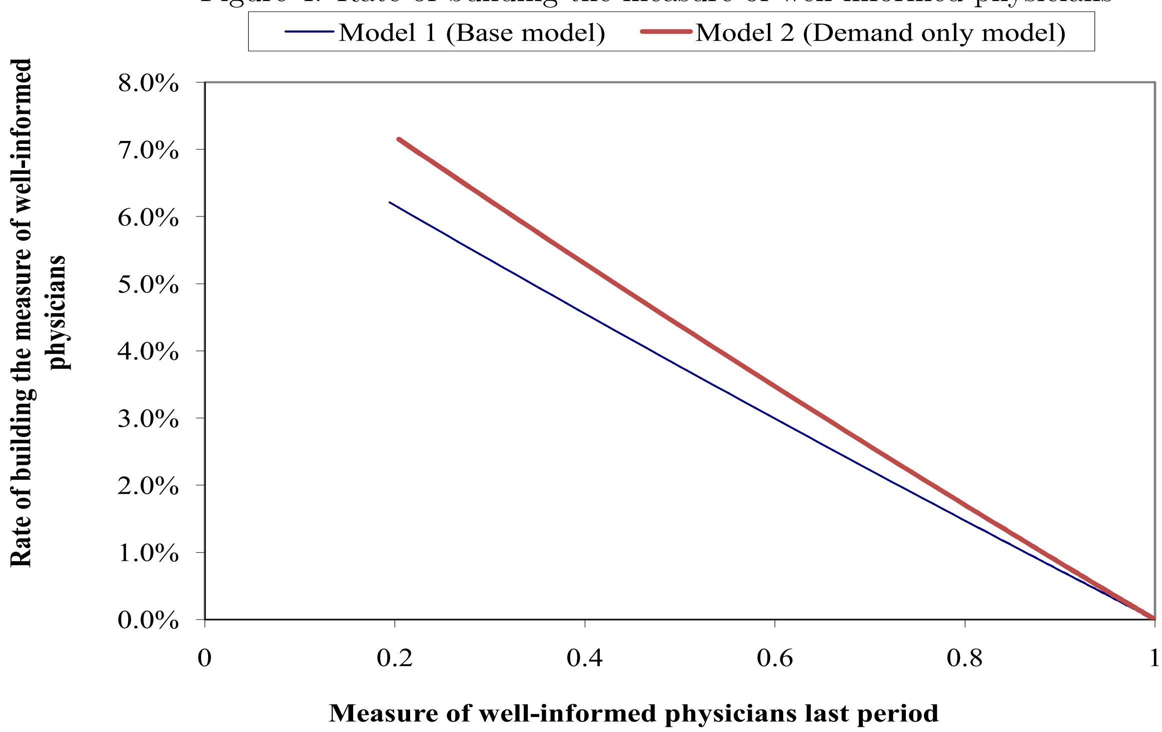

Figure 5: Measure of informed physicians

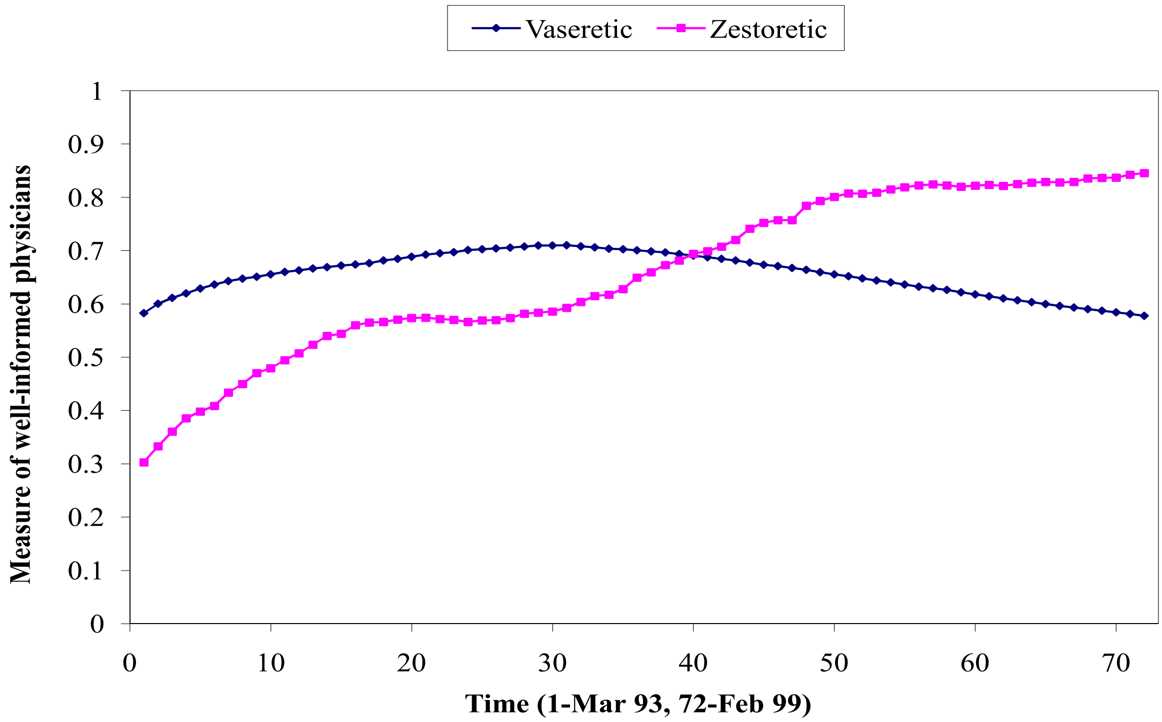

