Measuring the Informative and Persuasive Roles of Detailing on Prescribing Decisions

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Abstract

In the pharmaceutical industry, measuring the importance of informative and persuasive roles of detailing is crucial for both drug manufacturers and policy makers. However, little progress has been made in disentangling between informative and persuasive roles of detailing. In this paper, we provide a new identification strategy to separately identify these two roles. Our key identification assumption is that the informative component of detailing is chemical specific while the persuasive component is brand specific. Our strategy is to focus on markets where some drug manufacturers engage in a co-marketing agreement. Under a co-marketing agreement, two companies market the same chemical under two different brand-names. With our identification assumption, the relative market share of these two brands, together with their individual detailing efforts, would allow us to measure the persuasive component of detailing. The total market share of the chemical, and the sum of the brand-specific detailing efforts for this chemical, would allow us to measure the informative component of detailing. To demonstrate our identification strategy, we estimate two structural models of detailing and prescribing decisions that have been used in the literature, using monthly product level data on sales, prices, and detailing minutes for ACE-inhibitor with diuretic in Canada. This market has three brand-name drugs: Vaseretic, Zestoretic, and Prinzide. Zestoretic and Prinzide are made of the same chemicals, but co-marketed by two different companies. We find that the persuasive component mainly influences brand choice, and the informative component is mainly responsible for the growth of the demand for chemicals. Our results suggest that restricting the detailing budget for pharmaceutical products could potentially lower the consumer welfare because it slows down the rate of learning for physicians.

Keywords: Detailing, Informative Role, Persuasive Role, Prescription Drugs, Decisions Under Uncertainty, Diffusion

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

1 Introduction

In the pharmaceutical industry, measuring the importance of informative and persuasive roles of detailing is crucial for both drug manufacturers and policy makers. For drug manufacturers, this helps them allocate resources to detailing more efficiently. If the persuasive role is important, firms could create artificial product differentiation by increasing their detailing efforts. On the contrary, if detailing is mainly informative and its persuasive role is weak, the effectiveness of detailing intensity will highly depend on the actual quality of drugs (i.e., side-effects and efficacy profiles). Among policy debates, many people believe that detailing is mainly persuasive and consumers will be better off if the industry reduces their detailing budget. Consequently, there are frequent calls for the industry to restrict detailing activities. However, if detailing is mainly informative in nature, putting restrictions on it might slow down the adoption rate of new innovative drugs. Consequently, this could lower consumer welfare.

Despite its importance, little progress has been made in disentangling between informative and persuasive roles of detailing. The main difficulty is that both effects are likely to have positive impacts on the demand for prescription drugs. If one only observes sales and detailing efforts over time, it is hard to disentangle these two roles. In this paper, we provide a new identification strategy to separately identify the persuasive and informative roles of detailing. Our key identification assumption is that the informative component of detailing is chemical specific while the persuasive component is brand specific. Our strategy is to focus on markets where some drug manufacturers engage in a co-marketing agreement. Under a co-marketing agreement, two companies market the same chemical under two different brand-names. With our identification assumption, the relative market share of these two brands, together with their individual detailing efforts, would allow us to measure the persuasive component of detailing. The total market share of the chemical, and the sum of the brand-specific detailing efforts for this chemical, would allow us to measure the informative component of detailing.

More specifically, to model persuasive detailing, we follow the previous literature (e.g., Nerlove and Arrow 1962) and allow a brand specific persuasive detailing goodwill stock to enter physicians' utility functions. To model informative detailing, we consider two alternative models

of informative detailing that have been used in the literature. The first model follows Ching and Ishihara (2008), which models informative detailing as a means to build/maintain the measure of physicians who know the most updated information about drugs. The second model follows Narayanan, Manchanda, and Chintagunta (2005), in which detailing conveys noisy signals about the true quality of drugs to physicians.

As an application, we apply our identification strategy to the market of ACE-inhibitor with diuretic in Canada. This market has three brand-name drugs: Vaseretic, Zestoretic, and Prinzide. Zestoretic and Prinzide are made of the same chemicals, but are co-marketed by two different companies. To demonstrate the importance of our identification strategy, in addition to estimating the full model with all three brands, we also estimate a version with only two brands: Vaseretic and Zestoretic, which captures 80% of the market share. The identification of the informative and persuasive effects in the 2-brand version relies on the functional form assumption. Its estimation results are counterintuitive – the persuasive effect of detailing is negative and significant in the 2-brand version. On the contrary, the estimation results from the 3-brand version are much more sensible – the persuasive effect is positive and significant, regardless of the way we model the informative detailing.

Based on the parameter estimates from the 3-brand version, we investigate the importance of informative and persuasive detailing by simulating our model. We find that the informative component is mainly responsible for the growth of the demand for chemicals, and the persuasive component mainly influences brand choice. Our results suggest that restricting the detailing budget for pharmaceutical products could slow down the learning process for physicians, reduce the adoption rate of new superior drugs, and hence may potentially lower the consumer welfare.

The rest of the paper is organized as follows. Section 2 reviews the literature. Section 3 describes the demand model. Section 4 describes background and data. Section 5 discusses the results. Section 6 is the conclusion.

2 Literature Review

How does detailing affect physicians' prescribing decisions? Leffler (1981) argues that detailing plays both informative and persuasive roles. He finds that newly introduced drugs tend to receive more detailing than older drugs, and interprets this as evidence that supports detailing contain information. He argues that physicians are relatively unfamiliar with new drugs and hence if detailing provides information about drug's benefits and side-effects, drug manufacturers would spend more detailing efforts for newer drugs. However, he also finds that drug companies still spend significant amount of detailing efforts on old drugs and target older physicians. He interprets this as evidence for its persuasive role, assuming that older physicians should already know the older drugs' efficacy and side-effect profiles fairly well.

Hurwitz and Caves (1988) find that pre-patent expiration cumulative detailing efforts slow down the decline in post-patent expiry market shares of brand-name drugs. They interpret this as evidence for its persuasive role. Rizzo (1988) also finds evidence that detailing lowers the price elasticity of demand. He also argues this is evidence for persuasive detailing. However, it should be pointed out that the results from Hurwitz and Caves (1988) and Rizzo (1988) are also consistent with informative detailing. As argued by Leffler (1981), informative detailing reduces the uncertainty about drug qualities, and hence could also achieve similar empirical implications.

Narayanan et al. (2005) is the first paper that structurally estimates the informative and persuasive roles of detailing in the pharmaceutical market. They extend the framework of Erdem and Keane (1996). Their identification argument builds on Leffler (1981) - they assume that drug companies know the true quality of their products when they launch the products, and informative detailing provides physicians with noisy signals about their products' true qualities. With this assumption, physicians will eventually learn the true quality of the drugs and detailing no longer plays any informative role in the long-run. As a result, the long-run correlation between sales and cumulative detailing efforts will identify the parameters that capture the persuasive role of detailing. The product diffusion paths then identify the parameters that capture the informative role. It should be emphasized that in their framework, in order to separate out the

informative and persuasive roles of detailing, it is crucial that (i) one assumes detailing does not play any informative role in the long-run; (ii) the data set needs to be long enough so that it captures part of the product lifecycle after learning is complete. In contrast, this modeling assumption and data requirement are not necessary for our identification argument.[1]

[1]Another related paper is by Ackerberg (2001). He argues that one can empirically distinguish informative and persuasive effects of advertising by examining consumers' purchase behavior conditional on whether they have tried the product before. His argument is that advertisements that give consumers product information should primarily affect consumers who have never tried the brand, whereas persuasive advertisements should affect both inexperienced and experienced consumers.

3 Model

We now turn to describe the models that will be used to illustrate our new identification strategy for informative and persuasive detailing. We consider two structural models that have been used in the literature. They differ in terms of how to model the role of informative detailing. The first model (Model CI) follows Ching and Ishihara (2008), who model informative detailing as a means to build/maintain the measure of physicians who know the most updated information about drugs. The second model (Model NMC) follows Narayanan, Manchanda, and Chintagunta (2005), who model detailing as a way of conveying noisy signals about the true quality of drugs to physicians. In both models, we capture the persuasive role of detailing by including a persuasive detailing goodwill stock in the utility function for physicians. These two models allow us to capture the role of informative detailing under different environments. For example, when manufacturers know the true quality of their drugs from the beginning of the product lifecycle, Model NMC is particularly relevant. When manufacturers do not know the true quality and use detailing to inform or remind physicians of the most updated information, Model CI is more appropriate. Since these two models generate different empirical implications, it is of our interest to investigate how our identification strategy performs regardless of the way we model informative detailing.

