A Structural Model of Dynamic Competition in Advertising under Quality Uncertainty, with an Application to the Canadian ACE-inhibitor and Diuretic Market

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1 Introduction

The pharmaceutical industry is one of the most heavily advertised industries in North America. The expenditures on advertising is around 60% of that on R&D for the past five years, and increases fairly rapidlly over time. It was 12 billion dollars in 1997, and it became 15.7 billion dollars in 2000. The signifcance of the advertising activities has led the public to debate the roles of advertising in the prescription drug market. There are two major channels of pharmaceutical advertising: medical journal advertising and direct contact of physician (personal detailing).[1] If the main function of these advertising channels is to provide physicians with information (i.e., informative advertising), this should enhance competition and potentially improve welfare (Marshall[17], Telser[22], Nelson[20]). However, if their main role is to create "artifical" product differentiation or habit-formation (i.e., persuasuive advertising), (Chamberlin[5], Bain[3], Comanor and Wilson[8]), then the government should intervene and tighten the regulations on pharmaceutical advertising.

Due to this concern, there is a small but growing number of researchers who have studied the impact of advertising on the prescription drug market (Leffler[16], Hurwitz and Caves[14], Berndt et al.[4], Rizzo[21], Gonul et al.[13]). All these studies except Berndt et al. employ cross-market data to examine the nature of advertising. Both Leffler and Berndt et al. find evidence for informative and persuasive advertising. In particular, Berndt et al. finds evidence that advertising has long-lived impacts. Hurwitz and Caves examine advertising using a sample of drugs that faces generic competition. They conclude the presence of persuasive effects, but cannot rule out informative effects. Gonul et al. study an individual physician level data and confirms the informative role of advertising. Rizzo finds evidence that advertising lowers the price elasticity of demand and interpret this as evidence for persuasive advertising. However, his results are also consistent with informative advertising. As argued by Leffler, informative advertising may reduce the uncertainty about drug characteristics, and hence could also achieve the outcome of lowering price elasticity. These studies have provided many insights about how advertising affects demand in the prescription drug market. They also shed lights on policy issues regarding pharmaceutical marketing regulations. However, since all these studies use a

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[1] Direct-to-consumer (DTC) advertising has become the focus of public debates lately since the FDA loosens its regulatory constraints in 1997. However, expenditures on DTC is generally less than 25% of the total advertising expenditures in the US. In addition, it is not allowed in Canada.

reduced-form approach, their frameworks are not suitable for simulating effects of conuterfactual policy experiments.

Other than the impressive advertising activity, the prescription drug market is characterized by another feature: it often takes time for new drugs (either brand-name or generics) to penetrate the market. One explanation for this is that the public may be uncertain about the characteristics of the product. This is particularly relevant for new medicines (Lasser et al.[15]). Many adverse side effects are not found until the drugs are marketed. As a result, a few recent empirical studies formally introduced bayesian learning to model the prescription drug market (e.g., Crawford and Shum[9], Ching[6], Ching[7]). In general, the literature finds that learning plays an important role in explaining the slow diffusion of new drugs (both brand-name and generics). Crawford and Shum use a detailed physician level data and model individual level learning in a single-agent dynamic programming framework. In Ching[6][7], I use product level data and incorporate aggregate learning about generic qualities into a dynamic oligopoly problem, using a multi-agent dynamic programming framework. Although both studies use a structural approach and are capable of simulating policy experiments, they abstract away advertising, which plays an important role in this market.

This paper will overcome the shortcomings of the previous works and provide a new framework for the empirical analysis of the prescription drug market. The main contribution is that I tie together learning and advertising in an empirical dynamic oligopoly model. The model allows advertising to be both informative and persuasive. In my data set, I observe that when a drug is first introduced, its advertising expenditures are higher than its current revenue in some periods. To capture this and the long-lived effect of advertising, I model firms maximize their total expected discounted profits, and they need to use advertising to build a stock of physicians, who are familiar with their drug characteristics. Since a stock of informed physicians may take time to establish, it could be rational for a forward-looking firm to advertise more than its current revenue.

Other than being able to conduct policy experiments, modeling firm's behavior in an equilibrium model also provides a new way to disentangle and measure informative and persuasive advertising, even when only product level data is available. The identification is achieved by assessing firm's optimal advertising policy as a function of the perceived qualities of all products in the market. In particular, I argue that if advertising is primarily informative, a firm with a higher perceived quality drug should have a stronger incentive to advertise. Therefore, as

the relative perceived quality of a product improves over time via learning (as reflected from the increase in its market share), its manufacturer should advertise more relative to other competitors with lower perceived qualities. On the other hand, if advertising is primarily persuasive, the incentive to advertise across firms should be relatively symmetric. Consequently, all firms should advertise relatively equally even if their market shares vary due to quality differences.[2]

The model will be estimated using data from a Canadian prescription drug market – ace-inhibitor and diuretic. One advantage of implementing the model in Canada is that it has price regulations. The Patented Medicine Price Review Board restricts Canadian prices of patented drugs to be below the medium prices of G7 countries. Evidence suggests that firms in Canada are facing a binding constraints on average (Elgie[11]). Hence, it seems fair to assume that prices are exogeneous in Canada. This allows me to focus on modeling the effect of advertising in an equilibrium model.

The rest of the paper is organized as follows. Section 2 provides some background on the Canadian pharmaceutical industry, and the ACE-inhibitor and diuretic market. Section 3 describes the industry model. Section 4 describes the estimation strategy.

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[2] This is related to studies that have attempted to measure the content of advertising in other markets (e.g., Telser[22], Milyo and Waldfogel[19], Erdem and Keane[12], Ackerberg[2][1]).

2 Backgroud

2.1 Canadian Pharmaceutical Industry

With respect to prescription medicines, Canada's system of health insurance covers only medications received as part of institutional care (e.g., in hospital), and does not include drugs that are prescribed in the community. Unlike necessary hospital and medical care, which do fall under the Canada Health Act and are publicly-financed, multiple-payers are involved in the financing of prescription medicines. Payers include governments through pharmacare programs, hospitals, private insurers including insurance companies, employers and unions, and patients paying out-of-pocket.

