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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 these two roles of detailing in empirical research. In this paper, we provide a new identification strategy to address this problem. Our key identification assumptions are that the informative component of detailing is chemical specific and the persuasive component is brand specific. Our strategy is to focus on markets where some drug manufacturers engage in a comarketing agreement, under which two or more companies market the same chemical using their own brand names. With our identification assumptions, the variation in the relative market shares of these two brands, together with their brand specific detailing efforts, would allow us to measure the persuasive component of detailing. The variation in the market shares 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 for angiotensin-converting enzyme inhibitor with diuretic in Canada, we find evidence that our identification strategy can help disentangle these two effects. Although both effects are statistically significant, we find that the persuasive function of detailing plays a very minor role in determining the demand at the chemical level—the informative role of detailing is mainly responsible for the diffusion patterns of chemicals. In contrast, the persuasive role of detailing plays a crucial role in determining the demand for brands that comarket the same chemical.

Key words: detailing; informative role; persuasive role; prescription drugs; decisions under uncertainty; diffusion

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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 can help drug manufacturers allocate resources to detailing more efficiently. If the persuasive role is important, firms can 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 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. This in turn would hurt manufacturers' profits and their incentives to innovate, and 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 address this problem. Our key identification assumptions are that the informative component of detailing is chemical specific and the persuasive component is mainly brand specific. Our strategy is to focus on a market where some drug manufacturers engage in a comarketing agreement. Under such an agreement, two companies market the same chemical using two different brand names. With our identification assumptions, 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 have any persuasive effect 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 very different across these two brands (assuming the values of 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 follow Ching and Ishihara (2010), which models informative detailing as a means to build and maintain the measure of physicians who know the most updated information about drugs.

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 angiotensin-converting enzyme (ACE) inhibitor with diuretic (which is a subclass of hypertension drugs) in Canada. This market has three brand-name drugs: Vaseretic, Zestoretic, and Prinzide. Zestoretic and Prinzide are made of the same chemicals, but are comarketed by two different companies. To investigate the validity of our identification assumptions, we estimate two versions of the model: (i) *two-chemical version* that captures the comarketing environment and assumes that Zestoretic and Prinzide share one information set; (ii) *three-chemical version* that assumes that Zestoretic and Prinzide could be made of different chemicals, and hence each brand has its own information set, and both informative and persuasive effects of detailing are brand specific. We find that the estimation results are counterintuitive in the three-chemical version—the persuasive effect of detailing is negative and insignificant. On the contrary, the estimation results from the two-chemical version are much more sensible—the persuasive effect is positive and significant. This provides support for our identification assumptions.

Based on the parameter estimates from the two-chemical version of the model, we find that the persuasive function of detailing plays a very minor role in determining the demand at the chemical level—the informative function of detailing is mainly responsible for the diffusion patterns of chemicals. In contrast, the persuasive function of detailing plays a

crucial role in determining the demand for brands that comarket the same chemical.

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

2. Literature Review and Comarketing Agreement

2.1. Previous Literature on Persuasive Detailing

Leffler (1981) argues that detailing plays both informative and persuasive roles. He finds that new 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 continue to 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 informative and persuasive roles of detailing in the pharmaceutical market by extending the framework of Erdem and Keane (1996). Their identification argument builds on Leffler (1981). More specifically, they assume that drug companies know the true quality of their drugs when launching them, and informative detailing provides physicians with noisy signals about the true quality. With this assumption, physicians will eventually learn the true quality and hence detailing will not play any informative role in the long run. As a result, the long-run correlation between sales and cumulative detailing efforts will identify the persuasive role of detailing. The product diffusion paths then identify the informative role.

It should be emphasized that in their framework, 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, and (ii) the data set needs to be long enough so that it captures part of the product life cycle after learning is complete.[1] In contrast, these features are not necessary for our identification strategy.

Finally, Ackerberg (2001) 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 panel data, whereas our identification strategy applies even if one only observes product level panel data.

Compared with the previous studies, the main limitation of our identification strategy is that comarketing agreement only happens in a relatively small subset of product categories. Therefore, one should be cautious about how to generalize our results.

2.2. Comarketing Agreement
Comarketing 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 chemical and allow the partner company to use a different brand name.[2] According to CurrentPartnering (2009), the total number of comarketing 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 an originator of 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 as they need to know the clinical trials results of the drug being promoted and their rivals' drugs. Instead of paying such a high fixed cost, a company that is short in their sales force of promoting a certain category of drugs might find it worthwhile to sign a comarketing agreement with another company, and charge its partner a royalty fee.

Comarketing agreements have also appeared in the automobile industry (Sullivan 1998, Lado et al. 2003). Furthermore, for industrial products, it is common that different firms market identical products using their own brand names (Saunders and Watt 1979, Bernitz 1981). In some countries such as Australia and Japan, firms also market generic drugs with brand names (Birkett 2003, Iizuka 2011). Under these environments, we expect that our identification arguments could also be applied.[3]

3. Model
We modify the model proposed by Ching and Ishihara (2010) to implement our new identification strategy. They model informative detailing as a means to build and maintain the measure of physicians who know the most updated information about drugs, but ignore persuasive detailing. Here, we model persuasive detailing by including a detailing goodwill stock in the utility function for physicians.

The basic setup of the model is as follows. 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 comarketing agreement and are made of the same chemical. Let $k = 1, \ldots, K$ indexes for chemicals, where $K \leq J$. We assume that each brand is made of one chemical. Let A_k be the set of brands that are made of chemical k. The characteristics of brand $j \in A_k$ are given by p_j and q_k, where p_j is the price of brand 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. Ching and Ishihara (2010) assume that $I(t)$ is updated by a representative opinion leader based on past patients' experiences. Let $\underline{I}_k$ be the initial prior that physicians have when a drug made of chemical k is first introduced. For each chemical k, a physician either knows $I_k(t)$ or $\underline{I}_k$ at time t. For simplicity, we assume that physicians and the representative opinion leader share the same initial prior belief. Let M_{kt} be the measure of physicians who know $I_k(t)$; M_{kt} is modeled as a function of the cumulative detailing efforts at time t.