The following basic setup is common in both models. We consider a set of brand-name drugs, which treat the same illness using similar chemical mechanisms. Let $j = 1, \ldots, J$ index brands, $j = 0$ denotes an outside alternative, which represents other close substitutes. Some of the brands may be marketed under a co-marketing agreement and are made of the same chemical. Let $k = 1, \ldots, K$ indexes for chemicals, where $K \leq J$. Let A_k be the set of brands that are made of chemical k. We assume that each brand is made of one of K chemicals. The characteristics of brand $j \in A_k$ are given by p_j and q_k, where p_j is the price of product j, and q_k is the mean quality level of chemical k. Physicians are imperfectly informed about the chemical's mean quality level, q_k. Let $I(t) = (I_1(t), \ldots, I_K(t))$ be a vector of public information sets that describe the most updated belief about $q = (q_1, \ldots, q_K)$ at time t.

Model CI assumes that $I(t)$ is updated by a representative opinion leader based on past patients' experiences with the chemical.[2] For each chemical k, a physician either knows $I_k(t)$, or $\underline{I}_k$, which is the initial prior that physicians have when a drug made of chemical k is first introduced.[3] Let M_{kt} be the measure of physicians who know $I_k(t)$. M_{kt} depends on the cumulative detailing efforts at time t. Model NMC is similar in terms of the updating process for $I(t)$. The main difference is that (i) detailing also provides noisy signals about the true quality of the chemicals for updating the $I(t)$; (ii) $M_{kt} = 1, \forall k, t$. In other words, detailing does not influence M_{kt}.

Our key identification assumptions are: 1) informative detailing is chemical-specific; and 2) persuasive detailing is brand-specific. The first assumption implies: (a) $I_k(t)$ is updated based on past patients' experiences for all products made of chemical k; (b) in Model CI, M_{kt} depends on the sum of the cumulative detailing efforts for all drugs made of chemical k; and (c) in Model NMC, in addition to past patients' drug experiences, $I_k(t)$ are also updated based on the sum of the detailing signals for all drugs made of chemical k. The second assumption implies that the persuasive detailing goodwill stock for brand j is built based only on the detailing efforts for brand j. In what follows, we will describe Model CI first, and then Model NMC.

3.1 Model CI (Ching and Ishihara 2008)

3.1.1 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

[2]A representative opinion leader captures the following intuition. The medical continuing education literature finds that opinion leaders are 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.

[3]For simplicity, we assume that physicians and the representative opinion leader share the same initial prior belief. In general, we can allow them to be different.

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.[4]

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

$$\tilde{q}_{ikt} = q_k + \delta_{ikt}, \tag{1}$$

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

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

and the representative opinion leader's initial prior on q_k ($\underline{I}_k$) is also normally distributed:

$$q_k \sim N(\underline{q}_k, \underline{\sigma}_k^2). \tag{3}$$

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:

$$E[q_k|I(t+1)] = E[q_k|I(t)] + \iota_k(t)(\bar{q}_{kt} - E[q_k|I(t)]), \tag{4}$$

where $\bar{q}_{kt}$ is the sample mean of all the experience signals that are revealed in period t.[5] $\iota_k(t)$ is a Kalman gain coefficient, which is a function of the variance of the signal noise (σ_δ^2), perceived

[4]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.

[5]Let n_t^k be the total quantity prescribed for drugs made of chemical k at time t. Then, $\bar{q}_{kt}|(\kappa n_t^k, I(t)) \sim N(q_k, \frac{\sigma_\delta^2}{\kappa n_t^k})$.

variance ($\sigma_k^2(t)$), the quantities sold at time t (n_{jt}) for all drugs made of chemical k, and the proportion of experience signals revealed to the public (κ), and it can be expressed as:

$$\iota_k(t) = \frac{\sigma_k^2(t)}{\sigma_k^2(t) + \frac{\sigma_\delta^2}{\kappa n_t^k}}. \tag{5}$$

where n_t^k is the total quantity prescribed for chemical k at time t, including free samples measured in number of prescriptions. ι_k 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_k. In particular, $\iota_k(t)$ increases with $\sigma_k^2(t)$.

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

$$\sigma_k^2(t+1) = \frac{1}{\frac{1}{\sigma_k^2(t)} + \frac{\kappa n_t^k}{\sigma_\delta^2}}. \tag{6}$$

Equation (6) implies that, after observing a sufficiently large number of experience signals for a product, the representative opinion leader will learn about q_k, at any arbitrarily precise way (i.e., $\sigma_k(t) \to 0$ and $E[q_k|I(t)] \to q_k$ as the number of signals received grows large).

3.1.2 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 chemical k. A well-informed physician knows the current information set maintained by the representative opinion leader, i.e., $I_k(t)$. An uninformed physician only knows the initial prior, i.e., $\underline{I}_k$. This implies that the number of physician types is 2^K.

The measure of well-informed physicians for chemical k at time t, M_{kt}, is a function of M_{kt-1} and $D_{1t}, ..., D_{Jt}$. For simplicity, we assume that this function only depends on M_{kt-1} and $D_t^k = \sum_{j \in A_k} D_{jt}$, i.e., $M_{kt} = f(M_{kt-1}, D_t^k)$. We assume that $f(M_{kt-1}, .)$ is monotonically increasing in D_t^k. To capture the idea that physicians may forget, we assume that $f(M, 0) \leq M, \forall M$.

In our econometric model, we capture the relationship between M_{kt} and (M_{kt-1}, D_t^k) by introducing a detailing goodwill stock, G_{kt}^I, which accumulates as follows:

$$G_{kt}^I = (1 - \phi_I)G_{kt-1}^I + D_t^k, \tag{7}$$

where $\phi_I \in [0, 1]$ is the depreciation rate. We specify the relationship between M_{kt} and G_{kt}^I as:

$$M_{kt} = \frac{exp(\beta_0 + \beta_1 G_{kt}^I)}{1 + exp(\beta_0 + \beta_1 G_{kt}^I)}. \tag{8}$$

3.1.3 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:

$$E[\sum_{j \in \{0,1,\ldots,J\}} u_{ijt} \cdot d_{hij}(t) | I^h(t)], \tag{9}$$

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 made of chemical k at time t is given by the following expression:

$$u_{ijt} = \alpha_j - \exp(-r\tilde{q}_{ikt}) - \pi_p p_{jt} + \varsigma_{ilt} + \zeta_{ikt} + e_{ijt}, \tag{10}$$

where α_j is a brand-specific intercept; r is the risk aversion parameter; π_p is the utility weight for price; $(\varsigma_{ilt} + \zeta_{ikt} + e_{ijt})$ represents the distribution of patient heterogeneity; and k, l indexes nests.[6]

[6]This is equivalent to modeling physicians' choice as a three-stage nested process, where they choose between the inside goods and the outside good in the first stage, choose one of the chemicals in the second stage, and an alternative made of the chemical chosen in the second stage.

ς_{ilt}, ζ_{ikt}, and e_{ijt} are unobserved to the econometrician but observed to the physicians when they make their prescribing decisions. We assume that ς_{ilt}, 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 $\tilde{q}_{ikt}$ 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. For drug $j \in A_k$, if physician h is well-informed about chemical k at time t, his/her expected utility will be:

$$\begin{aligned} E[u_{ijt}|I^h(t)] &= E[u_{ijt}|I_k(t)] + \gamma_P G^P_{jt} + \gamma_S FS_{jt} \\ &= \alpha_j - exp(-rE[q_k|I(t)] + \frac{1}{2}r^2(\sigma^2_k(t) + \sigma^2_\delta)) - \pi_p p_{jt} \\ &\quad + \gamma_P G^P_{jt} + \gamma_S FS_{jt} + \varsigma_{ilt} + \zeta_{ikt} + e_{ijt}, \end{aligned} \tag{11}$$

where G^P_{jt} is a detailing goodwill stock for drug j at time t, and γ_P captures the effect of persuasive detailing. Similar to G^I_{kt}, we assume that G^P_{jt} accumulates as follows:

$$G^P_{jt} = (1 - \phi_P)G^P_{jt-1} + D_{jt}, \tag{12}$$

Note that G^P_{jt} is drug j specific rather than chemical k specific. Furthermore, we allow the depreciation rates to be different for G^I_{kt} and G^P_{jt}. FS_{jt} is the amount of free samples given for drug j at time t, and γ_S captures the effect of free samples.