The majority of Canadians have some form of coverage for prescription medicines. In 1995, it is estimated that 88 per cent of Canadians had coverage: 62 per cent were covered under private plans, 19 per cent under provincial plans, and 7 per cent were covered under both. Of the 12 per cent of the population without any drug coverage, more than half were employees and their dependents whose employers do not provide a supplementary drug benefit plan. Fewer than four per cent of Canadians without access to a drug benefit plan were self-employed entrepreneurs and their dependents, and two percent were without employment and did not qualify for government or private plans.

Provinces subsidize the cost of prescription medicines for at least some sectors of the population, most notably seniors and social assistance recipients. Four provinces have some form of universal program, but the benefits are usually linked to an individual's ability to pay through the application of copayments and deductibles. The federal government pays for drugs for specific groups within its jurisdiction, e.g., First Nations and veterans. Private sector plans are mostly offered through insurance companies and by employers as employee benefits.

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.

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The PMPRB maintains a comprehensive database on manufacturers' prices for patented medicines. As part of its responsibilities for monitoring the prices of patented medicines, the PMPRB has developed the Patented Medicine Price Index (PMPI).

According to PMPRB Guidelines, the prices of most new drugs may not exceed the maximum price of other drugs that treat the same disease. The introductory prices of "breakthrough" drugs may not exceed the median of the foreign prices of the drugs (from G7 countries). A PMPRB report (Elgie[11]) mentions that Canadian prices of patented drugs, relative to prices in other G7 countries, have declined from 20% higher than the medium in 1987, to about 10% below the medium in 1995-2000.

2.2 ACE-inhibitor and diuretic

Now I turn to discuss the market of ACE-inhibitor and diuretic, which treats hypertension. ACE-inhibitor (Angiotensin Converting Enzyme Inhibitor) works by limiting production of a substance that promotes salt and water retention in your body. Diuretic prompts your body to produce and eliminate more urine, which helps in lowering blood pressure. This class of combination drugs are usually not prescribed until therapy is already under way.

2.2.1 Overview of the Data

Data sources for this study comes from IMS Canada, a firm specializes in collecting sales and advertising data for the Canadian pharmaceutical industry. The revenue data is drawn from their Canadian Drugstore and Hospital Audit (D&H), the number of prescriptions is drawn from their Canadian Compuscript Audit (CCA), the advertising data (advertising expenditures, number of detail minutes and number of sample packages) are drawn from their Canadian Promotion Audit (CPA). Although D&H does not include purchases made by governmet, mail order pharmacies, nursing homes or clinics, IMS believes that it covers about 90% of the total sales.

The data set contains monthly data from March 1993 to February 1999. There are two drugs in the market – Zestoretic and Vaseretic. Both of them are present throughout the sample period. Treating product/quarter as one observation, total sample size is 144. 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, but it signed a co-marketing liscensing agreement with AstraZeneca. Although Merck also markets lisinopril hydrochlorothiazide, under the brand-name Prinzide, it has spent minimal marketing efforts on this brand in Canada. Canada sales of Prinzide is only about 25% of Zestoretic. It is not clear why Merck liscensed its patented product to a rival. However, liscensing among brand-name companies are quite common in the pharmaceutical industry. Investigating the benefits of this contractual arrangement is beyond the scope of this paper, though it is an important research area. Since Merck is not active in marketing Prinzide, for simplicity, the equilibrium model will assume Merck is a single-product firm and only market Vaseretic.

I now present an overview of the data. I first note that on average less than one percent of the sales are from the Hospital purchases. Due to the dominance of the drugstore market, I will only model this segment of the market and ignore how hospitals reach their purchase decisions. In figure 1 I plot market shares of Vaseretic and Zestoretic (Prinzide is not in the figure). Being the first in this market, Vaseretic controlled more than 80 percent of the market at the beginning of the sample, while Zestoretic's share was only about 10 percent. It took Zestoretic more than two years before it overtook Vaseretic's sales. though Zestoretic has a more favorable side-effects profile, The sales of Zestoretic continued to grow while Vaseretic's sales gradually declined. By the end of the sample in February 1999, Zestoretic captured nearly 80 percent of the market, and Vaseretic had merely 20 percent.

Although Vaseretic's share declined over time, its actual sales grew slowly and steadily from 2500 prescriptions to 4500 prescriptions, as shown in figure 2. Zestoretic's sales grew at a much higher rate, it increased from around 300 prescriptions to more than 14000 prescrptions. The sales trend of Zestoretic is remarkable, and illustrates the slow diffusion stylized fact observed in this industry.

An interesting pattern occurs in the advertising behavior of the two products over time. As shown in figure 3, Advertising expenditures on these two products were roughly the same for the first 30 months. But for the later period, Zestoretic on average advertised more than Vaseretic. It appears that there is a positive correlation between market share and advertising. However, this does not necessarily imply advertising raises the demand for a product (i.e., persuasive advertising). If such a causal relationship is present and strong, why would Vaseretic reduce its marketing effort later in the period? The observed advertising behavior could potentially be

explained in terms of informative advertising and learning. If a firm learns that its own product quality is superior (inferior) to its rival's, it will have stronger (less) incentive to disseminate this information to the demand side by informative advertising.[3]

Figure 4 also illustrates that the inital advertising expendiures are very high relative to the revenue for Zestoretic. There were even a few observations, which shows advertising expenditures were above revenue. This type of advertising behavior is clearly contradicted to static equilibrium models, where firms maximize their current profits. However, it is consistent with a model where firms are forward-looking and advertising has long-lived effect.

To capture the observations discussed above, I incorporate informative (and persuasive) advertising to a dynamic oligopoly model, where firms maximize their total discounted expected profits. I now turn to explain the model in details.

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[3] This kind of advertising behavior was observed in the US anti-ulcer market when Zantac's sales overtook Tagamet's (Berndt et al.[4]).

3   The Model

The model describes a finite-horizon discrete-time industry starting from the period when a new drug is launched. The industry structures are represented by states that summarize all currently available information relevant to current and future payoffs. There are three types of agents: physicians, firms, and a public agency (Health Canada). There are two types of products: inside goods that represent the products that use similar chemical compounds (so-called me-too drugs), and an outside good that represents its substitutes (0).

Product characteristics can be distinguished as p_j, q_j, and ξ_j, $j = 1, 2$, where p_j is the price of product j, q_j is the mean quality level of product j, and ξ_j represents some unobserved product characteristics (e.g., return policies or promotion effort). All agents in the model are perfectly informed about p_j and ξ_j, but are imperfectly informed about the drug's mean quality level, q_j.