Our key identification assumptions are that (1) informative detailing is chemical specific and (2) persuasive

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[1] Byzalov and Shachar (2004), Mehta et al. (2008), and Narayanan and Manchanda (2009) rely on similar identification arguments to estimate informative and persuasive advertising or detailing using individual level data.

[2] This definition of comarketing agreement is given by Current-Partnering (2009). There is another type of closely related marketing practice where two or more firms market the same chemical under *one* brand name. CurrentPartnering calls this type of arrangement *copromotion* agreement.

[3] However, the applicability of our identification strategy for industries other than pharmaceutical may depend on the existence of nonproduct factors that differentiate products under a comarketing agreement (e.g., after-sales services in automobile). If consumers care about such nonproduct factors and advertising help consumers learn about them over time, our identification strategy would not be applicable unless researchers can control for them.

detailing is brand specific. The first assumption implies that (a) $I_k(t)$ is updated based on past patients' experiences for all drugs made of chemical k and (b) M_{kt} depends on the sum of the cumulative detailing efforts for all drugs made of chemical k. The second assumption implies that the persuasive detailing goodwill stock for brand j only relies on the detailing efforts for brand j.

3.1. Updating of the Information Set

A drug is an experienced good. Consumption of a drug provides information about its quality. 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 (2010a, b), 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 independent and identically distributed (i.i.d.). We further assume that δ_{ikt} is normally distributed with zero mean, and the representative opinion leader's initial prior on q_k ($\underline{I}_k$) is also normally distributed:

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

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 experience signals revealed to the public is a random subsample of the entire set of experience signals.

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

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

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

$$\iota_k(t) = \frac{\sigma_k^2(t)}{\sigma_k^2(t) + (\sigma_\delta^2/(\kappa n_t^k))} \quad \text{and}$$

$$\sigma_k^2(t+1) = \frac{1}{(1/\sigma_k^2(t)) + ((\kappa n_t^k)/\sigma_\delta^2)}. \tag{4}$$

3.2. Detailing and Measure of Well-Informed Physicians

There is a continuum of physicians with measure one. They are heterogeneous in their information sets. A physician is either well informed or uninformed about chemical k. A well-informed physician knows the current information set maintained by the representative opinion leader ($I_k(t)$). An uninformed physician only knows the initial prior ($\underline{I}_k$). The number of physician types is then 2^K.

The measure of well-informed physicians for chemical k at time t, M_{kt}, is a function of M_{kt-1} and $D_t = (D_{1t}, \ldots, D_{Jt})$, where D_{jt} is the detailing efforts for brand j at time t. 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 capture the relationship between M_{kt} and (M_{kt-1}, D_t^k) by introducing an informative detailing goodwill stock, G_{kt}^I, which accumulates as follows:

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

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

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

3.3. Prescribing Decisions

Each physician's objective is to choose a drug so as to maximize the current period expected utility for his or her patients conditional on his or her information set and other marketing variables such as persuasive detailing and free samples. The demand system is obtained by aggregating this discrete choice model of an individual physician's behavior.

The utility of patient i who consumes drug j made of chemical k at time t is given by

$$u_{ijt} = \alpha_j - \exp(-r\tilde{q}_{ikt}) - \pi_p p_{jt} + s_{i1t} + \zeta_{ikt} + e_{ijt}, \tag{7}$$

where α_j is a brand-specific intercept; r is the coefficient of absolute risk aversion; π_p is the utility weight for price; $(s_{i1t} + \zeta_{ikt} + e_{ijt})$, which represents the distribution of patient heterogeneity, is unobserved to the econometrician but observed to the physicians when they make their prescribing decisions; and s_{ilt} corresponds to the shock associated with the outside alternative ($l = 0$) or inside alternatives ($l = 1$). This setup 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 (when s_{ilt} is realized), then choose one of the chemicals in the second stage (when ζ_{ikt} is realized), and then choose a brand in the third stage (when e_{ijt} is realized) if the chemical is comarketed by two or more firms. We assume that s_{ilt}, ζ_{ikt}, and e_{ijt} are i.i.d. extreme value distributed.

Note that $\tilde{q}_{ikt}$ is observed by physicians and patients only after patients have consumed the drug (but remains unobserved by the econometrician). Thus, physicians make their prescribing decisions based on the expected utility of their patients. Let $I^h(t)$ denote physician h's information set at time t. Suppose that drug j is made of chemical k. If physician h is well informed about chemical k at time t, then $I_j^h(t) = I_k(t)$ and his or her expected utility will be

$$
\begin{aligned}
E[u_{ijt} \mid I^h(t)] &= E[u_{ijt} \mid I_k(t)] + \gamma_P G_{jt}^P + \gamma_S FS_{jt} \\
&= \alpha_j - \exp\left(-rE[q_k \mid I(t)] + \tfrac{1}{2}r^2(\sigma_k^2(t) + \sigma_\delta^2)\right) - \pi_p p_{jt} \\
&\quad + \gamma_P G_{jt}^P + \gamma_S FS_{jt} + s_{i1t} + \zeta_{ikt} + e_{ijt},
\end{aligned} \tag{8}
$$

where G_{jt}^P is a persuasive detailing goodwill stock for drug j at time t with the depreciation rate ϕ_P, 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. If physician h is uninformed about chemical k at time t, his or her expected utility follows the same functional form as in Equation (8) except that $I_j^h(t) = \underline{I}_k$. We emphasize that (a) G_{jt}^P is drug j specific rather than chemical k specific, and (b) the depreciation rates for G_{kt}^I and G_{jt}^P are allowed to be different.

