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筧悠夫、中嶋亮

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Institute for Economic Studies, Keio University
2-15-45 Mita, Minato-ku, Tokyo 108-8345, Japan
ies-office@adst.keio.ac.jp
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【要旨】

This study investigates how pharmacists dispense generic drugs by considering patients' brand preferences. While the literature shows that pharmacists, as experts, underestimate brand premiums, our data show that they frequently dispense brand-identical generics, known as authorized generics. We model patients' generic drug choices and pharmacies' dispensing decisions to explain how patients' brand preferences vary across pharmacies and to determine for-profit pharmacists' heterogeneous dispensing behavior. Using Japanese pharmacists' dispensing data, our empirical results show significant variations in patients' brand preferences and perceived differences in the quality of antibiotics. Furthermore, our findings show that one of the factors behind these differences is the provision of information by pharmacists.

筧悠夫
慶應義塾大学経済学研究科
東京都港区三田２−１５−４５
haruokakehi@keio.jp

中嶋亮
慶應義塾大学経済学部
東京都港区三田２−１５−４５
nakajima@econ.keio.ac.jp

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Role of Pharmacists in Generic Pharmaceutical Adoption*

Haruo Kakehi†

Ryo Nakajima ‡

June 17, 2024

Abstract

This study investigates how pharmacists dispense generic drugs by considering patients' brand preferences. While the literature shows that pharmacists, as experts, underestimate brand premiums, our data show that they frequently dispense brand-identical generics, known as authorized generics. We model patients' generic drug choices and pharmacies' dispensing decisions to explain how patients' brand preferences vary across pharmacies and to determine for-profit pharmacists' heterogeneous dispensing behavior. Using Japanese pharmacists' dispensing data, our empirical results show significant variations in patients' brand preferences and perceived differences in the quality of antibiotics. Furthermore, our findings show that one of the factors behind these differences is the provision of information by pharmacists.

Keywords: Authorized generic; Brand premiums; Generic pharmaceuticals; Pharmacist behavior; Information provision
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†Graduate School of Economics, Keio University. 2-15-45 Mita, Minato-ku, Tokyo 108-8345, Japan. Email: haruokakehi@keio.jp

‡Faculty of Economics, Keio University. 2-15-45 Mita, Minato-ku, Tokyo 108-8345, Japan. Email: nakajima@econ.keio.ac.jp

1 Introduction

Understanding the source of preferences for health products is crucial for promoting cost-effective policies. The literature shows that in the healthcare market, consumers have a greater willingness to pay for brand products, attributed to their brand premiums, and preferences for these premiums depend largely on consumer characteristics such as education level and occupation (Bronnenberg et al., 2015; Janssen, 2023). For example, Bronnenberg et al. (2015) shows that consumers with medical expertise are less likely to purchase national-brand pharmaceuticals than are those without such expertise. Conversely, recent experimental studies suggest that consumers change their purchasing behavior depending on external information such as nutrition labels and other customers' purchases (Fichera and von Hinke, 2020; Carrera and Villas-Boas, 2023). Carrera and Villas-Boas (2023) shows that information on other consumers' purchases can significantly increase consumers' generic purchase probability. While these studies inform us of the importance of external information as the source of brand preferences, the relationship between changes in consumer brand preferences and external information outside experimental settings remains unclear.

Our study empirically demonstrates how consumers' brand preferences relate to the behavior of professional experts by investigating the dispensing of generic drugs among Japanese pharmacists. Within the generic pharmaceutical market, brand companies market authorized generics (AGs), which are completely identical to their brand-name counterparts and distinguished from ordinary generics (OGs), which are merely equivalent, according to their brand premium. The empirical puzzle is that despite extensive literature indicating a strong consumer preference for brand premiums (i.e., AGs), some consumers still opt for nonbrand OGs. To address this issue, we analyze the dispensing behavior of pharmacists, focusing specifically on their inventory choices between brand-identical AGs and brand-equivalent OGs.

One significant advantage of focusing on the Japanese market is that the government uniformly sets retail prices of generic pharmaceuticals, regardless of whether they are AGs or OGs, and simultaneously sells them[1]. Therefore, considering the bioequivalence of generic drugs, the distinction between AGs and OGs is due mainly to the perceived brand premium attached to AGs

[1] In Japan, the government prohibits physicians, pharmacists, and pharmaceutical companies from advertising prescription drugs to patients.

rather than to price differences. Furthermore, the Japanese government has recently enhanced the role of pharmacies alongside physicians. Each pharmacist exclusively chooses either an AG or an OG, considering the patient's preference for generic pharmaceuticals, independent of physicians' preferences. By utilizing these practices, our study investigates how consumers' brand preferences are formed by considering the interactions between pharmacists and patients.

We model both the consumer's choice of generics and the pharmacy's decision to adopt an AG to elucidate the roles of the demand side (patients) and supply side (pharmacists) of antibiotics. Initially, we define consumer demand for brand-name drugs, AGs, and OGs. Our model indicates that consumers' drug preferences differ across pharmacies, considering the prominent role of pharmacists in Japan. Given these patients' demands, each pharmacy determines whether to adopt an AG or an OG to maximize its profits, which is linked with its generic dispensing share. Expanding on the correlated random coefficient (CRC) model (Suri, 2011; Michler et al., 2019), our three-period CRC model shows that the adoption of an AG by pharmacies hinges on patients' preferences for AGs.

Our empirical findings reveal that patients generally prefer AGs over OGs. This preference implies that pharmacies substituting AGs for OGs can enhance the likelihood of generic substitution, with a potential increase in the generic share ranging from 1.00% to 1.56%—a notable increase considering the already substantial degree of adoption of generics across pharmacies. Additionally, our analysis demonstrates significant variations in patients' brand preferences across pharmacies. We find that these variations account for approximately one-third of the average preference for AGs. Moreover, our results suggest that a patient's brand preference varies even for identical products—brand-name products and AGs. These findings substantiate our assertion that patients have a heterogeneous preference for the perceived quality of brand-name drugs and their generic counterparts.

Finally, to understand the source of patients' heterogeneous preferences, we focus on the role of pharmacists in providing information, a key aspect of recent Japanese health care system reforms. Our findings indicate that although patients generally prefer AGs to OGs, patients are more likely to prefer OGs to AGs if pharmacies offer detailed drug information, leading to heterogeneous distribution practices among pharmacies. When pharmacies provide a minimal amount of drug information, patients favor AGs; however, when comprehensive pharmaceutical details are

available, patients lean toward OGs. Consequently, our findings suggest that the variation in pharmacists' information provision is a primary factor influencing brand preference.

This paper joins the growing empirical literature that examines the source of brand premiums. The literature examines the drivers of brand premiums from the consumer side, including consumers' information and expertise (Bronnenberg et al., 2015, 2020; Janssen, 2023), inertia and loyalty (Keane, 1997; Dubé et al., 2010), and search and learning (Crawford and Shum, 2005). Recent studies in the health product market show that information, such as nutrition labels for groceries (Fichera and von Hinke, 2020) and sales rankings for generic drugs (Carrera and Villas-Boas, 2023), influences consumer behavior and decision-making. Our study demonstrates that the source of brand premiums depends on the information-providing behavior of professional experts and that the direct pharmaceutical information provision of pharmacists, mandated by the Japanese government, is related to the change in consumers' brand premiums.

This paper is also a part of the literature exploring healthcare provider behavior. One strand of literature has focused mainly on physicians' behavior as professional experts (Chalkley and Tilley, 2005; Iizuka, 2007, 2012; Clemens and Gottlieb, 2014; Epstein and Ketcham, 2014; Chan et al., 2022). However, given the recent interest in generic drugs (Appelt, 2015; Ito et al., 2020; Janssen and Granlund, 2023) and the behavior of pharmacies (Bennett and Yin, 2019; Starc and Swanson, 2021; Atal et al., 2022; Janssen and Zhang, 2023), there is still a gap in the understanding of the role of pharmacists. Iizuka (2012), who has examined the financial incentives behind physicians' prescriptions of generic drugs in Japan, states that *in fact, the role of the pharmacist as another key agent for the patient is seriously understudied*. The most closely related study to ours is Brekke et al. (2013), which conducts a theoretical and empirical analysis of the financial incentives for pharmacists and the market share of generic drugs. Our paper differs from the literature in two main respects. First, we consider the role of patients' brand preferences, which vary across pharmacies. By utilizing the unique characteristics of AGs and Japanese regulations, we explicitly acknowledge the heterogeneity of patients' brand preferences to explain the different AG and OG dispensing patterns across pharmacies. Second, our study examines the informational role of pharmacists. The literature has not fully analyzed the influence of pharmacists on patient brand preferences. Drawing on the recent policy reforms enacted by the Japanese government since 2016, our research analyzes the relationship between information provided by pharmacists

and patients' pharmaceutical preferences.

The remainder of this paper is organized as follows. Section 2 provides background information on the Japanese healthcare market. Section 3 details the data used. In Section 4, we introduce a theoretical model that accounts for both patient demand and pharmacy adoption decisions. Section 5 outlines our empirical approach and estimation methodologies, emphasizing the identification assumptions. Section 6 presents the estimation results, focusing on patients' AG preferences and their heterogeneity. Section 7 elaborates on the pharmacist's factors that affect heterogeneous patient brand preferences. Finally, Section 8 concludes the paper.

2 Institutional Background

This section explains the supply side of the Japanese pharmaceutical system, elucidating the processes of prescribing and dispensing, especially focusing on the role of pharmacists. This study provides a brief summary of the Japanese government's efforts to promote the use of generic drugs. Furthermore, we explore a particular type of generic drug—*an AG*—which is identical to its brand-name equivalent and produced by the original manufacturer.

2.1 Japan's Pharmaceutical Supply System

Historically, in Japan, medical care was characterized primarily by prescribing and dispensing by physicians within hospitals and was heavily influenced by traditional Eastern medicine (Iizuka, 2012). However, since the 1940s, the Japanese government has promoted the separation of physicians' medical services and pharmacists' dispensing roles to deliver high-quality medical care. Therefore, when examining Japan's pharmaceutical system, it is critical to understand the roles of pharmacists[2].

Following these policy transitions, the role of pharmacists has significantly expanded, particularly in terms of how they affect patients' pharmaceutical choices. First, the introduction of

[2]This situation differs significantly from that of other countries, particularly the U.S. The U.S. pharmaceutical system involves multiple intermediaries, including insurers, pharmacy benefit managers (PBMs), and pharmacies. Within this system, insurers offer health plans that cover prescription drugs, dictate which drugs are included in their formularies, and set patients' out-of-pocket costs. PBMs, in contrast, act as negotiators, securing discounts and rebates from drug manufacturers, managing formularies, and processing prescription drug claims. Their negotiations can influence drug tiering, thus affecting patients' out-of-pocket costs.

nonproprietary name prescribing has facilitated the choices of patients and pharmacists between brand-name or generic drugs[3]. This flexibility was limited before 2012 when only proprietary name prescriptions were available, where in most cases, the brand-name drugs written on these prescriptions were dispensed as they were and provided to patients at pharmacies[4]. However, the implementation of the nonproprietary name prescription enabled generic and brand choices from physicians to pharmacists. A recent survey showed that nonproprietary name prescriptions account for the majority of all prescriptions (Ministry of Health, Labour and Welfare, 2023b)[5].

Second, most patients receive pharmaceutical dispensing outside hospitals. Under the Uniform Drug Pricing Policy, the Ministry of Health, Labour, and Welfare (MHLW) routinely sets and revises uniform drug prices based on wholesale market prices (Ito et al., 2020)[6]. In the past, physicians could profit from in-hospital dispensing due to significant price-cost margins[7]. However, to curb rising social security spending, the MHLW has reduced this margin to less than 10%, thereby suppressing such financial incentives[8]. Given the cost of dispensing-related equipment, the once-prevalent practice of in-hospital dispensing has declined, as it has become economically unsustainable for clinics or hospitals to maintain in-hospital dispensing. Consequently, the share of out-of-hospital dispensing services continues to increase. According to recent MHLW statistics (Ministry of Health, Labour and Welfare, 2023b), the out-of-hospital prescription rate has reached

[3]Physicians are responsible for prescribing drugs using two main methods. The first, called *proprietary name* prescription, involves prescribing a drug by its trade name. The second, known as *nonproprietary name* prescription, was introduced in 2012 and involves the pharmacist prescribing a drug by its active ingredient name. The difference between these two methods lies in the physician's approach when writing the prescription. In the former, the physician specifies the individual brand label, whether original or generic. Physicians prescribe the latter without focusing on those specific labels.

[4]Before 2006, pharmacies were strictly prohibited from selling nonprescription generic drugs. Until 2012, only proprietary name prescriptions were available, but it was a period when a specified brand-name drug in a prescription could be replaced by a generic equivalent. Iizuka (2012) studied the incentives affecting Japanese physicians' decision-making between generic and brand-name drugs during this period.

