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 the informative and persuasive roles of detailing in empirical research. 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 using two different brand-names. With our identification assumption, the variations in the relative market share of these two brands, together with their brand specific detailing efforts, would allow us to measure the persuasive component of detailing. The variations in the market share of chemicals, and the detailing efforts summed across brands made of the same chemical, would allow us to measure the informative component of detailing. Using the data from the Canadian market for ACE-inhibitor with diuretic, we find evidence that our identification strategy could outperform the traditional way of identifying these two effects. We find that both the informative and persuasive components are strong in this market. We also find that patients could be worse off if the government bans detailing for ACE-inhibitor with diuretic.

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

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. Understanding the relative importance of these two roles could help drug manufacturers 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 would not only hurt manufacturers' profits and their incentives to innovate, but also lower consumer welfare.

Despite its importance, little progress has been made in disentangling the informative and persuasive roles of detailing. The main difficulty is that both effects would likely 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 a market where some drug manufacturers engage in a co-marketing agreement. Under such an agreement, two companies market the same chemical under two different brand-names. With our identification assumption, the variation in the relative market share of these two brands, together with their brand specific detailing efforts, would allow us to measure the persuasive component of detailing. After controlling for the persuasive effect, the variation in the market share of chemicals, and the corresponding chemical specific detailing efforts summed across brands made of the same chemical, would allow us to measure the informative component of detailing. For instance, if detailing does not play any persuasive role at all, our assumptions would imply that the market shares

for two brand-name drugs made of the same chemical should be roughly the same over time even if the detailing efforts are different across these two brands (assuming other marketing-mix variables are about the same across brands).

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 (2010), 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 et al. (2005), in which detailing conveys noisy signals about the true quality of drugs to physicians.

Our identification strategy applies to both product level data and individual level data. As an application, we apply it to the product level data from the market of ACE-inhibitor with diuretic in Canada.[1] 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 usefulness of our identification strategy, in addition to estimating the full model with all three brands, we also estimate two versions with only two brands: Zestoretic and Prinzide, assuming that in one version, we treat the two brands as the same 1 chemical (i.e., we use our co-marketing identification argument), and in the other version, we treat the two brands as different two chemicals (i.e., we do not use the co-marketing identification argument). We argue that the identification of the informative and persuasive effects in the 2-chemical version relies more heavily on the functional form assumption. In particular, we find that the estimation results are counterintuitive in the 2-chemical version – the persuasive effect of detailing is negative and insignificant. On the contrary, the estimation results from the 1-chemical version are much more sensible – the persuasive effect is positive and significant, regardless of the way we model the informative detailing.

[1]Although we use product level data to illustrate our identification strategy, it should be emphasized that the argument applies to individual level data as well. The basic identification ideas are the same except that we will need to set up individual level likelihood when estimating the parameters.

Based on the parameter estimates from the full model with three brands, we investigate the importance of informative and persuasive detailing by simulating our model in the case of ACE-inhibitor with diuretic. We find that both informative and persuasive components are important. In particular, the informative component is mainly responsible for the growth of the demand for chemicals, and the persuasive component mainly influences brand choice. Furthermore, to examine the overall impact of detailing on patient welfare, we use compensating variation to measure changes in the patient's welfare over time from banning detailing activities. Our simulation results suggest that banning detailing could cost a patient as large as $160 per prescription during our sample period in the Canadian ACE-inhibitor with diuretic market.

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

2 Literature Review and Co-marketing Agreement

2.1 Previous Literature on Persuasive Detailing

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 informative detailing. 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 have already known the older drugs' efficacy and side-effect profiles.

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 (1999) also finds evidence that detailing lowers the price elasticity of demand and argues that it supports persuasive detailing. However, it should be pointed out that the results from Hurwitz and Caves (1988) and Rizzo (1999) 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 launching them, 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 separately identify 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.[2] In contrast, this modeling assumption and data requirement are not necessary for our identification strategy.

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 insight 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. His identification argument requires one to observe individual level

[2]Anand and Shachar (2005), Byzalov and Shachar (2004), Chan et al. (2007), Mehta et al. (2008), Narayanan and Manchanda (2009) rely on similar identification arguments to estimate the informative and persuasive roles of advertising using individual level data.

panel data, while our identification strategy applies as long as one observes product level panel data.

2.2 Co-marketing Agreement

Co-marketing in the pharmaceutical industry is a marketing practice where a company in addition to its own, uses another company's sales force to promote the same product, and allow another company to use a different brand name.[3] According to CurrentPartnering (2009), the total number of co-marketing deals announced in the United States between 2000 and 2008 is 208, and the yearly number has remained at fairly steady levels. One reason why a company that develops the drug is willing to partner with another company could be because it requires high fixed costs to build a sales force. The sales force in the pharmaceutical industry requires extensive training because they are required to know the clinical trials results of not only the drug being promoted, but also their rivals' drugs. Instead of paying such a high fixed cost, a company which is short in their sales force of promoting a certain category of drugs (say a high blood pressure drug) might find it worthwhile to sign a co-marketing agreement with another company, and charge its partner a royalty fee.

This type of marketing agreement has also appeared in the automobile industry (Sullivan 1998; Lado et al. 2003). Furthermore, for industrial products, it is common that different firms market essentially identical products using their own brand-names (Saunders and Watt 1979; Bernitz 1981). In some countries, firms also market generic drugs with a brand name (Birkett 2003). Under these environments, we expect that our identification arguments could also be applied.

[3]There is another type of related arrangement which is called co-promotion agreement where two or more firms market the same drug under one brand-name.

3 Model

We now turn to describe the models that will be used to implement our new identification strategy for informative and persuasive detailing. We consider two structural models that have been developed in the literature. They differ in terms of how to model the role of informative detailing. The first model (Model CI) extends Ching and Ishihara (2010). They 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 et al. (2005), who model detailing as a way of conveying noisy signals about the true quality of drugs to physicians. In both models, we model the persuasive role of detailing by including a 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 $j = 1, \ldots, J$ indexes 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.

As we mentioned, CI and NMC differ in terms of how they model informative detailing. Model CI assumes that $I(t)$ is updated by a representative opinion leader based on past patients' experiences with the chemical.[4] This is the only role that he/she plays. 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.[5] Let M_{kt} be the measure of physicians who know $I_k(t)$. In CI, M_{kt} depends on the cumulative detailing efforts at time t. The learning process for $I(t)$ is similar in NMC; however, they assume that detailing does not influence M_{kt}. More precisely, they assume $M_{kt} = 1, \forall k, t$. Moreover, other than consumption experience signals, detailing also provides noisy signals about the true quality of the chemicals for updating the $I(t)$.

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 2010)

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

[4]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 requires them to be much more updated about the current evidence about the drugs used in the field.

[5]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.

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]

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; 2010; 2011), 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, and the representative opinion leader's initial prior on q_k ($\underline{I}_k$) is also normally distributed:

$$\delta_{ikt} \sim N(0, \sigma_\delta^2), \quad \text{and} \quad q_k \sim N(\underline{q}_k, \underline{\sigma}_k^2). \tag{2}$$

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:

$$E[q_k|I(t+1)] = E[q_k|I(t)] + \iota_k(t)(\bar{q}_{kt} - E[q_k|I(t)]), \tag{3}$$

where $\bar{q}_{kt}$ is the sample mean of all the experience signals that are revealed in period t; $\iota_k(t)$ is a Kalman gain coefficient, which assigns the updating weight to $\bar{q}_{kt}$. Note that both $\iota_k(t)$ and the perception variance, $\sigma_k^2(t+1)$, are functions of the variance of the signal noise (σ_δ^2), perceived

[6]Obviously, drug qualities are multi-dimensional. Following Ching (2010), we implicitly 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.

variance ($\sigma_k^2(t)$), the quantities sold at time t for all drugs made of chemical k (n_t^k),[7] and the proportion of experience signals revealed to the public (κ). They can be expressed as:

$$\iota_k(t) = \frac{\sigma_k^2(t)}{\sigma_k^2(t) + \frac{\sigma_\delta^2}{\kappa n_t^k}}, \quad \text{and} \quad \sigma_k^2(t+1) = \frac{1}{\frac{1}{\sigma_k^2(t)} + \frac{\kappa n_t^k}{\sigma_\delta^2}}. \tag{4}$$

The above expressions imply: (i) $\iota_k(t)$ increases with $\sigma_k^2(t)$; (ii) 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.[8]

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 $f(M, 0) \leq M, \forall M$.

Following Ching and Ishihara (2010), 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:

$$G_{kt}^I = (1 - \phi_I) G_{kt-1}^I + D_t^k, \tag{5}$$

[7] n_t^k is the total quantity prescribed for chemical k at time t, including free samples measured in number of prescriptions.

[8] For justifications of this modeling assumption, see Ching and Ishihara (2010).

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

$$M_{kt} = \frac{exp(\beta_0 + \beta_1 G^I_{kt})}{1 + exp(\beta_0 + \beta_1 G^I_{kt})}. \tag{6}$$

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:

$$E[\sum_{j \in \{0,1,\ldots,J\}} u_{ijt} \cdot d_{hij}(t) | I^h(t)], \tag{7}$$

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:

$$u_{ijt} = \alpha_j - \exp(-r\tilde{q}_{ikt}) - \pi_p p_{jt} + \varsigma_{ilt} + \zeta_{ikt} + e_{ijt}, \tag{8}$$

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.[9] 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. In this specification, r represents the coefficient of absolute risk aversion. Also, we allow a brand-specific intercept to capture time-invariant differences among drugs.

[9]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.