If physician h is uninformed about chemical k at time t, his/her expected utility of choosing drug $j \in A_k$ becomes:

$$\begin{aligned} E[u_{ijt}|I^h(t)] &= E[u_{ijt}|\underline{I}_k] + \gamma_P G^P_{jt} + \gamma_S FS_{jt} \\ &= \alpha_j - exp(-r\underline{q}_k + \frac{1}{2}r^2(\underline{\sigma}^2_k + \sigma^2_\delta)) - \pi_p p_{jt} \\ &\quad + \gamma_P G^P_{jt} + \gamma_S FS_{jt} + \varsigma_{ilt} + \zeta_{ikt} + e_{ijt}. \end{aligned} \tag{13}$$

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

Equations (10)-(13) apply only to the inside goods. 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:

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

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 for drug $j \in A_k$, n_{jt}, can be expressed as,

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

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.

3.2 Model NMC (Narayanan et al. 2005)

Given that most of the elements in Model NMC are identical to Model CI, we will only discuss the elements that are specific to Model NMC. All the variables introduced in the previous section will be used here without repeating the descriptions.

3.2.1 Updating of the Information Set

In Model NMC, in addition to consumption experience signals, detailing provides physicians with noisy signals about the true quality of drugs. Let $\tilde{q}^d_{hkt}$ be the detailing signal about the quality of chemical k that physician h receives at time t. Similar to consumption experience signals, it may be expressed as,

$$\tilde{q}^d_{hkt} = q_k + \vartheta_{hkt}, \tag{16}$$

where ϑ_{hkt} is the signal noise. We assume that ϑ_{hkt} is an $i.i.d.$ normally distributed random variable with zero mean:

$$\vartheta_{hkt} \sim N(0, \sigma^2_\vartheta). \tag{17}$$

Signals from patients' experiences and detailing are used to update $I(t+1)$ in a Bayesian fashion. According to the Bayesian rule (DeGroot 1970), the expected quality is updated as follows:

$$E[q_k|I(t+1)] = E[q_k|I(t)] + \iota_k(t)(\bar{q}_{kt} - E[q_k|I(t)]) + \omega_k(t)(\bar{q}^d_{kt} - E[q_k|I(t)]), \tag{18}$$

where $\bar{q}^d_{kt}$ is the sample mean of all the detailing signals for chemical k in period t.[7] Note that unlike Model CI, the expected quality is updated based on consumption signals and detailing signals. $\omega_k(t)$ is expressed as

$$\omega_k(t) = \frac{\sigma^2_k(t)}{\sigma^2_k(t) + \frac{\sigma^2_\vartheta}{\kappa^d D^k_t}}. \tag{19}$$

where κ^d is a scaling parameter similar to κ. ι_k and ω_k can be interpreted as the weights that physicians attach to consumption experiences and detailing efforts in updating its expectation about the level of q_k.

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

$$\sigma^2_k(t+1) = \frac{1}{\frac{1}{\sigma^2_k(t)} + \frac{\kappa n^k_t}{\sigma^2_\delta} + \frac{\kappa^d D^k_t}{\sigma^2_\vartheta}}. \tag{20}$$

Physicians' prescribing decisions are identical to those of Model CI except that all physicians are informed of $I(t)$, i.e., $M_{kt} = 1 \forall k, t$.

[7] $\bar{q}^d_{kt}|(\kappa^d D^k_t, I(t)) \sim N(q_k, \frac{\sigma^2_\vartheta}{\kappa^d D^k_t})$.

4 Background and Data Description

4.1 Background

Now we turn to discuss the Canadian market of ACE-inhibitor with diuretic in Canada. ACE-inhibitor works by limiting production of a substance that promotes salt and water retention in the body. Diuretic prompts the body to produce and eliminate more urine. This helps in lowering blood pressure. This class of combination drugs are usually not prescribed until therapy is already underway. The majority of Canadian have some form of coverage for prescription drugs. In 1995, it is estimated that 88 % of Canadian had coverage: 62 % were covered under private plans, 19 % under provincial plans, and 7 % were covered under both. Provinces subsidize the cost of prescription drugs for at least some sectors of the population, most notably seniors and social assistance recipients. Patented drug prices are regulated in Canada by the Patented Medicine Prices Review Board (PMPRB). There are two components to this price regulation. One is the limit on increases of patented drugs already on the market; the other is the limit on introductory prices of new patented drugs. According to PMPRB guidelines, the prices of most new drugs may not exceed the maximum price of other drugs that treat the same disease.

4.2 Overview of the Data

Data sources for this study come from IMS Canada, a firm specializes in collecting sales and detailing 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 detailing and free sample data are drawn from their Canadian Promotion Audit (CPA). Although D&H does not include purchases made by government, mail order pharmacies, nursing homes or clinics, IMS believes that it covers more than 95% of the total sales.

The data set contains monthly data from March 1993 to February 1999. There are three drugs in the market - Zestoretic, Vaseretic and Prinzide. All of them are present throughout

the sample period. Treating product/quarter as one observation, the total sample size is 216. 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. Interestingly, Merck is the originator of lisinopril, and it signed a co-marketing agreement with AstraZeneca. Merck also markets lisinopril hydrochlorothiazide under the brand-name Prinzide. In other words, Zestoretic and Prinzide are made of exactly the same chemicals.

Table 1 shows the summary statistics of this market.[8] Figure 1 shows the detailing minutes for these three drugs over time. One common feature is that they fluctuate a lot over time. The detailing minutes for Vaseretic (incumbent) and Zestoretic (new entrant) are roughly the same for the first 30 months, but for the later period, Zestoretic on average details more than Vaseretic. In general, Prinzide details much less than Zestoretic.

Figure 2 shows the number of prescription dispensed in this market. Being the first in this market, Vaseretic controlled more than 80 percent of the sales at the beginning of the sample; Zestoretic's share was only about 10 percent; Prinzide's share is even smaller (about 5 percent). It takes Zestoretic more than two years before it overtakes Vaseretic's sales. However, Prinzide's sales remain below Zestoretic throughout the period, even though Prinzide and Zestoretic are made of the same chemicals. The distinct differences in the number of prescriptions and detailing efforts for Zestoretic and Prinzide indicate that the persuasive role of detailing is likely important. It should also be noted that the demands for all three brands continue to increase even near the end of our sample period. Thus there is no evidence that learning for their qualities has completed towards the end of our sample period.

[8]The original data on free samples are measured in sample extended units: the number of packages multiplied by the package contents. In order to incorporate the effect of free samples on the information updating process as part of consumption experience signals, we need to convert the sample extended units into the number of prescriptions. We assume that one prescription lasts for 100 days, and based on the daily dosages of Vaseretic and Zestoretic (Prinzide), we set the daily consumption to be 2.25 units for Vaseretic and 2 units for Zestoretic (Prinzide). The daily consumption times 100 would give us the amount of the sample extended units per prescription.

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.

5 Results

We estimate the models using the simulated maximum likelihood. The estimation procedure is similar to Ching (2008), and Ching and Ishihara (2008).

5.1 Parameter Estimates

We now discuss the parameter estimates for Models CI and NMC. In each model, in addition to our full model with 3 brands, we estimate a model with only 2 brands, Vaseretic and Zestoretic, which captures 80% of the market share. This 2-brand version is similar to the 3-brand version, except that it does not use the co-marketing identification argument to separate out the informative and persuasive effects. Thus the comparison of these two models allows us to demonstrate how our identification of the informative and persuasive effects of detailing is achieved with the presence of a co-marketing agreement. We will show that the estimated magnitude of persuasive effects are very different for these two versions.

In our full models with 3 brands, we treat Vaseretic, Zestoretic, and Prinzide as inside goods. We combine all other drugs that belong to ACE-inhibitor with diuretic, ACE-inhibitor, and Thiazide Diuretic as the outside good. In the 2-brand version, we treat Vaseretic and Zestoretic as inside goods. The outside good is defined in a similar way except that it includes Prinzide as well. For identification reasons, we need to normalize the scaling parameters for the number of consumption experience signals, κ, and detailing signals, κ^d, the intercept term for the utility of the outside good, α_0, and the true mean quality of the chemical for Vaseretic, q_1. We set $\kappa = \kappa^d = 1/30000$, and $\alpha_0 = q_1 = 0$.