[5]The exact figures are 52.8% for nonproprietary name prescriptions and 29.3% and 13.6% for proprietary name prescriptions specifying the original brand-name drug and generic drug, respectively, in 2022. Pharmacists can interchange brand-name and generic drugs regardless of a physician's specific prescription.

[6]Until 2018, drug price revisions occurred every two years. Afterward, such revisions have been carried out annually.

[7]Once physicians issue a prescription, pharmacists dispense the medication. This process can occur in one of two settings. The first is *in-hospital* dispensing, in which patients receive their medications within the same medical institution where they consulted. Alternatively, *out-of-hospital* dispensing occurs when patients go to independent pharmacies that are not affiliated with the hospital. In in-hospital dispensing, both pharmacists and physicians can dispense pharmaceuticals, whereas only pharmacists conduct out-of-hospital dispensing.

[8]The MHLW conducts a *drug survey* and publishes the average disparity rate, which indicates the deviation between the official price (i.e., the uniform drug price) and the actual market price at which transactions occur. For example, the average overall gap rate for pharmaceuticals in 2020 was 8%, which has decreased in recent years.

almost 80%. Since only pharmacists can dispense drugs in out-of-hospital dispensing, this transition further amplifies the impact of pharmacists on patients.

Third, pharmacists have multiple financial incentives to provide information to patients. In Japan, since April 1986, pharmacists have received additional payments for providing patients with pharmaceutical information. The family pharmacist program, launched by the MHLW in April 2016, has especially intensified the role of pharmacists. Family pharmacists can secure additional payments by satisfying rigorous criteria for exclusive and continuous treatment for a patient. Once pharmacists are certified as family pharmacists, they can access all patient prescriptions and visiting histories of healthcare providers. The literature shows that family pharmacists provide high-quality information to change patients' drug usage[9].

These institutional and environmental changes in Japan's healthcare system indicate that pharmacists play a more prominent role in dispensing pharmaceuticals than they used to. In addition, Japanese pharmacists are obliged and financially incentivized to provide pharmaceutical counseling to ensure that medications are used safely and appropriately. Therefore, patients' choice between generic or brand-name drugs is largely influenced by the guidance they receive from pharmacists.

2.2 Generic Drug Promotion Policies in Japan

Promoting the use of generic drugs is an effective way in which to control healthcare costs. Since the 2000s, the Japanese government has actively promoted the use of generic drugs by setting numerical targets. Consequently, the substitution rate of generic drugs, which was relatively low among developed countries and did not even reach 40% in 2010, nearly reached 80% by 2024.

Most generic promotion policies are based primarily on financial incentives. Subsidy-based incentives on the drug supply side have been implemented to encourage the prescription and dispensing of generic drugs. For example, pharmacies that achieve a certain rate of generic prescriptions can receive a special subsidy (referred to as a generic dispensing add-on)[10]. Since drug price-

[9]For example, Nishikawa et al. (2023) shows that family pharmacists can prevent polypharmacy by providing high-quality medication assessments.

[10]Physicians also have financial incentives, and when a physician writes a nonproprietary name prescription and prescribes a drug under its generic name, the government provides an increased medical payment to the clinic or hospital with which the physician is affiliated (referred to as a nonproprietary name prescription add-on).

cost margins have been set at low levels in recent years, pharmacies seek to increase their generic prescription rate and receive greater compensation by dispensing these generics. Other financial incentives are also provided to patients on the demand side. Specifically, the uniform drug prices set by the MHLW are set to 40% to 50% for generic drugs compared to original drugs, providing patients with an economic incentive to purchase less expensive but bioequivalent generic drugs.

In addition to these monetary incentives, healthcare policy changes, such as the introduction of nonproprietary name prescriptions in 2012, have played an important role. The new system allows patients to choose between brand and generic drugs at the pharmacy, encouraging generic substitution. Notably, proprietary prescriptions that prohibit substitution still exist today as an exception due to physician requests, representing less than 5% of all prescriptions, but substitution from brand to generic is generally encouraged[11].

2.3 AGs

OGs are designed to be *equivalent* to their brand-name counterparts, encompassing identical active ingredients, efficacy, and dosage. They become available when the patent of the original drug expires and the drug can legally be manufactured and sold by other companies[12]. However, their manufacturing processes and additives often differ, due primarily to different production methods or cost-saving measures[13]. In contrast, *AGs* are essentially brand-name drugs repackaged and sold under generic names by the original manufacturer.[14]. Therefore, AGs are *identical* to their brand-name counterparts in terms of quality, strength, additives, manufacturing process, and dosage form.

There are specific reasons why Japanese pharmaceutical companies choose to sell AGs. First, the perceived identical qualities of AGs compared to brand-name drugs can foster patient loyalty

[11]The exact percentage of proprietary name prescriptions for which substitution for generic drugs is prohibited was 4% in 2022 (Ministry of Health, Labour and Welfare, 2023b), as is the above percentage of nonproprietary name prescriptions.

[12]The World Health Organization (WHO) defines a generic drug as "a pharmaceutical product, usually intended to be interchangeable with an innovator product, that is manufactured without a license from the innovator company and marketed after the expiry date of the patent or other exclusive rights."

[13]Two main factors contribute to the differences between generic and brand-name drugs. First, even after the primary patent expires, other patents, generally related to manufacturing, often remain, thus prompting alternative production methods by generic manufacturers to avoid patent violation. Second, profitability demands may lead generic manufacturers to utilize less costly excipients.

[14]The Food and Drug Administration (FDA) in the U.S. defines an AG drug as "an approved brand-name drug that is marketed without the brand-name on its label."

and potentially higher demand than those for other generics. Second, the infrastructure used to produce the original branded drug can be used to produce an AG, allowing companies to maintain economies of scale[15]. Nevertheless, reduced profitability due to a potential lack of first-mover advantage, which originates from the Japanese patent examination system, can dampen manufacturers' motivation to enter the generic market through prescribing AGs[16][17]. Consequently, only some new generics are sold as AGs in Japan.

In Table B1, we present the names of the main oral AG drugs available on the Japanese market from 2014 to 2021[18]. During this period, 775 drugs were marketed as generics, but only 74 (9.54%) were marketed as AGs by December 2020. In addition, to keep inventory costs as low as possible, pharmacies commonly refrain from carrying both an OG and an AG with the same active ingredient. For example, our data show that only 4.3% of pharmacies maintain an inventory of both AG and OG antibiotics.

3 Data

3.1 Claim Data

The main analysis draws on medical claim data from 2014 to 2021 provided by Japan System Techniques (JAST). This dataset comprises claim details from the Health Insurance Society (for employees of large corporations) and the Mutual Aid Association (for public servants and educators). Moreover, this dataset offers detailed information on medical procedures performed at

[15]Refer to Hirosaki (2019) for a comprehensive discussion on the AG market in Japan and the pricing strategies of original drug manufacturing companies.

[16]For example, manufacturing and branding AGs in the U.S. can offer a significant strategic advantage compared to OGs, as noted by the Federal Trade Commission in 2011. Specifically, pharmaceutical companies with patents on branded drugs have the exclusive right to market AGs six months before their patents expire. Introducing their generics during this window allows them to generate large revenues and increase their market share. This early entry into the market gives them a distinct advantage, positioning them firmly in the generic market before other potential generic manufacturers can begin selling the versions of their drugs.

[17]In Japan, unlike in other countries, the timeline for introducing AGs is impacted by a re-evaluation requirement for the safety and efficacy of authorized drugs. Due to this re-evaluation requirement, neither AGs nor OGs can be sold during the re-evaluation period. Consequently, the earliest that a company that manufactures a brand-name drug can launch an AG drug is either six months before the patent expires or after the re-evaluation period, whichever comes later. If a basic patent expires before the end of the re-evaluation period, then the introduction of the AG coincides with that of the OG.

[18]In proprietary name prescriptions, drugs are prescribed under a name that combines generic name ingredients, dosage form, and contents.

healthcare facilities, the names of ailments and injuries, and prescription drugs dispensed by pharmacies[19]. During the study period, 114,121,902 claims were observed, representing 7,839,803 patients. The gender ratio was 90.47, with average ages of 38.5 and 39.08 years for males and females, respectively.

3.2 Antibiotics

We explore the dispensing decision of pharmacies regarding the antibiotic levofloxacin, marketed under the brand name *Cravit*[20]. This drug is prescribed for various infections, including pharyngitis, tonsillitis, pneumonia, otitis media, chlamydia, and gonorrhea. We focus on 250mg and 500mg levofloxacin for the following reasons: (1) the introduction of its generics within our data period, (2) the availability of an AG, and (3) the consistent demand for the drug, given that no new alternative is introduced during the period. Notably, the patent for the original brand-name drug lapsed in 2010. Both the OG and AG versions of *Cravit* began being offered for sale simultaneously in December 2014. Figure 1 displays the prescription shares for brand-name levofloxacin and the OG and AG versions, broken down by quarter. Importantly, the data used in the analysis are limited to out-of-hospital prescriptions.

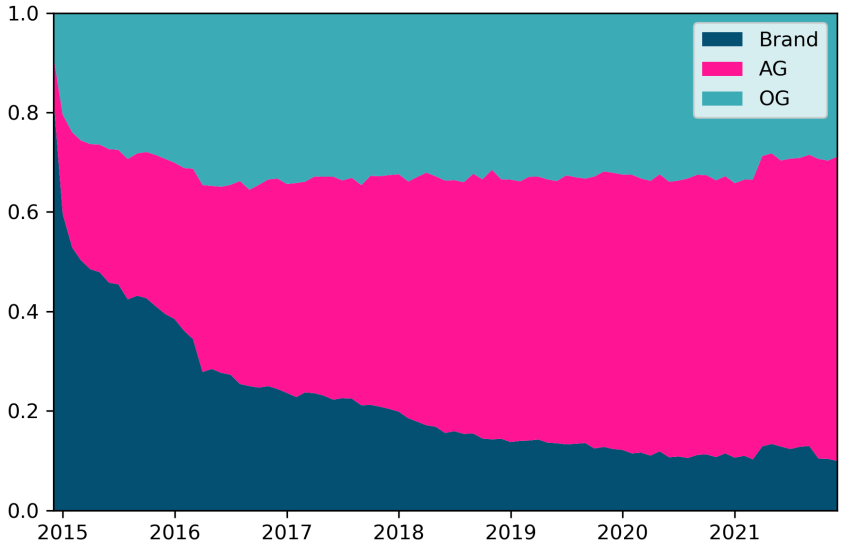
JAST collects an extensive range of claim data for corporate and public employees but omits data for self-employed and elderly people. Compared with the MHLW's National Database (NDB), which offers publicly accessible but aggregated data for the entire Japanese population, the average age in the JAST dataset is approximately 10 years younger for both genders[21]. Nonetheless, we confirm the consistency between the NDB and JAST datasets in terms of the brand-to-generic ratio and the AG-to-OG ratio of levofloxacin across gender and age groups, which suggests that the JAST data are reasonably representative of the broader population regarding levofloxacin prescriptions.

[19] All information that can identify individuals is anonymized, and unique IDs are assigned.

[20] According to the Anatomical Therapeutic Chemical (ATC) Classification System, levofloxacin is denoted as ATC4 J01MA12.

[21] The NDB managed by the MHLW compiles comprehensive health claim data, including a wide array of health services provided to individuals across all age groups. This database is a critical resource for public health research and policy analysis, although data are aggregated at the yearly prefecture level and are used primarily for macrolevel studies.

Figure 1: Prescription share of antibiotics



Notes: This figure shows the transition of share regarding brand-name, OG, and AG drugs for the antibiotic levofloxacin (its brand name is *Cravit*). The data period is from January 2015 to December 2021 and aggregated at the month level.

3.3 Survey on Pharmacists

Given these claim data, we carry out a survey to clarify the dispensing practices of Japanese pharmacists in partnership with MCI Co., Ltd. This company maintains a pharmacist survey panel with 7,481 registered pharmacists. Our survey targets a randomly selected sample of 100 supervising pharmacists who are in charge of drug procurement. We specifically design questionnaires to explore the dispensing patterns of generic antibiotics. Appendix A shows the detailed results of our survey.

For the dispensing practices of antibiotic generic drugs, including AGs and OGs, our survey first suggests that pharmacists generally prioritize a stable drug supply and reliability of pharmaceutical companies over procurement costs in selecting generic drug manufacturers. However, this trend differs when dispensing AGs. When pharmacists adopt AGs, patient preferences for and trust in AGs become more crucial factors than does the stability of the AG supply. These results indicate that AGs retain brand premiums due to their bioequivalence with brand-name drugs, and pharmacists sell AGs considering patients' brand preferences toward AGs. Finally, the majority of

pharmacists provide information about the efficacy and safety of generic drugs or dispense AGs when patients refuse generic dispensing. These patterns indicate that the brand premiums of AGs and the information that pharmacists provide may affect patients' decision-making.

Based on these findings, we assume that pharmacists weigh patients' demands when dispensing AGs. Consequently, we propose a behavioral model in which pharmacists dispense AGs considering patients' preferences.