There are three stages in each period. In the first stage, firms access the public information set and simultaneously choose advertising expenditures for their drugs. If a physician is contacted by firm j's advertising activities, he will have the most current information about product j. Otherwise, his information set will simply be the initial prior. In the second stage, each physician makes his prescribing decision based on his information about the drugs, and his patients consume the prescribed drugs accordingly. In the third stage, patient experience signals about the products are revealed to the public, and the public agency use these experience signals to update the public information set about the qualities of the products.

The equilibrium used here is Markov-Perfect Nash Equilibrium (MPNE). MPNE, as defined by Maskin and Tirole[18], restricts the subgame perfect equilibria to those where actions are a function only of payoff relevant state variables, and hence eliminates many of the vast multiplicity of subgame perfect equilibria that would normally exist in this type of model. Firms maximize their expected discounted value of profits conditional on their expectations about the evolution of the perceived mean quality levels and the perceived variances. Equilibrium occurs when all firms' expectations are consistent with the process generated by the optimal policies of their rivals.

The model can be broken up into three components: (1) learning about product qualities, (2) physician's problem, and (3) firms' problem. I now describe them in turn.

3.1 Learning about Product Qualities

A drug is an experienced good. Consumption of a drug provides information about its quality. But each patient i's experience of the quality of drug j at time t ($\tilde{q}_{ijt}$) may differ from its mean attribute level q_j. The difference between $\tilde{q}_{ijt}$ and q_j could be due to the idiosyncratic differences of human bodies in reacting to drugs. For instance, when different patients take the same pain-relief drug, the time that they need to wait before their headache disappears may vary, simply because they have different metabolic rates. Even when a patient takes the same drug at different points of time, the waiting time may still change, as the body conditions may vary (it may depend on how much sleep one had, how much one ate, how much alcohol one recently drank, etc.). I refer to this variation in effectiveness as "experience variability".

The experience variability may be expressed as

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

where

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

$\tilde{q}$ stands for the quality level that a patient actually receives, t indexes time ($t = 1, \cdots, T$); and i indexes the patients ($i = 1, \cdots, M$). The error term associated with the experience variability (δ_{ijt}) is treated as an *i.i.d.* random variable, with zero mean and a variance that is constant over time.

I assume that the public agency learn about the mean attribute levels in a Bayesian fashion. The signal noise δ_{ijt}, and the initial prior on q_j are assumed to be normally distributed.

When a new drug j is first introduced, the initial prior is given by:

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

The public agency updates the public information set at the end of the period (i.e., until all experience signals are revealed in that period). According to the Bayesian rule (DeGroot[10]), the expected quality is updated as follows:

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

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where $\bar{q}_{jt}$ is the sample mean of all the experience signals that are realized in period t.[4] $\beta_j(t)$ is a Kalman gain coefficient, which is a function of experience variability (σ_δ), perceived variance $(\sigma_j^2(t))$, and the quantity sold at time t (n_{jt}) and the proportion of experience signals revealed to the public (κ), can be expressed as:

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

$\sigma_j^2(t)$ is the perceived variance of q_j, given the information available to the public at the beginning of time t. The β_j coefficient can be interpreted as the weights that the patients and the firms attach to the information source in updating their expectation about the levels of q_j. Each time $\sigma_j^2(t)$ is updated, the β_j coefficient will be updated accordingly.

The perception variance at the beginning of time $t+1$ is given by (DeGroot[10]):

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

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

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

Equations (6) and (7) suggest that the perceived variance associated with q_j (and consequently the perceived variance of q_{ij}) will be lower, ceteris paribus: (a) the more precise the information gained via consumption experience (i.e., the lower the experience variability of the product); (b) the more experience the public has about generic drugs.

Equation (6) implies that, after observing a sufficiently large number of experience signals for a product, the patients and the firms will learn about q_j, at any arbitrary precise way (i.e., $\sigma_j(t) \to 0$ and $E[q_j|I(t)] \to q_j$ as the number of signals received grows large).

3.2 Physicians' problem

The demand system is obtained by aggregating a discrete choice model of individual physician's behavior. There is a continuum of physicians with measure one. I consider physicians who maximize the current expected utility of his patients. Each physician h sees m patients in each period, and he chooses a drug j among J possible alternatives for each patient i. Alternatives are

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

defined to be mutually exclusive and a physician's choice may vary across patients due to their heterogeneity. The choice set J includes inside goods ($j = 1, ..., N$), and an "outside" alternative (0). The inside alternatives use similar chemical mechanisms (so-called mee-too drugs). The outside alternative includes other substitutes, which could treat the same disease.

Let $I(t)$ and $I_h(t)$ denote the public information set and physician's h information set at time t. Associated with physician h's choice for patient i at time t is a current period expected utility $E[U_{hij}(t)|I_h(t)]$, where $E[.]$ is the mathematical expectation operator. The specific form of the expected utilities $E[U_{hij}(t)|I_h(t)]$ will be introduced in the next section. Note that due to the heterogeneity of patients' preferences, it could be that $E[U_{hkj}(t)|I_h(t)] \neq E[U_{hlj}(t)|I_h(t)]$ for $k \neq l$. A physician's choice is modeled as a two-stage nested process, where he chooses between inside good and outside good first, and then choose an alternative among the inside goods. His objective is to maximize the current period expected utility:

$$E[\sum_{j \in J} U_{hij}(t) d_{hij}(t)|I_h(t)], \tag{8}$$

$d_{hij}(t) = 1$ indicates that alternative j is chosen by physician h for patient i at time t and $d_{hij}(t) = 0$ indicates otherwise. Note that $\sum_{j \in J} d_{hij}(t) = 1$.