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:

$$\begin{aligned} E[u_{ijt}|I^h(t)] &= E[u_{ijt}|I_k(t)] + \gamma_P G^P_{jt} + \gamma_S FS_{jt} \\ &= \alpha_j - exp(-rE[q_k|I(t)] + \frac{1}{2}r^2(\sigma^2_k(t) + \sigma^2_\delta)) - \pi_p p_{jt} \\ &\quad + \gamma_P G^P_{jt} + \gamma_S FS_{jt} + \varsigma_{ilt} + \zeta_{ikt} + e_{ijt}, \end{aligned} \tag{9}$$

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

$$G^P_{jt} = (1 - \phi_P)G^P_{jt-1} + D_{jt}, \tag{10}$$

We emphasize 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}. We should also note that Ching and Ishihara (2010) just focus on modeling the informative role of detailing, and they do not allow for G^P_{jt} in the utility function. They also do not control for 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:

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

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 (8)-(11) 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:

$$E[u_{i0t}|I^h(t)] = \alpha_0 + \pi_t t + \varsigma_{i0t} + \zeta_{i0t} + e_{i0t}. \tag{12}$$

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,

$$n_{jt} = Size_t \cdot S(j|D_t, (E[q_k|I(t)], \sigma_k(t), M_{kt-1})_{k=1}^K; \theta_d) + \epsilon_{jt}, \tag{13}$$

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)

Many elements in Model NMC are similar to Model CI. Therefore, 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,

$$\tilde{q}^d_{hkt} = q_k + \vartheta_{hkt}, \tag{14}$$

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

$$\vartheta_{hkt} \sim N(0, \sigma^2_\vartheta). \tag{15}$$

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:

$$E[q_k|I(t+1)] = E[q_k|I(t)] + \iota_k(t)(\bar{q}_{kt} - E[q_k|I(t)]) + \omega_k(t)(\bar{q}^d_{kt} - E[q_k|I(t)]), \tag{16}$$

where $\bar{q}^d_{kt}$ is the sample mean of all the detailing signals for chemical k in period t.[10] Note that unlike Model CI, the expected quality is updated based on consumption signals and detailing signals. $\iota_k(t)$ and $\omega_k(t)$ are expressed as

$$\iota_k(t) = \frac{\frac{\kappa n^k_t}{\sigma^2_\delta}}{\frac{1}{\sigma^2_k(t)} + \frac{\kappa n^k_t}{\sigma^2_\delta} + \frac{\kappa^d D^k_t}{\sigma^2_\vartheta}}, \quad \text{and} \quad \omega_k(t) = \frac{\frac{\kappa^d D^k_t}{\sigma^2_\vartheta}}{\frac{1}{\sigma^2_k(t)} + \frac{\kappa n^k_t}{\sigma^2_\delta} + \frac{\kappa^d D^k_t}{\sigma^2_\vartheta}}, \tag{17}$$

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):

$$\sigma^2_k(t+1) = \frac{1}{\frac{1}{\sigma^2_k(t)} + \frac{\kappa n^k_t}{\sigma^2_\delta} + \frac{\kappa^d D^k_t}{\sigma^2_\vartheta}}. \tag{18}$$

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

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

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

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.[11] 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. Since Vaseretic

[11] http://www.paho.org/english/sha/prflcan.htm

was launched earlier, we consider Vaseretic as the incumbent, and Zestoretic & Prinzide as new entrants.

Table 1 shows the summary statistics of this market.[12] 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 and Zestoretic 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.

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.

[12]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.

5 Results

We estimate the models using the method of simulated maximum likelihood. In particular, we apply the pseudo-policy function approach proposed by Ching (2010) to control for the potential endogeneity problem of detailing. In appendix B, we present the specifications of the pseudo-detailing policy functions. They are similar to the one used in Ching and Ishihara (2010). Readers who are interested in this estimation approach may refer to Ching (2010) and Ching and Ishihara (2010) for the details.

5.1 Two-brand version

This subsection demonstrates how the presence of a co-marketing agreement helps us disentangle the informative and persuasive effects of detailing. For each model (CI and NMC), we estimate two versions: one makes use of the co-marketing identification argument and the other one does not. We will show that the estimated persuasive effects are very different for these two versions. In particular, the estimated persuasive effect of detailing is negative and insignificant under the version which assumes there is no co-marketing agreement.

To simplify the analysis, we consider a 2-brand version of the model, in which we treat Zestoretic and Prinzide as inside goods. The outside good includes Vaseretic and all other drugs that belong to ACE-inhibitor with diuretic, ACE-inhibitor and Thiazide Diuretic. In the version that uses the co-marketing identification argument, we assume that Zestoretic and Prinzide are made of the same chemical, and thus the information sets for the two brands are identical. We refer to this version as "2-chemical/2-brand." In the version that does not use the co-marketing identification argument, we assume that Zestoretic and Prinzide could be made of different chemicals, and thus the updating of the information set for the two brand solely depends on the past experience signals revealed from that brand. But we still maintain the assumption that the true mean qualities for the two brands are the same. We refer to this version as "1-chemical/2-brand." For identification reasons, we need to normalize the scaling parameters for the number of consumption experience signals, κ, and detailing signals, κ^d, and the intercept term for the utility of the outside good, α_0. We set $\kappa = \kappa^d = 1/30000$, and $\alpha_0 = 0$.

The parameter estimates are reported in Table 2. Most of the parameters are qualitatively similar across these two versions under both Model CI and NMC, with the exception in the persuasive effects of detailing. In particular, the coefficient for the persuasive effect, γ_P, is negative and insignificant in the 2-chemical/2-brand version, while it is positive and significant in the 1-chemical/2-brand version. The result from the 2-chemical/2-brand version is counterintuitive, and highlight that the potential weakness of the traditional identification argument.

Under Model CI, the identification of informative and persuasive effects under the 2-chemical/2-brand version is mainly achieved by the functional form assumption. Note that the way CI model the informative effect of detailing is also able to capture 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. Under Model NMC, the identification of the informative and persuasive detailing requires a data set that is long enough to capture part of the product lifecycle after learning is complete. Although our data set contains data for 72 months, it might still be too short for the uncertainty to be resolved in this case. Consequently, the data might fail to provide the "long-run" correlation between sales and cumulative detailing efforts to identify the persuasive effect.[13]

However, the 1-chemical/2-brand version makes use of two extra sources of data variation to help identify the model: (i) the persuasive effect is identified by the correlation between the relative market share of Zestoretic and Prinzide and their relative cumulative detailing efforts; (ii) the informative effect is identified by the correlation between the relative market share of chemicals and the chemical specific detailing efforts (summed across brands that are made of the same chemical). In this case, the improved estimates of the persuasive effect demonstrates that our new identification strategy allows us to use the data more accurately and efficiently when estimating these two effects.

Since the estimated persuasive effect in the 1-chemical/2-brand version is positive (instead of negative in the 2-chemical/2-brand version), we expect that the magnitude of the informative effects in the 1-chemical/2-brand version becomes smaller. By examining other parameter

[13]Recall that by "long-run,", we mean learning is completed.

estimates, this seems to be the case. In Model CI, we find that the coefficient for the informative detailing goodwill stock (i.e., β_1) is smaller, while the parameter that determines the base level of the measure of well-informed physicians (i.e., β_0) is larger in the 1-chemical/2-brand version, implying that the measure of well-informed physicians has been already large initially and built up at a much slower rate. This indicates that the estimated informative effect in the 1-chemical/2-brand version is smaller than that in the 2-chemical/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 full version of the model, which explicitly model all three brands as inside goods.

In Model NMC, we find that the true mean quality (i.e., q_1) and the variances of the signal noises (σ_δ^2 and σ_ϑ^2) become much smaller in the 1-chemical version. Also, the initial prior mean quality (i.e., $\underline{q}_1$) in the 1-chemical version becomes larger compared to both $\underline{q}_1$ and $\underline{q}_2$ in the 2-chemical version. This again implies that learning will be completed sooner under the 1-chemical version, and hence the importance of the informative effect could be overestimated in the 2-chemical version where it does not take advantage of the co-marketing agreement environment.

5.2 Full version

Having demonstrated the potential of our identification strategy using a simplified 2-brand environment, we now discuss the results of the full specification of our model where we explicitly model all three brands in the ACE-inhibitor with diuretics. In other words, 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. 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.

Parameter estimates for Model NMC and CI are reported in Table 3. Most of the parameters appear to be qualitatively similar across them. 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 the demand for Vaseretic, Zestoretic, and Prinzide. The parameter estimates for the true mean quality and initial priors are all statistically significant. 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 worse 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 significant, but the magnitude is very small. 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. We find that the persuasive effect of detailing is positive and significant, but the effects of free samples are insignificant.

Both Model CI and Model NMC provide a good fit to the data. To illustrate this, we simulate 5000 sequences of quantity demanded (expressed in terms of number of prescriptions) for Vaseretic, Zestoretic, and Prinzide. 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 Quantifying 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 & Prinzide, respectively (recall that Zestoretic and Prinzide are made of the same chemicals). 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, being the incumbent, 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 still increases over time in this counterfactual exercise. It turns out that the demand for Vaseretic without informative function overtakes that under the base case in the later periods. 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 18,800 at the end of our sample period. After eliminating the informative function of detailing, their predicted total number of prescriptions drops to 7,700.

Figures 6 and 7 plot the average predicted quantities of Vaseretic, and Zestoretic & 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 the

predicted demand from the version without informative detailing need not converge to that for the base case.