In each period, physicians may also choose an outside alternative (i.e., other nonbioequivalent drugs). We assume the expected utility associated with the outside alternative takes the following functional form:

$$
E[u_{i0t} \mid I^h(t)] = \alpha_0 + \pi_t t + s_{i0t} + \zeta_{i0t} + e_{i0t}. \tag{9}
$$

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. With the above setup, we can construct the market shares in a standard way. The quantity demanded for drug j (n_{jt}) can then be expressed as

$$
\begin{aligned}
n_{jt} &= Size_t \cdot S\big(j \mid D_t, (E[q_k \mid I(t)], \sigma_k(t), M_{kt-1})_{k=1}^K; \theta_d\big) \\
&\quad + \epsilon_{jt}, \tag{10}
\end{aligned}
$$

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

3.4. Identification

It should be highlighted that if $K = J$ (i.e., each brand corresponds to a distinct chemical), the parameters of the informative and persuasive effects will mainly be identified based on the functional form restrictions. 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. As a result, some empirical patterns (e.g., increasing sales trend) could be explained by either informative or persuasive detailing. If the functional form assumptions specified here precisely capture the true nonlinear nature of these two effects, we can still separately identify them and obtain consistent estimates in principles. Under this situation, however, the main source of data variation for identification is only the diffusion patterns of each brand.

If one has data from a market where some drugs use a comarketing agreement (i.e., $K < J$), one will be able to use an additional source of data variation to help identify the persuasive effect: When two or more companies use their own brand names to market the same chemical, our identification assumptions imply that the variation of their relative market shares and their relative detailing efforts would be mainly responsible for identifying the persuasive effect of detailing. For instance, if the persuasive effect is close to zero, we expect to see that the relative market shares should remain roughly the same across brands that are made of the same chemical even if their relative detailing efforts vary significantly over time. On the contrary, if the data shows that their relative market shares are highly positively correlated with their relative detailing efforts, this tells us that the persuasive effect is strong and positive. With this additional source of data variation, we can control for the persuasive effect and use the diffusion paths of each drug to identify the informative effect (i.e., the parameters of learning process and initial prior beliefs).

We should reemphasize that the traditional identification argument also relies on two sources of data variation to disentangle informative and persuasive effects. It requires one (i) to have a sufficient number of observations of sales and detailing efforts in the long run in order to identify the persuasive effect, and (ii) to use the diffusion patterns of brands to identify the informative effect after controlling for the persuasive effect. Nevertheless, such a long panel may not be readily available. Under this situation, having data from markets with comarketing arrangement will be particularly helpful in identifying these two effects.

We should note that like all structural estimation research, our results still need to rely on functional form assumptions (Keane 2010). But with the extra source of data variation provided by the comarketing environment, we should be able to identify informative and persuasive effects more accurately compared with the traditional approach. It is also important to recognize that our specification ignores one possible function of detailing—it might increase physicians' awareness of some brands sharing the same chemicals. If this function is important, our estimates would suffer misspecification bias. In particular, the

importance of the persuasive effect would be over-estimated.[4] Admittedly, with only product level data, it is very difficult to empirically tease out the importance of this function from other potential structural explanations of slow diffusion. Nevertheless, we feel that simply informing physicians that two brands are made of the same chemical is relatively easy to accomplish. We also find that such information is not hard for physicians to obtain. For instance, *Physicians' Desk Reference* (a standard reference about drugs) shows that Prinzide is another brand name of Zestoretic right under its heading, and vice versa. Many popular online resources also provide this information in the first few lines of their search results (e.g., http://www.MedicineNet.com). So relative to the information about the chemical (its efficacy and side-effect profile), it seems much more likely that physicians know which brands are made of the same chemical. These institutional details suggest that the awareness issue should be of second-order importance in our context. We therefore decide not to model this alternative explanation and leave it for future research. Nevertheless, in §5, we will compare our proposed framework with an alternative specification, which assumes the demand side does not know that there are two brands that comarket the same chemical under different brand names throughout the analysis. This allows us to shed some light on the validity of our identification assumptions.

4. Data Description

We apply our identification strategy to the market of ACE inhibitor with diuretic in Canada. This class of combination drugs is for treating hypertension. Data come from IMS Canada. 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 minutes 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, 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—Vaseretic, Zestoretic, 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 comarketing 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. Because Vaseretic was launched earlier, we consider Vaseretic as the incumbent, and Zestoretic and Prinzide as new entrants. The potential market size 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.

Table 1 shows the summary statistics. Figure 1 shows the detailing minutes for the three drugs over time. One common feature is that they all have high fluctuation. 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 prescriptions dispensed in this market. The sales for all three brands continue to increase even near the end of our sample period. Being the first in this market, Vaseretic controlled more than 80% of the sales at the beginning of the sample; Zestoretic's

Table 1   Summary Statistics

Brand	Mean	SD	Max	Min
	Number of prescriptions			
Vaseretic	4,007.6	676.8	5,446	2,429
Zestoretic	6,388.8	4,900.3	16,330	322
Prinzide	1,814.8	1,168.9	4,447	131
	Detailing minutes			
Vaseretic	1,032.8	689.1	3,240	97
Zestoretic	1,625.4	828.6	4,203	93
Prinzide	512.6	650.7	3,566	0
	Free sample (no. of prescriptions)[a]			
Vaseretic	71.8	52.8	290.8	0
Zestoretic	152.5	100.1	545.4	0
Prinzide	20.8	24.0	83.1	0
	Price			
Vaseretic	40.5	8.76	69.2	24.5
Zestoretic	34.3	8.65	61.5	15.7
Prinzide	38.7	15.6	87.5	16.2

[a]The original data on free samples are measured in sample extended units: the number of packages multiplied by the number of pills per package. 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. Following Tu et al. (2005), we assume that one prescription lasts for 100 days. Based on the daily dosages of Vaseretic and Zestoretic/Prinzide, we set the daily consumption to be 2.25 units for Vaseretic and two units for Zestoretic/Prinzide. The daily consumption times 100 would give us the amount of the sample extended units per prescription. It turns out that free samples represent less than 12% of the total number of prescriptions and hence it has negligible impacts on consumer learning.