5.1.1 Model CI

Parameter estimates for Model CI are reported in Table 2. Brand 1 is Vaseretic, brand 2 is Zestoretic, and brand 3 is Prinzide. q_1 is the quality for Vaseretic. q_2 is the quality for Zestoretic and Prinzide, which are made of exactly the same chemicals.

The time trend of the outside good (π_t) is negative and significant in both 2-brand and 3-brand versions, indicating that the value of the outside good relative to inside goods is declining over time. This is consistent with the continuous expansion of the demand for Vaseretic, Zestoretic, and Prinzide. The parameter estimates for the true mean quality and the initial priors are all statistically significant. In both versions, the true mean quality of the chemical for Zestoretic and Prinzide (q_2) is higher than that of the chemical for Vaseretic (q_1). The initial prior mean qualities of both chemicals are lower than their true mean qualities. This indicates that the market has pessimistic priors about both chemicals when they are first introduced into the market. It should also be noted that the initial prior mean quality of the chemical for Vaseretic is better than that of the chemical for Zestoretic and Prinzide. Most of the preference parameters are significant and have the right sign. Note that the coefficients for prices (π_p) is not significant. This is not surprising because Canada provides prescription drug coverage to patients who are 60 or older, and most of the patients who have hypertension are elderly.

Although the parameters are qualitatively similar for the 2-brand and 3-brand versions of Model CI, they are quite different quantitatively. First of all, the coefficient for the persuasive effect, γ_p, is negative and significant in the 2-brand version, while it is positive and significant in the 3-brand version. The result from the 2-brand version is counterintuitive. To understand why the results are so different for these two versions, it should be highlighted that its identification of informative and persuasive effects are mainly achieved by the functional form assumption. In particular, the way CI models the informative effect of detailing has captured the main empirical implications of the persuasive effect. This is because the measure of well-informed physicians (which is the main driver for the informative effect), similar to the persuasive effect, is also governed by a detailing goodwill stock. However, the 3-brand version gives us another source of data variation to identify the persuasive effect – the correlation between the relative market share of Zestoretic and Prinzide and their relative cumulative detailing efforts. The informative effect is identified by the correlation between the relative market share of chemicals and the chemical specific detailing efforts.

Since the estimated persuasive effect in the 3-brand version is positive (instead of negative in the 2-brand version), we expect that the magnitude of the informative effects in the 3-brand version should become smaller. By examining other parameter estimates, this seems to be the

case. Note that the true quality of Zestoretic and Prinzide (i.e., q_2) and the risk coefficient (i.e., r) are much smaller in the 3-brand version. This reflects that their market growth relies less on the informative effect, and the persuasive effect is partly responsible for the growth. Moreover, we also find that the coefficient for the informative detailing goodwill stock (i.e., β_1) becomes smaller, implying that the measure of well-informed physicians has been built up at a much slower rate. This further indicates that the estimated informative effect in the 3-brand version is smaller than that in the 2-brand version. However, the nonlinear nature of the model makes it difficult for us to conclude to what extent the market growth is due to the informative or persuasive role of detailing. We will demonstrate their relative importance later by simulating the model.

5.1.2 Model NMC

The parameter estimates for Model NMC are also reported in Table 2. Most of the learning and preference parameters are significant in both the 2-brand version and the 3-brand version. Interestingly, the differences between the 2-brand and 3-brand versions are similar to what we find in Model CI. In particular, the persuasive effect is also negative and significant in the 2-brand version, while positive and significant in the 3-brand version. We also find that the true mean quality of Zestoretic and Prinzide (i.e., q_2) and the variances of the signal noises (σ_δ^2 and σ_θ^2) become much smaller, and the initial prior mean qualities (i.e., q_1 and q_2) become much larger in the 3-brand version. This also indicates that the informative effect becomes smaller in the 3-brand version.

5.2 Goodness-of-fit

Both Model CI and Model NMC provide a good fit to the data. To illustrate this, we simulated 5000 sequences of quantity demanded (expressed in terms of number of prescriptions) for Vaseretic, Zestoretic, and Prinzide based on the estimates for the 3-drug version. We compute the average predicted quantity by averaging simulated quantities. Figures 2 and 3 plot the average predicted demand and the actual demand for the three brands using the estimates from

Model CI and Model NMC, respectively. In general, both models are able to fit the diffusion pattern of demand very well.

5.3 The Importance of Informative and Persuasive Detailing

In this subsection, we examine the economic importance of the informative and persuasive roles of detailing. In particular, we are interested in investigating how the demand for individual brands as well as the total market demand change when we eliminate: 1) the informative function of detailing; and 2) the persuasive function detailing. We will use the estimates for the 3-brand version of Model CI and Model NMC to conduct this simulation exercise.

We first consider the importance of informative detailing. To simulate the demand without informative detailing, we set $\beta_1 = 0$ in Model CI. We simulate 5000 sequences of quantity demanded for Vaseretic, Zestoretic, and Prinzide with and without informative detailing and compare their average predicted quantities. Figures 4 and 5 plot the average predicted quantities of Vaseretic, and Zestoretic and Prinzide, respectively. In both figures, we see that the average predicted quantities decrease due to the elimination of informative detailing. The main effect behind this counterfactual exercise is that the measure of well-informed physicians effectively stays at a very low level (determined by β_0) over time (not shown in the figure). In the earlier periods, Vaseretic is mainly competing with the outside alternative. As a result, this creates an immediate negative impact on its number of prescription. Note that the time trend of the outside alternative is negative. So the demand for the inside alternatives increases over time. It turns out that the demand for Vaseretic without the informative function is very similar to the base case in the long run. However, eliminating the informative function has much larger impact on Zestoretic and Prinzide in the long run. In the base case, the predicted total number of prescriptions for Zestoretic and Prinzide is roughly 18,400 at the end of our sample period. After eliminating the informative function of detailing, their predicted total number of prescriptions drops to 7,400.

Figures 6 and 7 plot the average predicted quantities of Vaseretic, and Zestoretic and Prinzide, respectively, based on Model NMC. We assume that detailing does not provide noisy

signals about the true quality of drugs in Model NMC. Figure 6 shows that unlike Model CI, the demand for Vaseretic increases in the later periods relative to the base case. This is mainly because physicians learn at a much slower rate without informative detailing, and the initial prior for Vaseretic is more favorable than that for Zestoretic and Prinzide. Consequently, the expected quality for Vaseretic stays above that for Zestoretic and Prinzide for an extended period of time, resulting in an increase in demand for Vaseretic. In Figure 7 we also see that the demand for both Zestoretic and Prinzide decreases in the earlier periods, but is converging to the base case over time. This is because consumption experience signals and detailing signals are perfect substitutes in Model NMC, and hence physicians eventually learn the true quality of every products in the long run. This is in contrast to the prediction of Model CI, where there is no sign of convergence between the predicted demand from the base case and that from the version without informative detailing.

We next consider the importance of persuasive detailing. To simulate the demand without persuasive detailing, we set $\gamma_P = 0$ in both Model CI and Model NMC. Figures 8 and 9 plot the average predicted quantities of Vaseretic, and Zestoretic and Prinzide, respectively, based on Model CI. In Figure 8, the decrease in demand for Vaseretic is almost zero. In Figure 9, we see that the elimination of persuasive detailing causes brand switching. After eliminating the persuasive function, many physicians switch from Zestoretic to Prinzide, causing the demand for Zestoretic to decrease and the demand for Prinzide to increase. Overall, the persuasive effect of detailing plays an important role in determining the relative demand for Zestoretic and Prinzide. However, it appears to be unimportant in determining the total demand, which decreases only slightly without the persuasive effect – the number of prescriptions is only 600 lower than the base case.

Figures 10 and 11 plot the average predicted quantities of Vaseretic, and Zestoretic and Prinzide, respectively, based on Model NMC. Figure 10 show that unlike Model CI, we see that the demand for Vaseretic decreases. Figure 11 shows a similar pattern to Figure 9. The impact of removing persuasive detailing on the total demand for Zestoretic and Prinzide is stronger here compared with Model CI – the reduction in the number of prescriptions is 2,600 at the end of the sample period.