4 Model

In this section, we develop a model delineating both patient choice in generic drug consumption and pharmacy decisions concerning their generic drug inventory. Upon visiting a pharmacy with a prescription, we assume a scenario wherein patients receive a brand-name drug, an OG, or an AG, contingent on his or her preferences and subject to the limitations imposed by the pharmacy's available stock. Initially, we define patients' preferences for brand-name and generic drugs, which are crucial in shaping patients' demand-side decisions. Subsequently, we model the pharmacy's decision to hold an inventory of generic drugs, representing the supply-side perspective. The distinctive features of our model are that (1) there is variation in patient preferences for pharmaceuticals across pharmacies and that (2) pharmacies, knowing these heterogeneous preferences, choose their generic drug inventory.

4.1 Patient Demand

Consider a scenario where patient i receives a prescription for a generic antibiotic from a physician and goes to pharmacy j. At this point, the patient is presented with the following option: a brand-name drug or its generic counterpart. If he or she chooses the generic option, then he or she is given either an OG or an AG. Importantly, the choice between an OG and an AG is not at the patient's discretion because the pharmacy's inventory includes only one of the two alternatives.

A patient is assumed to make a decision based on immediate utility maximization rather than dynamic utility maximization when selecting an antibiotic type. As such, our analysis does not consider the learning effect and inertia concerning the choice of medications[22]. The data corrobo-

[22] Iizuka (2012) and Ito et al. (2020) focus on chronic diseases such as hypertension and dyslipidemia, demonstrating

rate that patients do not use antibiotics frequently in a short period[23].

Let the utility functions of patient i visiting pharmacy j in period t for a brand-name drug, an AG and an OG, respectively, be specified as follows:

$$\begin{aligned} U_{ijt}^{B} &= \alpha P_{t}^{B} + \beta_{t}^{B} + \beta_{jt}^{B} + \varepsilon_{ijt}^{B} \\ U_{ijt}^{A} &= \alpha P_{t}^{G} + \beta_{t}^{A} + \beta_{jt}^{A} + \varepsilon_{ijt}^{A} \\ U_{ijt}^{O} &= \alpha P_{t}^{G} + \varepsilon_{ijt}^{O}, \end{aligned} \tag{1}$$

where P_t^B and P_t^G are the regulated uniform prices of the brand-name and generic pharmaceuticals, respectively, and U_{ijt}^B, U_{ijt}^A, and U_{ijt}^O denote the utilities of patient i at pharmacy j during period t for the brand name drug, the AG, and the OG, respectively. In the utility specifications, the utility for the OG serves as a baseline option.

The parameter β_t^B encapsulates the average preference for the higher quality of the brand-name drug relative to that of the OG drug. The underlying presumption is that despite the biosimilarity of brand names and generic drugs, patients are generally more willing to opt for brand names than for their generic counterparts, which is considered a brand premium. Conversely, as an AG originates from the same manufacturers as does a brand-name drug, patients often perceive the AG more favorably than they do the OG. Consequently, β_t^A can signify the *drug-specific (context-independent)* patient's preference, which is also a part of the brand premium. Furthermore, given the significant role of pharmacists, as discussed in Section 2.1, patient preferences may vary across pharmacies. We assume that β_{jt}^B and β_{jt}^A represent the *pharmacy-specific (context-dependent)* patient brand-name preference and AG preference, respectively. These parameters capture the varied preferences of patients purchasing drugs at different pharmacies. We posit that these patients' preferences regarding brand names or AG drugs can vary, even for the same drug, influenced by factors such as the pharmacist's explanation, drug information provided by the pharmacist, and how the drug is prescribed.

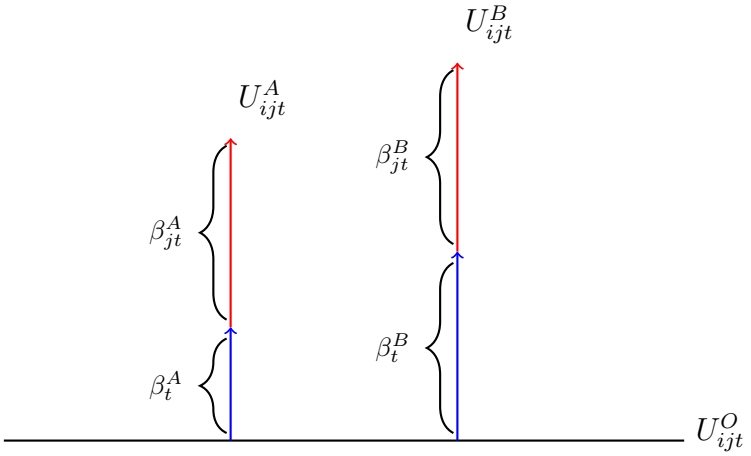
Although the coefficients β_t^B and β_t^A, alongside β_{jt}^B and β_{jt}^A, capture the brand premium that

that brand-name drug inertia plays a significant role in consumer choices of generic pharmaceuticals. In contrast, our study concentrates on antibiotics, analyzing the short-term choices between brand and generic drugs.

[23]The claim data described below show that 77.3% of all patients receive a prescription for levofloxacin only once. Additionally, the average duration of each levofloxacin prescription is 264 days, while the majority of prescription days reported in Ito et al. (2020), which examines the inertia of brand-name drugs in dyslipidemia, is 28 days.

arises from the commonality of the manufacturers of brand names and AGs, they are subject to a distinct interpretation. The brand premium that consumers attribute to a brand-name drug and an AG is derived from context-independent factors, including scientific differences in minor efficacy, color, and additives in comparison to an OG, and context-dependent factors, such as a patient's perceived quality and misperception of brand benefits due to pharmaceutical information provided by pharmacists. The parameters β_t^B and β_t^A encapsulate context-independent factors, which are uniform among patients and pharmacies. Conversely, the parameters β_{jt}^B and β_{jt}^A represent context-dependent factors that vary by pharmacy. Therefore, β_{jt}^B and β_{jt}^A reflect patients' perceived quality differences across pharmacies. These parameters can influence patients' perceptions of brand-name drug and AG quality.

Figure 2: Brand Preferences



Notes: This figure shows that the patients receive utility from two different sources, which are context-independent factors β_t^B and β_t^A and context-dependent factors β_{jt}^B and β_{jt}^A. Note that we abbreviate the utility from price and preference shock. While context-independent factors remain uniform across pharmacies, context-dependent factors vary, leading to different perceptions across patients of identical products, namely, AGs and brand-name products.

Figure 2 shows how these brand premiums are different. In each pharmacy, patients receive context-independent utility (blue line) for AGs β_t^A and brand-name drugs β_t^B and context-dependent utility for AGs β_{jt}^A and brand-name drugs β_{jt}^B (red line). Note that we assume that the utility from price and preference shocks is negligible, simplifying the illustration. This diagram suggests that patients derive utility from two different sources and that context-dependent utility results in differing preferences for entirely identical AGs and brand-name drugs. In the provided

equations, the terms $\varepsilon_{ijt}^{O}, \varepsilon_{ijt}^{A}$, and ε_{ijt}^{B} denote the idiosyncratic preference shocks for individual patients, which emphasizes our assumption that the unique attributes of patient i do not systematically affect the utility of consuming any drug type.

Let Y_{jt}^{ℓ} be the share of type-ℓ generic drugs at pharmacy j in period t. Since a pharmacy dispenses either an OG or an AG, but not both, the share of a brand-name drugs is given by $Y_{jt}^{B} = 1 - Y_{jt}^{\ell}$ for $\ell \in \{O, A\}$, where O and A are the OG and the AG, respectively. $y_{jt}^{\ell} = ln(Y_{jt}^{\ell}) - ln(Y_{jt}^{B})$ is defined as the patient's log odds of purchasing ℓ generic drugs at pharmacy j during period t relative to those of brand-name drugs. Assuming that each of the tuples $(\varepsilon_{ijt}^{O}, \varepsilon_{ijt}^{A}, and \varepsilon_{ijt}^{B})$ adheres to an i.i.d. type-I extreme value distribution, we have the following equations for the log odds associated with brand-name drug and AG premiums:

$$\begin{aligned} y_{jt}^{A} &= \alpha \Delta P_t + (\beta_t^{A} - \beta_t^{B}) + (\beta_{jt}^{A} - \beta_{jt}^{B}) \\ y_{jt}^{O} &= \alpha \Delta P_t - (\beta_t^{B} + \beta_{jt}^{B}). \end{aligned} \tag{2}$$

where $\Delta P_t = P_t^{G} - P_t^{B}$.

4.2 Pharmacy's Supply

Let us now turn to a pharmacy's decisions regarding generic antibiotics, assuming that each pharmacy stocks either an OG or an AG and dispenses one of the two types. Specifically, let pharmacy j choose $\ell \in \{O, A\}$ generic drug type at time t. We assume that since the price–cost margins of brand-name and generic antibiotics are negligibly small, the primary determinant of a pharmacy's revenue from the sale of antibiotics is the generic dispensing subsidy, denoted by $subsidy_{jt}^{\ell}$. Once the subsidy is granted, it is added to the total sales volume, encompassing the sales of generic and brand-name drugs. Therefore, the profit function π_{jt}^{ℓ} is given by

$$\pi_{jt}^{\ell} = subsidy_{jt}^{\ell} \cdot n_{jt} - (f_j^{B} + f_j^{\ell}), \tag{3}$$

where n_{jt} is the number of patients who visit pharmacy j at time t to purchase antibiotics and f_j^{B} and f_j^{ℓ} represent the fixed costs incurred by the pharmacy for holding inventories of the brand-name and type ℓ generic antibiotic drugs, respectively. We assume, for simplicity, that the number of

patients n_{jt} is exogenous in that patients do not discriminate between pharmacies when purchasing antibiotics and invariably purchase either a brand name antibiotic or a generic antibiotic at the pharmacy they enter[24].

As noted in the previous section, the amount or level of subsidy that a pharmacy can receive depends on its overall prescription rate for generic drugs. Let us denote the ratio of the number of antibiotics to the total number of prescriptions at pharmacy j during period t as r_{jt}. We calculate the total generic share as $Y_{jt}^{\ell} r_{jt} + g_{jt}$, with g_{jt} being the overall generic share of drugs excluding antibiotics[25]. Consequently, the generic dispensing subsidy is given as follows:

$$subsidy_{jt}^{\ell} = s_t \mathbb{1}\left(Y_{jt}^{\ell} r_{jt} + g_{jt} \geq c_t\right), \tag{4}$$

where s_t represents the amount of the subsidy and c_t represents the threshold of the generic prescription share that determines whether the subsidy is granted. While both values fluctuate over time, they remain constant across all pharmacies.

We define h_{jt}^{A} as a binary indicator that signifies whether pharmacy j opts for an AG in period t. Guided by profit maximization, a pharmacy is led to select the AG (represented as $h_{jt}^{A} = 1$) if the profit obtained from doing so exceeds that from choosing an OG, that is, if $\pi_{jt}^{A} \geq \pi_{jt}^{O}$. This condition holds if the following inequality is met:

$$\mathbb{1}\left(Y_{jt}^{A} \geq c_{jt}\right) - \mathbb{1}\left(Y_{jt}^{O} \geq c_{jt}\right) \geq \frac{(f_j^A - f_j^O)}{s_t n_{jt}}, \tag{5}$$

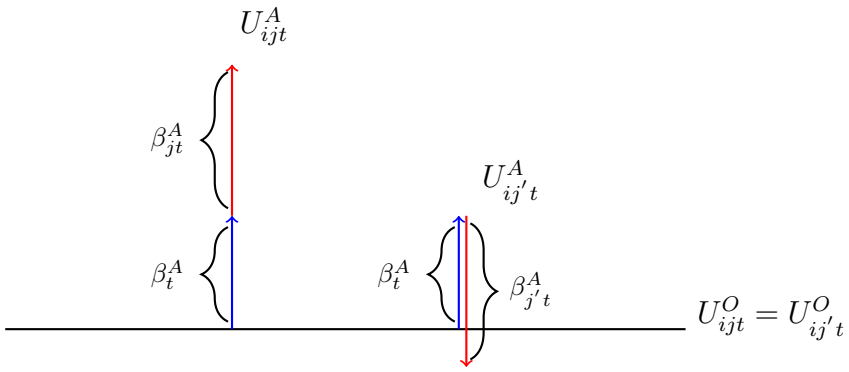
where to simplify the notation, the original threshold of generic prescription share c_t is referred to as the pharmacy-specific threshold c_{jt}, defined as $(c_t - g_{jt})/r_{jt}$.

If we consider the indicator function $\mathbb{1}(Y \geq c)$ to be a nondecreasing function of Y and the threshold c to be common on the left-hand side of Equation (5), then the profit difference $\pi_{jt}^{A} - \pi_{jt}^{O}$ also becomes a nondecreasing function of the log share difference $\ln(Y_{jt}^{A}) - \ln(Y_{jt}^{O})$. In summary, the share of generic antibiotics Y_{jt}^{ℓ} is the key factor in a pharmacy's decision to stock either an AG

[24] In Japan, pharmacies are prohibited from advertising and promoting their own pharmaceutical products. Therefore, patients do not know ex ante which pharmacies have AGs and which have OGs.

