Literature Review on Physician Learning

Wonjun Choi

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1 Introduction

Physician learning literature studies how physicians learn about newly introduced things such as new drugs or new procedures. By examining how physicians, the agents who make medical decisions on behalf of the patients, we can understand how the medical market works better.

One example is that the learning process could be a reason for the delay in the diffusion of new technology (Chan et al., 2013) or could be a source of first-mover advantage in a differentiated market (Coscelli and Shum, 2004).

A typical application of physician learning is learning on pharmaceutical prescriptions (Coscelli and Shum, 2004; Ferreyra and Kosenok, 2011; Dickstein, 2021). Gong (2018) examined the case of surgical treatment for brain aneurysms.

Application of the idea of learning can be found in various literature. In marketing, how consumers learn about a new product from their purchase has been a popular topic in consumer behavior literature (Van Osselaer and Alba, 2000; Villas-

Boas, 2004; Hoch and Ha, 1986). There is also a growing interest in how policymakers learn the optimal treatment rule in policy evaluation literature (Athey, Wager, et al., 2017; Kitagawa and Tetenov, 2018).

2 Physician Learning

All of the listed papers in this section use the Bayesian learning structural model or its variant and hence share some common structure. First, a new thing is introduced to a market, causing a variance in the data. The utility function of Bayesian learning physicians is then constructed and assumptions are made on the way uncertainty is *learned* by agents to capture the variance. The source of identification is discussed, followed by estimation. After the estimation of the structural parameters, counterfactual simulation studies are conducted to answer the research questions. In what follows, I focus on the situation of the study, research questions, and the construction of structural models.

2.1 Chan, Narasimhan, and Xie, 2013

Chan et al. (2013) study how physicians learn effectiveness and side effects of newly introduced drugs. The authors analyze the pharmaceutical market for erectile dysfunction where an existing drug Viagra was the dominant drug. In 2003, Levitra and Cialis were introduced to the market and dragged down the market share of Viagra from over 70% to below 50%. The paper concerns a structural model to explain how the physicians' behavior of learning plays a role in their prescription.

In the model, the authors set the utility function of a physician i prescribing drug j for patient h on occasion t as

$$U^j_{ih,t} = f(e^j_h, s^j_h) + X^j_{ih,t}\beta + \epsilon^j_{ih,t}$$

where $f(\cdot)$ represents the physician's preference over the effectiveness e^j_h and the side-effect s^j_h. $\epsilon^j_{ih,t}$ is an i.i.d. random component that is observed by physicians but not by econometricians. Physicians Bayesian update their prior of e^j_h and s^j_h, which is assumed to be

$$e_h = (e^1_h, ..., e^J_h) \sim N(\bar{E}, \Sigma^E_h), \quad s_h = (s^1_h, ..., s^J_h) \sim N(\bar{S}, \Sigma^S_h)$$

so that a patient has different e^j_h and s^j_h for different drug j's.

Physicians learn the distribution of the effectiveness and side effects from two sources in the model. The first source is from detailing. After the release of the new drugs, physicians receive detailing visits from the firms for persuasive and/or informative purposes. Another source of learning is from returning patients. If a patient returns after trying a certain drug, a physician can get feedback from the patient and use it to update his prior belief.

Chan et al. (2013) use 828 physicians' prescription history data (13619 prescriptions) obtained from a pharmaceutical consulting firm (ImpactRX). From the data, they also use detailing visit information of pharmaceutical firms, which contains information that can be matched to physician panel data using physician ID. From the physician panel, they use patient characteristics ($X^j_{ih,t}$ in the utility). They have physician panel data, but not patient panel data. Thus, identifying repeated visits from the data is limited.

The estimation results suggest that Cialis is the best in both effectiveness and side effects. From the covariance between the estimators, the authors suggested that there is heterogeneity in treatment effectiveness and side effects. A negative correlation implies that if one drug is effective to him, the other drug would be less effective to him.

To answer the original research question, Chan et al. (2013) conduct several counterfactual simulations. In one of the simulations, they simulate the prescription decisions for revisiting patients. They found the uncertainty disappears faster through detailing than through learning from patients, which might highlight the important role of informative detailing for market entrants.

2.2 Coscelli and Shum, 2004 and Ferreyra and Kosenok, 2011

Coscelli and Shum (2004) examine the introduction of new molecule *omeprazole* into the anti-ulcer drug market and study how the gradual diffusion pattern can be explained by learning of physicians.