I assume that the utility of consuming a drug can be adequately approximated by a quasi-linear utility specification, additively separable in a concave subutility function of drug return, and a linear term in price and advertising expenditures. I assume an exponential specification for the subutility function (CARA). Utility of prescribing a drug at time t is given by the following expression:

$$u_{hijt} = -exp(-r\tilde{q}_{ijt}) - \alpha p_{jt} + \gamma \chi_{hjt} + \xi_{jt} + \zeta_{ikt} + e_{ijt}, \tag{9}$$

where u_{hijt} is the utility for physician h conditional on patient i and choice of drug j, at time t; p_{jt} is the price for product j at time t; χ_{hjt} equals one if physician h has current information about drug j at time t, and zero otherwise;[5] r is the risk aversion parameter; α is the utility weight for price; γ is the coefficient for persuasive advertising; ξ_{jt} represents the mean valuation of product j's unobserved demand shock at time t; $(\zeta_{ikt} + e_{ijt})$ represents the distribution of preferences about this mean; k indexes nest (i.e., inside good or outside good). The parameters α, ζ_{ikt} and e_{ijt} are unobserved to the econometrician but observed to the physicians when they

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[5] Having the current information means that the physician has been contacted by firm j's marketing force either at time t or before. I capture persuasive advertising by allowing the indicator function χ_{hjt} to enter the utility function.

make their prescribing decisions. Note that $\tilde{q}_{ijt}$ is not observed to the physician or patients when prescribing decisions are made. It is observed to the patients only after they consume the drug, but remains unobserved to the econometrician. It should be emphasized that utility is a function of experienced quality levels ($\tilde{q}_{ijt}$) but not the true mean quality level (q_j).

It is assumed that physicians in the model can measure drug qualities according to a fixed scale. (For example, a consumer can measure quality as how long he needs to wait before the drug becomes effective to relieve his headache. Or, he can measure quality as how long his stomach pain would be suppressed after taking the drug.[6]) Hence, one can represent patients' risk averse behavior with respect to $\tilde{q}$ by modeling their utility functions to be concave in $\tilde{q}$. The physicians are risk averse, risk neutral or risk seeking as $r > 0$, $r = 0$ or $r < 0$, respectively with respect to $\tilde{q}$.

If a physician is exposed to firm j's advertising activity at time t, he will have the most current information about drug j and his expected utility will be:

$$E[U_{hijt}|I_h(t), \chi_{hjt} = 1] = exp(-rE[q_j|I(t)] + \frac{1}{2}r^2\sigma_j(t)^2) - \alpha p_{jt} + \gamma + \xi_{jt} \tag{10}$$
$$+\zeta_{ikt} + e_{ijt},$$

However, if a physician is not exposed to the firm j advertising activity at time t, his information about drug j will simply be the initial prior. His expected utility becomes:

$$E[U_{hijt}|I_h(t), \chi_{hjt} = 0] = exp(-r\underline{q} + \frac{1}{2}r^2\underline{\sigma}^2) - \alpha p_{jt} + \xi_{jt} + \zeta_{ikt} + e_{ijt}. \tag{11}$$

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

The measure of physicians, who have updated information about product j at time t ($M_j(t)$), depends on the advertising expenditures of firm j and potentially $M_j(t-1)$, i.e., $M_j(t) = f(A_{jt}, M_j(t-1))$. I assume that the relationship can be specified as:

$$f(A, M) = \frac{exp(\beta_0 + \beta_1 A + \beta_2 M) - exp(\beta_0)}{1 + exp(\beta_0 + \beta_1 A + \beta_2 M)}. \tag{12}$$

This specification implies that the measure of informed physicians is zero (i.e., $M_j(t) = 0$) when $A_{jt} = 0, M_j(t-1) = 0$. This will ensure that the set informed physicians is the same as the set of

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[6]Obviously, drug qualities are multi-dimension. Implicitly, I 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.

physicians influenced by persuasive advertising. Assume that physicians are randomly selected to obtain current information about the product, and assume that there are two drugs. Then there are four types of physicians in each period: (i) physicians who have current information about both drugs ($\rho_1 = M_1 M_2$); (ii) physicians who have current information about drug 1 only ($\rho_2 = M_1(1 - M_2)$); (iii) physicians who have current information about drug 2 only ($\rho_3 = (1 - M_1)M_2$); (iv) physicians who do not have current inofrmation at all ($\rho_4 = (1 - M_1)(1 - M_2)$). Conditioning on each type of physicians, one can derive the choice probailities using standard nested logit formula. The aggregate choice probability will simply be the weighted average of these four types of conditional probabilities, using ρ_j as the weight accordingly.

Equations (9)-(11) apply only to the inside alternatives. In each period, patients may also choose an outside alternative that is not included in my analysis (i.e., other non-bioequivalent drugs). I assume the expected utility associated with the outside alternative to be a time trend plus a stochastic error component:

$$E[U_{i0t}|I(t)] = \phi_0 + \phi_t t + \tilde{e}_{i0t}, \tag{13}$$

where $\tilde{e}_{i0t} = \zeta_{it} + e_{i0t}$.

The presence of the outside alternative allows us to model aggregate demand for the brand-name drug and generic drugs as a function of prices and product characteristics. In the absence of an outside alternative, patients are forced to choose from the inside goods and demand depends only on differences in prices. Therefore, a general increase in prices will not decrease aggregate output. Furthermore, when there is only one firm in the market the monopolist can keep raising its price without losing any patients.

3.3 Firm's problem

In this section I discuss how firms compete. Since my focus is to investigate the role of advertising in the pharmaceutical market, I will not model firm's entry decision in this paper (i.e., their decision to start doing R&D). As discussed in the introduction, it is likely that prices are exogeneously determined due to price regulations in Canada. Therefore I assume firms only choose their advertising expenditures to maximize their total discounted profits.

The model takes the number of firms that decides to enter as given. It contains two stages every period. In the first stage, the nature determines whether a potential entrant can enter

the market. In the second stage, firms (including a new entrant if there is one) simultaneously choose their advertising expenditures to maximize the expected discounted value of their net future profits.

I denote (s_j, s, S) be the state variable faced by firm j, where s_j is firm j's own triple $(E[q_j|I(t)], \sigma_j(t), M_{jt})$; s is a vector containing the number of firms at each possible state triple; S is the potential size of the market.[7]

Intuitively, s represents the industry structure. The Bellman's equation for incumbent firms can be written as:

$$V(s_{jt}, s_t, S(t)) =$$
$$\sup_{A_{jt} \geq 0} [\pi(s_{jt}, s_t, S(t), A_{jt}, A_{-jt}) + \beta\{P(\chi_{et} = 1)E[V(s_{jt+1}, s_{t+1}, S(t+1))|s_{jt}, s_t, A_{jt}, A_{-jt}, \chi_{et} = 1)]$$
$$+ P(\chi_{et} = 0)E[V(s_{jt+1}, s_{t+1}, S(t+1))|s_{jt}, s_t, A_{jt}, A_{-jt}, \chi_{et} = 0)]\}], \tag{14}$$

where

$$\pi(s_{jt}, s_t, S(t), A_{jt}, A_{-jt}) = p_{jt}S(t)Pr(j|s_{jt}, s_t, A_{jt}, A_{-jt}); \tag{15}$$

$\chi_{et} = 1$ means there is one entrant, 0 otherwise. The perception variance and the expected quality level evolves stochastically according to the bayesian updating formulas. I have described in details how to solve for the expected value function in Ching[6]. Similar techniques will be used here. To ease the computational burden of solving the Markov-perfect Nash equilibrium, I also make several simplifying assumptions: (i) the uncertainty about each firm's quality is completely resolved in the terminal period T; (ii) the entry probability of a potential entrant increases over time; and (iii) there exists a period $\bar{t}$ in which all potential entrants will enter.