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[4] The direction of bias for the informative effect is ambiguous.

Figure 1   Detail Minutes vs. Time

Time (1 = March 1993; 72 = February 1999)
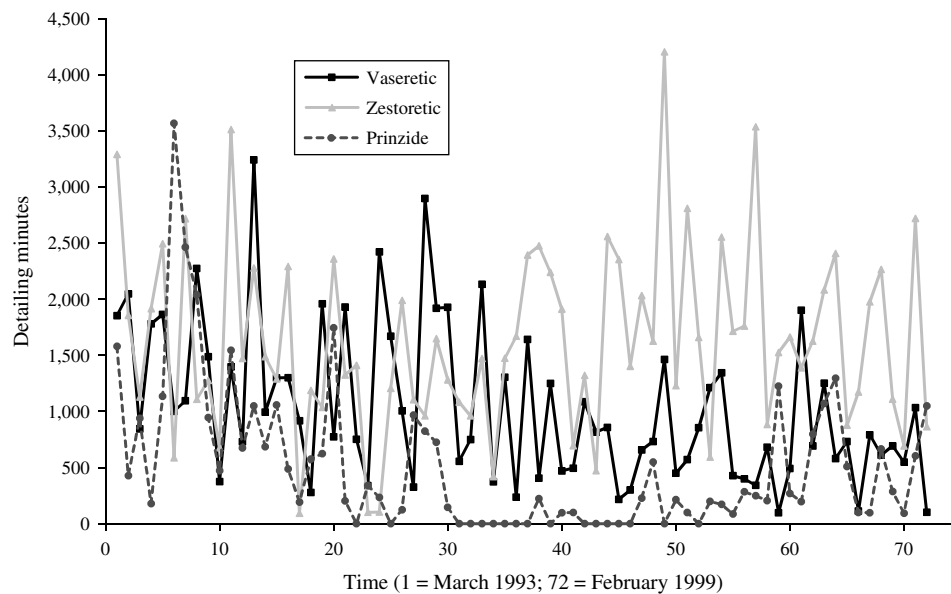
Figure 2   Predicted and Actual Demand

Time (1 = March 1993; 72 = February 1999)
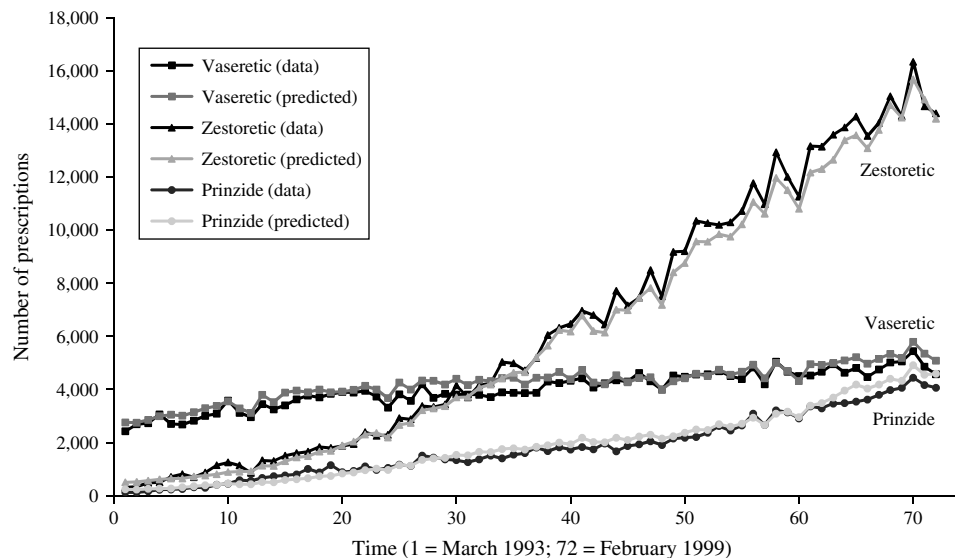
share was only about 10%; Prinzide's share was even smaller (about 5%). It takes Zestoretic more than two years before it overtakes Vaseretic's sales. However, Prinzide's sales remain below Zestoretic throughout the period, even though Prinzide and Zestoretic are made of the same chemicals. The differences in the number of prescriptions and detailing efforts for Zestoretic and Prinzide indicate that the persuasive role of detailing is likely important.

Our identification strategy requires the informative component of detailing to be chemical specific. One implication of this assumption is that when positive information about a chemical becomes available, the sales of a brand should be positively influenced by the detailing efforts of the other brand

that comarkets the same chemical. We conduct a simple test for this implication. Following Ching and Ishihara (2010), we collect data on clinical trials that compare the efficacy of Zestoretic/Prinzide and Vaseretic to create a measure of cumulative clinical outcome variable, and use it as a proxy for the updated information sets.[5] 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); or (iii) no difference between Vaseretic and

[5] The published clinical trial data is obtained from PubMed (http://www.pubmed.gov).

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. We should also point out that all the medical journal publications mention chemical names instead of brand names when they report clinical trial findings. Therefore, if sales representatives refer physicians to some medical journal publications for evidence to support their claims, physicians will see the chemical name in those articles, suggesting that the informative detailing should have a spillover effect across brands that share the same chemical.

To test whether such a spillover effect exists, we regress the number of prescriptions on the interaction between the cumulative clinical outcomes of the chemical and cumulative comarketing partner's detailing, controlling for other factors, and assuming the coefficients are the same across all brands. When creating the cumulative detailing stock, we set the depreciation rate to be 4.2% as in Berndt et al. (1997).[6] We report two specifications here. Table 2 shows the specifications and results. In both specifications, we find that the interaction between the cumulative clinical outcomes and comarketing partner's cumulative detailing to be positive and statistically significant. This provides support for our hypothesis that there is a spillover effect of informative detailing for drugs that are comarketed.