The authors simplify the problem into a choice between two alternatives, the new molecule omeprazole ($d = 1$) and other molecules ($d = 0$). They construct the utility functions as

$$U^i_{1,jkt} = \alpha^*_1 x^i + \beta_1 p_{1t} + \xi^*_1(t) + \delta^*_{1j} + \epsilon^i_{1,jkt},$$
$$U^i_{0,jkt} = \alpha^*_0 x^i + \beta_0 p_{1t} + \xi^*_0(t) + \delta^*_{0j} + \epsilon^i_{0,jkt}$$

for patient k with diagnosis j during period t. In the functions, x^i is a covariate that includes doctor's characteristics, p_{dt} is the (average) price of d. $\xi^*_d(t)$ is a time effect that also captures learning from other than the modeled Bayesian learning. δ^*_{dj} is the unobserved quality of the drugs. They are not observed by econometricians, but doctors have prior about them and learn the distribution from observations.

For estimation, Coscelli and Shum (2004) assume ϵ is iid type-1 extreme distributed and assume a priori distribution of δ. Then, they work on the likelihood. Since their likelihood contains noise from the signal, they used simulated likelihood.

Coscelli and Shum (2004) use the data collected by the Italian National Institute of Health. It is a 10%-sample panel data of the doctors in the metropolitan area of Rome, which has complete prescription histories over periods. This data was also used in Crawford and Shum (2005) and Ferreyra and Kosenok (2011). The latter paper studies the same case, the adoption of omeprazole in the Italian anti-ulcer drug market, by solving the dynamic choice problem of Bayesian learning doctors (and also using simulated likelihood).

Both Crawford and Shum (2004) and Ferreyra and Kosenok (2011) suggested a framework for analyzing the entry of a new product into the market. Crawford and Shum (2004) found there is a spillover effect in learning. Ferreyra and Kosenok

(2011) found forward-looking physicians learn faster than myopic physicians.

2.3 Gong, 2018

Gong (2018) examines how physicians learn treatment-patient match values for the case of brain aneurysms. There are three major options when there is a brain aneurysm. The first option is surgical clipping, which is the traditional option. The second option is endovascular coiling, which is a relatively new option. The third option is waiting for the progression without intervention, which is a natural outside option.

Unlike the treatment choice in prescription drugs, surgical practice choice could depend on the skill of a physician. Gong (2018) constructed the utility function of physicians with two separate learning components.

$$u_t^d(\theta_t^d, e_t^d, k_t, r_t^{dk}) = \mathbb{E}[y_t^{dk}|\theta_t^{dk}, k_t] + \alpha r_t^{dk} - c(e_t^d)$$

where d is an indicator of treatment (clipping, coiling, no intervention), k is a patient type, θ_t^d is a belief about the treatment-patient match value, e_t^d is the physician's cumulative skill, r_t^{dk} is revenue. $\mathbb{E}[y_t^{dk}|\theta_t^{dk}, k_t]$ is the expected patient outcome, and $c(e_t^d)$ is a cost of the cost of the treatment d that is decreasing in its component.

A physician's skill e_t^d accumulates as the physician practice more treatment d, so the author called this by *learning by doing* part. The expected outcome is the Baysian learning component that changes as the belief is updated. Usually, patient outcome after treatment is not observed in the literature, but in the case of a brain aneurysm, it is observed from the patient data.

Gong (2018) uses the New York Statewide Inpatient Database (SID). It has case-level information on diagnoses, treatments, outcomes, and patient and physician information. Using the data, the author constructs the physician's history of brain aneurysm cases.

Given the model in hand, Gong (2018) works out the dynamic treatment choice problem by fitting the problem into a multi-armed bandit framework and modifying Gittins index (Gittins, 1979) and Brezzi and Lai, 2002's approach. Using the solution of the dynamic choice problem, Gong (2018) constructs a likelihood function and estimates it using MLE.

Gong (2018) conducts simulation studies to understand how Bayesian learning and learning by doing shape physicians' preferences. She simulates the probability of treatment choice with and without each component and finds that Bayesian learning dominates in clipping, but it is dominated in the adoption of coiling. The results vary significantly for different types of patients. Moreover, in another simulation, she experiments with the different payment policies (uniform payment vs outcome-contingent payment) and evaluates how various outcomes are realized.

2.4 Dickstein, 2021

Dickstein (2021) studies patient-treatment matching problems where the patient and the physician jointly search for the most efficient treatment. He studies the market of depression care with 6 different classes of drugs. He constructs a utility function similar to what we have seen so far and works on the likelihood function for Bayesian updating. Similarly to Gong (2018), he relies on the MAB framework to work out the optimization problem and does policy experiment simulations.

3 Discussion

First of all,

Lastly,

3 open questions, at least 1 proposal with solution.

Can I form this question into treatment rule?

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