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Consumer learning and heterogeneity: Dynamics of demand for prescription drugs after patent expiration

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ABSTRACT

This paper introduces an empirical demand model with aggregate learning and consumer heterogeneity in price sensitivity. The model is applied to the prescription drug market after patent expiration during the 80s, when the diffusion of generic drugs is fairly slow and consumer price sensitivity is known to be heterogeneous. I also introduce a new estimation approach to take the price endogeneity problem into account for this class of models. My approach is to estimate the demand model jointly with a pseudo-pricing policy function, which is a reduced-form function of observed and unobserved state variables. My estimation and counterfactual exercises demonstrate the value of estimating such a structural demand model, e.g., it allows one to learn whether consumers have optimistic or pessimistic prior, how aggregate learning affects the product diffusion rates in different latent segments of the population, and quantify the role of learning in explaining new product diffusion. I also find evidence that the brand-name price elasticities of demand (evaluated at the observed prices) are often less than one and increase over time, suggesting that brand-name firms might set their prices lower than what they would do if they were myopic, in order to slow down the learning process for generic qualities. But such an incentive might diminish over time as the uncertainty slowly resolves.

1. Introduction

When new products enter the market, it often takes time for consumers to adopt them. One potentially important explanation for the slow diffusion of new products is that consumers are risk-averse and have uncertainty about the qualities of new products. This explanation is particularly relevant when there are alternative products that are close substitutes for the new ones. Under this environment, many consumers are reluctant to adopt the new product until they see enough evidence to change their beliefs that the older products are safer or better choices. One way for consumers to obtain such evidence is to communicate with those who have already tried the new products. This type of information acquisition may take place via word-of-mouth between friends and relatives. Consumer heterogeneity in price sensitivity also plays an important role in this environment. Knowing the potential benefits that consumers may share their consumption experiences, it is common for new entrants to set their prices lower than their rivals' to attract price-sensitive consumers to try their products first, so that they reveal their experiences to others and hopefully speed up the diffusion process.

In some markets, there are social networks which facilitate information sharing. For instance, in the practice of medicine, patients' experiences with new drugs could be shared via physicians as each physician sees many patients. Moreover, there are conferences and seminars where physicians regularly attend to update their knowledge about new drugs. It is conceivable that informal discussions with their colleagues during these meetings would lead to more exchange of information. With the advance of internet, information sharing has become much easier than before even for markets without the traditional social networks described above. Many online vendors such as Amazon.com allow and encourage their users to post their experiences of using new products. These institutional settings allow the market to aggregate consumers' past experiences to update a common belief about the new product's quality over time. I call this type of learning behavior/environment *aggregate learning*.

Despite the importance of aggregate learning, most of the existing empirical industrial organization literature studying the entry of new products does not explicitly model this explanation. One reason why the previous literature has not examined this structural explanation

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is because estimating a model with aggregate learning is very challenging, in particular, when using product level data. The main issue is that price could be endogenous. The standard approach to address this endogeneity problem is developed by Berry (1994) and Berry et al. (1995)(BLP). Their GMM-based approach requires models to have one unobserved product characteristic per product. However, when applying a model with aggregate learning to product level data, another unobserved product characteristic needs to be introduced — perceived product quality. With two unobserved product characteristics per product, this additional complexity has limited the application of the standard BLP approach. An alternative approach is to use full-information maximum likelihood (FIML), which requires econometricians to explicitly specify the supply side where firms choose prices, and then use the oligopolistic equilibrium of the demand and supply to generate the likelihood of observed prices and quantities sold. However, in the presence of consumer uncertainty about product quality, firms may choose prices dynamically by taking the impact of aggregate learning on the future demand into account. To use FIML, it then becomes important for researchers to allow firms to be forward-looking. Unfortunately, the computational burden of solving a stochastic dynamic oligopoly is typically so high that FIML is infeasible in this setting.

The contributions of this paper are two-fold. First, to demonstrate the values of modeling aggregate learning together with consumer heterogeneity, I develop an empirical structural demand model for prescription drugs after patent expiration by incorporating these two features. In particular, I apply my demand model to explain the demand for a brand-name drug and its generic counterparts during the 80s, when the diffusion of generic drugs is fairly slow, and consumer price sensitivity is known to be heterogeneous. The advantages of estimating a structural learning model are that one can give more concrete interpretations to the parameter estimates and conduct counterfactual exercises. For example, this could allow us to learn whether consumers have optimistic or pessimistic prior, understand how aggregate learning affects the product diffusion rates in different latent segments of the population, quantify the role of learning in explaining the new product diffusion, etc. It would be difficult to answer such questions if one simply fits diffusion patterns using reduced-form demand models.