6 Conclusion

In this paper, we propose a new way to measure the informative and persuasive roles of detailing. Our identification argument makes use of time series properties of sales and detailing efforts for markets where some brands are marketed under a co-marketing agreement. Using the data on ACE-inhibitor with diuretic in Canada, we show that our identification strategy allows us to disentangle these two roles of detailing. We find evidence that detailing influences the demand for ACE-inhibitor with diuretic via both the informative and persuasive roles. By simulating our model, we show that the informative role of detailing is mainly responsible for the market expansion for chemicals, and the persuasive role is mainly responsible for brand switching for brands that share the same chemicals.

Our results could have important implications for both policy makers and drug manufacturers. One implication is that if we follow some policy advocates' suggestions and limit the amount of detailing done by drug manufacturers, this may slow down the rate of learning for physicians significantly. As a result, physicians may make less informed decisions for their patients. Another implication for drug manufacturers is that there is an informational externality problem for companies that engage in a co-marketing agreement. This suggests that when they structure the contract for the co-marketing agreement, it is important to take this externality into account. Our proposed identification strategy potentially allows drug companies to quantify the values of the externality.

There are two limitations that should be noted. First, our results only rely on one subclass of drugs. It would be important to examine whether the quantitative results obtained here are robust by applying our identification strategy to more classes of drugs. Second, the choice of co-marketing agreement is endogenous. It is possible that (i) one of the partners in the agreement is constrained by the number of sales persons employed, or (ii) one of the partners has a much weaker sales force in marketing the particular type of drug in question. The former reason should not pose a problem in affecting the parameter estimates, but the later one could because our econometric specification essentially assumes away the potential heterogeneity in the efficiency of sales force. However, Zestoretic and Prinzide are marketed by AstraZeneca and

Merck, respectively, and both drug companies are very well-established in the industry. We feel that their sales force training should be fairly similar and hence the heterogeneity of their sales force quality would unlikely be an issue. Investigating how companies choose their partners to co-market products and its implications on our identification argument will be an important topic for future research.

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Table 1: Summary statistics

Variable	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
	Prinzide	1,814.82	1,168.92	4,447	131
Detailing Minutes	Vaseretic	1,032.83	689.10	3,240	97
	Zestoretic	1,625.43	828.61	4,203	93
	Prinzide	512.75	650.67	3,566	0
Free Samples (number of prescriptions)	Vaseretic	71.81	52.76	290.83	0
	Zestoretic	152.49	100.08	545.40	0
	Prinzide	20.83	24.01	83.10	0
Price	Vaseretic	40.54	8.76	69.21	24.45
	Zestoretic	34.29	8.65	61.48	15.74
	Prinzide	38.68	15.60	87.46	16.15

Table 2: Parameter estimates

Brands (j): 1 - Vaseretic (incumbent), 2 - Zestoretic (entrant), 3 - Prinzide (entrant)
q_1: quality for Vaseretic; q_2: quality for Zestoretic and Prinzide

	Model CI				Model NMC			
	2 brands		3 brands		2 brands		3 brands	
	estimates	s.e.	estimates	s.e.	estimates	s.e.	estimates	s.e.
Learning parameters								
σ_δ^2	**8.447**	0.497	**7.554**	0.922	**0.177**	0.008	**0.055**	0.021
σ_θ^2					**0.319**	0.013	**0.108**	1.97E-02
$\underline{q}_1$	**-7.611**	1.274	**-33.806**	2.184	**-4.096**	0.113	**-2.022**	0.125
$\underline{q}_2$	**-15.352**	0.504	**-38.670**	2.037	**-5.108**	0.234	**-2.955**	0.175
$\underline{\sigma}^2$	**3.462**	0.345	**4.736**	0.463	**0.026**	0.001	**0.010**	0.003
q_1	0		0		0		0	
q_2	**27.828**	2.480	**14.563**	1.384	**6.066**	0.226	**0.936**	0.142
κ	1/30000		1/30000		1/30000		1/30000	
κ^d					1/30000		1/30000	
Preference parameters								
α_0	0		0		0		0	
α_1	**-3.786**	0.062	**-3.442**	0.072	**-3.522**	0.018	**-3.742**	0.060
α_2	**-3.832**	0.024	**-3.287**	0.092	**-3.684**	0.044	**-3.306**	0.064
α_3			**-3.311**	0.089			**-3.435**	0.078
r	**0.057**	0.002	**0.025**	4.93E-04	**0.202**	0.003	**0.420**	0.013
π_p	4.79E-04	4.54E-04	6.48E-05	5.40E-05	-1.22E-04	4.31E-04	**2.42E-04**	1.10E-04
π_t	**-0.006**	0.001	**-0.008**	6.45E-04	**-0.004**	0.001	**-0.004**	0.001
γ_P	**-1.53E-05**	3.93E-06	**2.29E-06**	3.39E-07	**-2.71E-06**	1.07E-06	**6.03E-06**	1.25E-06
γ_S	-1.16E-07	1.42E-07	-6.1E-09	2.45E-08	-1.18E-07	9.83E-08	-4.98E-09	1.10E-08
Detailing stock parameters								
Φ_P	**0.194**	0.039	**0.103**	0.014	**0.230**	0.021	**0.065**	0.005
Φ_I	**0.043**	0.008	**0.004**	0.001				
β_0	**-2.086**	0.308	**-1.072**	0.154				
β_1	**9.49E-05**	1.54E-05	**1.47E-05**	1.06E-06				
Other parameters for error terms								
s.d.(ε)	**171.845**	11.114	**167.373**	9.744	**182.382**	8.359	**160.874**	7.666
s.d.(ς)	1		1		1		1	
s.d.(ζ)	**0.671**	0.039	**0.328**	0.026	**0.563**	0.030	**0.661**	0.045
s.d.(e)			**0.041**	0.004			**0.190**	0.037
log likelihood	-2103.166		-2482.923		-2129.388		-2472.735	