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. Note that if Zestoretic and Prinzide set the same prices, use exactly the same promotional strategies (other than detailing), their market shares should be the same under this counterfactual exercise. But Figure 9 shows that Zestoretic still has higher market share than Prinzide. This could be due to their differences in free samples, prices, or other missing factors (such as other missing promotional activities, publicity, brand-name recognition, etc.) captured by α_j's. We have done more simulations to investigate the reason behind our results and find that this is mainly due to the differences in their α_j's. The coefficients for prices and free samples are so small that they do not lead to any material impacts. Overall, our results show that 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 400 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 shows 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 3,300 at the end of the sample period.

5.4 Welfare Analysis

The previous subsection has shown that both informative and persuasive effects of detailing have a significant impact on physicians' prescribing decisions. Under this situation, it is not clear whether disallowing drug manufacturers to detail at all would increase or decrease patients' welfare. On the one hand, the informative effect enables physicians to be better informed about which drug has higher average quality. On the other hand, the persuasive effect may cause physicians to choose an inferior drug for their patients because it creates artificial product differentiations among drugs.

In this subsection, we propose a procedure to examine the effect of detailing on the patient's welfare if manufacturers were not allowed to do any detailing for ACE-inhibitor with diuretics. We use compensating variation (CV) to measure changes in patient's welfare (Hicks 1939). CV is the dollar amount that a patient would need to receive in order to be indifferent between the benchmark situation with detailing activities and the hypothetical situation without detailing. We will report the average CV. Note that if average CV is positive, it indicates that patients on average would be better off with detailing activities, and vice versa.

We now describe our simulation procedure. We first simulate the prescription decisions for $R = 100,000$ patients over time. For each t and $r = 1, \ldots, R$, we determine the prescribed drug in the three-stage decision-making process outlined in the model section. In the first stage, physicians choose inside or outside goods. If they have chosen inside goods, then in the second stage, they will choose a chemical. If they have chosen a chemical that is co-marketed, then in the third stage, they will choose a brand. We assume that physicians/patients' idiosyncratic errors in each stage, $(\varsigma_{rlt}, \zeta_{rkt}, e_{rjt})$, are not realized until physicians reach that stage. For each patient, we simulate 5,000 sequences of $(\varsigma^s_{rlt}, \zeta^s_{rkt}, e^s_{rjt})_{t=1}^T$. For simplicity, we set p_{jt} to be the average price of drug j across time when simulating the prescribing decisions. For each sequence s, to obtain the welfare of patient r at time t, we divide his/her utility from the prescribed drug by the price coefficient, assuming that the experience signal, $\tilde{q}_{rkt}$, is equal to the true mean quality, q_k. For the benchmark situation, we take the detailing data as given; for the hypothetical situation, we set detailing to be zero. We then compare the patient welfare between these two situations.

Figure 12 plots the average CV over time under both Model CI and Model NMC. Under Model CI, the average CV increases from \$14 to around \$150. Under Model NMC, the average CV starts off at around \$5. It then increases to \$50 after 55 months, and then gradually reduces to around \$22 at the end of our sample period. We should highlight two results. First, we find that patients are on average better off with detailing activities in this drug market. This indicates that the gain for patients from the informative effect outweighs the potential loss from the persuasive effect. Second, the average compensating variation keeps increasing throughout the sample period under CI; however, it increases initially and then starts decreasing in the later part of the sample period under NMC. The reason behind the difference between the two models is that in Model NMC, informative detailing signals and consumption signals are substitutes, and the impact of the informative detailing is diminishing over time (Ching and Ishihara 2010). Thus, even if detailing is banned, physicians will eventually learn about the true quality of drugs. As a result, the welfare loss due to no informative detailing will diminish over time. On the contrary, eliminating informative detailing in CI implies that the measure of physicians who have the most updated information stays constant over time. Thus, if detailing is banned, the welfare loss (relative to the benchmark situation with detailing) gradually increases over time. This is because the value of keeping physicians well-informed increases as $I(t)$ improves over time.

We should highlight three limitations regarding our welfare analysis. First, we only focus on patients' welfare, and do not analyze the welfare of pharmaceutical companies. If detailing is banned, they will certainly save the costs of detailing. To analyze welfare for firms, one would need to obtain an estimate of hourly rate for the sales representatives. Second, our result is based on a specific drug market (ACE-Inhibitor with diuretic in Canada). We certainly do not claim that our finding here can be generalized to other drug markets. Rather, the main purpose of the exercise here is to show how one could make use of the parameter estimates to conduct welfare analysis. To fully understand the patient's welfare, we need to analyze an extensive number of drug markets. This would be an important direction for future research. Third, we conduct partial equilibrium analysis. Our assumption is that while restricting the detailing amount to zero in ACE-inhibitor with diuretics, other anti-hypertension drugs will continue to do the same amount of detailing as before. In general, this assumption would not hold and the

utility of outside good would change. Moreover, manufacturers may react to this regulation by increasing other marketing communication activities such journal advertising and giving away free samples. To address these issues, one would need to take a general equilibrium approach. Building such a model is beyond the scope of this paper.

6 Conclusion

In this paper, we propose a new identification strategy for measuring 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 could allow us to disentangle these two roles of detailing more effectively compared with the traditional approach. 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 in this particular market. We also demonstrate how one could make use of our framework to evaluate the welfare impact of detailing on patients.

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.

Finally, we note two limitations of our study. First, our results only rely on one subclass of drugs. In the future, 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 the firm which decides to license the drug (i) maybe constrained by the number of sales persons employed, or (ii) has a much weaker sales force in marketing the therapeutic class to which the drug belongs. 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 may not be a serious concern. Investigating how companies choose their partners to co-market products and its implications on our identification argument will also 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: 2-brand versions

	Model CI				Model NMC			
	2-chemical/2-brand		1-chemical/2-brand		2-chemical/2-brand		1-chemical/2-brand	
	estimates	s.e.	estimates	s.e.	estimates	s.e.	estimates	s.e.
Learning parameters								
σ_δ^2	**0.057**	1.49E-03	**0.090**	0.008	**0.035**	0.016	**0.006**	3.25E-04
σ_θ^2					**0.023**	0.010	**0.011**	6.54E-04
$\underline{q}_1$	**-21.8**	0.050	**-20.4**	1.03	**-2.13**	0.071	**-1.45**	0.020
$\underline{q}_2$	**-19.8**	0.124			**-1.85**	0.068		
$\underline{\sigma}^2$	**0.022**	3.71E-04	**0.039**	6.46E-04	**-0.004**	0.002	**-0.002**	3.1588E-05
q_1	**15.9**	0.576	**18.3**	3.66	**2.01**	0.760	**-0.196**	0.005
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	**-3.72**	0.010	**-4.78**	0.153	**-3.51**	0.358	**-3.44**	0.029
α_2	**-4.18**	0.031	**-5.23**	0.192	**-4.16**	0.581	**-3.78**	0.020
r	**0.053**	2.89E-04	**0.048**	5.08E-04	**0.702**	0.049	**0.994**	0.012
π_p	**8.16E-04**	3.03E-04	**1.72E-03**	4.16E-04	**1.38E-03**	4.59E-04	**1.29E-03**	1.12E-04
π_t	**-0.006**	2.11E-04	**-0.012**	9.14E-04	-2.94E-04	1.97E-03	**-0.010**	3.17E-04
γ_P	-1.31E-06	7.15E-07	**2.13E-05**	2.11E-06	-1.23E-07	5.79E-06	**7.34E-06**	5.75E-07
γ_S	-1.93E-07	1.21E-07	**-1.95E-07**	9.11E-08	-7.64E-08	1.15E-07	-1.18E-07	8.56E-08
Detailing stock parameters								
Φ_P	**0.851**	0.001	**0.068**	0.006	**0.234**	0.054	**0.072**	0.004
Φ_I	**0.011**	9.97E-05	**0.023**	0.002				
β_0	**-0.049**	0.017	**2.54**	0.421				
β_1	**2.35E-05**	8.97E-07	**7.96E-06**	2.22E-07				
Other parameters for error terms								
s.d.(ε)	**170.2**	7.34	**148.0**	7.57	**134.3**	10.6	**125.1**	5.07
s.d.(ς)	1		1		1		1	
s.d.(ζ)	**0.753**	0.025	**0.637**	0.090	**0.964**	0.125	**0.382**	0.016
log likelihood	-2079.0		-2082.7		-2070.7		-2068.6	

Notes:

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

brands (j): 1 - Zestoretic (entrant), 2 - Prinzide (entrant)

Table 3: Parameter estimates: Full version

	Model CI		Model NMC	
	estimates	s.e.	estimates	s.e.
Learning parameters				
σ_δ^2	**0.174**	0.025	**0.041**	0.001
σ_θ^2			**0.057**	4.13E-03
$\underline{q}_1$	**-24.2**	3.96	**-1.77**	0.095
$\underline{q}_2$	**-14.6**	4.83	**-2.73**	0.097
$\underline{\sigma}^2$	**0.166**	0.025	**0.007**	1.85E-04
q_1	1		1	
q_2	**36.9**	6.29	**1.21**	0.084
κ	1/30000		1/30000	
κ^d			1/30000	
Preference parameters				
α_0	0		0	
α_1	**-3.69**	1.80	**-4.04**	0.023
α_2	**-4.26**	1.20	**-3.46**	0.030
α_3	**-4.27**	1.37	**-3.59**	0.032
r	**0.031**	0.005	**0.436**	0.011
π_p	**4.43E-05**	1.26E-05	**4.91E-04**	6.51E-05
π_t	**-0.014**	0.004	**-0.005**	2.35E-04
γ_P	**9.48E-07**	9.26E-08	**4.58E-06**	2.62E-07
γ_S	-5.59E-09	4.74E-09	-4.34E-08	1.04E-08
Detailing stock parameters				
Φ_P	**0.084**	0.015	**0.036**	0.003
Φ_I	**0.013**	0.003		
β_0	**-1.20**	0.381		
β_1	**3.07E-05**	7.62E-06		
Other parameters for error terms				
s.d.(ε)	**170.8**	37.6	**173.8**	5.03
s.d.(ς)	1		1	
s.d.(ζ)	**0.116**	0.031	**0.591**	0.015
s.d.(e)	**0.024**	0.004	**0.177**	0.007
log likelihood	-2500.0		-2517.8	