[25] To elaborate, suppose that there are K drugs other than antibiotics, with r_{jkt} being the share of drug k at pharmacy j during period t; thus, $r_{jt} + \sum_{k=1}^{K} r_{jkt} = 1$ must be satisfied. Let G_{jkt} present the generic share of drug k at pharmacy j during period t. With these conditions, we compute the total generic share as $Y_{jt}^{\ell} r_{jt} + \sum_k G_{jkt} r_{jkt} = Y_{jt}^{\ell} r_{jt} + g_{jt}$, where we define $g_{jt} = \sum_{k=1}^{K} G_{jkt} r_{jkt}$.

Figure 3: Pharmacists' Comparative Advantage



Notes: This figure shows how pharmacies' comparative advantage drives their AG adoption. Note that we abbreviate the utility from price and preference shock. While context-independent factors remain uniform across pharmacies, context-dependent factors vary as the degree of comparative advantage varies, leading to different AG adoption levels across pharmacies .

or an OG, even when considering other pharmacy-specific variables $(f^A_j, f^O_j, n_{jt}, c_{jt}, s_t)$.

4.3 Pharmacies' Comparative Advantage

Assume that each pharmacy, fully aware of patient preferences for antibiotics, optimizes its generic drug inventory to maximize its generic dispensing share. In period t, pharmacy j faces two potential choices, to select an AG or to select an OG, associated with the potential generic shares Y^A_{jt} and Y^O_{jt}, respectively. If the pharmacy chooses to stock and dispense an AG, then Y^A_{jt} is realized; otherwise, Y^O_{jt} is realized. According to Equation (2) from the demand-side model, the difference in the potential shares in logs is connected to the AG premiums perceived by patients.

$$\ln(Y^A_{jt}) - \ln(Y^O_{jt}) = y^A_{jt} - y^O_{jt} = \beta^A_t + \beta^A_{jt}. \tag{6}$$

Equation (6) demonstrates that the difference in the potential shares in the logarithm correlates positively with the difference in patient preferences. Therefore, pharmacy j in period t maximizes its generic share by stocking an AG if patients have higher AG premiums $\beta^A_t + \beta^A_{jt}$.

While the context-independent preference for AGs is assumed to be positive, denoted by $\beta^A_t > 0$, individual pharmacies may face positive or negative context-dependent patient preferences, denoted by β^A_{jt}. For example, let us consider pharmacies j and j' with $\beta^A_{jt} > 0 > \beta^A_{j't}$. If

all other factors are equal, then pharmacy j is more inclined to stock an AG in period t, while pharmacy j' favors an OG. Although the actual inventory choice may depend on various factors, this illustrates a relative difference in their tendencies to dispense either AG or OG. In essence, a pharmacy's decision to carry a particular generic depends crucially on the context-dependent preferences of its patients. Given the knowledge pharmacies have about these patient preferences, a higher β_{jt}^{A} signals a *comparative advantage* for pharmacy j in terms of selling AGs, while a lower $\beta_{j't}^{A}$ suggests that pharmacy j' has a sales advantage in terms of selling OGs. Figure 3 illustrates how comparative advantage drives the AG adoption choices of pharmacies. Note that the context-independent preferences β_{t}^{A} (blue lines) are the same across pharmacies and that the context-dependent preferences β_{jt}^{A} and $\beta_{j't}^{A}$ (red lines) differ across pharmacies. While pharmacy j has a comparative advantage in terms of selling AGs, pharmacy $j^{'}$ has a disadvantage in terms of selling AGs.

Therefore, we are interested in how context-dependent AG preferences β_{jt}^{A} vary across pharmacies since this parameter captures how pharmacists respond to patients' brand preferences. The below section describes how we empirically estimate this heterogeneous preference.

5 Empirical Specification

This section outlines the procedure for estimating a patient's AG premium, which may vary across pharmacies. According to the above model, the patient's choice of generic drug type depends not only on his or her preferences (demand side) but also on the availability of the generic drug at his or her pharmacy (supply side). Since pharmacies make dispensing decisions based on their knowledge of patients' generic drug preferences, the type of generic that a patient can access is influenced by his or her own preferences. In this situation, unobserved heterogeneous patient preferences introduce endogeneity into the estimation of AG premiums.

Furthermore, we introduce an additional framework on patient preferences, as outlined in Lemieux (1998) and Carneiro et al. (2001). Let us decompose the patient's heterogeneous prefer-

ences as follows:

$$\begin{aligned} \beta_{jt}^{B} &= \theta_{j}^{B} + \xi_{jt}^{B} \\ \beta_{jt}^{A} &= \theta_{j}^{A} + \xi_{jt}^{A}, \end{aligned} \tag{7}$$

where θ_j^B and θ_j^A represent a patient's *permanent* preferences for brand-name drugs and AGs drugs at pharmacy j, respectively. Similarly, ξ_{jt}^B and ξ_{jt}^A denote the *transitory* preference shocks for these drugs in the same pharmacy[26]. We assume that transitory preferences are uncorrelated with each other and with other preference parameters.

To address the challenge of identifying heterogeneous preferences, θ_j^B and θ_j^A, we adopt a projection method based on the approach taken by Lemieux (1998) and Suri (2011). This method involves considering the linear projections of θ_j^B onto θ_j^A, leading to subsequent orthogonal decomposition as follows:

$$\theta_j^B = \phi\theta_j^A + \tau_j \tag{8}$$

where ϕ is the projection coefficient given by

$$\phi = \frac{\mathrm{Cov}(\theta_j^B, \theta_j^A)}{\mathrm{Var}(\theta_j^A)} = \sqrt{\frac{\mathrm{Var}(\theta_j^B)}{\mathrm{Var}(\theta_j^A)}}\,\mathrm{Corr}(\theta_j^B, \theta_j^A). \tag{9}$$

The sign of ϕ corresponds to the correlation between brand-name preference θ_j^B and AG preference θ_j^A. Additionally, the parameter τ_j represents a residual component of θ_j^B that is orthogonal to θ_j^A. If the patient's brand name and AG preferences are exactly the same, then the parameter ϕ is 1. If ϕ is not 1, then patients perceive quality differences between brand-name products and AGs, indicating the over- or underestimation of brand benefits. While we do not assume a perfect correlation, it is reasonable to anticipate a positive sign for ϕ given the perceived similarity of the two types of products by patients.

We obtain the following results by reformulating these decomposition outcomes into log odds

[26]This transformation implies that context-dependent factors are decomposed into permanent factors, such as the existence of family pharmacists, and transitory factors, including the method of providing information.

equations, as specified by Equation (2):

$$\begin{aligned} y_{jt}^{A} &= \alpha \Delta P_t + (\beta_t^A - \beta_t^B) + (1-\phi)\theta_j^A - \tau_j + (\xi_{jt}^A - \xi_{jt}^B) \\ y_{jt}^{O} &= \alpha \Delta P_t - \beta_t^B - \phi\theta_j^A - \tau_j - \xi_{jt}^B. \end{aligned} \tag{10}$$

Then, the difference in the log odds, given by Equation (6), can be expressed as

$$y_{jt}^{A} - y_{jt}^{O} = \beta_t^A + \theta_j^A + \xi_{jt}^A. \tag{11}$$

The decision for pharmacy j to offer AGs, denoted by h_{jt}^A, is correlated with the patient's permanent preference for AGs, which is expressed as θ_j^A. Furthermore, θ_j^A empirically represents the comparative advantage for each pharmacy in adopting an AG.

Consider y_{jt} as the *observed* log odds of generic antibiotics at pharmacy j in period t. Given that a pharmacy carries either an AG or an OG exclusively, the log odds y_{jt} can be depicted as a linear combination of two *potential* log odds.

$$y_{jt} = h_{jt}^A y_{jt}^A + (1 - h_{jt}^A) y_{jt}^O \tag{12}$$

Substituting Equation (10) into Equation (12) yields

$$y_{jt} = \alpha \Delta P_t - \beta_t^B + \beta_t^A h_{jt}^A + \theta_j^A h_{jt}^A - \phi\theta_j^A - \tau_j + \xi_{jt}^A h_{jt}^A - \xi_{jt}^B \tag{13}$$

Rearranging the above equation, we then obtain the following empirical specification:

$$y_{jt} = \alpha \Delta P_t - \beta_t^B + (\beta_t^A + \theta_j^A) h_{jt}^A - \phi\theta_j^A - \tau_j + \nu_{jt}, \tag{14}$$

where $\nu_{jt} = \xi_{jt}^A h_{jt}^A - \xi_{jt}^B$ is a composite error term.

Equation (14) is a CRC model, as discussed in (Heckman and Vytlacil, 1998; Suri, 2011). In this model, the coefficient $\beta_t^A + \theta_j^A$ for a pharmacy's inventory choice h_{jt}^A is correlated with the choice itself. If incorrectly specified as a fixed effects model, then the equation becomes the following:

$$y_{jt} = \alpha \Delta P_t - \beta_t^B + \beta_t^A h_{jt}^A - \tau_j' + \nu_{jt}', \tag{15}$$

where τ'_j denotes individual fixed effects. The relationships between the estimated and original parameters are $\tau'_j = \tau_j + \phi\theta^A_j$ and $\nu'_{jt} = \nu_{jt} + \theta^A_j h^A_{jt}$. The term $\theta^A_j h^A_{jt}$ is part of the composite error, as it is unobservable and varies across pharmacies and time. In the special case where $\theta^A_j = 0$, the CRC model reduces to the fixed effects model. Otherwise, the endogeneity issue remains due to the inherent correlation between h^A_{jt} and the composite error ν'_{jt}. Therefore, using the fixed effects model generally yields a biased estimate of overall AG premiums β^A_t and fails to identify the projection coefficient ϕ related to brand and AG premiums.

5.1 Estimation Method

To estimate the structural parameters $(\beta^A_t, \theta^A_j, \phi)$ specified in Equation (14), we apply the projection method developed by Suri (2011) in the framework of the CRC model. The core idea is that pharmacies use their knowledge of patients' preferences for generics as a comparative advantage in deciding whether to stock an AG or an OG. This decision is correlated with patients' heterogeneous preferences θ^A_j, as captured by linearly projecting $\theta^A j$, representing the AG preference associated with pharmacy j, onto the history of its inventory decisions $h^A jt$. By embedding the projection equation in the estimation strategy, we aim to mitigate the endogeneity problem caused by the correlation between θ^A_j and h^A_{jt}.

For clarity, we outline the two-period estimation method; a three-period approach is detailed in Appendix F. Aligned with the approach of Chamberlain (1984), the linear projection in the two-period case is given as follows[27]:

$$\theta^A_j = \lambda_0 + \lambda_1 h^A_{j1} + \lambda_2 h^A_{j2} + \lambda_3 h^A_{j1} h^A_{j2} + \upsilon_j. \tag{16}$$

[27]The key difference between Chamberlain's original projection method and Suri's generalized approach concerns the interaction term from the historical endogenous choice variables. When the interaction term $h^A_{j1} h^A_{j2}$ is omitted from the projection equation, Equation (16), the orthogonal residual obtained from the projection υ_j may be correlated with the interaction term in the reduced form of the two-period CRC model. This correlation can generate endogeneity issues in the reduced-form estimation based on Equations (18).