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

Figure 1: Detail minutes vs. time

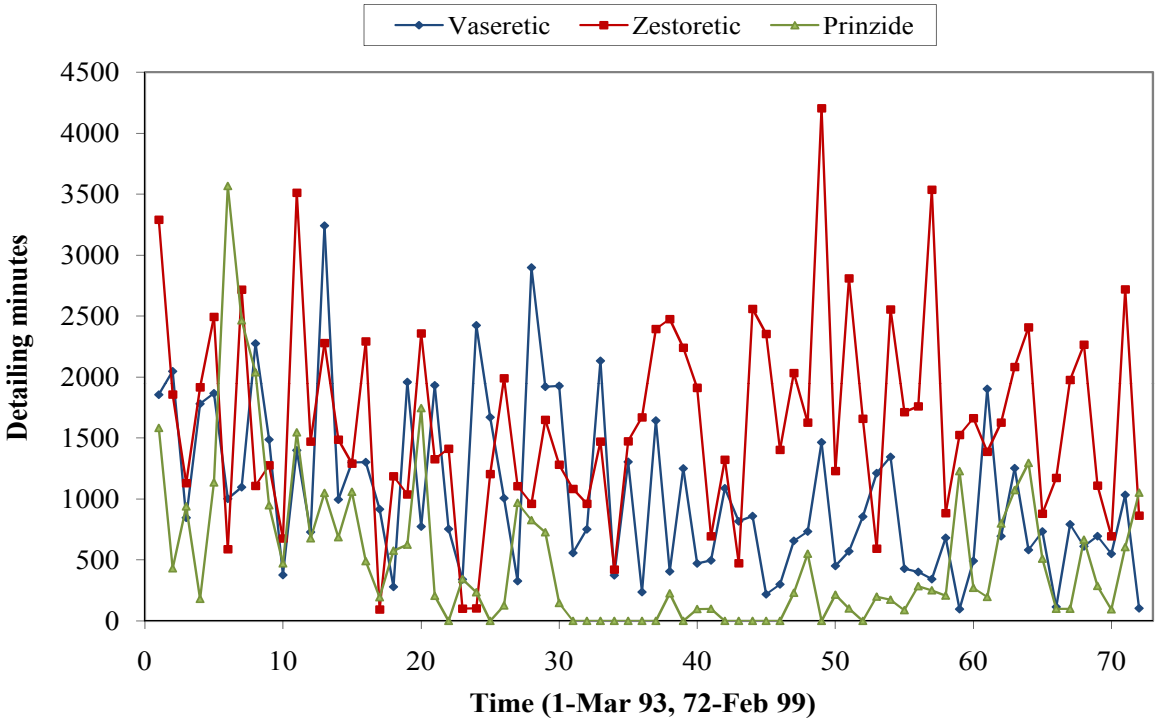

Figure 2: Predicted and Actual Demand: Model CI

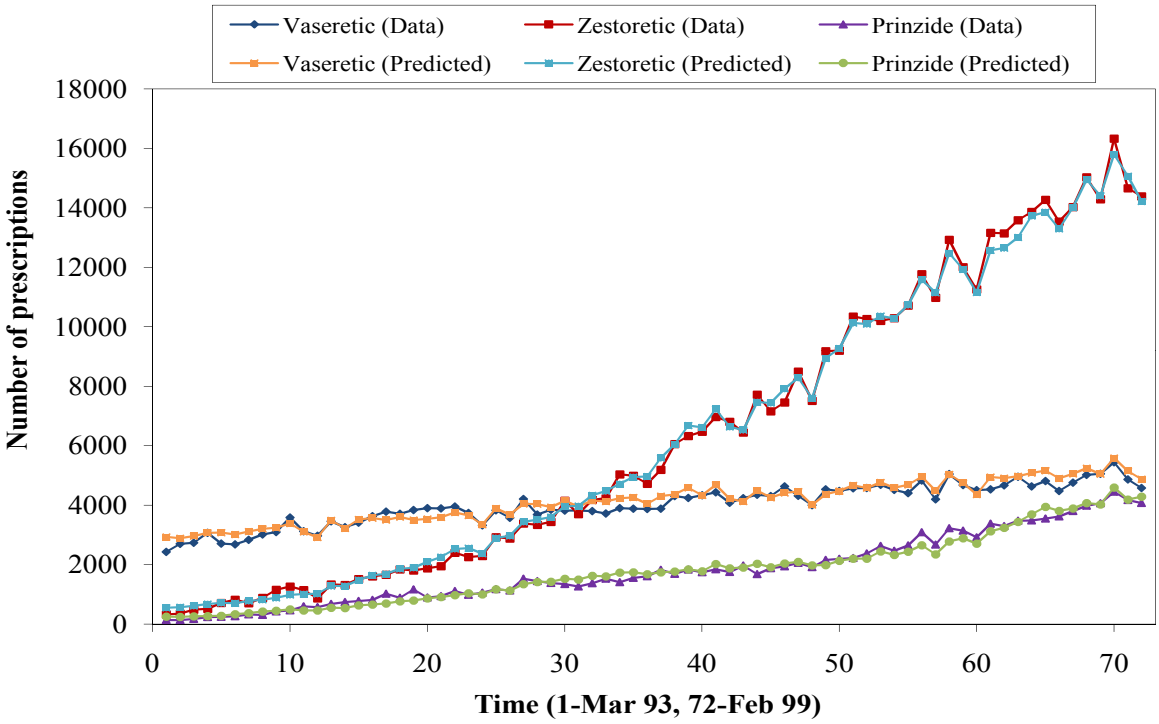

Figure 3: Predicted and Actual Demand: Model NMC

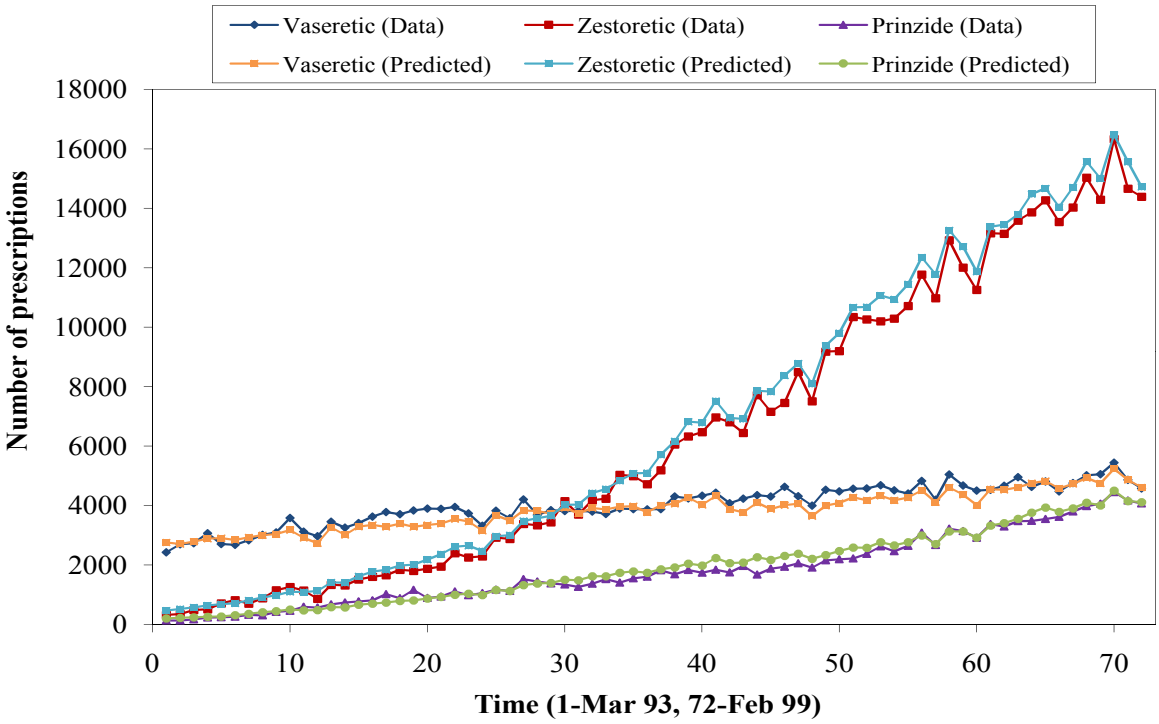

Figure 4: No Informative Effect of Detailing: Vaseretic, Model CI