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[7] To obtain the potential size of the market, I use the total sales of all ace-inhibitor and hydrocholorthiazide.

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4   Estimation

In this section I discuss how to estimate the preference parameters using a new likelihood based method which involves approximating the true advertising policy function.

The potential endogeneity problem of advertising expenditures is the main concern in estimating this model. If producers know the values of the unobserved product characteristics, $E[q|I(t)]$ and ξ, it is likely that prices are correlated with them. If this correlation exists and the econometrician ignores it when estimating the learning model, the estimated advertising effect may be biased.

In models of product differentiated markets where the demand system is obtained by aggregating the individual demands, this simultaneity problem is further complicated by both the individual's discrete choice set and interaction of preferences distribution and product characteristics. These makes the market level demand a complicated nonlinear function of product characteristics, including the unobserved characteristics. Hence, the market level demand is a complicated nonlinear function of the structural disturbances.

4.1   Maximum Likelihood: Approximation Approach

In Ching[7], I develop a new estimation method to handle the simultaneity problem in this class of discrete choice product differentiation market. I will apply this method to estimate the model here. To understand the how the estimation strategy works, it would be useful to review the classical full information maximum likelihood approach (FIML). In this approach, the econometrician needs to model the oligopolistic supply side explicitly, and derives an advertising policy function that depends on observed and unobserved product characteristics, and other state variables. Then the econometrician forms the joint likelihood function of a sequence of advertising vectors and quantity vectors, and consistent estimates of the parameters can be obtained by using FIML. Full information maximum likelihood estimation involves an iterative process, solving numerically the supply-side multi-agent dynamic programming problem for a given set of parameter values, then evaluating the likelihood function, etc., until the likelihood is maximized. However, as the demand involves learning, the full solution of the multi-agent dynamic programming problem is very computationally demanding. Hence, in this context FIML is typically infeasible except for some very simple static supply-side models. In addition, even if

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the econometrician has the computation power to apply FIML, biased estimates may still result if the equilibrium model is misspecified.

Instead of generating an advertising policy function by solving a supply-side model explicitly, my estimation approach approximates the advertising policy function by expressing it as a polynomial of the state variables. As explained above, $E[q|I(t)]$ and ξ_t may be correlated with A_t, where $A_t = (A_{1t}, A_{2t})$. In addition, A_{jt} may also depend on $(\sigma_j(t), M(t), t)$ because they affect the equilibrium prices via the oligopolistic equilibrium. Hence, the true advertising policy function should be a function of $((\xi_{jt}, E[q_j|I(t)], \sigma_j(t), M_j(t))^2_{j=1}, S(t))$. Let $a_j(.)$ denote the "true" advertising policy function for firm j. Then,

$$A_{jt} = a_j((\xi_{jt}, E[q_j|I(t)], \sigma_j(t), M_j(t)), (\xi_{-jt}, E[q_{-j}|I(t)], \sigma_{-j}(t)), M_{-j}(t), S(t))\nu_{jt}, \qquad (16)$$

where ν is a prediction error term, which could capture some productivity shocks that are not modeled explicitly. Taking log on both sides of Equation (16), I obtain,

$$\begin{aligned} log(A_{jt}) &= log(a_j((\xi_{jt}, E[q_j|I(t)], \sigma_j(t), M_j(t)), (\xi_{-jt}, E[q_{-j}|I(t)], \sigma_{-j}(t)), M_{-j}(t), S(t)) \\ &+ log(\nu_{jt}). \end{aligned} \qquad (17)$$

To approximate $log(a_j(.))$, I use a polynomial series estimator, that is, I project A_{jt} to a polynomial of $(\xi_{jt}, E[q_j|I(t)], \sigma_j(t), M_j(t)), (\xi_{-jt}, E[q_{-j}|I(t)], \sigma_{-j}(t), M_{-j}(t)), S(t))$. Assuming that the prediction error, ν_{jt}, is distributed log normal, I obtain the conditional likelihood of observing A_t,

$$f_a(A_t|(\xi_{jt}, E[q_j|I(t)], \sigma_j(t), M_j(t))^2_{j=1}, S(t); \theta_s), \qquad (18)$$

where θ_s is the vector of parameters.

Let θ_d denotes a set of demand-side parameters. I assume the quantity output, n_{jt}, can be expressed as,

$$n_{jt} = S(t)Pr(j|A, (\xi_{jt}, E[q_j|I(t)], \sigma_j(t), M_j(t))^2_{j=1}; \theta_d) + \eta_{jt}, \qquad (19)$$

where η_{jt} represents the measurement error. It should be emphasized that the main sources of uncertainty for the quantity demanded should come from the structural disturbances: $E[q|I(t)]$ and ξ_t. I denote $f_n(n_t|A_t, (\xi_{jt}, E[q_j|I(t)], \sigma_j(t), M_j(t))^2_{j=1}; \theta_d)$ as the likelihood of observing n_t conditional on $(A_t, (\xi_{jt}, E[q_j|I(t)], \sigma_j(t), M_j(t))^2_{j=1})$.