Substituting Equation (16) into Equation (14) for each period yields

$$
\begin{aligned}
y_{j1} &= (\alpha \Delta P_1 - \beta_1^B - \phi\lambda_0) + (\beta_1^A + \lambda_0 + \lambda_1 - \phi\lambda_1)h_{j1}^A - \phi\lambda_2 h_{j2}^A + (\lambda_2 - \phi\lambda_3 + \lambda_3)h_{j1}^A h_{j2}^A \\
&\quad + (\upsilon_j h_{j1}^A - \phi\upsilon_j + \tau_j + \nu_{jt}) \\
y_{j2} &= (\alpha \Delta P_2 - \beta_2^B - \phi\lambda_0) - \phi\lambda_1 h_{j1}^A + (\beta_2^A + \lambda_0 + \lambda_2 - \phi\lambda_2)h_{j2}^A + (\lambda_1 - \phi\lambda_3 + \lambda_3)h_{j1}^A h_{j2}^A \\
&\quad + (\upsilon_j h_{j2}^A - \phi\upsilon_j + \tau_j + \nu_{jt})
\end{aligned}
\tag{17}
$$

We derive the following two reduced-form equations from the above equations :

$$
\begin{aligned}
y_{j1} &= \delta_1 + \kappa_1 h_{j1}^A + \kappa_2 h_{j2}^A + \kappa_3 h_{j1}^A h_{j2}^A + \zeta_{j1} \\
y_{j2} &= \delta_2 + \kappa_4 h_{j1}^A + \kappa_5 h_{j2}^A + \kappa_6 h_{j1}^A h_{j2}^A + \zeta_{j2},
\end{aligned}
\tag{18}
$$

where ζ_{j1} and ζ_{j2} are composite error terms in the estimation. The association between the reduced form and structural parameters is illustrated as follows:

$$
\begin{aligned}
\kappa_1 &= (1-\phi)\lambda_1 + \beta_1^A + \lambda_0, \\
\kappa_2 &= -\phi\lambda_2, \\
\kappa_3 &= (1-\phi)\lambda_3 + \lambda_2, \\
\kappa_4 &= -\phi\lambda_1, \\
\kappa_5 &= (1-\phi)\lambda_2 + \beta_2^A + \lambda_0, \\
\kappa_6 &= (1-\phi)\lambda_3 + \lambda_1
\end{aligned}
\tag{19}
$$

There are six reduced-form parameters $(\kappa_1, \kappa_2, \kappa_3, \kappa_4, \kappa_5, \kappa_6)$ and six structural parameters $(\lambda_1, \lambda_2, \lambda_3, \beta_1^A, \beta_2^A, \phi)$[28] Considering the normalization $\sum_j \theta_j^A = 0$, we can express λ_0 in terms of $\lambda_1, \lambda_2, \lambda_3$. Specifically, λ_0 can be represented as $\lambda_0 = -\lambda_1\bar{h}_1 - \lambda_2\bar{h}_1 - \lambda_3\bar{h}_1\bar{h}_2$, where $\bar{h}_1$ and $\bar{h}_2$ represent the average AG adoption rates across pharmacies in each period. The estimation procedure consists of two steps. First, we perform seemingly unrelated regressions on Equation (18). We obtain the reduced-form parameters and the variance-covariance matrix from this estimation. Second, we estimate the

[28] In the three-period model, there are 21 reduced-form parameters and 11 structural parameters, which indicates that the structural parameters are overidentified.

structural parameters using optimal minimum distance (OMD) estimates based on the first-stage estimates under an appropriate restriction matrix that embodies the parameter restrictions given by Equation (19)[29].

5.2 Identification

This section provides the necessary identification assumptions for estimating the structural parameters, as stated in Equation (14). Following the approach in Suri (2011), we require the assumption of the mean zero of the composite error term $\tau_j + \nu_{jt}$ conditional on the patient's heterogeneous preference θ_j^A and the pharmacy's historical adoption patterns $(h_{j1}^A, h_{j2}^A, h_{j1}^A h_{j2}^A)$ for the two-period CRC model; that is,

$$\mathrm{E}(\tau_j + \nu_{jt} | \theta_j^A, h_{j1}^A, h_{j2}^A, h_{j1}^A h_{j2}^A) = 0. \tag{20}$$

The conditional mean zero assumption for the composite error can be discussed in two parts, one for τ_j and the other for ν_{jt}. First, we can immediately show that the condition for τ_j is satisfied: the orthogonality of τ_j on θ_j^A implies that $\mathrm{E}(\tau_j | \theta_j^A) = 0$. It should be obvious that $\mathrm{E}(\tau_j | \theta_j^A, h_{j1}^A, h_{j2}^A, h_{j1}^A h_{j2}^A) = 0$ holds from the law of iterated expectation. Second, the conditional mean zero assumption for ν_{jt} is not immediately obvious and requires some preconditions for its validation. Considering that $\nu_{jt} = h_{jt}^A \xi_{jt}^A - \xi_{jt}^B$, the condition $\mathrm{E}(\nu_j | \theta_j^A, h_{j1}^A, h_{j2}^A, h_{j1}^A h_{j2}^A) = 0$ is satisfied if the transitory preference shocks ξ_{jt}^A and ξ_{jt}^B do not affect the decision of pharmacy j to introduce AGs, denoted by h_{jt}^A[30].

Based on the behavioral model of patients and pharmacies presented in the previous section, pharmacies dispense the generic drug type to maximize their generic share by using their knowledge of their patients' heterogeneous preferences. If the pharmacy focuses only on the permanent (long-term) part of the patient's preference, θ_j^A and θ_j^B, and ignores the transitory (short-term) part, ξ_{jt}^A and ξ_{jt}^B, then the conditional zero mean assumption in Equation (20) holds. This assumption may be justified because the pharmacy's inventory decisions are based on long-term contracts and

[29] We refer to a Stata package provided by Cabanillas et al. (2018) to perform the OMD estimation.

[30] This line of reasoning, linking the conditional mean zero assumption for the composite error term in the empirical model with the relationship between an agent's temporary shocks and his or her decision-making in the theoretical model, draws parallels with arguments presented in Lemieux (1998).

are therefore less sensitive to patients' short-term preferences for generics, which change from period to period. Thus, patients' permanent (long-term) preferences are predetermined, and conditional on this assumption, it seems plausible to argue that patients' transitory (short-term) preferences and decisions about generic inventories are independent.

While the zero conditional mean assumption given in Equation (20) is reasonable to some extent, we also estimate it under an alternative assumption as follows:

$$\mathrm{E}(\tau_j + \nu_{jt} | \theta_j^A, h_{j1}^A, h_{j2}^A, h_{j1}^A h_{j2}^A, M_{jt}) = 0, \tag{21}$$

where M_{jt} represents a vector of local market characteristics at time t for pharmacy j. In the subsequent empirical analysis, this term encompasses an interaction term between time and the prefecture dummy for the pharmacy's location.

Given that we control for relevant time-variant market characteristics, which can confound both the patient's transitory preference shock and the pharmacy's generic introduction, we find it more convincing that changes in patient preference shocks ξ_{jt}^A and ξ_{jt}^B do not influence the pharmacy's introduction of whether to carry AG drugs, as indicated h_{jt}^A. Under the weaker assumption of a conditional zero mean, as described by Equation (21), we conduct empirical analysis by incorporating the market characteristics into a reduced-form equation, Equation (18):

$$\begin{aligned} y_{j1} &= \delta_1 + \kappa_1 h_{j1}^A + \kappa_2 h_{j2}^A + \kappa_3 h_{j1}^A h_{j2}^A + \iota_1 M_{j1} + \zeta_{j1} \\ y_{j2} &= \delta_2 + \kappa_4 h_{j1}^A + \kappa_5 h_{j2}^A + \kappa_6 h_{j1}^A h_{j2}^A + \iota_2 M_{j2} + \zeta_{j2}, \end{aligned} \tag{22}$$

5.3 Validating the Model Assumptions

Given patients' different preferences, the behavioral model posits that pharmacies maximize their profits when dispensing generics. We examine the consistency of our model assumptions with empirical data in the below three ways.

First, a positive estimate for the parameter ϕ should be observed. Given that ϕ denotes the correlation between brand-name drug preferences and those for AG drugs, we anticipate a positive value. This expectation arises because both types of drugs produced by the same company are identical in terms of their appearance and content. If there is a departure from the perfect cor-

relation case, $\phi = 1$, then patients perceive quality differences between the essentially identical brand-name and AG drugs.

Second, we explore the relationship between heterogeneous patient preferences θ_j^A and pharmacy inventory choices h_{jt}^A within the framework of the supply-side model. This model posits that such preferences directly influence which drug types pharmacies choose to stock, as presented by the linear projection shown in Equation (16). To confirm the validity of this relationship, the significance of parameters $(\lambda_1, \lambda_2, \lambda_3)$ should be confirmed through a joint test[31]. Additionally, if $\theta_j^A = 0$, then we cannot observe a correlation between θ_j^A and h_{jt}^A. Therefore, the significant relationship between θ_j^A and h_{jt}^A suggests that the specification of our CRC model is valid over the fixed effects model.

Finally, we examine the distribution of the context-dependent patient AG preferences θ_j^A. The significant variation indicates that differences in generic drug inventories across pharmacies are driven by patient preferences, consistent with our model assumptions. We calculate this heterogeneous preference using Equation (16) with the structural parameters $(\hat{\lambda}_0, \hat{\lambda}_1, \hat{\lambda}_2, \hat{\lambda}_3)$ and set ν to zero. To gauge the relative importance of context-dependent patient preference θ_j^A, we compare its standard deviation to the magnitude of the time-averaged context-independent preferences β_i^A.

6 Estimation Results

In examining the adoption of AG drugs by pharmacies, we focus on pharmacies prescribing levofloxacin. For consistency in the empirical analysis, we exclude pharmacies, as identified in the JAST claim data, that prescribe both OG and AG forms of levofloxacin (constituting 4.32% of the sample). Furthermore, small pharmacies with extremely low numbers of prescriptions are excluded from our main analysis. Therefore, pharmacies in the bottom 5% of the total number of prescriptions are excluded from the analysis. Moreover, as shown in Figure 1, in 2015, when the first-year generic levofloxacin was fully introduced, both OG and AG adoption rates by pharmacies increased but were not stable. In addition, the dispensing behavior of pharmacies may have changed due to the introduction of the family pharmacist program in 2016. Therefore, the empiri-

[31]The same joint test for parameter significance can also be performed in a three-period example based on the corresponding linear projection equation.

cal analysis was conducted from April 2016 to December 2021, with two consecutive years as one period of the empirical model presented in Section 4.

6.1 Sample Statistics

Table 1, Panel A, provides statistics on levofloxacin prescriptions across various pharmacies concerning the ratio of the number of generic levofloxacin prescriptions (generic prescription ratio) and the number of AG levofloxacin prescriptions (AG prescription ratio) for each period. Importantly, the value of the brand-name share of levofloxacin is 0 or 1. In the theoretical model, Y_{jt}^B and Y_{jt}^ℓ represent the probabilities of pharmacy j adopting a brand drug or ℓ type generic drug in year t, respectively, and they are never equal to 0 or 1. However, if these probabilities are sufficiently close to 0 or 1, then the observed brand or generic share, the empirical analog of those probabilities, may take a value of 0 or 1. In such cases, y_{jt}^ℓ, the log odds of the left-hand side of the empirical model shown in Equation (14), cannot be defined. Therefore, for pharmacies with a brand-name share of 0, namely, a generic share of 1, we replace the share with a small positive constant $\epsilon > 0$ to perform the empirical analysis. In the baseline analysis, estimation is performed as $\epsilon = 10^{-2}$ considering the size of prescription numbers in Table 1, but estimation is also performed for several alternative values of ϵ to check the robustness of the estimation results.

For pharmacies that have a brand share of 1, which means a generic share of 0, it is not possible to determine whether the pharmacy holds an AG, and thus, the value h_{jt} representing whether pharmacy j holds an inventory in period t cannot be determined[32]. Consequently, we omit pharmacies from the sample if they have a generic share of zero at any point during period t in our baseline analysis. However, we assume that if a pharmacy has no observed generic prescriptions during a particular period, then it still holds the type of generic drug it most recently had in stock. Specifically, if pharmacy j has a zero generic share in period t but had prescribed a generic drug before period t, then we derive h_{jt} from the observed generic types. We then estimate the generic share for pharmacy j in t to check the robustness of the results.

Table 1, Panel B, shows the distribution of pharmacy store attributes (number of prescriptions, whether the pharmacy is a chain or individual store, and the concentration index of prescriptions

[32]Even if a pharmacy's observed generic drug share is zero, it may still stock generic drugs. However, this absence of prescriptions prevents the determination of whether the inventory includes AG or OG types.

Table 1: Sample Statistics

		2016-2017	2018-2019	2020-2021
Panel (A)				
Generic Share	min	0.00	0.00	0.00
	max	1.00	1.00	1.00
	median	0.90	1.00	1.00
	mean	0.72	0.82	0.87
	s.d.	0.35	0.29	0.27
AG share	min	0.00	0.00	0.00
	max	1.00	1.00	1.00
	median	1.00	1.00	1.00
	mean	0.56	0.59	0.62
	s.d.	0.48	0.47	0.47
Panel (B)				
Number of Prescriptions	mean	113.05	119.86	61.55
	s.d.	476.31	527.58	236.12
Concentration Index	mean	0.83	0.81	0.83
	s.d.	0.24	0.25	0.24
Chain Store	mean	0.07	0.14	0.14
	s.d.	0.26	0.35	0.35
Family Pharmacists Prescriptions	mean	0.02	0.03	0.2
	s.d.	0.33	0.37	0.27
Observations		12164	12164	12164

Notes: This table shows the descriptive statistics of our three-period data on the antibiotic levofloxacin (brand name is Cravit). In each period, data start from April and end in March, except for the last period. We aggregate the data in each period. In Panel A, the generic share is defined as the ratio of the number of generic drug prescriptions to the number of total prescriptions for antibiotics. The AG share is defined as the ratio of the number of AG prescriptions to the number of generic drugs, including both AG and OG prescriptions. In Panel B, we report pharmacy characteristics. In the first row, we define the number of prescriptions as the total number of prescriptions in all prescribed drugs groups. The concentration index is the Herfindahl–Hirschman index using the share of antibiotic prescriptions from hospitals. Chain store is the dummy concerning whether or not each pharmacy is chain. Family pharmacist prescriptions denotes the share of prescriptions by family pharmacists.