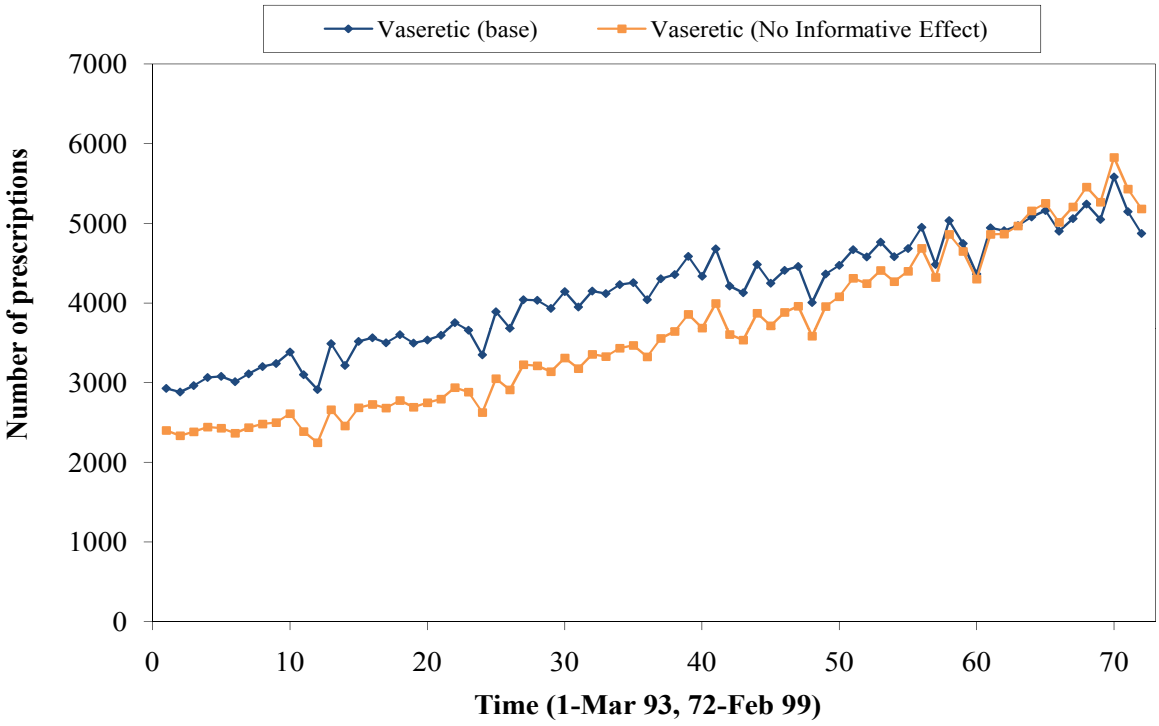

Figure 5: No Informative Effect of Detailing: Zestoretic and Prinzide, Model CI

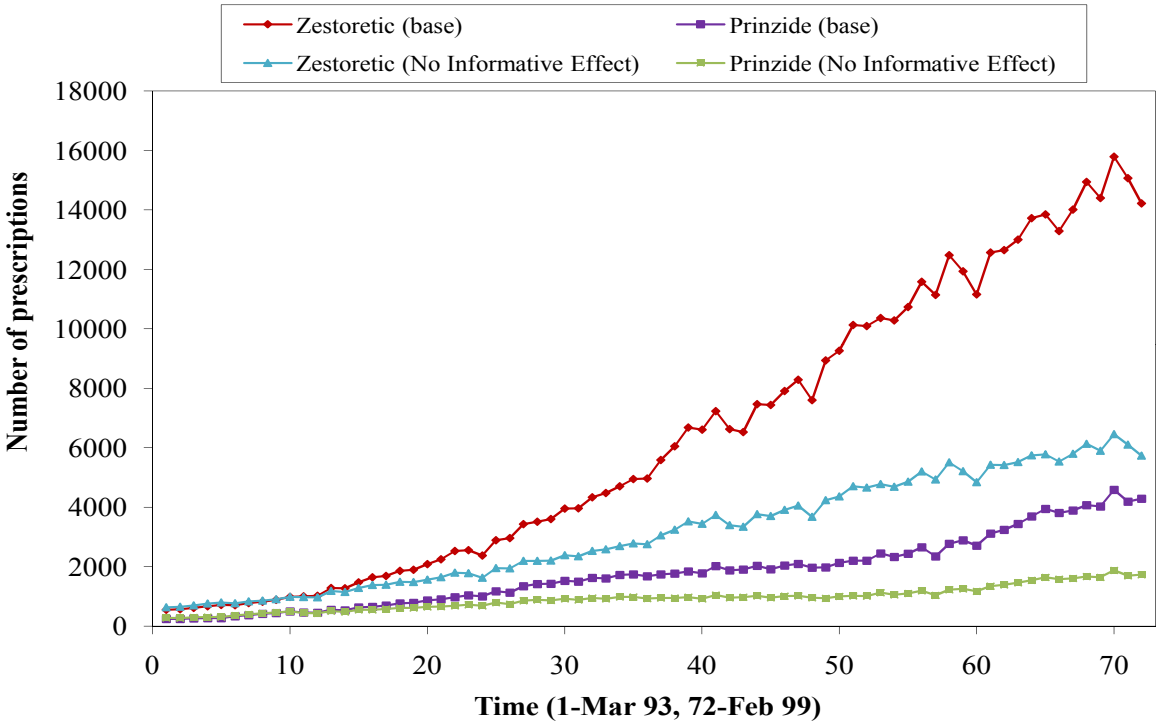

Figure 6: No Informative Effect of Detailing: Vaseretic, Model NMC

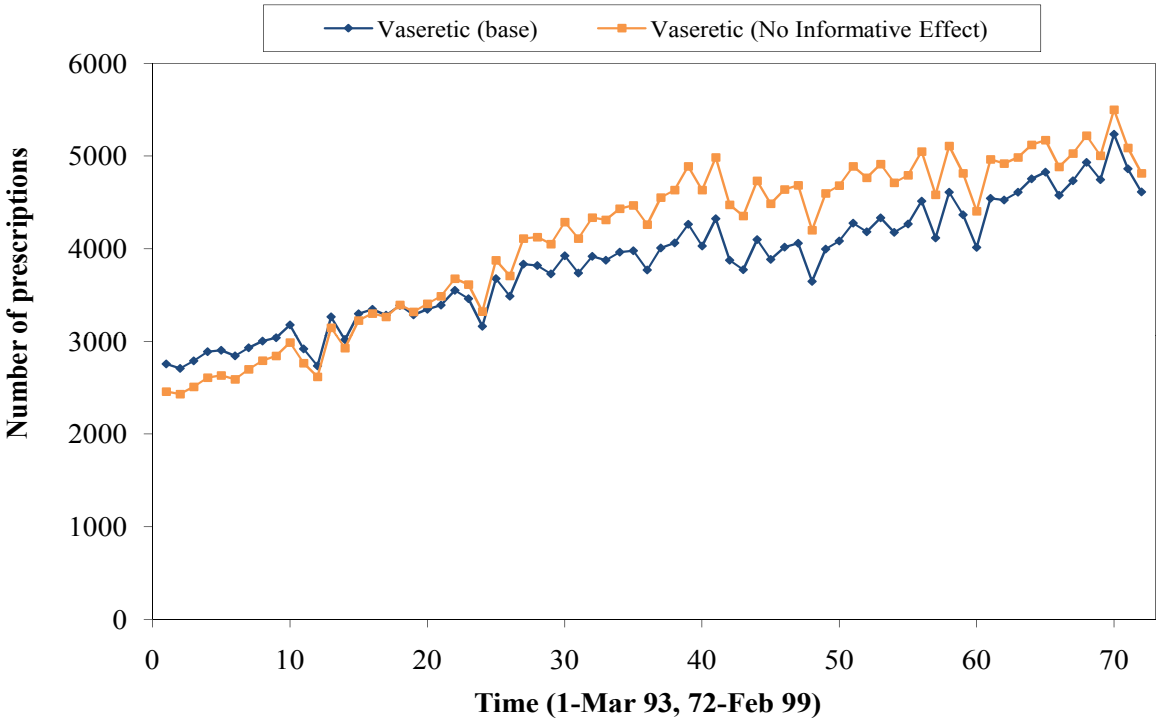

Figure 7: No Informative Effect of Detailing: Zestoretic and Prinzide, Model NMC

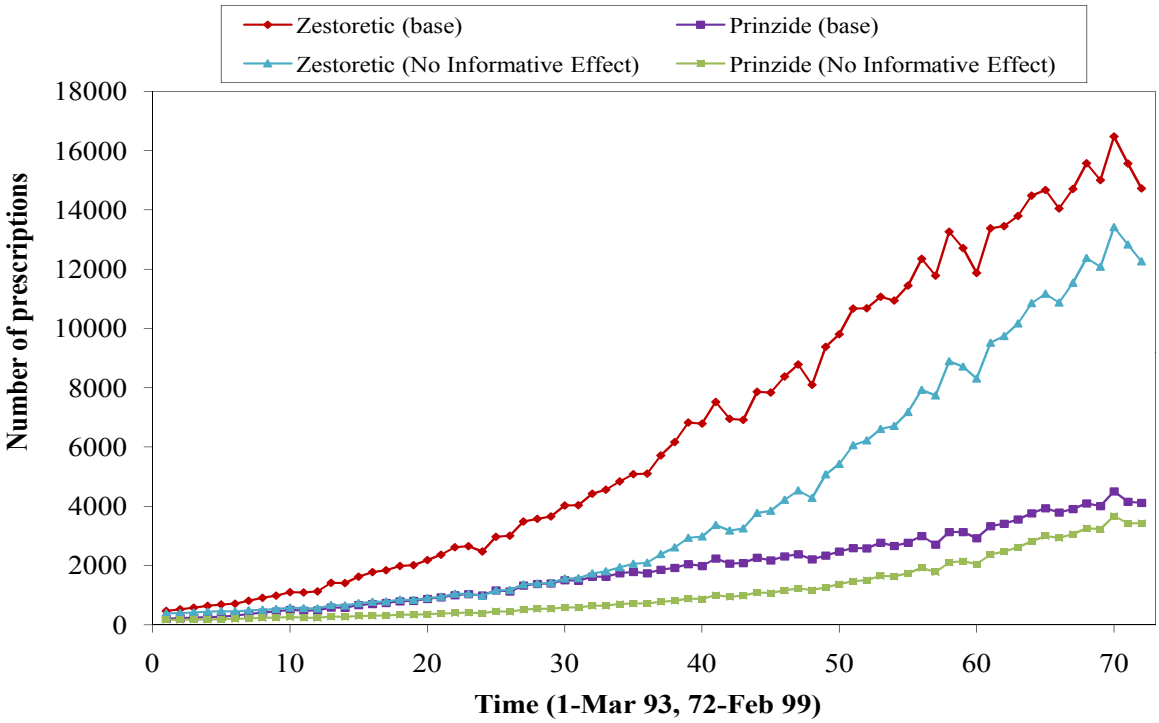