The joint likelihood of observing (n_t, A_t) is simply the product of $f_n(n_t|A_t, .)$ and $f_a(A_t|.)$, that is,

$$l(n_t, A_t|(\xi_{jt}, E[q_j|I(t)], \sigma_j(t), M_j(t))_{j=1}^2; \theta_d, \theta_s) = \qquad (20)$$

$$f_n(n_t|A_t, (\xi_{jt}, E[q_j|I(t)], \sigma_j(t), M_j(t))_{j=1}^2; \theta_d) f_a(A_t|(\xi_{jt}, E[q_j|I(t)], \sigma_j(t), M_j(t))_{j=1}^2, S(t); \theta_s).$$

Now note that $\sigma_j(t)$ is a function of $\{n_{j\tau}\}_{\tau=0}^{t-1}$ (see (7)). Therefore, one can rewrite (20) as,

$$l(n_t, A_t|(\xi_{jt}, E[q_j|I(t)], \sigma_j(t), M_j(t))_{j=1}^2; \theta_d, \theta_s) = \qquad (21)$$

$$l(n_t, A_t|(\xi_{jt}, E[q_j|I(t)], \{n_{j\tau}\}_{\tau=0}^{t-1}, M_j(t))_{j=1}^2; \theta_d, \theta_s).$$

For each market, the likelihood of observing $n = \{n_t\}_{t=0}^T$ and $A = \{A_t\}_{t=0}^T$ is,

$$L(n, A|\{\xi_\tau, E[q|I(\tau)], M(\tau), S(\tau)\}_{\tau=0}^T; \theta_d, \theta_s) = \qquad (22)$$

$$\prod_{t=0}^T l(n_t, A_t|(\xi_{jt}, E[q_j|I(t)], \{n_{j\tau}\}_{\tau=0}^{t-1}, M_j(t))_{j=1}^2; \theta_d, \theta_s).$$

But $(\xi_t, E[q|I(t)])$ are unobserved to the econometrician and therefore must be integrated over to form the unconditional sample likelihood for (n, A). Evaluating such an integral numerically is very difficult. It involves high order integrals because $E[q|I(t)]$ is autocorrelated. I resolve this problem by using the method of simulated maximum likelihood. The details of the simulation procedures are similar to Ching[7].

4.2 Identification

The identification arguments to distinguish between persuasive and informative advertising outlined in the introduction involves using the supply side behavior. It should be noted that the estimation strategy used here does not incorporate the supply side. Therefore, it is important to see how we achieve the identification.

Suppose that learning is completed in the long run. The steady state level of market shares difference identifies the difference in true qualities after controlling the advertising levels. (The advertising levels will determine the stocks of physicians, who are influenced by informative and persuasive advertising.)

The observed rate of diffusion helps pinning down the rate of learning (i.e., $r, (\underline{q}, \underline{\sigma}_j), \sigma_\delta$) and the rate of building up an informed physician stock (i.e., $f(A, M; \beta)$). A Bayesian learning

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model implies that the rate of learning will diminish with the cumulative sales. Therefore if every physician is well-informed about the current public information set, the slow diffusion rate on demand will typically be fairly steep at the beginning and then slow down. Adding the stock of informed physicians to the model helps slowing down the implied diffusion rate initially and makes the model more flexible in fitting the diffusion pattren. The persuasive advertising term (i.e., γ) increases the flexibility of the implied diffusion pattern further.