Figure 6: Expected qualities

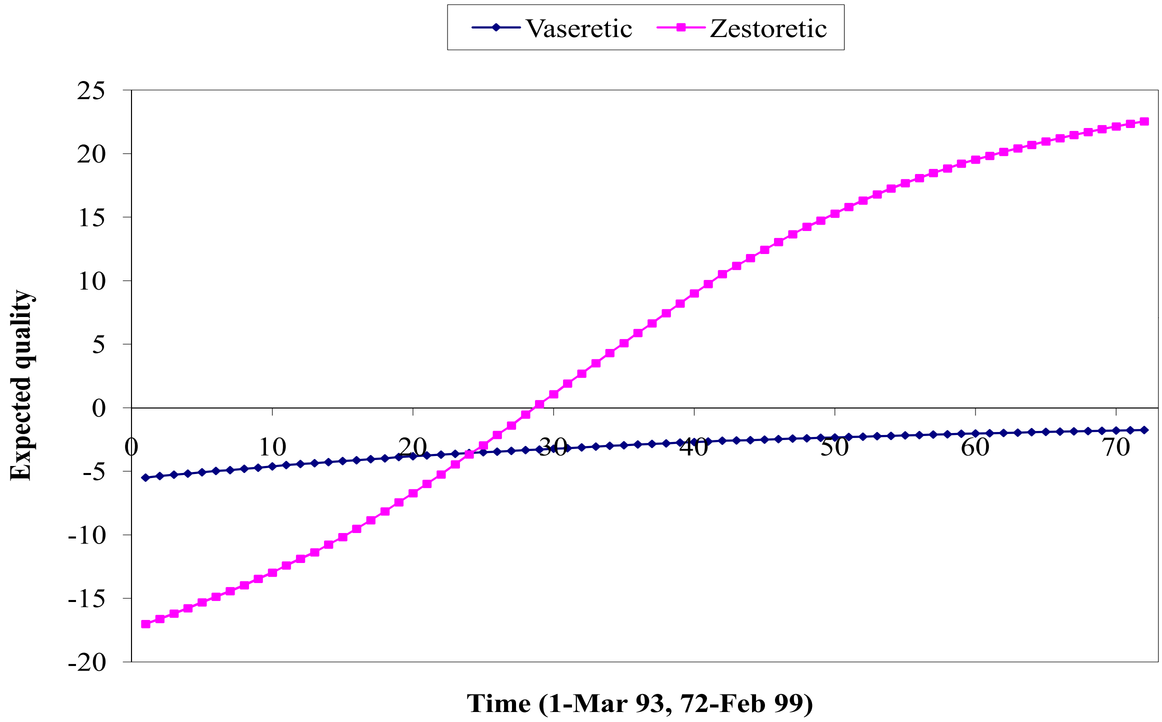

Figure 7: Predicted and Actual Demand for Vaseretic

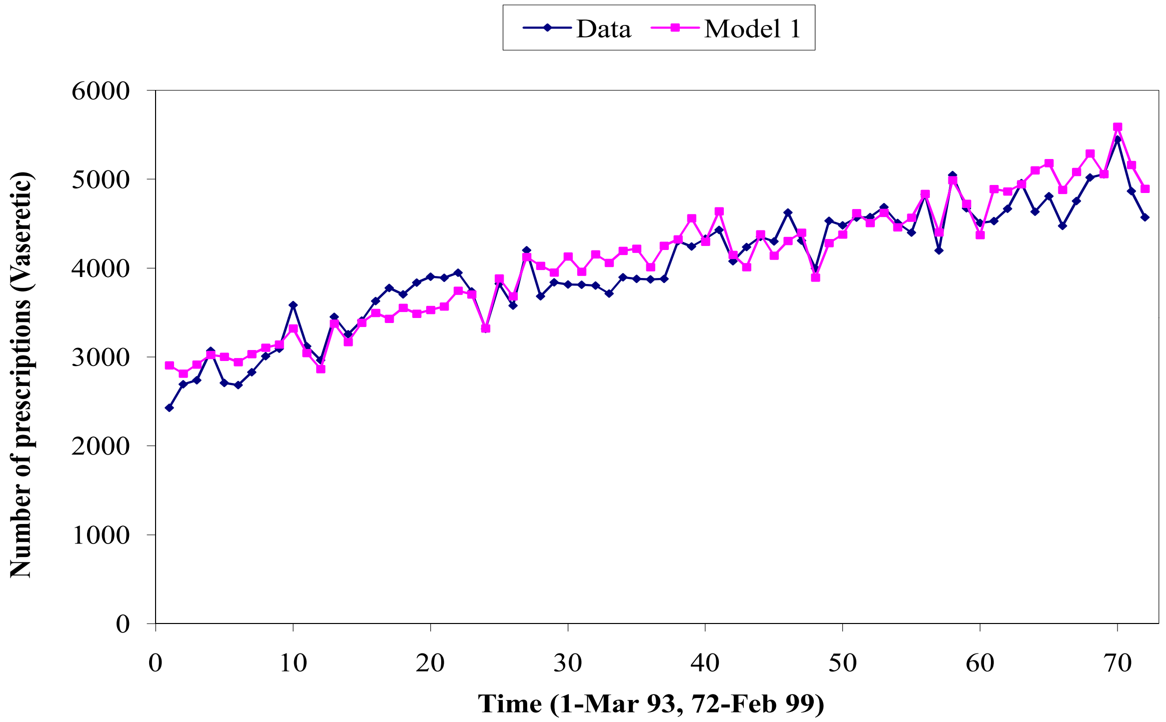