Notes:

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

brands (j): 1 - Vaseretic (incumbent), 2 - Zestoretic (entrant), 3 - Prinzide (entrant)

q_1: quality for Vaseretic, q_2: quality for Zestoretic and Prinzide

Figure 1: Detail minutes vs. time

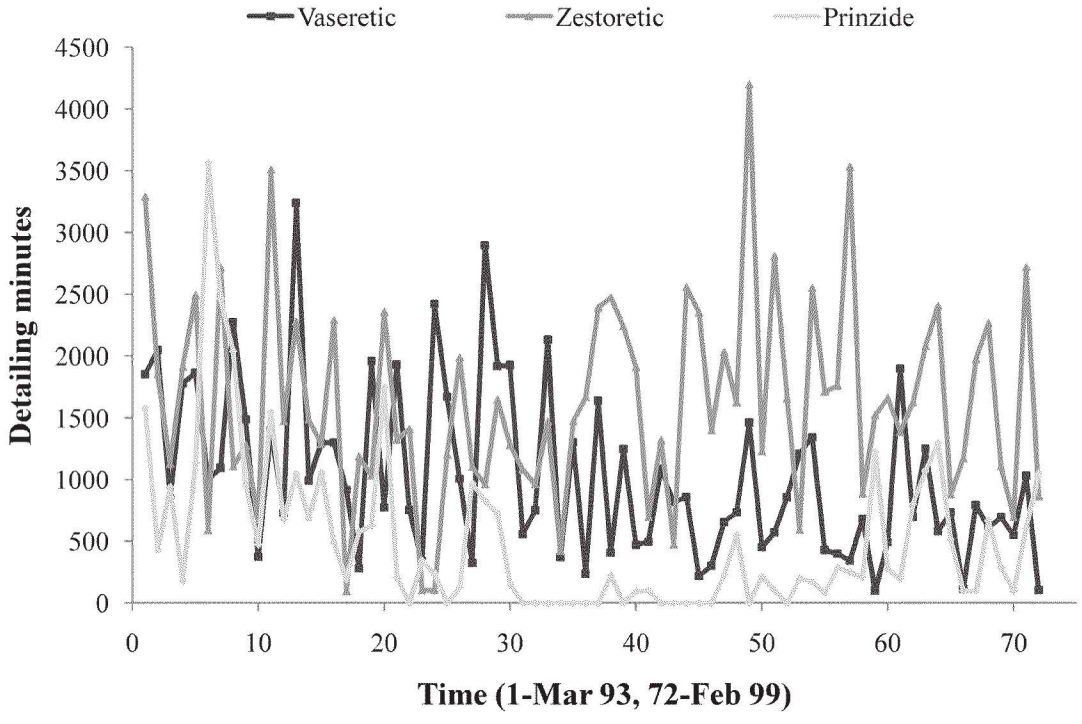


Figure 2: Predicted and Actual Demand: Model CI

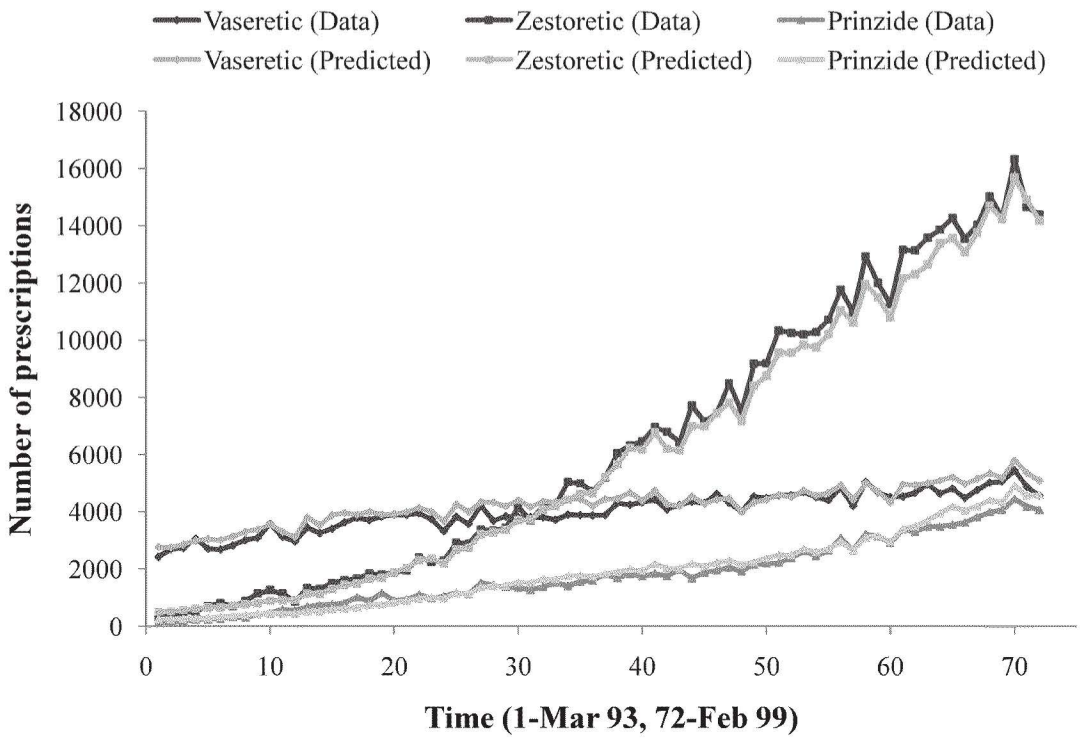


Figure 3: Predicted and Actual Demand: Model NMC

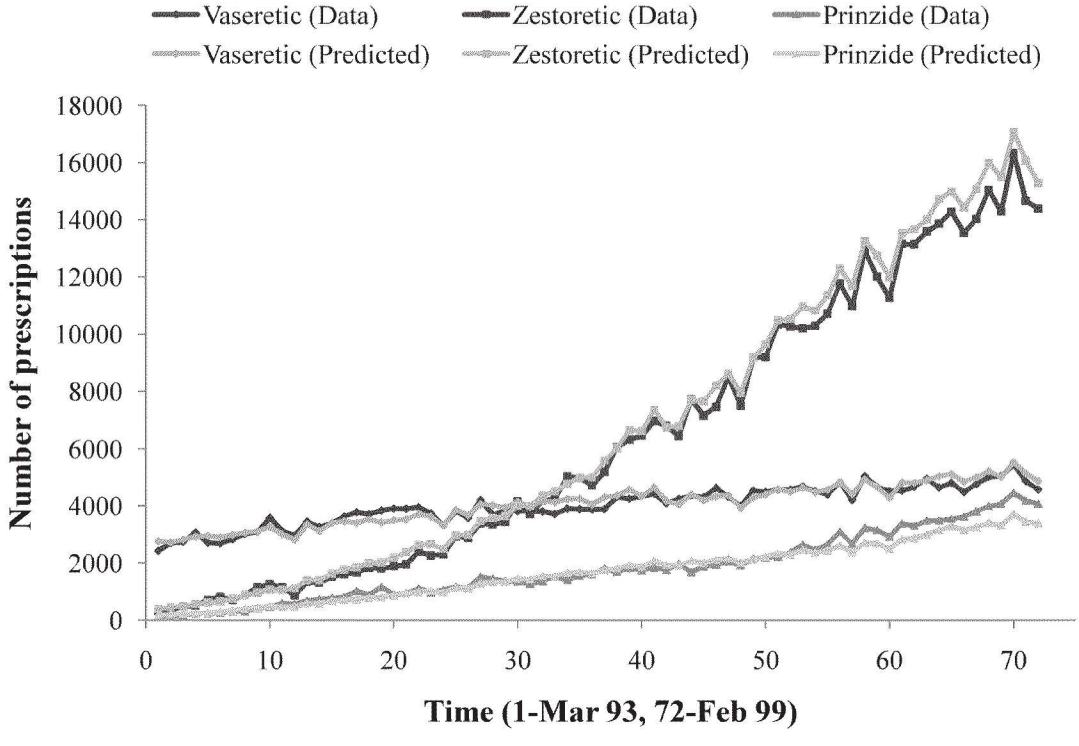


Figure 4: No Informative Effect of Detailing: Vaseretic, Model CI

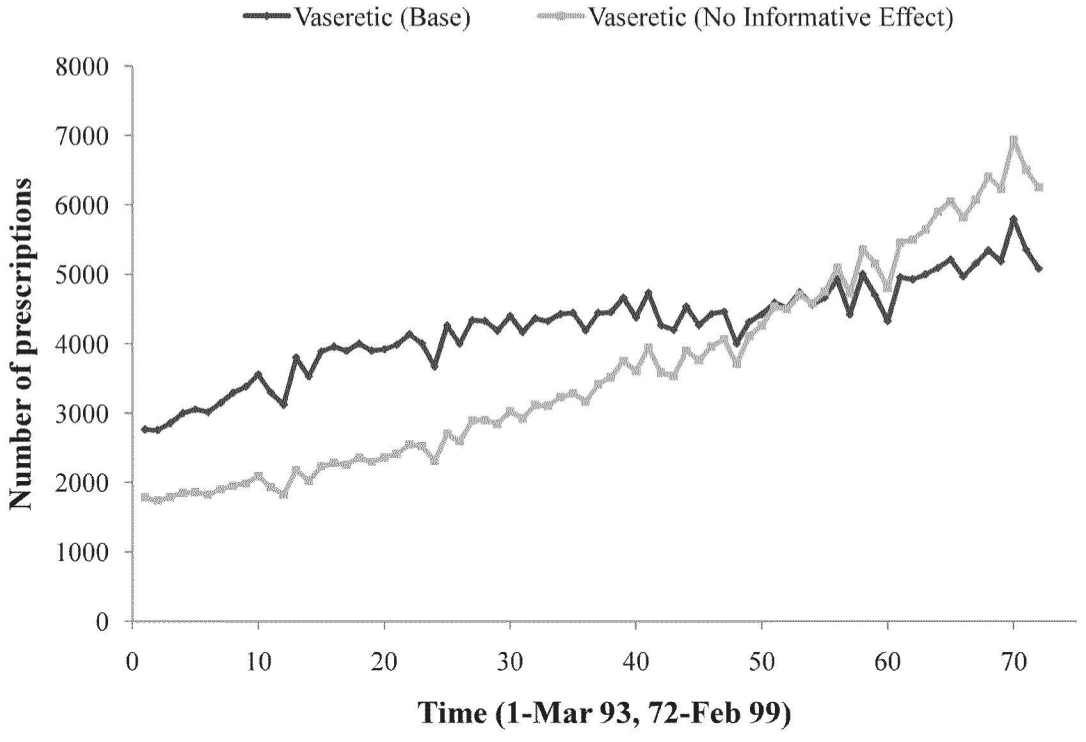


Figure 5: No Informative Effect of Detailing: Zestoretic and Prinzide, Model CI

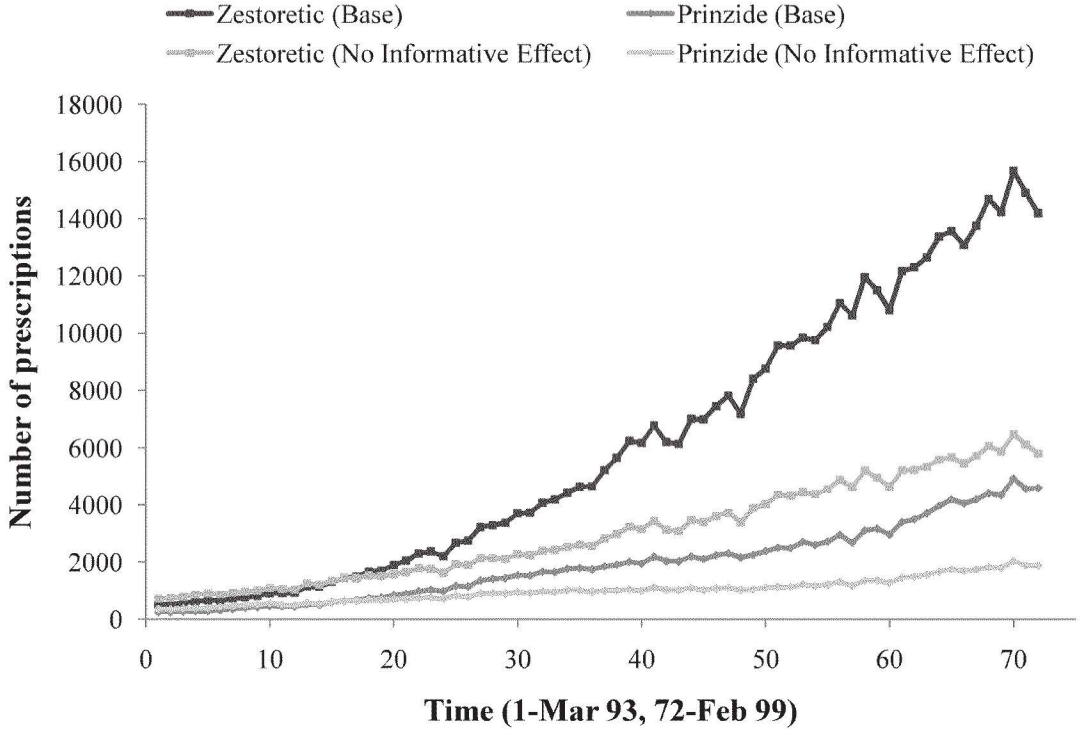


Figure 6: No Informative Effect of Detailing: Vaseretic, Model NMC

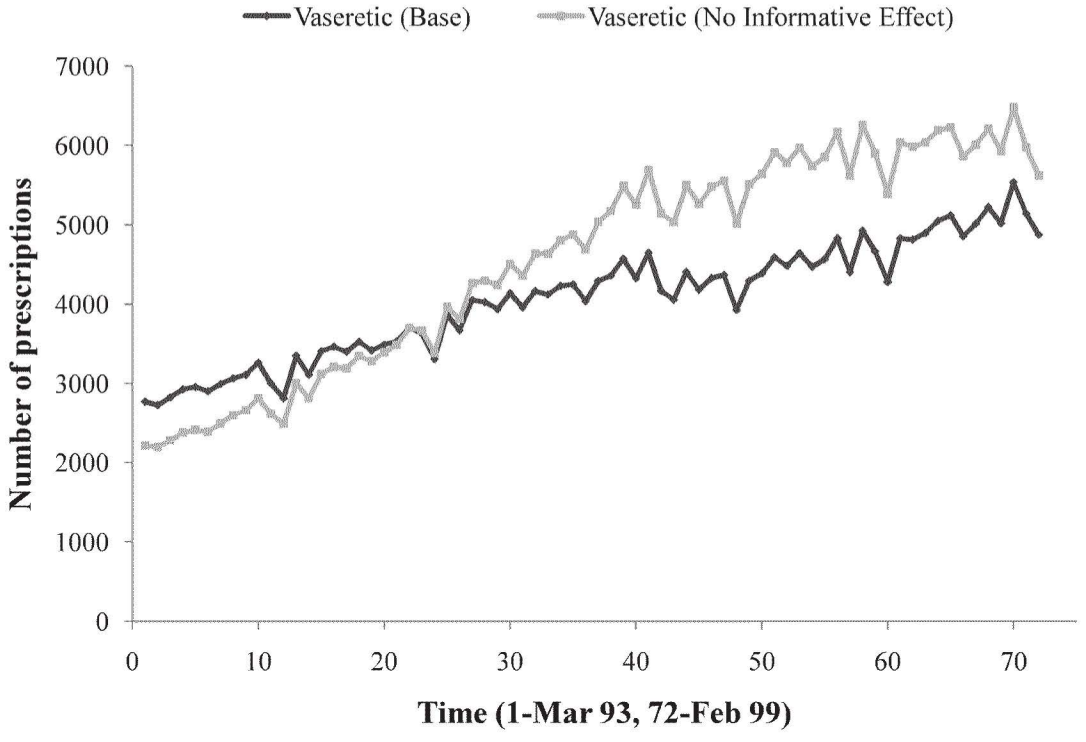


Figure 7: No Informative Effect of Detailing: Zestoretic and Prinzide, Model NMC

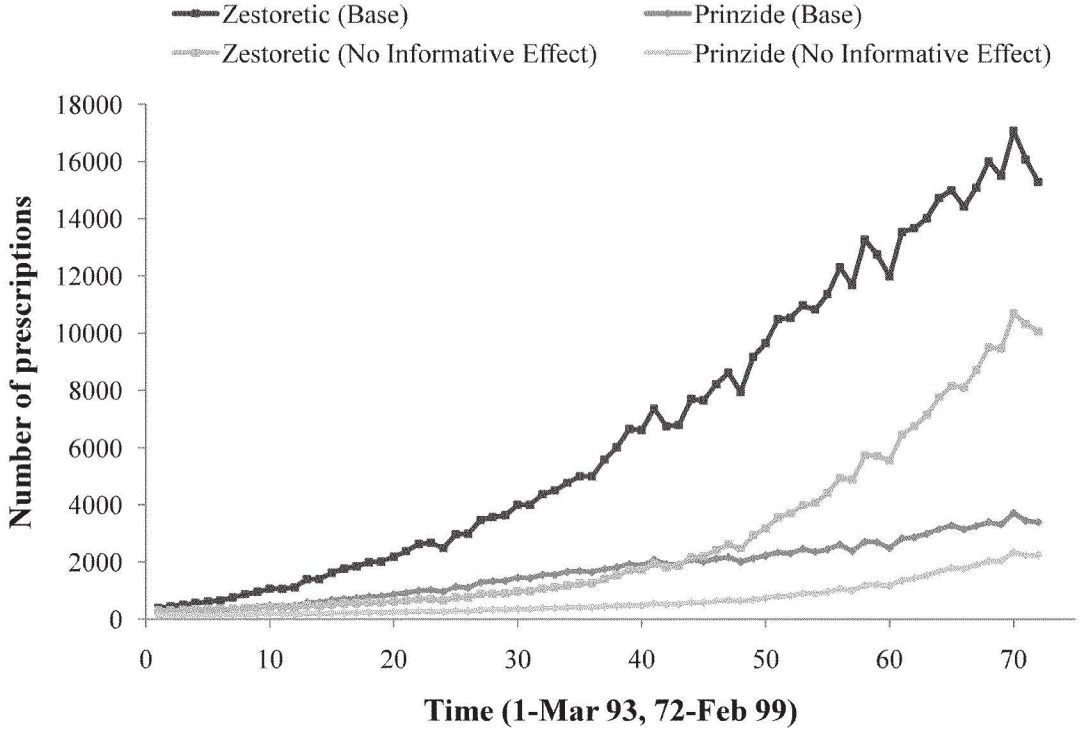


Figure 8: No Persuasive Effect of Detailing: Vaseretic, Model CI

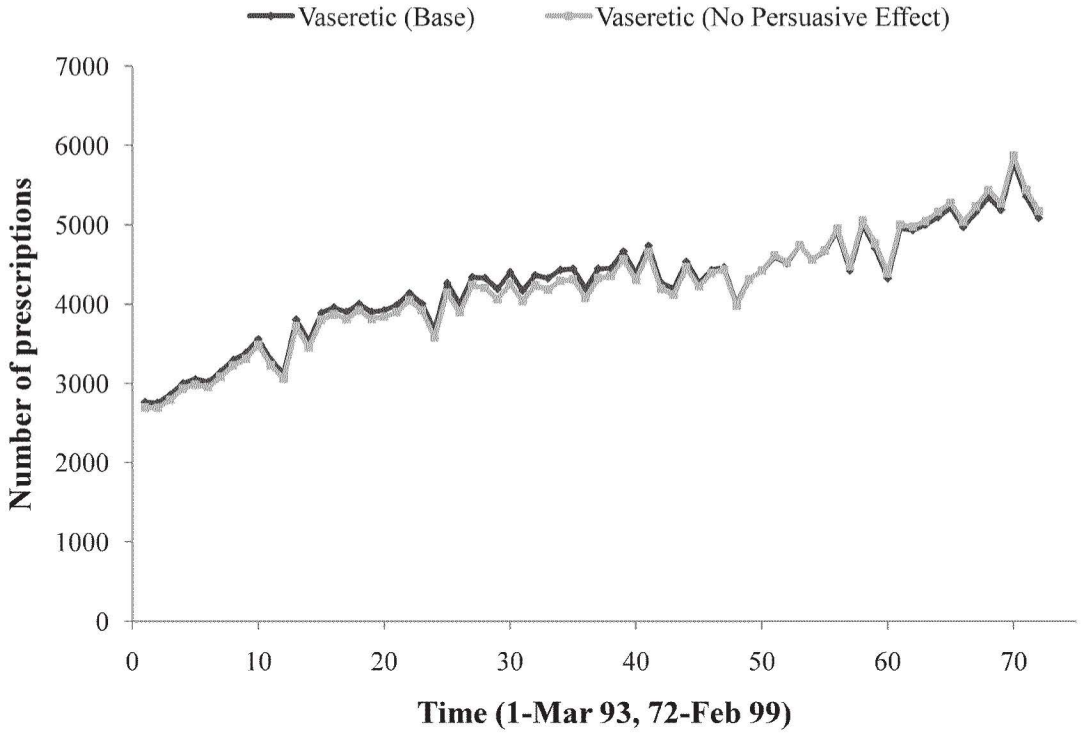


Figure 9: No Persuasive Effect of Detailing: Zestoretic and Prinzide, Model CI

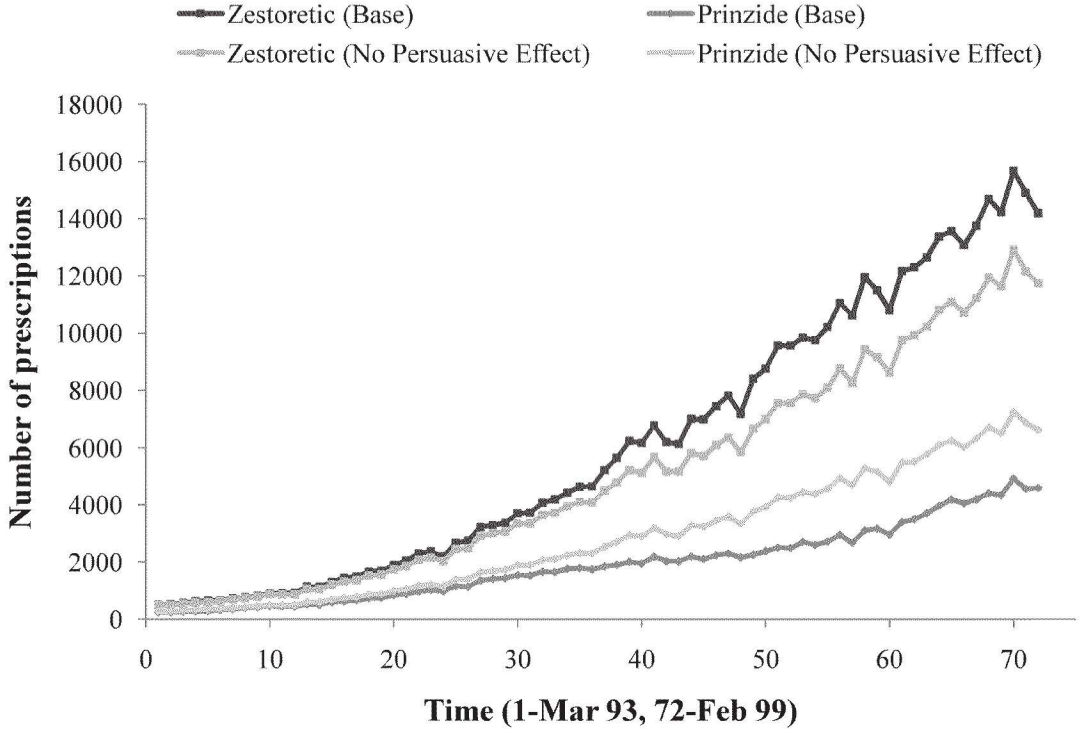


Figure 10: No Persuasive Effect of Detailing: Vaseretic, Model NMC

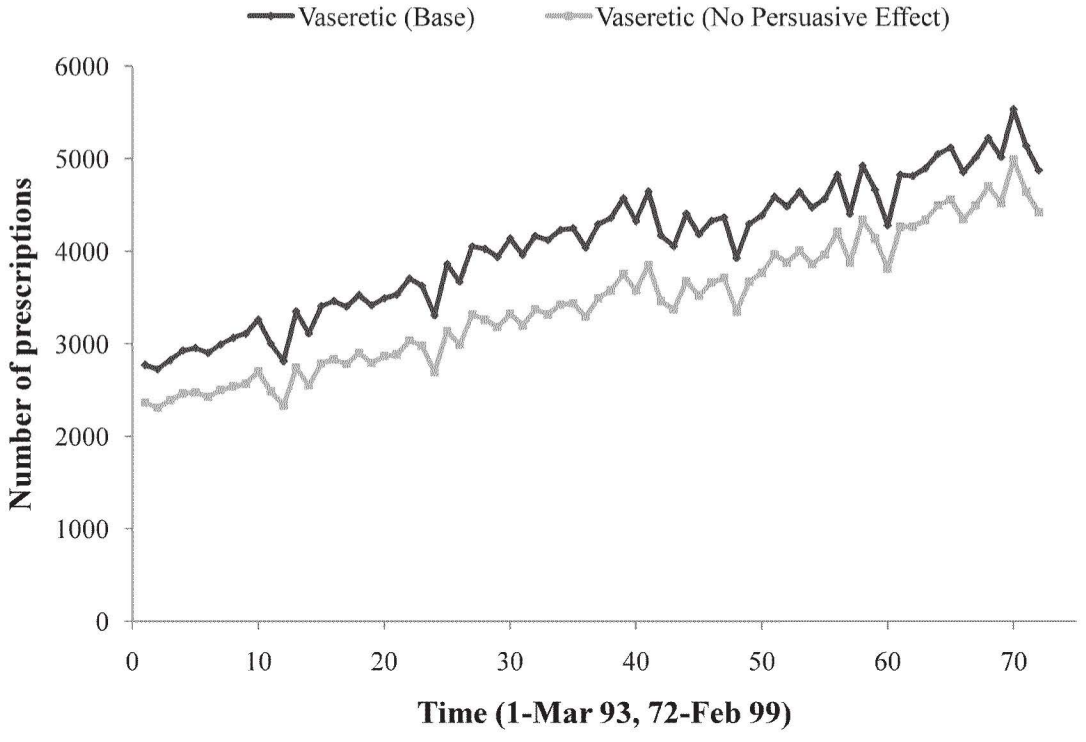


Figure 11: No Persuasive Effect of Detailing: Zestoretic and Prinzide, Model NMC

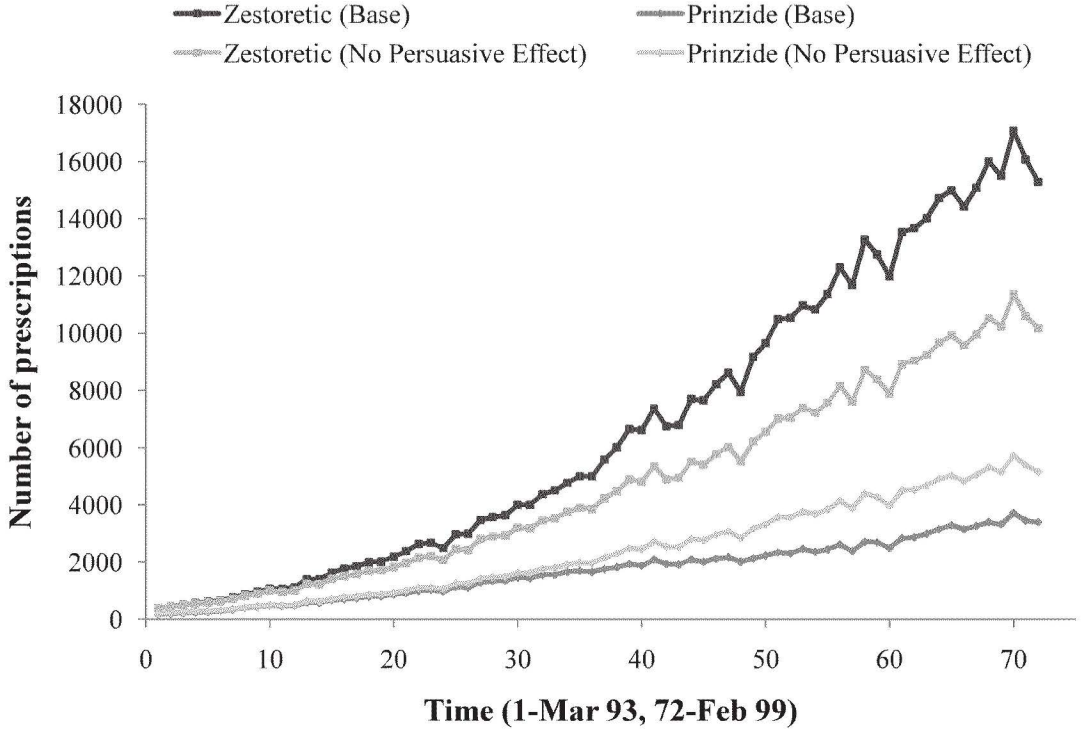
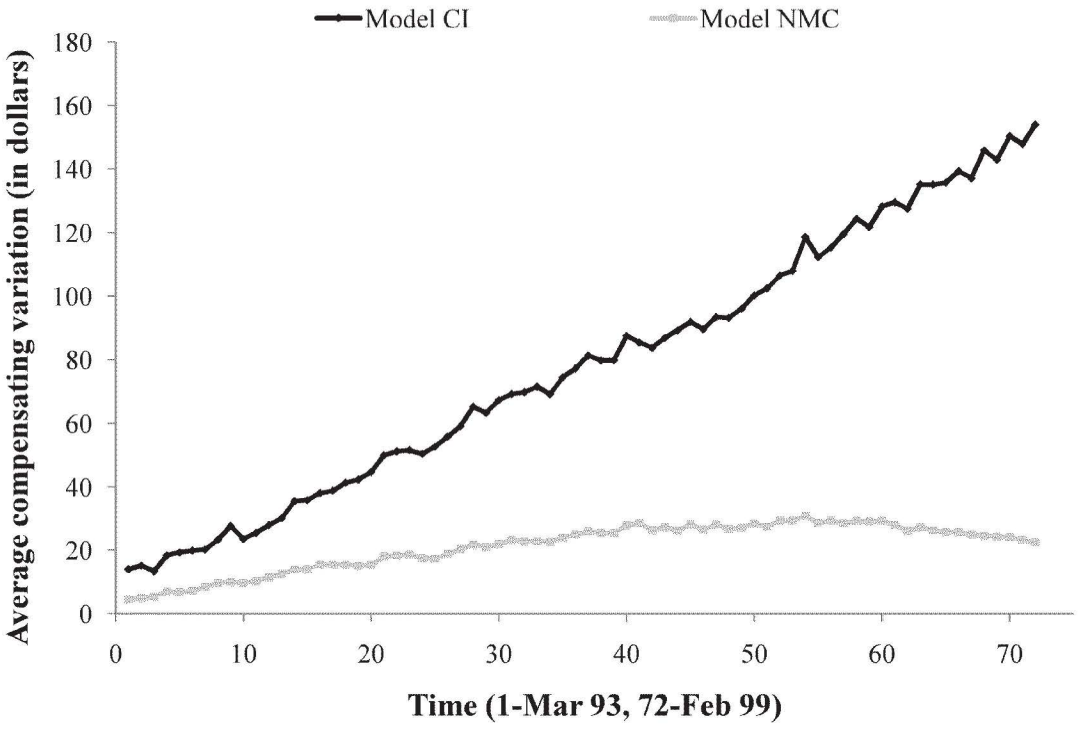


Figure 12: Average Compensating Variation per patient



Appendix

A Reduced-form evidence for spillover effects