In addition to the regressors used in specification (i), specification (ii) includes comarketing partner's cumulative detailing stock. This variable allows us to test whether there is any additional spillover effect of detailing from a comarketing partner after controlling for its interaction with the cumulative clinical outcomes. According to the CI model, additional informative spillover effect is possible because detailing could trigger or stimulate physicians to find out more information about the drug themselves by contacting opinion leaders of the field (captured by the representative opinion leader in the model). This allows them to learn about the patients' consumption experiences revealed to the public, in addition to the information signals available from the published clinical trials. However, at the same time, we expect that the partner's cumulative detailing stock also captures the brand-specific persuasive effect, which should have a negative impact on the number of prescription of the focal drug. Overall, when combining these two counteracting effects, we expect that the effect of the comarketing partner's cumulative detailing should be smaller than that of one's own cumulative detailing

[6] The depreciation rate of detailing stock estimated by Ching and Ishihara (2010) is 4.5%, which is very close to what Berndt et al. (1997) find.

Table 2 Ordinary Least Squares Regression of the Number of Prescriptions on the Interaction Between the Cumulative Clinical Outcomes and Comarketing Partner's Cumulative Detailing

Dependent variable: $Number\ of\ prescriptions_{jt}$	Specification	
Variable	(i)	(ii)
$Price_{jt}$	−4.56	−4.68
	(7.63)	(7.41)
$Cum\_Clinical_{jt}$	**−5,862.1**	**−6,212.84**
	(370.4)	(371.9)
Cum_Det_{jt}	**0.183**	**0.241**
	(0.013)	(0.020)
$Cum\_Det_{jt} \times Cum\_Clinical_{jt}$	**0.215**	**0.215**
	(0.012)	(0.012)
$Cum\_Det\_Partner_{jt}$		**0.062**
		(0.017)
$Cum\_Det\_Partner_{jt} \times Cum\_Clinical_{jt}$	**0.148**	**0.144**
	(0.008)	(0.008)
$Constant$	**−1,120.5**	**−3,060.4**
	(444.3)	(678.4)
Adjusted R-squared	0.871	0.878
No. of observations	216	216

Notes. Standard errors are in parentheses. Estimates shown in bold are significant at the 5% level. Definition of variables are as follows:
Cum_Det_{jt}: cumulative detailing minutes for brand j at time t.
 —We follow Berndt et al. (1997) and set the depreciation rate at 4.2%.
$Cum\_Det\_Partner_{jt}$: cumulative detailing minutes for brand j's partner at time t.
 —If j is Zestoretic (Prinzide), $Cum\_Det\_Partner_{jt} = Cum\_Det$ for Prinzide (Zestoretic) at time t.
 —If j is Vaseretic, $Cum\_Det\_Partner_{jt} = 0$.
$Price_{jt}$: price of drug j at time t.
$Cum\_Clinical_{jt}$: cumulative outcomes of direct comparison clinical trials for brand j's chemical at time t.
 —For Zestoretic (j) and Prinzide (l), $Cum\_Clinical_{jt} = Cum\_Clinical_{lt}$.

(and its sign could be either positive or negative). This is consistent with our estimation results for specification (ii)—we find that the comarketing partner's cumulative detailing stock is positive and significant, and *is much smaller than own cumulative detailing stock* (0.062 versus 0.241). The evidence provides support for using the Ching and Ishihara (2010) approach to model consumer learning and informative detailing.

5. Results
We estimate the models using the method of simulated maximum likelihood. We apply the pseudo-policy function approach proposed by Ching (2010b) to control for the potential endogeneity problem of detailing. In the appendix, we present the specifications of the pseudo-detailing policy functions. They are similar to the one used in Ching and

Table 3 Parameter Estimates

	Three-chemical		Two-chemical	
	Estimates	SE	Estimates	SE
Learning parameters				
σ_δ^2	**0.620**	0.296	**0.174**	0.025
$\underline{q}_1$	**−20.6**	5.47	**−24.2**	3.96
$\underline{q}_2$	**−18.9**	4.12	**−14.6**	4.83
$\underline{q}_3$	**−17.9**	3.86		
$\underline{\sigma}^2$	**0.320**	0.142	**0.166**	0.025
q_1	1		1	
q_2	**62.0**	7.27	**36.9**	6.29
κ	1/30,000		1/30,000	
Preference parameters				
α_0	0		0	
α_1	**−3.30**	0.195	**−3.69**	1.80
α_2	**−3.78**	0.294	**−4.26**	1.20
α_3	**−3.91**	0.107	**−4.27**	1.37
r	**0.034**	0.001	**0.031**	0.005
π_p	6.71E−05	1.01E−04	**4.43E−05**	1.26E−05
π_t	**−0.011**	0.001	**−0.014**	0.004
γ_P	−4.90E−06	4.72E−06	**9.48E−07**	9.26E−08
γ_S	**−4.56E−08**	1.34E−08	−5.59E−09	4.74E−09
Detailing stock parameters				
Φ_P	**0.010**	0.005	**0.084**	0.015
Φ_I	**0.013**	0.001	**0.013**	0.003
β_0	**−2.22**	0.127	**−1.20**	0.381
β_1	**4.01E−05**	3.41E−06	**3.07E−05**	7.62E−06
Other parameters for error terms				
SD (ϵ)	**175.8**	9.67	**170.8**	37.6
SD (ς)	1		1	
SD (ζ)	**0.264**	0.020	**0.116**	0.031
SD (e)			**0.024**	0.004
Log likelihood	−2,490.8		−2,500.0	

Notes. Estimates shown in bold are significant at the 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 (in the two-chemical version).