Table 2: Share and Characteristics

		Categories		Test Statistics (p-value)
		Large	Small	
Pharmacy Size	AG Share	0.580	0.618	-2.993 (0.002)
		Chain	Individual	
Pharmacy Type	AG Share	0.531	0.602	-7.267 (<0.001)
		High	Low	
Concentration Index	AG Share	0.624	0.438	16.945 (<0.001)
		Presence	Absence	
Family Pharmacist	AG Share	0.359	0.597	-9.104 (<0.001)

Notes: This table presents the average AG share based on patients' attributes. For each pharmacy, we categorize two groups and test the significance of the share difference between them. In the first row, we define pharmacy size as the number of prescriptions and distinguish between the top 10% (large) and bottom 10% (small) sizes. Similar categorizations are applied to the concentration index. We assume that if family pharmacists dispense the antibiotics even once, then it indicates the presence of family pharmacists at that pharmacy. For the concentration index, we use the Herfindahl–Hirschman index.

from hospitals to pharmacies) for each period. The number of prescriptions refers to the number of all prescriptions, including antibiotics and other pharmaceuticals, dispensed by each pharmacy[33]. The prescription concentration index is the Herfindahl–Hirschman index, which is given by the sum of the squares of the shares of prescriptions from each pharmacy in a given pharmacy. The index, ranging from 0 to 1, reflects prescription sourcing—a higher value indicates that a larger proportion of prescriptions are received from a single hospital. Chain store is a dummy variable indicating whether a pharmacy is part of a chain store. Family pharmacist prescriptions are the share of prescriptions by family pharmacists. These descriptive statistics indicate that our data target primarily small-scale, privately owned pharmacies that receive many prescriptions from a specific hospital.

Table 2 compares the mean AG prescription share of levofloxacin to identify various phar-

[33]Note that our claim data constitute only a subset of the total prescriptions dispensed by pharmacies.

Table 3: Adoption Transition

Adoption Pattern	AAA	OOO	AAO	AOO	OOA	OAA	AOA	OAO
Fraction of Sample (%)	52.98	34.52	1.75	2.36	3.74	4.26	0.15	0.20
Number of Switch	0	0	1	1	1	1	2	2

Notes: The table illustrates the adoption patterns of AGs and OGs in pharmacies across three periods. Pattern AAA signifies that the pharmacy consistently adopts AGs throughout all periods, whereas OOO denotes the exclusive dispensing of OGs.

macy characteristics. For pharmacy size, we categorize pharmacies based on their prescription volumes—those in the top 10% quantile are classified as large pharmacies, and those in the bottom 10% quantile are classified as small pharmacies. The results show that small pharmacies are more likely to dispense AGs than are large pharmacies. For pharmacy type, we classify pharmacies according to whether or not they are chain stores. We also categorize the top and bottom deciles of the pharmacy's concentration index into high and low groups, respectively. Finally, we categorize pharmacies based on the presence of family pharmacists. We assume that if family pharmacists dispense antibiotics even once, then this indicates the presence of family pharmacists at that pharmacy. These results reveal significant disparities in AG dispensing rates across pharmacy attributes.

According to our CRC model, a pharmacy's adoption history plays a significant role. We define the adoption status of a pharmacy in each period h_{jt} based on the predominant generic type dispensed during that period. Importantly, pharmacies do not frequently change their generic inventory types and typically alter them annually. However, some pharmacies switch between stocking AGs and stocking OGs during the analysis period spanning two years for three-period estimates. Therefore, we consider a pharmacy to have adopted the generic type most frequently dispensed during the period. Specifically, a pharmacy is considered to have adopted AGs if it dispensed more AGs than it did OGs during a given period.

Table 3 shows the pattern of transitions of the generic type introduced by pharmacies. The pattern AAA signifies that the pharmacy consistently adopts AGs throughout all periods, whereas OOO denotes the exclusive dispensing of OGs. While the majority of pharmacies continue to use AGs or OGs in these three periods, 12.46% of the pharmacies change the generic type at least once during the three periods.

6.2 Average Brand Preference

Table 4 presents the fixed effects estimates derived from Equation (15). We report the estimated average preference β_t^A in both the two- and three-period models. The estimated coefficient β_t^A is positive in both the two- and three-period models, regardless of the fixed effects specifications. However, the fixed effects model does not completely rectify adoption endogeneity and considers the effect of pharmacists β_{jt}^A. Nonetheless, our descriptive results suggest a positive preference for AG among patients.

Table 4: Fixed Effects Estimates

	Two Period		Three Period	
	(1)	**(2)**	**(3)**	**(4)**
β_1^A	0.198	0.202	0.167	0.167
	(0.066)	(0.066)	(0.057)	(0.057)
β_2^A	0.305	0.336	0.283	0.293
	(0.067)	(0.067)	(0.055)	(0.056)
β_3^A			0.284	0.308
			(0.057)	(0.057)
Pharmacy FE	×	×	×	×
Year FE	×	×	×	×
Year × Local Market FE		×		×
Observations	19636	19636	29454	29454

Notes: Cluster-robust standard errors are in parentheses. In the two-period analysis, we utilize data from the first and last periods of the three-period dataset. Our model incorporates both pharmacy-level fixed effects and year-level dummies. In Columns (2) and (4), we include a year × prefecture-level dummy.

Table 5 displays our model estimation results from Equation (16) for both the two- and three-period models. Note that the estimated parameters do not provide a behavioral interpretation, serving primarily for model assumption validation. As discussed in Section 5.3, the joint test of parameters $(\lambda_1, \ldots, \lambda_7)$ allows us to evaluate the model assumption represented in Equation (16). Therefore, we implement a Wald test on the null hypothesis that all parameters equal zero. The Wald statistics indicate that while the assumption does not apply to the two-period model, as shown in Columns (1)–(2), it is valid for the three-period model, as shown in Columns (3)–(4). Given that the two-period model exhibits less variation in adoption h_{jt} than does the three-period model, it is plausible that the two-period model is insufficient for extracting heterogeneous preference θ_j^A

Table 5: Projection Estimates

	Two Period		Three Period	
	(1)	**(2)**	**(3)**	**(4)**
λ_1	-0.168	0.052	0.068	0.017
	(2.852)	(0.314)	(0.054)	(0.049)
λ_2	-0.154	0.075	0.248	0.243
	(2.692)	(0.474)	(0.211)	(0.191)
λ_3	0.209	-0.082	0.063	0.100
	(3.237)	(0.564)	(0.052)	(0.050)
λ_4			-0.110	-0.046
			(0.230)	(0.208)
λ_5			-0.957	-0.958
			(0.210)	(0.200)
λ_6			-0.083	-0.097
			(0.220)	(0.199)
λ_7			0.742	0.824
			(0.275)	(0.267)
Wald Statistics	0.748	0.242	27.212	25.434
	[0.861]	[0.970]	[0.000]	[0.000]
Local Market Controls		×		×
Observations	19636	19636	29454	29454

Notes: Standard errors are in parentheses. P values are in brackets. The table presents the parameter estimates from Equation (16). In the two-period model, data from the first and last periods of the three-period dataset are utilized. The Wald test assesses the joint significance of these estimated parameters.

from adoption history h_{jt}. In the following analysis, our primary empirical approach employs the three-period model.

Table 6 provides our empirical findings on the context-independent preference of β_t^A, interpreted as the average patient preference for AGs during period t. Column (2) shows our baseline results. In Columns (1) and (2), our results show a consistently positive average AG preference β_t^A over all three periods, suggesting that patients prefer AGs over OGs because of the greater premiums for AGs compared to those for OGs in terms of scientific efficacy, color, and additives. While β_t^A varies across periods, the magnitude of the preference stays relatively steady, and patients consistently prefer AGs. Furthermore, from a pharmacy perspective, pharmacies dispensing AGs stand to gain a greater generic share by taking the average positive AG preference among patients. Consequently, pharmacies that dispense AGs likely capture a larger share of the generic market, benefiting from the patients' overall positive preference for AGs.

Table 6: Average AG Preference

	Three Period					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
β_1^A	0.080	0.124	0.157	0.130	0.159	0.233
	(0.112)	(0.094)	(0.159)	(0.190)	(0.156)	(0.088)
β_2^A	0.206	0.255	0.349	0.335	0.353	0.369
	(0.112)	(0.094)	(0.160)	(0.191)	(0.157)	(0.090)
β_3^A	0.201	0.266	0.348	0.354	0.362	0.435
	(0.112)	(0.093)	(0.157)	(0.185)	(0.155)	(0.106)
χ^2	17.04	18.25	17.12	16.31	16.42	19.65
Local Market Controls		×	×	×	×	×
Observations	29454	29454	30516	28098	29454	30483

Notes: Standard errors are in parentheses. Columns (1) and (2) are our main results. Variations in data and model specifications are seen in Columns (3)–(6). In Column (3), we include all pharmacies without excluding the bottom 5% according to size. Column (4) omits those pharmacies that fall within the bottom 10% in terms of size. The values of ε are adjusted in Column (5) to 0.001. Moreover, in Column (6), if pharmacies dispense only brand-name drugs, then the adoption measure h_{jt} is sourced from the previous year for each period.

Columns (3)–(6) investigate the robustness of our primary findings. In Column (3), we consider all pharmacies, omitting the exclusion of the bottom 5% based on prescription size, whereas Column (4) excludes the bottom 10% of pharmacies. Column (5) presents the outcome when ε is set to 0.001. Finally, in our primary analysis, we exclude pharmacies that dispense only brand-name drugs. Column (6) addresses this sample selection by imputing the adoption h_{jt} for pharmacies that do not dispense generic drugs. We posit that if a pharmacy does not dispense generics in a specific period but had prescribed either AGs or OGs in the previous period, then it would continue that adoption in the current period. These analyses confirm that patients consistently and positively prefer AGs to OGs across all three periods.

We can also interpret these results in terms of generic substitution. For each pharmacy adopting OGs, we can calculate the counterfactual generic share if AGs are adopted instead of OGs, using the average AG preference β_t^A[34]. Table 7 shows how much the generic shares would change if pharmacies counterfactually adopted AGs instead of OGs in each adoption group, except for those that adopt AGs throughout all periods. This finding indicates a 1.00–1.56% increase in the generic

[34]For each adoption pattern group g, we calculate the change in the generic share when pharmacies adopt AGs instead of OGs as follows: $\Delta\widehat{Y_g} = \frac{1}{T_g J_g}\sum_{t=1}^{T_g}\sum_{j=1}^{J_g}\frac{\widehat{Y_{jt}^A}-\widehat{Y_{jt}^O}}{\widehat{Y_{jt}^O}}$, where T_g and J_g are the number of periods in which pharmacies adopt OGs and the number of pharmacies in each adoption pattern group, respectively. See Appendix C for the detailed calculation.

Table 7: Generic Substitution via Average AG Preference

Adoption Pattern	AAA	OOO	AAO	AOO	OOA	OAA	AOA	OAO
Generic Share Change (%)		1.16	1.56	1.34	1.04	1.00	1.21	1.10
Generic Share (%)		89.02	89.67	91.16	85.83	81.47	98.65	86.36
Fraction of Sample (%)	52.98	34.52	1.75	2.36	3.74	4.26	0.15	0.20
Number of Switch	0	0	1	1	1	1	2	2

Notes: This table reports the magnitude of generic substitution via estimated average AG preference β_t^A in Table 6, Column (2). For each pharmacy adopting OGs, we can calculate the counterfactual generic share if it adopts AGs instead of OGs and take the average in each adoption group. Since pharmacies categorized in the adoption pattern AAA have already adopted AGs, we cannot calculate the degree of generic substitution. We report the actual average generic share in each adoption group during the three periods. The fraction of samples is the same as that in Table 3.

share. As the table illustrates, the prevalence of generic drug adoption is already high in every pharmacy, and substituting OGs with AGs could yield an appreciable increase in the generic share, which should not be overlooked.

6.3 Recovered Context-Dependent Preference

Table 8: Recovered Context-Dependent Preference

Adoption Pattern	AAA	OOO	AAO	AOO	OOA	OAA	AOA	OAO
Context-dependent Preference: $\hat{\theta}_j^A$	0.021	-0.062	0.152	-0.044	0.038	0.184	-0.902	0.181
Fraction of Sample (%)	52.98	34.52	1.75	2.36	3.74	4.26	0.15	0.20
Number of Switch	0	0	1	1	1	1	2	2

Notes: This table reports the recovered context-dependent preference $\hat{\theta}^A$. Estimates correspond to Column (2) in Table 6. The fraction of samples is the same as that in Table 3.

Table 8 reports the recovered context-dependent AG preference. Since we estimate the context-dependent preference θ_j^A by the linear projection of the adoption history h_{jt}, the recovered preference $\hat{\theta}_j^A$ depends on the adoption patterns, as shown in Table 3. The results suggest that a substantial difference in AG preference exists across pharmacies. The one-standard-deviation change in the recovered context-dependent AG preference $\hat{\theta}_j^A$ is 0.073. Given that the estimated context-independent patient preference β_t^A over three periods averages 0.215, as reported in Column (2) of Table 6, the context-dependent preference $\hat{\theta}_j^A$ represents 36.52% of the average preference β_t^A.