Our proposed identification strategy assumes a spillover effect of informative detailing among the drugs that are co-marketed. To provide evidence that sales of a drug could be influenced by its co-marketing partner's detailing (or cumulative detailing) when good information about the chemical is discovered, we regress the number of prescriptions on the interaction between the cumulative clinical outcomes and co-marketing partner's detailing (or cumulative detailing), controlling for other factors, and assuming the coefficients are the same across all drugs.

To compute the cumulative clinical outcomes, we collected data on clinical trials that compare the efficacy of Vaseretic and Zestoretic/Prinzide from medical journal articles archived in PubMed.[14] We focus on the clinical trials that involve *direct comparison* between Vaseretic and Zestoretic/Prinzide because they should be of first order importance in affecting physician's choice between these two chemicals. We collect the clinical trials data from September 1990 to February 1999. We started in September 1990 because this is the inception date of the incumbent drug. For each clinical trial, the *relative* outcome could either be (i) positive for Vaseretic (i.e., negative for Zestoretic/Prinzide), (ii) positive for Zestoretic/Prinzide (i.e., negative for Vaseretic), (iii) no difference between Vaseretic and Zestoretic/Prinzide. We then create a cumulative outcome variable for each chemical as follows. For each clinical trial, we code its outcome as +1 (positive), -1 (negative), and 0 (no difference), and compute a cumulative measure.