Another subtle identification of $f(A, M; \beta)$ relies on the empirical fluctuation of the consumption path. In bayesian learning the variance of $E[q_j|I(t)]$ is large initially and then reduces over time as it converges to the true q_j. Again, if every physician is well-informed, the empirical variance of the consumption path should also appears to reduce over time. As shown in figure 2, this is not the case for Zestoretic. Instead, the consumption path for Zestoretic was quite smooth when it just entered the market, then its empirical variance increased with the demand. Such empirical fluctuation pattern helps identifying the rate of accumulating the stock of physicians. According to the model, only informed physicians have $E[q_j|I(t)]$ enters their utility function. Hence, small variance of the inital observed consumption path suggests that it takes time to build a stock informed physicians.
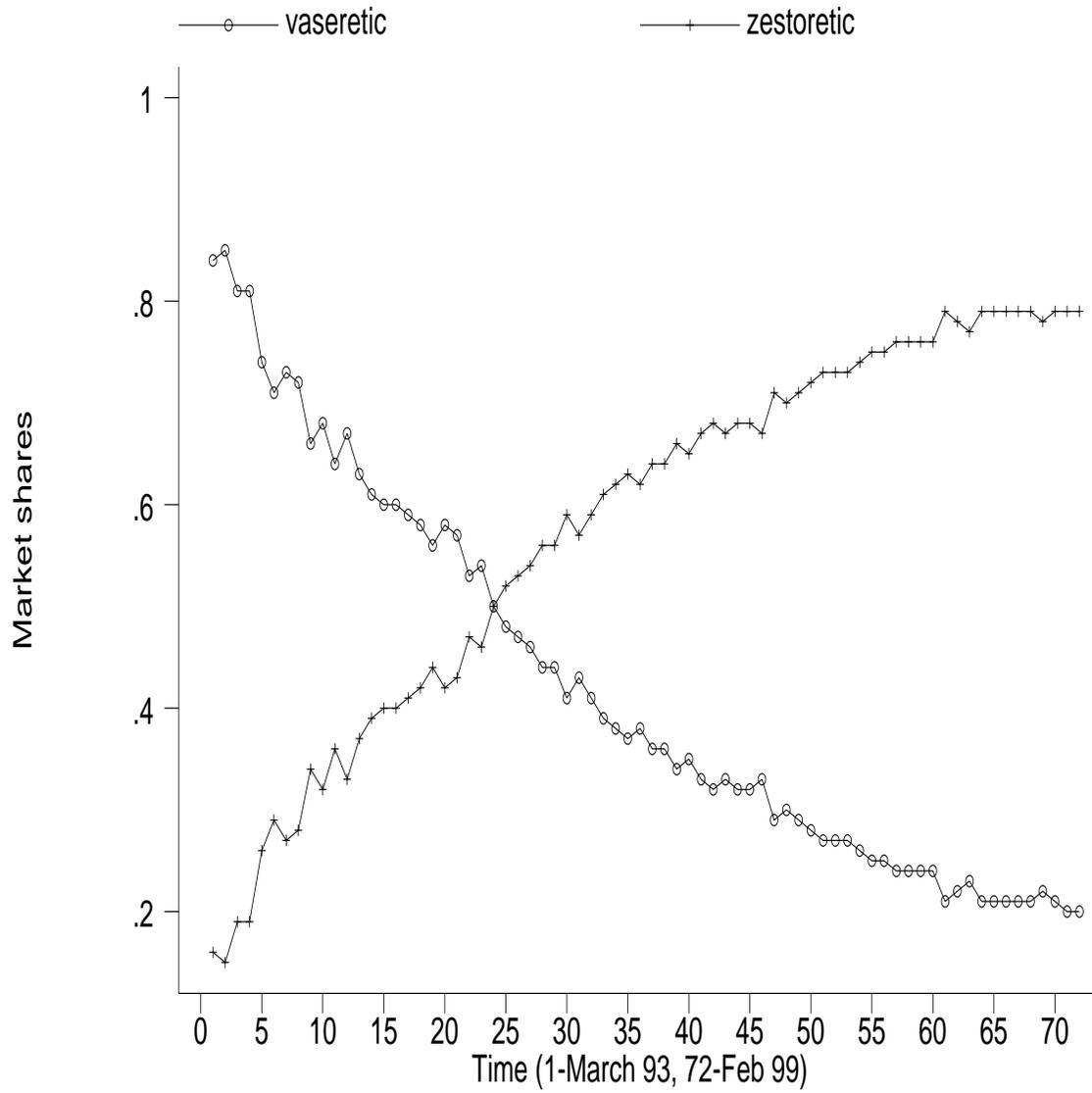
5   Conclusion
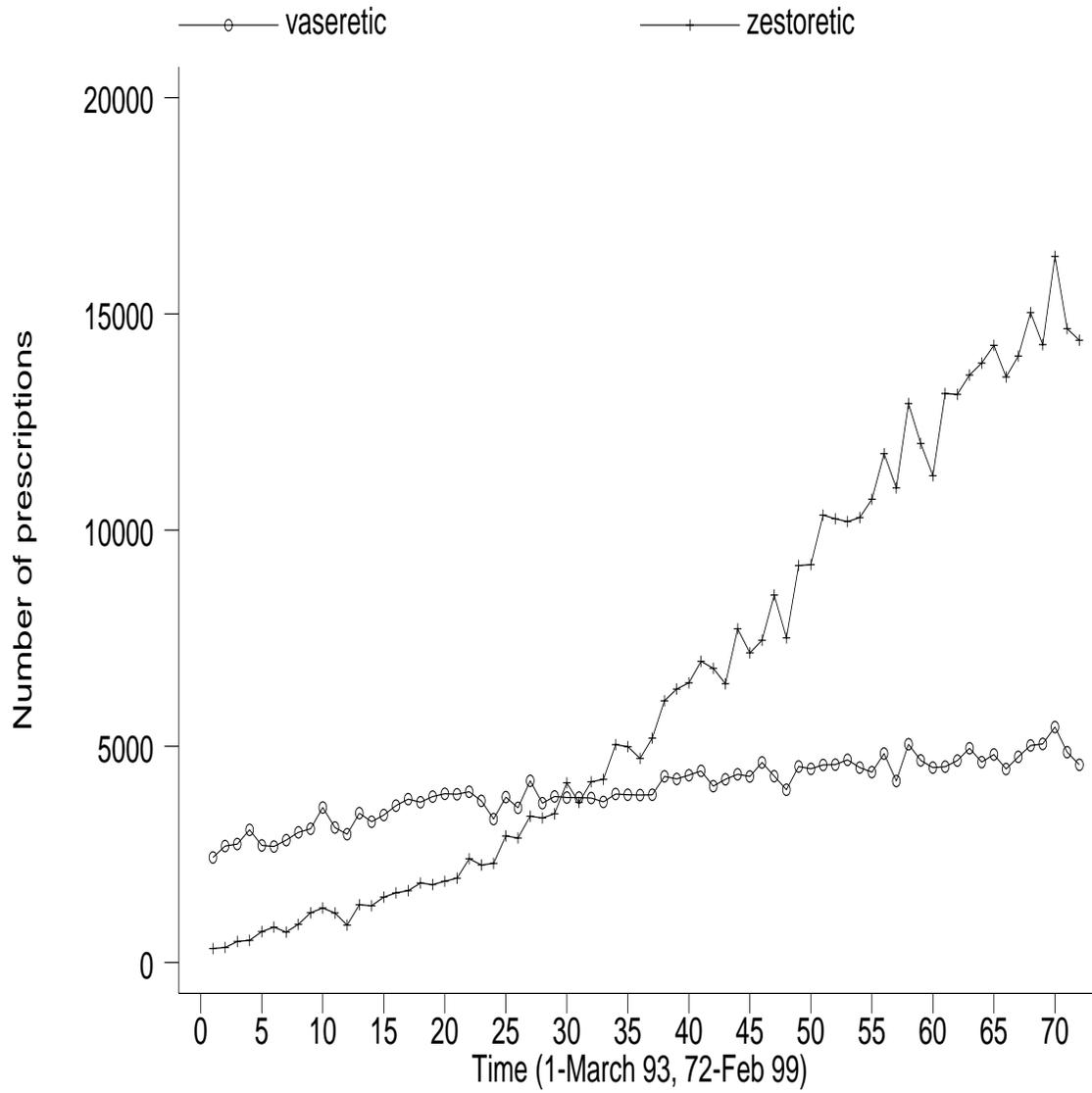
Figure 1: Market shares vs time
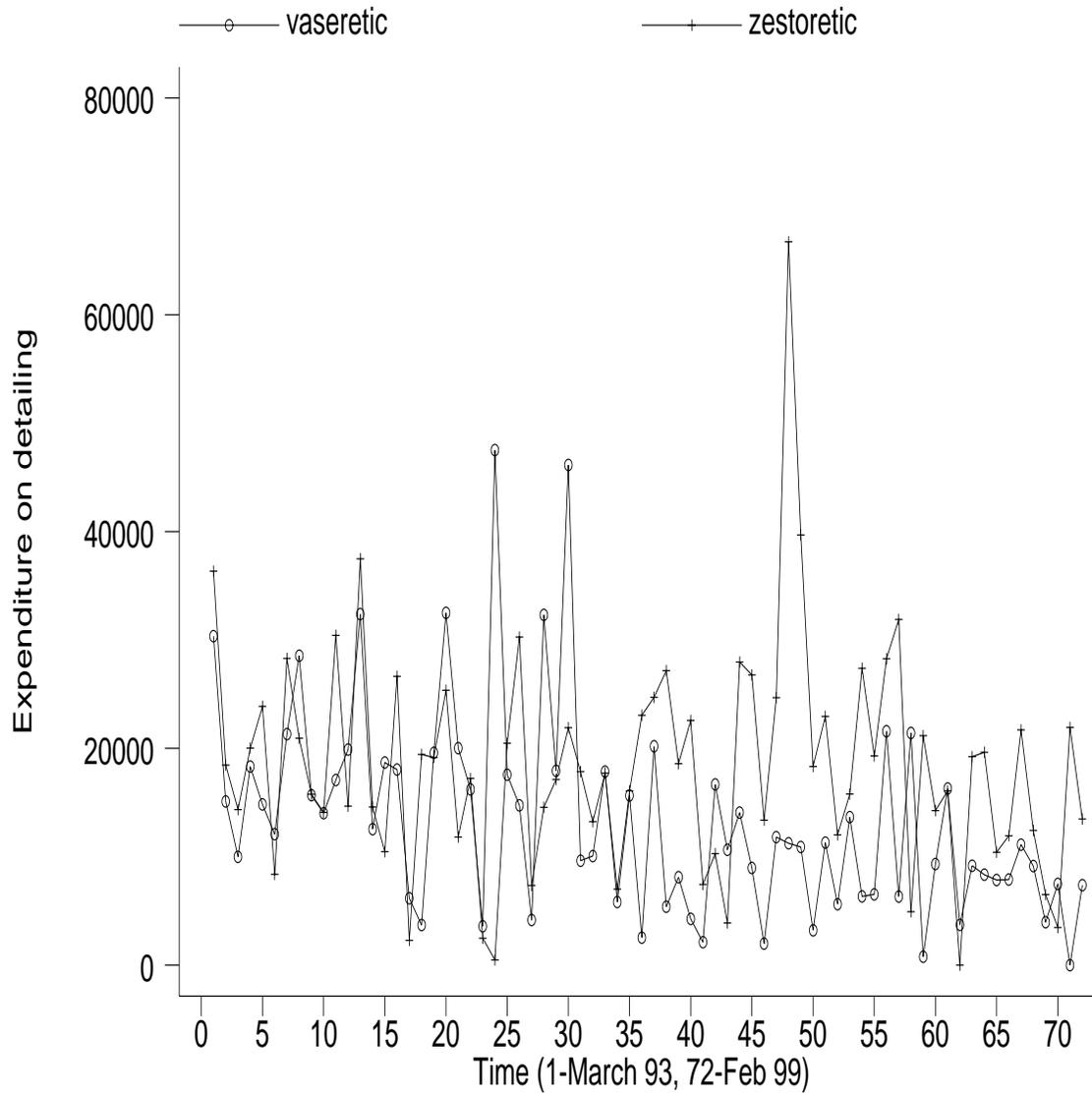
20