Ishihara (2010). We also use their procedure to handle the initial conditions problem.[7]

5.1. Parameter Estimates
In our specification, 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. Let q_1 be the quality for Vaseretic, and let q_2 be the quality for Zestoretic and Prinzide. For identification reasons, we need to normalize q_1, the scaling parameters for the number of consumption experience signals, κ, and the intercept term for the utility of the outside good, α_0. We set $q_1 = 1$, $\kappa = 1/30,000$, and $\alpha_0 = 0$.

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[7] Because our focus is on identifying the informative and persuasive roles of detailing, instead of the relative importance of different sources of information, we do not include the data on clinical trials outcomes when estimating the structural model here. Ching and Ishihara (2010) show how to incorporate data on clinical trials in the learning process.

We estimate two versions of the model: One makes use of the comarketing identification argument and the other does not. More specifically, in the version that uses the comarketing identification argument, we assume that the demand side knows Zestoretic and Prinzide are made of the same chemical, and thus the information sets for the two brands are identical for all time periods. We refer to this version as the *two-chemical version*. In the version that does not use the comarketing identification argument, we assume the demand side does not know that Zestoretic and Prinzide are made of the same chemical, and thus the updating of each brand's information set is based solely on the past experience signals revealed from that brand. But we still maintain the assumption that the true mean qualities for Zestoretic and Prinzide are the same. We refer to this version as the *three-chemical version*.

Parameter estimates are reported in Table 3. Other than the persuasive effect of detailing (γ_P), most of the parameter estimates appear to be qualitatively

similar for both versions. 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. Most of the preference parameters are significant and have the right sign. Note that the price coefficient (π_p) is significant in the two-chemical version, but very small; moreover, it is insignificant in the three-chemical version. This is not surprising because Canada provides prescription drug coverage to patients who are 60 or older, and most patients who have hypertension are the elderly. We find that the effects of free samples (γ_S) are negative in both versions and significant in the three-chemical version. This suggests that some physicians may use free samples as a substitute of writing prescriptions. But we should note that the impact of free samples is very small.

The parameter that appears to be estimated very differently across these two versions is the persuasive effect of detailing (γ_P). It is negative and insignificant in the three-chemical version, whereas it is positive and significant in the two-chemical version. The result in the three-chemical version contradicts the conventional beliefs that the persuasive effect of detailing is present (see, e.g., *The Economist* 2003). Why is the estimated persuasive effect negative and insignificant in the three-chemical version? As discussed earlier, the identification of informative and persuasive effects in the three-chemical version is mainly achieved by the functional form assumption, and relies on one source of data variation—the diffusion patterns of brands. For this data set and the functional forms chosen here, the model can fit the diffusion patterns well without relying on the persuasive effect.[8]

Recall that the two-chemical version makes use of an extra source of data variation to help identify the model: The persuasive effect is identified by the correlation between the relative market shares of Zestoretic and Prinzide and their relative cumulative detailing efforts. After controlling for the persuasive effect, the informative effect is identified by the correlation between the relative market share of chem-

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[8] Note that this identification problem is not specific to the way we model informative detailing. We obtain similar results when we follow Narayanan et al. (2005) and model informative detailing as noisy signals of the true quality. The results are available upon request.

Table 4 Goodness of Fit: Mean Absolute Percentage Error

	Three-chemical	Two-chemical
Vaseretic	0.049	0.068
Zestoretic	0.077	0.083
Prinzide	0.234	0.146
Total	0.360	0.297

icals and the chemical specific detailing efforts. The more sensible estimate of the persuasive effect in the two-chemical version provides support for our comarketing identification assumption, and demonstrates that our estimation strategy uses the information in the data more accurately when estimating these two effects of detailing.

To show the goodness of fit of the model, we simulate 5,000 sequences of quantity demanded (expressed in terms of number of prescriptions) for Vaseretic, Zestoretic, and Prinzide, where each sequence corresponds to a simulated sequence of $(E[q \mid I(t)]^s)_{t=1}^T$ obtained from the demand model and Equation (3). We simulate the model from the inception date of Vaseretic (the first ACE inhibitor with diuretic). Because we do not observe the data between the inception dates of the drugs and the first period in our data, we need to impute the missing values of detailing, free sample, price, and size of the market. We follow the procedure explained in §4.4 of Ching and Ishihara (2010).

To investigate the goodness of fit for the two- and three-chemical versions, Table 4 reports the mean absolute percentage error by comparing the simulated demand and actual demand for three brands. It shows that the two-chemical version provides better overall goodness of fit (0.297 versus 0.360). This provides additional support for the two-chemical version, which assumes that the demand side knows which brands engage in a comarketing agreement. In Figure 2, we graphically show the goodness of fit for the two-chemical version. It shows that the model is able to fit the data quite well.

5.2. Quantifying the Importance of Informative and Persuasive Detailing

In this subsection, we examine the economic importance of informative and persuasive detailing. In particular, we are interested in investigating how the demand for each brand as well as the total market demand change when we eliminate (1) the informative function of detailing and (2) the persuasive function of detailing. We use the two-chemical version to conduct this simulation exercise.