Figure 8: No Persuasive Effect of Detailing: Vaseretic, Model CI

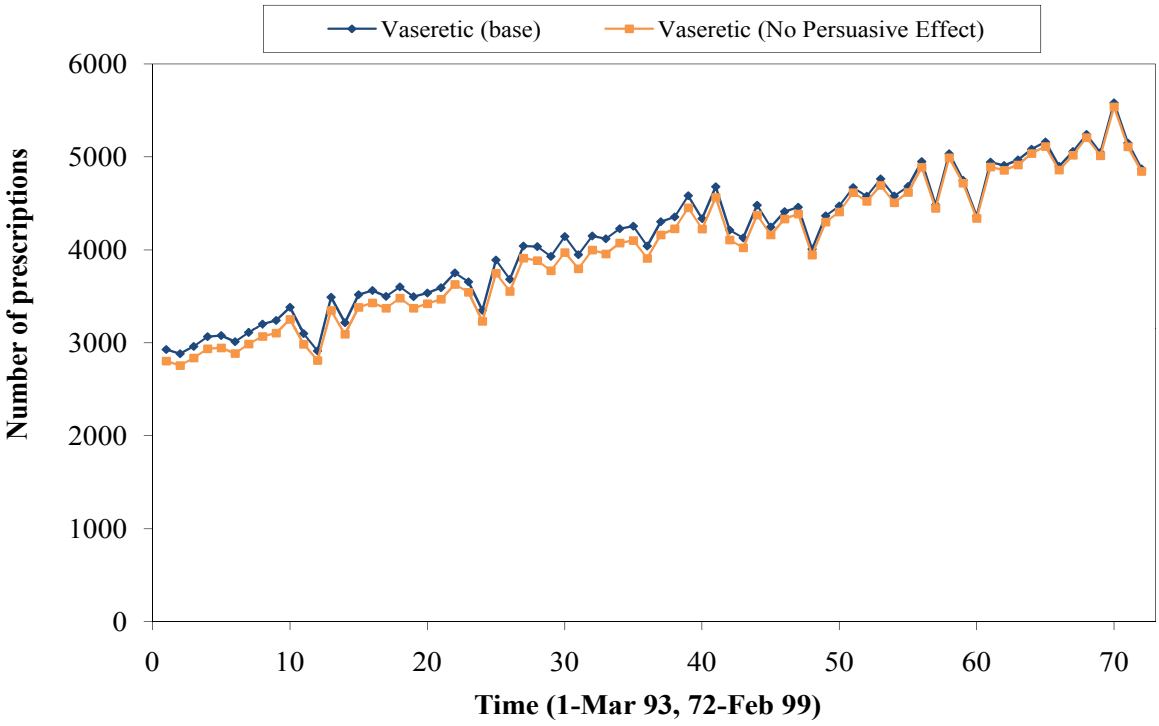

Figure 9: No Persuasive Effect of Detailing: Zestoretic and Prinzide, Model CI

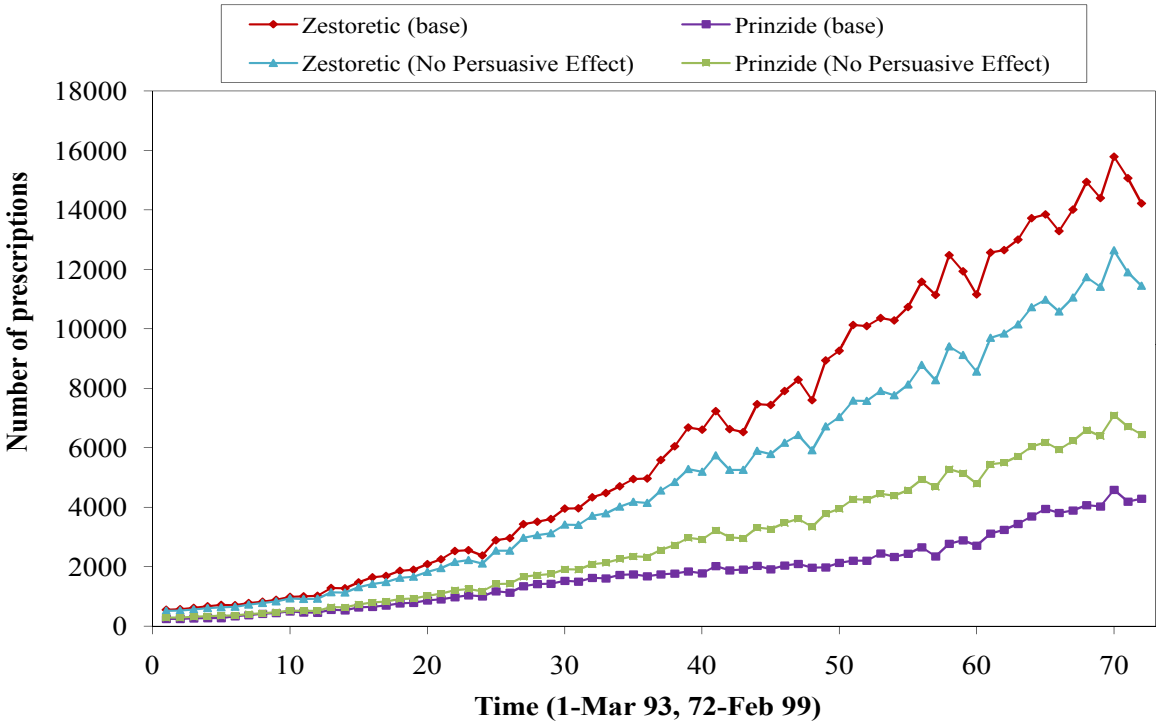

Figure 10: No Persuasive Effect of Detailing: Vaseretic, Model NMC

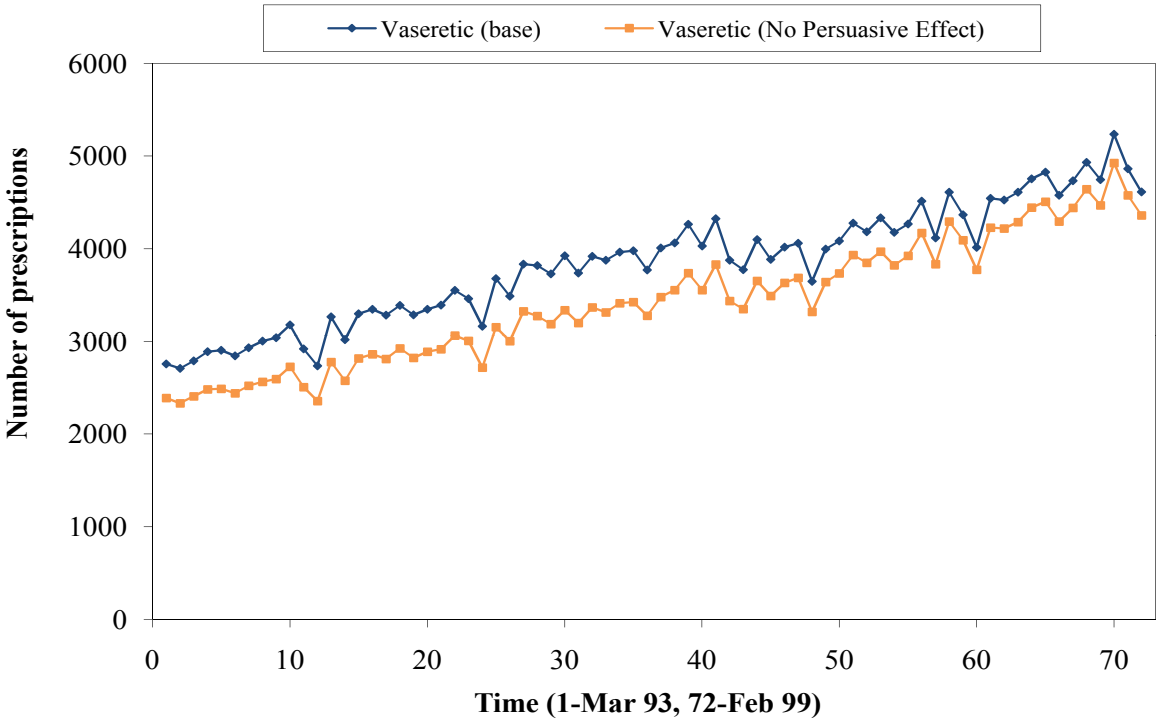

Figure 11: No Persuasive Effect of Detailing: Zestoretic and Prinzide, Model NMC