Table 4 shows the results. We find that the interaction term between the cumulative clinical outcomes and co-marketing partner's detailing are positive, and statistically significant across all regressions except one, after controlling for own detailing efforts and its interaction with the cumulative clinical outcomes. The results support our hypothesis that there is a spillover effect

[14]PubMed (www.pubmed.gov) is a service of the U.S. National Library of Medicine (NLM) that includes over 18 million citations from MEDLINE, the NLM's premier bibliographic database for the life sciences, and other life science journals for biomedical articles back to 1948.

of informative detailing for drugs that are co-marketed. This also confirms our prior belief that our model should be applicable to ACE-inhibitors with diuretics.

B Controlling for endogeneity problem of detailing

To control for the potential endogeneity problem of detailing, we apply the pseudo-policy function approach proposed by Ching (2010). In Ching's approach, we approximate manufacturers' detailing policy functions by a polynomial of the state variables (both observed and unobserved), and jointly estimate this pseudo-detailing policy functions and the demand model. In our model, the state variables consist of $(E[q_k|I(t)], \sigma_k^2(t), M_{kt-1})\ \forall k$. In addition, we include an instrumental variable, F_{jt}, in the pseudo-detailing policy functions. F_{jt} is computed as the total detailing minutes for the set of drugs in the cardiovascular category, which are produced by the manufacturer of brand j, but not explicit substitutes for ACE-Inhibitors with diuretics. For more detail, see Ching and Ishihara (2010).