We first examine the importance of informative detailing. The left-hand side panel of Figure 3 shows

Figure 3   Importance of Informative and Persuasive Detailing

Time (1 = March 1993; 72 = February 1999)
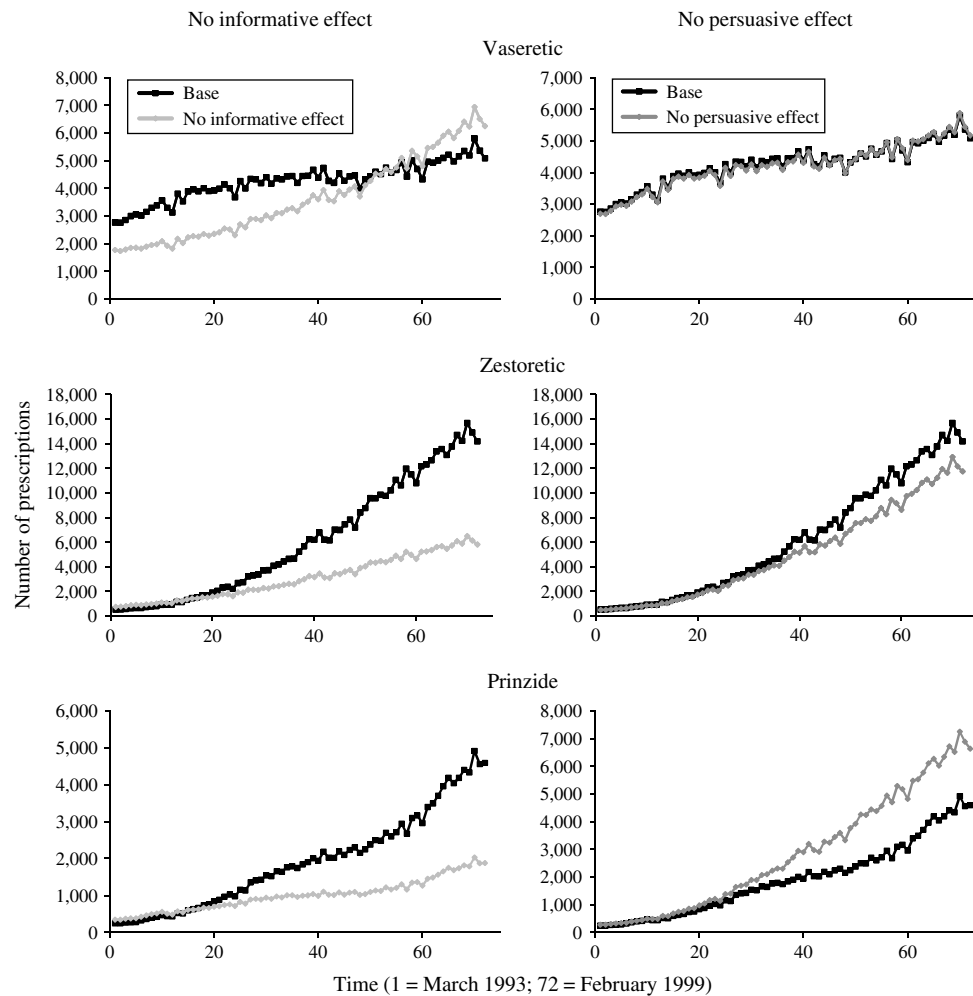
the results. To simulate the demand without informative detailing, we set $\beta_1 = 0$. We simulate 5,000 sequences of quantity demanded for Vaseretic, Zestoretic, and Prinzide with and without informative detailing and compare their average predicted quantities taking the data on detailing, free samples, and price as given. We see that the average predicted quantities decrease because of the elimination of informative detailing except at the later periods for Vaseretic. The main driving force 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. 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 prescriptions. Note that the time trend of the outside alternative is negative. As a result, the demand for the inside alternatives still increases over time in this counterfactual exercise. It turns out that the demand for Vaseretic without the informative function exceeds that under the base case in the later peri-

ods. This is because there are very few physicians who know Zestoretic/Prinzide has higher quality than Vaseretic. On the contrary, the magnitudes of the negative impact on Zestoretic and Prinzide increase over time. 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.

We next consider the importance of persuasive detailing. The simulation exercise is done in a similar fashion as above. To simulate the demand without persuasive detailing, we set $\gamma_P = 0$. The right-hand side panel of Figure 3 displays the results. It shows that the decrease in demand for Vaseretic is almost zero, and many physicians switch from Zestoretic to Prinzide, causing the demand for Zestoretic to decrease and the demand for Prinzide to increase. Interestingly, the total combined demand for Zestoretic and Prinzide has hardly changed.

Overall, our results show that even though the persuasive effect is statistically significant, and plays an

important role in determining the relative demand of brands that share the same chemical, it plays a very minor role for the demand at the chemical level—the diffusion patterns of chemicals are mainly explained by the informative effect. The reasons why the persuasive effect has very little influence on the demand at the chemical level is because its impact on physicians' expected utility is small relative to the impact due to the informative effect. However, conditioning on choosing a chemical being comarketed by more than one brand name, physicians' decisions on which brand to prescribe no longer depend on the informative role of detailing. Thus, the persuasive effect has a much stronger influence on the comarketing brands. It is important to note that our models do not assume the diffusion patterns of chemicals are mainly driven by the informative role of detailing a priori. For instance, the data could reveal that the persuasive effect is so strong that it explains not only the brand switching behavior for comarketing brands, but also most of the diffusion patterns at the chemical level.

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 comarketing agreement. Using the data on ACE inhibitor with diuretic in Canada, we find that both the informative and persuasive roles of detailing are statistically significant in this market. By simulating our model, we show that the persuasive role is mainly responsible for brand switching for brands that share the same chemicals. However, the persuasive effect plays a very small role in explaining the diffusion patterns at the chemical level—the informative role of detailing is mainly responsible for this.

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 comarketing agreement. This suggests that when they structure the details of a comarketing 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 comarketing agreement is endogenous. It is possible that the firm that decides to license the drug (i) may be 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 latter one could because our econometric specification essentially assumes away the potential heterogeneity in the efficiency of sales force. However, in our application, 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 comarket products and its implications on our identification argument will also be an important topic for future research.