Figure 8: Predicted and Actual Demand for Zestoretic

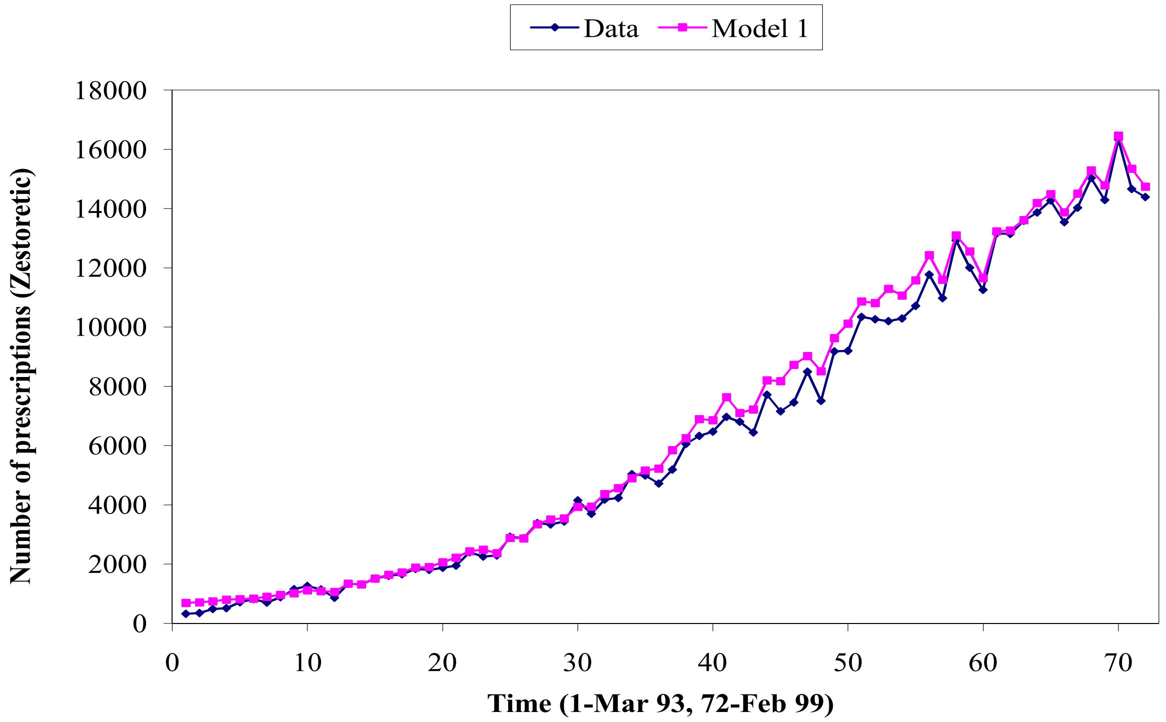

Figure 9: Predicted and Actual