In Table 8, the recovered preference for pharmacies that adopt AGs in all three periods (AAA) is positive, whereas it is negative for pharmacies that adopt OGs throughout the same periods (OOO). The sign of $\hat{\theta}_j^A$ indicates a pharmacy's comparative advantage for dispensing generic drugs, as explained in Section 4.3. While the majority of pharmacies have a comparative advantage for AGs, more than one-third of pharmacies have a comparative advantage for OGs. These estimation results imply that although patients generally prefer AGs over OGs, the degree of this relative preference varies among pharmacies, leading them to stock either AGs or OGs based on their respective comparative advantages.

However, the recovered context-dependent AG preference may reflect cost factors affecting the pharmacy's inventory decisions beyond the patient's context-dependent preference. In the previous section, we assume that pharmacists adopt AGs to maximize profits, and Equation (5) shows that the adoption decision h_{jt} hinges on (1) patients' brand preferences (i.e., β_{jt}^A) and (2) the inventory cost difference between AGs and OGs (i.e., $f_j^A - f_j^O$). Consequently, the recovered $\hat{\theta}_j^A$ from the linear projection in Equation (16) may conflate demand factors such as patient preferences with supply factors such as adoption costs. To isolate these conflating demand and supply factors, we regress $\hat{\theta}_j^A$ on a nonlinear function of pharmacy-specific, time-invariant characteristics F_j, related mainly to the cost of dispensing generics.

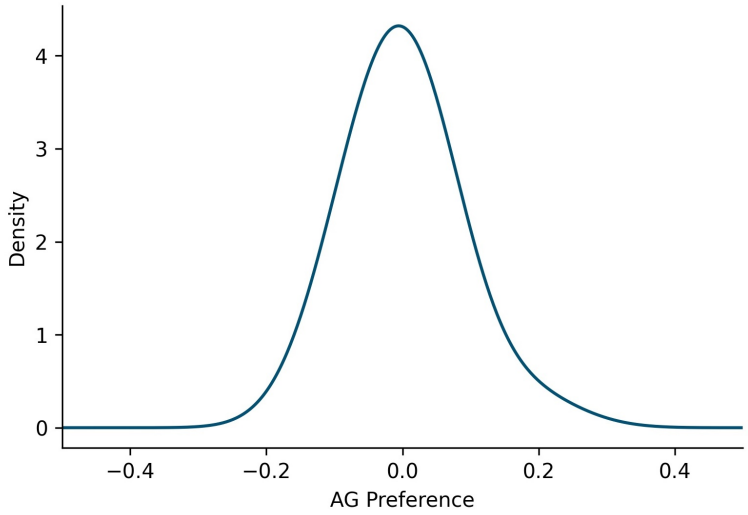
The residual from the regression is considered the "true demand-driven" patient preference, having partialled out the cost factors related to pharmacy inventory decisions. We use this residualized or "partialled-out" context-dependent AG preference $\tilde{\theta}_j^A$ to validate the model's assumptions. In the empirical specification, we include the pharmacy's (1) management type (small chain, large chain, near hospital, or individual), (2) size, (3) concentration index, and (4) size of prescription-issuing hospitals. Our main analysis employs a random forest for nonlinear functions. Even when utilizing other methodologies, including lasso, Xgboost, and polynomial functions, as alternative specifications, the magnitude of the residual remains consistent.

In Appendix E, we detail the estimation procedures and confirm the robustness of the results across various specifications. In addition, we investigate which cost factors at pharmacies are associated with recovered context-dependent preferences $\tilde{\theta}_j^A$. Figure E1 uses the feature importance measures from our baseline random forest to show which cost factors are related to $\hat{\theta}_j^A$[35]. The

[35]We evaluate feature importance in the random forest model based on Gini importance, which measures the im-

results highlight the substantial contributions of the pharmacy's size and the characteristics of the hospital issuing prescriptions to the recovered context-dependent preferences.

Figure 4: Recovered Preference $\tilde{\theta}_j^A$



Notes: This figure reports the estimated probability density of empirically estimated AG preference $\tilde{\theta}_j^A$. To estimate the AG preference $\tilde{\theta}_j^A$, we regress the estimated $\hat{\theta}_j^A$ on the nonlinear function of the pharmacy's cost-related factors.

Figure 4 displays the distribution of $\tilde{\theta}_j^A$, highlighting variations in patient AG preferences across pharmacies. Given that one standard deviation of $\tilde{\theta}_j^A$ is computed at 0.070, it accounts for approximately 34% of the time-averaged context-independent AG preference β_t^A. Remarkably, even after accounting for factors potentially related to inventory costs, the relative importance of context-dependent AG preference to context-independent AG preference remains largely unchanged, dropping only slightly from 36.52% to 34.88%. This minor decrease underscores the robustness of the substantial role played by context-dependent AG preferences, despite the potential influence of inventory-related factors. Furthermore, the shape of the distribution shown in the figure indicates that pharmacies with a comparative advantage for AGs and those with a comparative advantage for OGs are evenly distributed, showing no significant skew toward one side of the comparative advantage. These estimation results suggest that despite accounting for cost factors related to inventory decisions, the variation in patients' context-dependent preferences remains considerable

portance of each feature by the total decrease in Gini impurity that it brings about across all the trees in the forest.

across pharmacies.

6.4 Correlation of Brand Preferences

While we find significant heterogeneity in patients' AG preferences, Table 9 also suggests that such heterogeneity exists in patients' perceived preferences for brand-name drugs. This table reports positive values of ϕ, reflecting a positive correlation between preferences for brand-name drugs and AGs. However, since the estimated ϕ significantly differs from $\phi = 1$, patients' preferences for brand-name drugs and AGs are not perfectly identical, even though they are identical products differing only in terms of their packaging. An inspection of Equation (9) identifies the determinants behind this phenomenon. Given that $\phi > 1$, (1) $\mathrm{Corr}(\theta_j^B, \theta_j^A)$ is close to one, and/or (2) $\mathrm{Var}(\theta_j^B)$ is larger than $\mathrm{Var}(\theta_j^A)$. Given that brand-name drugs and AGs are identical products, we would expect $\mathrm{Corr}(\theta_j^B, \theta_j^A) \simeq 1$, implying that $\mathrm{Var}(\theta_j^B)$ is larger than $\mathrm{Var}(\theta_j^A)$, or that patients' preference for brand-name drugs is more widely distributed across pharmacies compared to their preference for AGs.

Table 9: Relationship between Brand-Name and AG Preference

	Three Period					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
ϕ	1.415	1.497	1.467	1.385	1.505	1.674
	(0.241)	(0.249)	(0.253)	(0.234)	(0.264)	(0.294)
P-values for $H_0 : \phi = 1$	0.000	0.000	0.000	0.000	0.000	0.000
Local Market Controls		×	×	×	×	×
Observations	29454	29454	30516	28098	29454	30483

Notes: Standard errors are in parentheses. All columns correspond to the specifications in Table 6. Columns (1) and (2) display the primary results. Variations in data and model specifications are seen in Columns (3)–(6). In Column (3), we include all pharmacies without excluding the bottom 5% by size. Column (4) omits those pharmacies that fall within the bottom 10% in terms of size. The value of ε is adjusted in Columns (5) to 0.001. Moreover, in Column (6), if pharmacies dispense only brand-name drugs, then the adoption measure h_{jt} is sourced from the previous year for each period.

Further analysis is needed to understand why the distribution of patient preferences differs between brand-name drugs and AGs. However, one possible explanation may be the provision of information by pharmacists. As discussed in Section 2, pharmacists in Japan are mandated

to provide information about generic drugs when dispensing medications based on prescriptions. Therefore, compared to brand-name drugs, patients may be more informed about the quality of AGs, resulting in a relatively smaller variance in the perceived quality of AGs across pharmacies.

In the next section, to further corroborate the significant role of information in shaping patients' perceived preferences, we investigate the impact of information provided by pharmacists on patients' preferences for generic drugs.

7 Role of Information

In the preceding section, we illustrate that patient preferences for AGs exhibit significant variation across pharmacies, and this variation arises from differences in patients' perceptions of quality between AGs and OGs. However, the specific factors that account for patients' heterogeneous AG preferences remain undetermined. Given pharmacists' primary responsibility for drug dispensation and information provision, we investigate how their role in conveying information affects patients' context-dependent generic preferences.

Table 10: Role of Information for Pharmacists

	Three Period			
	(1)	**(2)**	**(3)**	**(4)**
Family Pharmacist: Presence	-0.0228	-0.0191	-0.0169	-0.0139
	(0.0035)	(0.0045)	(0.0033)	(0.0042)
Family Pharmacist: Prescription Share		-0.0040		-0.0033
		(0.0023)		(0.0023)
Observations	9818	9818	9818	9818

Notes: Standard errors are in parentheses. The table shows the relationship between a patient's AG brand preference and information provided by pharmacists. An estimate of intercept is omitted. In Columns (1)–(2), the dependent variables represent recovered AG preferences as shown in Table 8, whereas in Columns (3)–(4), the dependent variables are depicted in Figure 4. We use three-period data and the patient AG preference derived from Column (2) in Table 6. Family pharmacist presence is defined as a dummy variable representing the presence of family pharmacists at pharmacy j. Family pharmacist prescription share is defined as the dispensing share by family pharmacists at pharmacy j.

Table 10 illustrates the relationship between the recovered AG preference and the information provision by family pharmacists in pharmacy j. We utilize two indicators as proxies for the

pharmacist's information-providing behavior—(1) a dummy variable representing the presence of family pharmacists in the pharmacy and (2) the share of prescriptions processed by family pharmacists. In Columns (1)–(2), the dependent variables are recovered AG preference in Table 8, while the dependent variables in Columns (3)–(4) are in Figure 4. Column (1) shows that patients are less likely to present brand preference when they receive drugs in pharmacies where family pharmacists exist. Given the advanced drug instructions that family pharmacists are equipped to provide, these findings suggest that providing expert information changes patients' perceived quality differences between AGs and OGs. Column (2) investigates to what extent family pharmacists' information provision is related to patient brand preference. The results show that the more family pharmacists dispense drugs, the less patients present brand preference, but the magnitude is relatively small. From Columns (3)–(4), we observe a similar trend between AG preferences and information provision[36].

This result reveals a strong positive relationship between the provision of information by pharmacies and their comparative advantage over OGs. The decision to stock either an AG or an OG is affected by both demand factors, such as patients' generic preferences, and supply factors, such as inventory costs, which may differ based on the pharmacy's location and organizational structure. However, pharmacies facing higher costs for introducing AGs may employ family pharmacists to deliver comprehensive information on generic drugs, thus offsetting the cost-based disadvantages of providing AGs to patients. This strategic provision of information can facilitate a shift from brand-name drugs to generics by reducing the patient's context-dependent preference for AGs compared to OGs, even when stocking OGs is more cost-effective for pharmacies.

8 Conclusions

This paper focuses on pharmacists who dispense AGs that are identical to the original brand-name drugs and analyzes how consumers' brand preferences change with professional experts. Our model and empirical results indicate that patients have a heterogeneous brand preference for AGs,

[36] In Appendix E, we examine the relationship between information provision by family pharmacists and context-dependent preferences $\hat{\theta}_j^A$, similar to our investigation of cost factors in Section 6.3. Figure E2 reveals that the relative importance of information provision to context-dependent preferences is considerable, ranking as the third most influential factor after pharmacy size and the characteristics of hospitals issuing prescriptions.

which varies among pharmacists. Moreover, we show that one of the factors behind this difference is related to the provision of information by pharmacists, which implies that when pharmacists have fewer opportunities to provide detailed information about drugs to patients, patients are more likely to respond to brand premiums. In contrast, patients are less likely to respond to brand premiums and use OGs when pharmacists can provide detailed information. Consequently, our results suggest that a consumer's brand premium assessment is tethered to the granularity of information shared with experts.

There are several limitations to our analysis. First, our study is limited to antibiotics. While antibiotics are typically prescribed for short-term ailments, the decision-making horizon for pharmacists may differ in medications addressing chronic conditions such as hypertension and allergies. Second, our dataset lacks detailed pharmacy cost information, preventing us from performing counterfactual analyses of pharmacy adoption behavior. Finally, unlike Starc and Swanson (2021), our model does not explicitly consider the negotiations between pharmacies and drug wholesalers. Notably, pharmacy costs are intrinsically linked to bargaining power, implying that they may sway pharmacists' dispensing behavior.

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Appendix

A Survey Results

We surveyed pharmacists working in Japanese dispensing pharmacies. This survey targeted 100 pharmacy managers responsible for drug procurement, who were randomly selected from 7,481 pharmacists registered in the healthcare consulting company MCI Co., Ltd., survey panel, all working in dispensing pharmacies across Japan. In this study, the inquiries posed exclusively pertain to generic drugs within the realm of antibiotics. Furthermore, the identities of the pharmacists who provided responses were anonymized to maintain confidentiality.