Second, I introduce a new approach to estimate this type of models. To handle the potential endogeneity problem of prices, I propose a quasi-structural method. My approach is to estimate the structural demand model jointly with a pseudo-pricing policy function, which is a reduced-form function of observed and unobserved state variables. Since some of the state variables are unobserved to the econometrician, I obtain parameter estimates by using simulated maximum likelihood. In applying this estimation approach, if the sample size is large, one can formulate the pseudo-pricing policy function using a flexible functional form. In addition, it would help further if exogenous observed state variables are available. This would allow the pseudo-pricing policy function to explain exogenous movements in prices, and further reduce the reliance of using functional form restrictions for identification. In my application, I argue that the number of generic entrants over time could serve this purpose because generic firms usually do not have complete control over the exact timing of entry. My main argument is that although entry decisions are endogenous, generic firms need to obtain an approval from the FDA before they can sell their generic version of a chemical, and it is common that the FDA requires generic firms to revise their applications several times before approving it. The uncertainty about adopting the manufacturing process and how to meet the FDA's standard has introduced exogenous randomness in their entry time. This in turn generates exogenous variations in prices and choice sets, and helps identify the price coefficients and heterogeneity in price sensitivity, respectively.

Although this method increases the number of parameters to be estimated (for the pseudo-pricing policy function), it is computationally feasible and does not impose strong assumptions about the process by which the pricing policy functions are formed. Using this framework and a data set detailing the evolution of prices and market shares of brand-name and generic drugs for 14 markets from 1984–1990, I estimate the price coefficients, the extent of consumer heterogeneity in price sensitivity, and the structural learning parameters which describe how the demand side evaluates risks and perceived attribute levels of drugs. My results are summarized as follows. The estimates suggest that the price coefficients of the two segments of patients are very different: their ratios are 4 for heart disease drugs, and 4 for anti-depressants and anti-psychotic drugs. The proportion of price-sensitive patients are roughly 0.56 for high blood pressure drugs, 0.31 for irregular heart beat/chest pain drugs, 0.24 for regular anti-depressants/psychotics, and 0.13 for highly potent anti-depressants/psychotics. Patients are risk-averse, and on average have pessimistic prior expectation about the quality of generics. Although I only observe aggregate market share data, the estimated model allows me to show that generic diffusion rates vary systematically across consumer types. I find that the diffusion rate of generics for price-sensitive consumers is much faster than that for price-insensitive consumers.[1] Moreover, I find that the static brand-name price elasticities of demand, evaluated at the observed prices, are often less than one at the beginning and increase over time. This suggests that brand-name firms might be forward-looking and take learning into account when setting prices. The brand-name firms might try to price their products lower than what they would do if they were myopic, in order to slow down the learning process for the generic quality. The increase in the magnitude of the brand-name price elasticities over time might reflect that the uncertainty about the generic quality has been slowly resolved, causing the forward-looking incentive to diminish over time.

The rest of the paper is organized as follows. Section 2 provides some background on the U.S. pharmaceutical industry and discusses the related literature. In particular, it discusses the regulatory delay in approving generic drugs, and other competing hypotheses that could explain the slow diffusion of generics. Section 3 describes the demand model. Section 4 describes the data set and explains the estimation strategy. Section 5 presents the results of estimation and counterfactual exercises. The last section concludes by discussing the limitations and future extensions.

2. Background and literature review

2.1. Slow diffusion of generic drugs and pricing pattern

To illustrate the slow diffusion of generics, I consider the co-movements of average market share of generics and average relative price of generics. Fig. 1 plots the average relative price of generics against time and the average market share of generics against time, respectively. I use my data set, which consists of 14 drugs, to obtain average market shares of generics and average relative prices of generics. The data is quarterly and period 0 refers to the first quarter that generics enter the market. Although generic drugs and brand-name drugs are made of the same chemicals and the average initial price of generics is 40% cheaper, the average initial market share of generics is only 0.05. It then slowly increases to 0.3 in period 5 even though the average relative price of generics remains fairly stable at around 0.6 for the first five periods.

I illustrate the pricing pattern of my sample (altogether 14 markets) in Fig. 2, which plots the average price per patient day for the brand-

[1] It should be emphasized that the model assumes that aggregate learning is homogeneous across consumer types. The different diffusion rates across consumer types are due to the heterogeneity in price sensitivity.