Appendix. 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 (2010b). To use his method, we approximate manufacturers' detailing policy functions, and jointly estimate them together with the demand model. In our model, the state variables consist of $(E[q_k \mid I(t)], \sigma_k^2(t), M_{kt-1})\ \forall k$. In addition, we include an instrumental variable in the pseudo-detailing policy functions. We follow Ching and

Table A.1   Parameter Estimates for Pseudo-Detailing Policy Functions

	Three-chemical		Two-chemical	
	Estimates	SE	Estimates	SE
λ_{10}	**6.02**	2.20	**6.50**	1.41
λ_{11}	**3.52**	1.00	**2.54**	0.986
λ_{12}	−0.430	20.9	−4.01	4.10
λ_{13}	−8.96	10.0	**−13.9**	3.57
λ_{14}	3.30	57.0	5.44	32.0
λ_{15}	0.113	0.712	−0.006	0.141
λ_{20}	**7.21**	0.969	**7.24**	0.308
λ_{21}	14.47	32.9	−13.6	9.32
λ_{22}	**−226.0**	96.1	**146.5**	6.54
λ_{23}	−83.4	120.4	18.9	16.4
λ_{24}	**647.0**	301.8	**−383.8**	15.2
λ_{25}	0.027	0.111	0.027	0.041
λ_{30}	**12.9**	2.16	**10.3**	1.08
λ_{31}	144.6	103.8	**164.4**	5.91
λ_{32}	98.3	125.8	**−157.2**	7.54
λ_{33}	−1,732.9	1,260.8	**−293.4**	10.6
λ_{34}	111.3	395.4	**420.3**	17.7
λ_{35}	−0.244	0.712	**−0.297**	0.112
s.d.(ν)	**1.58**	0.097	**1.52**	0.025

Notes. Estimates shown in bold are significant at the 5% level. Brands (j):
1—Vaseretic (incumbent); 2—Zestoretic (entrant); 3—Prinzide (entrant).

Ishihara (2010) and define F_{jt} 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. The specifications of the pseudo-policy functions are discussed below. In Table A.1, we report the estimates for the pseudo-detailing policy functions that correspond to the demand-side estimates in Table 3.

In the two-chemical version, we assume the researcher knows that Zestoretic and Prinzide are made of the same chemical. Let us index Vaseretic, Zestoretic, and Prinzide as brand 1, 2, and 3, respectively. Also, let us index the chemical for Vaseretic as chemical 1 ($k = 1$), and the chemical for Zestoretic and Prinzide as chemical 2 ($k = 2$). Let us define the following variables:

$$\Delta u^q_{kk't} = E[u^q_{kt} \mid I(t)] - E[u^q_{k't} \mid I(t)],$$

$$E[u^q_{kt} \mid I(t)] = -\exp\left(-rE[q_k \mid I(t)] + \tfrac{1}{2}r^2(\sigma^2_k(t) + \sigma^2_\delta)\right).$$

Note that $E[u^q_{kt} \mid I(t)]$ is part of the expected utility that depends on $E[q_k \mid I(t)]$ and $\sigma^2_k(t)$; $\Delta u^q_{kk't}$ is the difference between this partial expected utility from choosing chemical k and k'.

Let $\mathbb{I}(\cdot)$ be an indicator function. We specify the pseudo-detailing policy function for Vaseretic ($j = 1$) as

$$\log D_{1t} = \lambda_{10} + (\lambda_{11} + \lambda_{13} \cdot M_{2t}) \cdot (1 - M_{1t}) \cdot |\Delta u^q_{12t}| \cdot \mathbb{I}(\Delta u^q_{12t} > 0)$$

$$+ (\lambda_{12} + \lambda_{14} \cdot M_{2t}) \cdot M_{1t} \cdot |\Delta u^q_{12t}| \cdot \mathbb{I}(\Delta u^q_{12t} < 0)$$

$$+ \lambda_{15} \cdot F_{1t} + \nu_{1t},$$

where ν_{jt} is a prediction error. The pseudo-detailing policy functions for Zestoretic and Prinzide ($j = 2, 3$) are specified as

$$\log D_{jt} = \lambda_{j0} + (\lambda_{j1} + \lambda_{j3} \cdot M_{1t}) \cdot (1 - M_{2t}) \cdot |\Delta u^q_{21t}| \cdot \mathbb{I}(\Delta u^q_{21t} > 0)$$

$$+ (\lambda_{j2} + \lambda_{j4} \cdot M_{1t}) \cdot M_{2t} \cdot |\Delta u^q_{21t}| \cdot \mathbb{I}(\Delta u^q_{21t} < 0)$$

$$+ \lambda_{j5} \cdot F_{jt} + \nu_{jt}.$$

In the three-chemical version, we assume the researcher does *not* know that Zestoretic and Prinzide are made of the same chemical. Let us index Vaseretic, Zestoretic, and Prinzide as brand 1, 2, and 3, respectively. Also, let us index the chemicals for Vaseretic, Zestoretic, and Prinzide as chemical 1, 2, and 3, respectively. For $j = 1, 2, 3$, define

$$k^*_j = \arg \max_{k \in \{1,2,3\} \setminus \{j\}} E[u^q_{kt} \mid I(t)].$$

We specify the pseudo-detailing policy function for brand j as

$$\log D_{jt} = \lambda_{j0} + (\lambda_{j1} + \lambda_{j3} \cdot M_{k^*_j t}) \cdot (1 - M_{jt}) \cdot |\Delta u^q_{jk^*_j t}| \cdot \mathbb{I}(\Delta u^q_{jk^*_j t} > 0)$$

$$+ (\lambda_{j2} + \lambda_{j4} \cdot M_{k^*_j t}) \cdot M_{jt} \cdot |\Delta u^q_{jk^*_j t}| \cdot \mathbb{I}(\Delta u^q_{jk^*_j t} < 0)$$

$$+ \lambda_{j5} \cdot F_{jt} + \nu_{jt}.$$

In this specification, each firm's detailing policy function depends on the strongest competitor's state. This simplifying approach offers the advantage that we do not need to increase the number of parameters. Yet the above specification still captures that firms care about the states of all the rivals in the sense that they need to find out who their strongest competitor is.

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