B.1 Two-brand version

In the two-brand version, we treat Zestoretic and Prinzide as inside goods, and include Vaseretic in the outside good. In Table 5, we report the estimates for the pseudo-detailing policy functions that correspond to the demand-side estimates in Table 2.

B.1.1 2-chemical/2-brand version

In this version, we assume that two brands are made of different chemicals. Let k be the chemical for brand j, and k' be the chemical for the opponent brand $(-j)$.

In Model CI, the pseudo-detailing policy function for brand j is specified as

$$\begin{aligned}\log D_{jt} &= \lambda_{j0} + (\lambda_{j1} + \lambda_{j3} \cdot M_{k't}) \cdot (1 - M_{kt}) \cdot |\Delta u^q_{kk't}| \cdot \mathbb{I}(\Delta u^q_{kk't} > 0) \\ &\quad + (\lambda_{j2} + \lambda_{j4} \cdot M_{k't}) \cdot M_{kt} \cdot |\Delta u^q_{kk't}| \cdot \mathbb{I}(\Delta u^q_{kk't} < 0) + \lambda_{j5} \cdot F_{jt} + \nu_{jt},\end{aligned}$$

where

$$\begin{aligned} \Delta u^q_{kk't} &= E[u^q_{kt}|I(t)] - E[u^q_{k't}|I(t)], \\ E[u^q_{kt}|I(t)] &= -exp\left(-rE[q_k|I(t)] + \frac{1}{2}r^2(\sigma^2_k(t) + \sigma^2_\delta)\right), \end{aligned}$$

ν_{jt} is the prediction error, and $\mathbb{I}(\cdot)$ is an indicator function. Note that $E[u^q_{kt}|I(t)]$ is part of the expected utility that depends on $E[q_k|I(t)]$ and $\sigma^2_k(t)$. $\Delta u^q_{kk't}$ is the difference between this partial expected utility from choosing chemical k and k'.