Detailing Minutes for Vaseretic

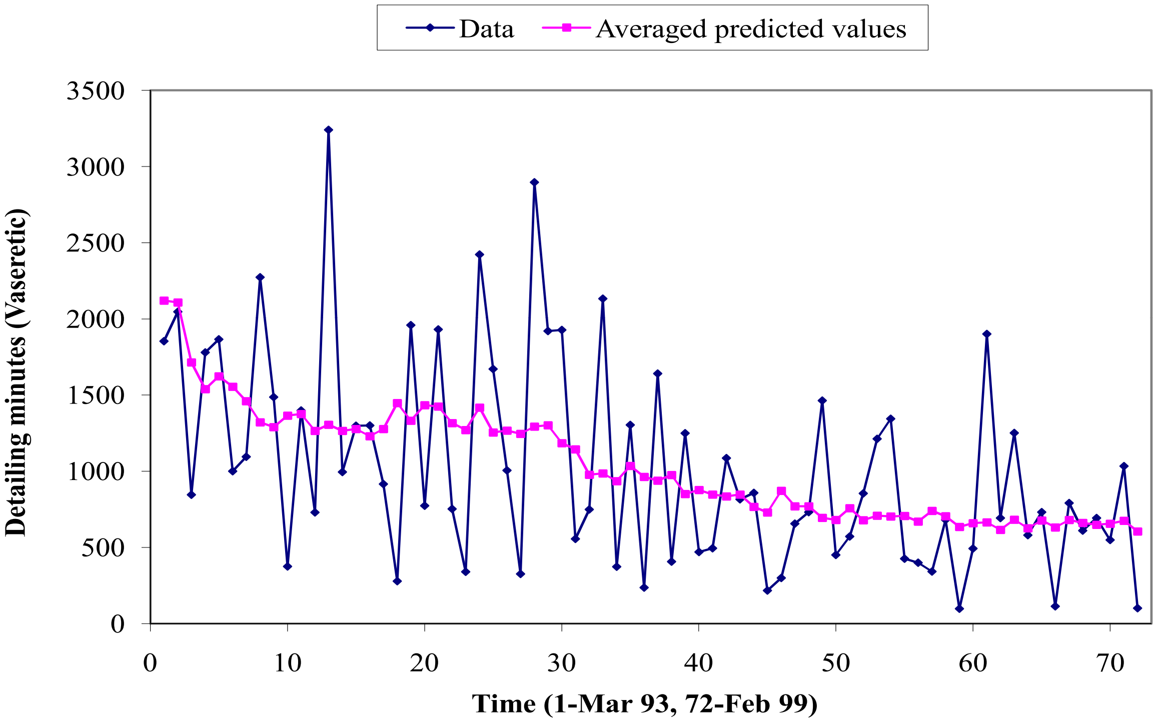

Figure 10: Predicted and Actual Detailing Minutes for Zestoretic