Figure 2: Total sales vs time

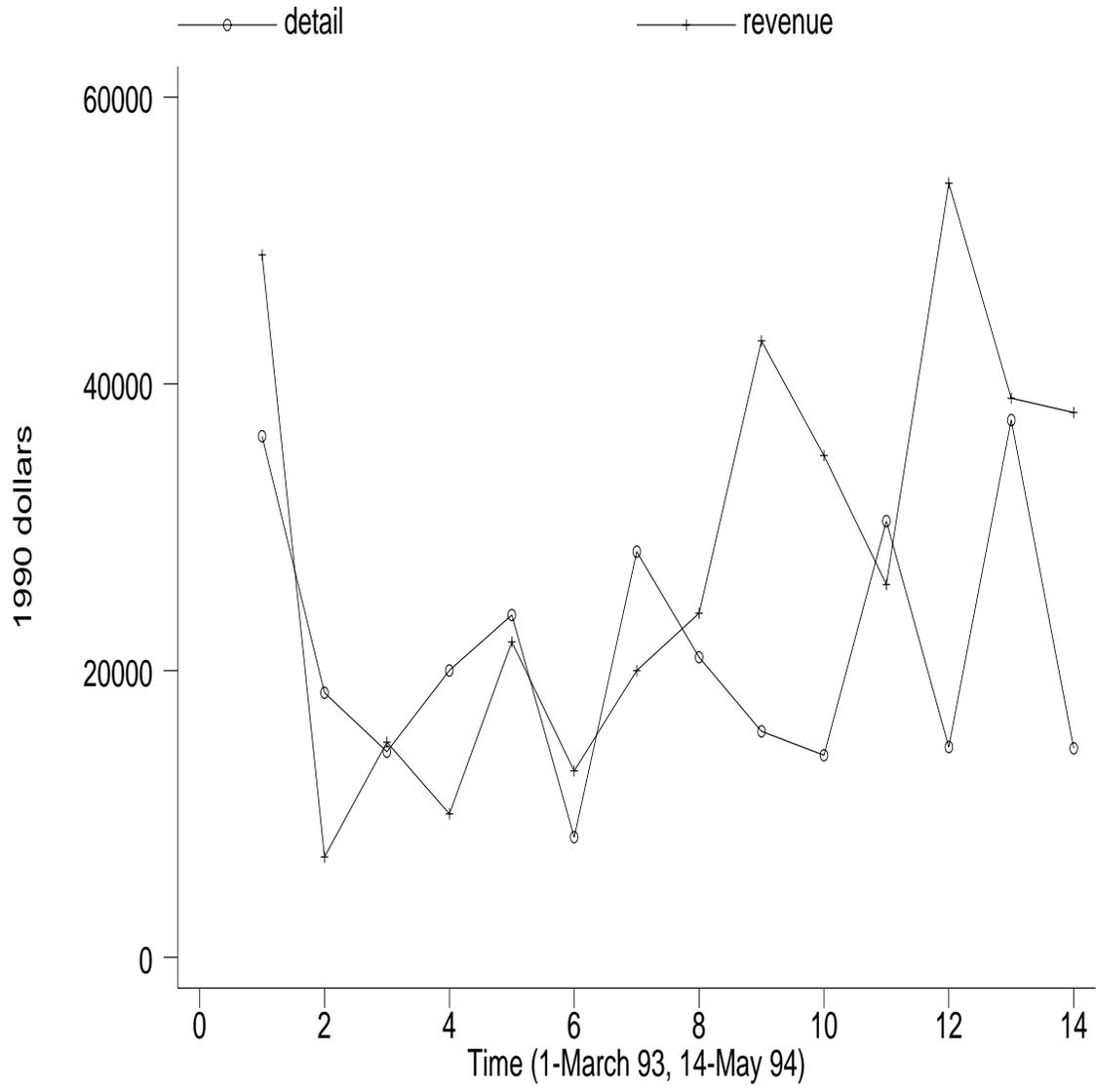Figure 3: Expenditures on detailing vs time

Figure 4: Total sales and detailing expenditures

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