In Model NMC, the pseudo-detailing policy function is specified as

$$\begin{aligned} \log D_{jt} &= \lambda_{j0} + \lambda_{j1} \cdot |\Delta u^q_{kk't}| \cdot \mathbb{I}(\Delta u^q_{kk't} > 0) \\ &\quad + \lambda_{j2} \cdot |\Delta u^q_{kk't}| \cdot \mathbb{I}(\Delta u^q_{kk't} < 0) + \lambda_{j3} \cdot F_{jt} + \nu_{jt}. \end{aligned}$$

B.1.2 1-chemical/2-brand version

In this version, we assume that two brands are made of the same chemical. Let us index the chemical for the two brands as chemical 1 ($k = 1$). Then, in both Model CI and NMC, we specify the pseudo-detailing policy function for brand j as

$$\log D_{jt} = \lambda_{j0} + \lambda_{j1} \cdot E[q_1|I(t)] + \lambda_{j2} \cdot \sigma^2_1(t) + \lambda_{j3} \cdot F_{jt} + \nu_{jt}$$

B.2 Full version

In the full version, two brands (Zestoretic and Prinzide) are made of the same chemical. Let's index Vaseretic, Zestoretic, and Prinzide as brand 1, 2, and 3, respectively. Also, let's index the chemical for Vaseretic as chemical 1 ($k = 1$), and the chemical for Zestoretic and Prinzide as chemical 2 ($k = 2$). In Table 6, we report the estimates for the pseudo-detailing policy functions that correspond to the demand-side estimates in Table 3.

In Model CI, we specify the pseudo-detailing policy function for Vaseretic ($j = 1$) as

$$\begin{aligned} \log D_{1t} &= \lambda_{10} + (\lambda_{11} + \lambda_{13} \cdot M_{2t}) \cdot (1 - M_{1t}) \cdot |\Delta u^q_{12t}| \cdot \mathbb{I}(\Delta u^q_{12t} > 0) \\ &\quad + (\lambda_{12} + \lambda_{14} \cdot M_{2t}) \cdot M_{1t} \cdot |\Delta u^q_{12t}| \cdot \mathbb{I}(\Delta u^q_{12t} < 0) + \lambda_{15} \cdot F_{1t} + \nu_{1t}. \end{aligned}$$

The pseudo-detailing policy functions for Zestoretic and Prinzide ($j = 2, 3$) are specified as

$$\begin{aligned}\log D_{jt} &= \lambda_{j0} + (\lambda_{j1} + \lambda_{j3} \cdot M_{1t}) \cdot (1 - M_{2t}) \cdot |\Delta u^q_{21t}| \cdot \mathbb{I}(\Delta u^q_{21t} > 0) \\ &\quad + (\lambda_{j2} + \lambda_{j4} \cdot M_{1t}) \cdot M_{2t} \cdot |\Delta u^q_{21t}| \cdot \mathbb{I}(\Delta u^q_{21t} < 0) + \lambda_{j5} \cdot F_{jt} + \nu_{jt}.\end{aligned}$$

Similarly, in Model NMC, we specify the pseudo-detailing policy function for Vaseretic ($j = 1$) as

$$\begin{aligned}\log D_{1t} &= \lambda_{10} + \lambda_{11} \cdot |\Delta u^q_{12t}| \cdot \mathbb{I}(\Delta u^q_{12t} > 0) \\ &\quad + \lambda_{12} \cdot |\Delta u^q_{12t}| \cdot \mathbb{I}(\Delta u^q_{12t} < 0) + \lambda_{13} \cdot F_{1t} + \nu_{1t}.\end{aligned}$$

The pseudo-detailing policy functions for Zestoretic and Prinzide ($j = 2, 3$) are specified as

$$\begin{aligned}\log D_{jt} &= \lambda_{j0} + \lambda_{j1} \cdot |\Delta u^q_{21t}| \cdot \mathbb{I}(\Delta u^q_{21t} > 0) \\ &\quad + \lambda_{j2} \cdot \cdot |\Delta u^q_{21t}| \cdot \mathbb{I}(\Delta u^q_{21t} < 0) + \lambda_{j3} \cdot F_{jt} + \nu_{jt}.\end{aligned}$$

Table 4: OLS regression of the number of prescriptions on the interaction between the cumulative clinical outcomes and co-marketing partner's detailing (or cumulative detailing)

DV: Number of prescriptions$_{jt}$	Specification				
variable	(i)	(ii)	(iii)	(iv)	(v)
Det_{jt}	-0.135	**-0.716**		-0.381	
	(0.227)	(0.188)		(0.306)	
Cum_Det_{jt}		**0.319**	**0.241**	-0.109	**-0.329**
		(0.032)	(0.020)	(0.156)	(0.091)
Det_{lt}	**-2.08**	-0.187		0.675	
	(0.242)	(0.242)		(0.393)	
Cum_Det_{lt}		0.049	**0.062**	**-1.25**	**-0.929**
		(0.027)	(0.017)	(0.155)	(0.073)
$Price_{jt}$	-28.9	**-31.8**	-4.69	**-39.3**	**-26.9**
	(15.0)	(11.5)	(7.41)	(13.3)	(11.4)
$Cum\_Clinical_{kt}$	-140.0	-292.1	**-6212.8**	**906.0**	**-1350.6**
	(298.1)	(279.6)	(371.9)	(298.8)	(359.7)
Det_{jt} X $Cum\_Clinical_{kt}$	**1.44**	**0.687**		**1.07**	
	(0.209)	(0.171)		(0.187)	
Det_{lt} X $Cum\_Clinical_{kt}$	**0.485**	**0.548**		0.158	
	(0.214)	(0.164)		(0.200)	
Cum_Det_{jt} X $Cum\_Clinical_{kt}$			**0.215**		**0.843**
			(0.012)		(0.075)
Cum_Det_{lt} X $Cum\_Clinical_{kt}$			**0.144**		**0.270**
			(0.008)		(0.065)
Constant	**5996.1**	-1949.3	**-3060.4**	**8084.3**	**7243.8**
	(679.9)	(1139.3)	(678.4)	(800.3)	(678.9)
Adjusted R-squared	0.492	0.705	0.878	0.617	0.715
No. of observations	216	216	216	216	216

* Standard errors are in parentheses; Estimates shown in bold are significant at 5% level.

Definition of variables:

Det_{jt} : Detailing minutes for brand j made of chemical k at time t.

- Det_{lt} : Detailing minutes for the brand made of the same chemical as brand j (chemical k) at time t.

Cum_Det_{jt} : Cumulative detailing minutes for brand j at time t.

- In Specification (ii) and (iii), we follow Berndt et al. (1997) and set the depreciation rate at 4.2%.
- In Specification (iv) and (v), we follow Narayanan et al. (2005) and set the depreciation rate at 30%.
- Cum_Det_{lt} : Cumulative detailing minutes for the brand made of the same chemical as brand j (chemical k) at time t.

$Price_{jt}$: Price of brand j at time t.

$Cum\_Clinical_{kt}$: Cumulative outcomes of direct comparison clinical trials for chemical k at time t.

Table 5: Parameter estimates for pseudo-detailing policy functions: 2-brand versions

	Model CI				Model NMC			
	2-chemical/2-brand		1-chemical/2-brand		2-chemical/2-brand		1-chemical/2-brand	
	estimates	s.e.	estimates	s.e.	estimates	s.e.	estimates	s.e.
Parameters for pseudo-detailing policy funcitons								
λ_{10}	**6.10**	0.418	**5.49**	0.831	**6.53**	0.854	**6.45**	0.462
λ_{11}	**-65.0**	2.52	**0.054**	0.005	1.01	1.04	-0.068	0.131
λ_{12}	**36.6**	7.81	**55.6**	17.0	-2.82	3.41	**3.65**	1.01
λ_{13}	**110.7**	5.51	0.092	0.070	0.018	0.107	0.094	0.054
λ_{14}	**-79.6**	14.4						
λ_{15}	**0.100**	0.050						
λ_{20}	**13.9**	2.60	**25.9**	4.84	**22.6**	3.89	**23.9**	1.18
λ_{21}	**-11.7**	2.81	**-0.101**	0.002	5.28	3.11	**-2.36**	0.112
λ_{22}	**73.8**	6.04	**-39.3**	17.8	1.58	1.13	**7.87**	1.06
λ_{23}	**-7.35**	1.79	**-2.06**	0.476	**-1.76**	0.369	**-2.10**	0.118
λ_{24}	**-73.7**	8.28						
λ_{25}	**-0.630**	0.265						
s.d.(v)	**1.14**	0.034	**1.83**	0.078	**1.76**	0.105	**1.79**	0.062

Notes:

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

brands (j): 1 - Zestoretic (entrant), 2 - Prinzide (entrant)

Table 6: Parameter estimates for pseudo-detailing policy functions: Full version

	Model CI		Model NMC	
	estimates	s.e.	estimates	s.e.
Parameters for pseudo-detailing policy functions				
λ_{10}	**6.50**	1.41	**4.51**	1.84
λ_{11}	**2.54**	0.986	**0.720**	0.221
λ_{12}	-4.01	4.10	1.98	1.31
λ_{13}	**-13.9**	3.57	0.188	0.188
λ_{14}	5.44	32.0		
λ_{15}	-0.006	0.141		
λ_{20}	**7.24**	0.308	**6.41**	0.621
λ_{21}	-13.6	9.32	-2.67	1.75
λ_{22}	**146.5**	6.54	-0.049	0.265
λ_{23}	18.9	16.4	0.106	0.067
λ_{24}	**-383.8**	15.2		
λ_{25}	0.027	0.041		
λ_{30}	**10.3**	1.08	-1.29	2.06
λ_{31}	**164.4**	5.91	**6.18**	1.21
λ_{32}	**-157.2**	7.54	**-1.11**	0.208
λ_{33}	**-293.4**	10.6	**0.690**	0.207
λ_{34}	**420.3**	17.7		
λ_{35}	**-0.297**	0.112		
s.d.(v)	**1.52**	0.025	**0.878**	0.022

Notes:

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

brands (j): 1 - Vaseretic (incumbent), 2 - Zestoretic (entrant), 3 - Prinzide (entrant)