Table A1 presents the characteristics of the responding pharmacies and pharmacists. Pharmacies are categorized by pharmacy type according to a mutually exclusive classification by the MHLW, influencing the basic technical fees for dispensing (Ministry of Health, Labour and Welfare, 2023a). A pharmacy is classified as near a hospital if 70% or more of its prescriptions are hospital specific, regardless of whether it is a chain or independent pharmacy. The main revenue source section indicates the primary income for dispensing generic antibiotics; notably, 76% cited subsidies for generic drugs. Position details the job titles of respondents, all in charge of drug procurement. Finally, qualification shows that a significant 84% of respondents hold a family pharmacist qualification.

Table A2 details the factors influencing the selection of generic pharmaceutical manufacturers by pharmacies. Note that the pharmacists provided up to three responses to this query. In Japan, numerous pharmaceutical companies produce and market identical generic drugs at different wholesale prices, and pharmacies purchase from one of them in practice. According to Table A2, a stable supply and the trustworthiness of manufacturers are pivotal in selecting these manufacturers. Interestingly, only 13.85% of the pharmacists deem the wholesale price a significant factor. These findings suggest that when introducing generic drugs encompassing both AGs and OGs, pharmacies tend to prioritize the stability of generic drug sales over wholesale pricing.

Table A3 shows the factors influencing the selection of AGs among generic pharmaceuticals. In this query, 91 pharmacists with experience selling AG antibiotics responded to up to three options. Table A3 indicates that while 20.32% of the pharmacists consider a stable supply to

Table A1: Pharmacy and Pharmacist Characteristics

	Categories	Number	% of Total
Pharmacy Type	Near hospitals	58	58.00
	Chain	36	36.00
	Individual	35	35.00
	Inside hospitals	1	1.00
Main Revenue Source	Generic subsidy	76	76.00
	Prescription margin	24	24.00
Position	Supervising pharmacist	100	76.00
	Others	0	100.00
Qualification	Family pharmacist	84	84.00
	Non-Family pharmacist	16	16.00
Observations		100	100

Notes: The table shows the characteristics of the pharmacies and pharmacists in our survey. We target 100 supervising pharmacists who are responsible for drug procurement. We classify pharmacy type based on the basic technical fees for dispensing (Ministry of Health, Labour and Welfare, 2023a). This table reports all the options we asked pharmacists about in our survey.

be important, factors such as AGs' identical nature to the original brand (28.38%) and patient preference for AGs (26.62%) were deemed more significant. These results suggest that although pharmacists generally value a stable supply of generic drugs, they prioritize the identical nature and patient brand preference when introducing AGs. Furthermore, only 3.53% of the pharmacists reported adopting AGs based on doctors' directives, indicating the minimal influence of physician intervention in this context.

Finally, Table A4 illustrates pharmacists' actions when patients refuse to accept generic pharmaceuticals. Approximately 25% of pharmacists provide information about the efficacy and safety of generic drugs. Note that while 46% of pharmacists prescribe the brand-name drug, this includes those cases where patients continue to refuse generics even after receiving information. This highlights that pharmacists tend to alter patients' preferences toward generic drugs by providing them with relevant information.

The overall findings of these surveys indicate that (1) pharmacists dispense brand-name drugs, OGs, and AGs, operating independently from physicians; (2) pharmacists derive financial benefits from subsidies allocated for generic drugs; (3) pharmacists dispense AGs taking into account pa-

Table A2: Selection Factors for Generic Drugs

	Options	Number	% of Total
Why pharmacies choose the generic manufacturer	Stable supply	81	31.51
	Reliability of the manufacturer	42	23.86
	Chain store policy	23	17.16
	Low procurement cost	32	13.85
	Sales from wholesalers	22	11.05
	Sales from the manufacturer	20	7.22
	Physician's requests	6	5.17
	Others	5	2.59
Observations		231	100

Notes: This table shows the reasons why pharmacies select a specific generic manufacturer. Pharmacists can select up to three options for this question. This table reports all the options we asked pharmacists about in our survey.

tient preferences; and (4) pharmacists influence patients' preferences for generic drugs through the provision of information.

Table A3: Selection Factors for AGs

	Options	Number	% of Total
AG Adoption Factors	Equivalence to brand	67	28.38
	Patients prefer AG	45	26.62
	Stable supply	37	20.32
	Patients prefer brand	12	9.67
	Pharmacy adopt AG in other drugs	9	8.03
	Physician's direction	5	3.93
	Others	7	3.53
Observations		182	100

Notes: This table reports the reasons why pharmacists adopt AGs. Pharmacists can select up to three options for this question. This table reports all the options we asked pharmacists about in our survey.

Table A4: Handling of Patients Refusing Generic Drugs

	Options	Number	% of Total
Handling Patients Refusing Generics	Dispense brand drugs	46	46.00
	Dispense AG	29	29.00
	Provide information of generic drugs	24	24.00
	Others	1	1.00
Observations		100	100

Notes: This table shows how pharmacists handle patients who refuse to be dispensed generic drugs. This table reports all the options we asked pharmacists about in our survey.

B Major Authorized Generics

Table B1 presents the launch dates and market shares of major AG in Japan, calculated using data from the JAST database. The fourth and fifth columns detail the market shares of AG one year and three years post-launch, respectively. These data highlight that AG consistently achieves high market shares across various therapeutic categories. Furthermore, the sixth and seventh columns illustrate the percentages of pharmacies that dispense both AG and OGs at one and three years following the introduction of AG. This reveals a trend where most pharmacies do not simultaneously dispense both types of generics.

Table B1: Major Authorized Generics in Japan

Name	Release Date	Therapeutic Class	AG Share (%) 1 year from release	AG Share (%) 3 years from release	Pharmacy with AG and OG (%) 1 year from release	Pharmacy with AG and OG (%) 3 year from release
Valsartan	2014/06	Hypertension	23.08	23.46	0.88	0.05
Levofloxacin	2014/12	Antibiotic	37.57	38.08	2.96	0.36
Clopidogrel	2015/06	Antiplatelet	50.63	45.48	4.76	0.38
Dienogest	2017/06	Endometriosis	73.21	71.62	4.96	1.02
Olmesartan	2017/09	Hypertension	65.74	60.43	10.08	0.69

Notes: This table represents the release dates, therapeutic classification, and market share after release for major AG in Japan. AG share indicates the proportion of an AG to the prescribed generic pharmaceuticals, including OG. The last two columns show the proportion of pharmacies that hold both AG and OG.

C Generic Substitution via Average AG Preference

Given the average AG preference estimates in our three-period model in Table 6 column (2), we conduct a counterfactual analysis to interpret the average AG preference in terms of generic substitution. To calculate the generic share under counterfactual AG adoption, we only consider periods t in which pharmacies originally adopted OG. To be precise, let $J_g \in \{J_{OOO}, \ldots, J_{OAO}\}$ be the number of pharmacies in the adoption group g (e.g., OOO, OAO, AAO, etc.), and $T_g \in \{T_{OOO}, \ldots, T_{OAO}\}$ be the number of period in which pharmacies originally adopted OG. For instance, if a pharmacy's adoption pattern is OAO, $J_{OAO} = 59$ and $T_{OAO} = 2$. Then, for each pharmacy j in the group g during period t, we predict the actual and counterfactual generic shares as follows:

$$ln(\widehat{Y_{jt}^O}) - ln(1 - \widehat{Y_{jt}^O}) = \hat{\alpha}\Delta P_t - \hat{\beta}_t^B + \hat{\beta}_t^A \times 0 - \hat{\phi}\hat{\theta}_j^A - \hat{\tau}_j + \hat{\imath} M_{jt} + \nu_{jt}, \quad \text{(Actual)}$$

$$ln(\widehat{Y_{jt}^A}) - ln(1 - \widehat{Y_{jt}^A}) = \hat{\alpha}\Delta P_t - \hat{\beta}_t^B + \hat{\beta}_t^A \times 1 - \hat{\phi}\hat{\theta}_j^A - \hat{\tau}_j + \hat{\imath} M_{jt} + \nu_{jt}. \quad \text{(Counterfactual)}$$

Note that the difference between the two equations is solely the average AG preference $\hat{\beta}_t^A$. Then, we report the average change in generic share in each adoption group g and period t given as,

$$\Delta\widehat{Y_{gt}} = \frac{1}{J_g} \sum_{j=1}^{J_g} \frac{\widehat{Y_{jt}^A} - \widehat{Y_{jt}^O}}{\widehat{Y_{jt}^O}}. \tag{23}$$

In Table 7, we report the average change in generic share in each adoption group g:

$$\Delta\widehat{Y_g} = \frac{1}{T_g J_g} \sum_{t=1}^{T_g} \sum_{j=1}^{J_g} \frac{\widehat{Y_{jt}^A} - \widehat{Y_{jt}^O}}{\widehat{Y_{jt}^O}}. \tag{24}$$

Table C1 shows the generic substitution across all adoption-type pharmacies in each period. Note that we cannot calculate the counterfactual share for the periods where AG has already been adopted, resulting in a blank. These results indicate that the magnitude of average AG preference corresponds to 0.70% – 1.56% increase in generic share.

Table C1: Generic Substitution via Average AG Preference in Three Periods

Adoption Pattern	AAA	OOO	AAO	AOO	OOA	OAA	AOA	OAO
Generic Share Change via β_1^A (%)		0.70			0.70	1.00		0.72
Generic Share Change via β_2^A (%)		1.37		1.32	1.37		1.21	
Generic Share Change via β_3^A (%)		1.42	1.56	1.37				1.47
Generic Share (%)		89.02	89.67	91.16	85.83	81.47	98.65	86.36
Fraction of Sample (%)	52.98	34.52	1.75	2.36	3.74	4.26	0.15	0.20
Number of Switch	0	0	1	1	1	1	2	2

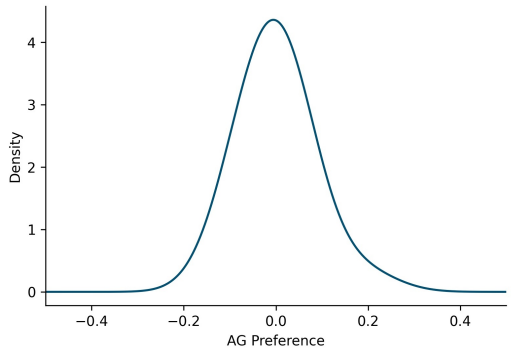
Notes: This table reports the magnitude of generic substitution via estimated average AG preference β_t^A in Table 5 column (2). For each pharmacy adopting OG, we can calculate the counterfactual generic share if it adopts AG instead of OG and take the average in each adoption group. We cannot calculate the generic substitution for pharmacies that have already adopted AG. The fraction of samples is the same in Table 3.

D Recovered Heterogeneous Preference

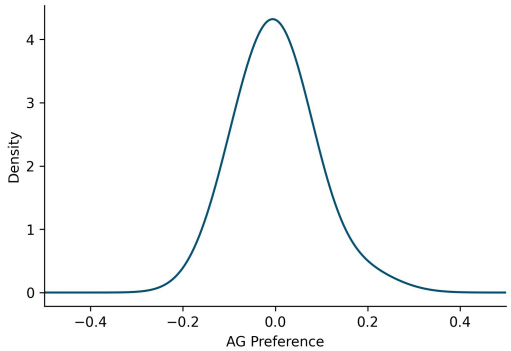
As discussed in section 5.3, we regress $\hat{\theta}_j^A$ on a nonlinear function of pharmacy characteristics $f(F_j)$ to estimate the patient AG preferences denoted as $\tilde{\theta}_j^A$. Formally, we estimate the following Equation,

$$\hat{\theta}_j^A = f(F_j) + \varepsilon_j \tag{25}$$

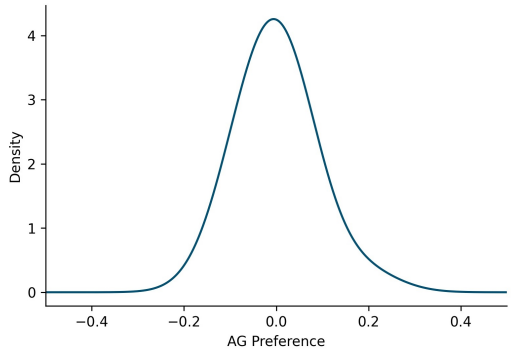
where ε_j is the error term. The primary analysis in figure 4 employs a fifth-degree polynomial of the cost-associated variable F_j. Figure D1 shows the AG preference estimated by various nonlinear functions. Panels (a) and (b) illustrate the AG preference estimations using fourth and sixth-degree polynomials, respectively. Panel (c) presents the outcomes using Lasso (Tibshirani, 1996), panel (d) details the results from Xgboost (Chen and Guestrin, 2016), and panel (e) displays the findings from the Random Forest (Breiman, 2001). For the Lasso, Xgboost, and Random Forest models, we use up to fifth-order cross terms in cost variables and employ the hyperparameters in their default configurations.



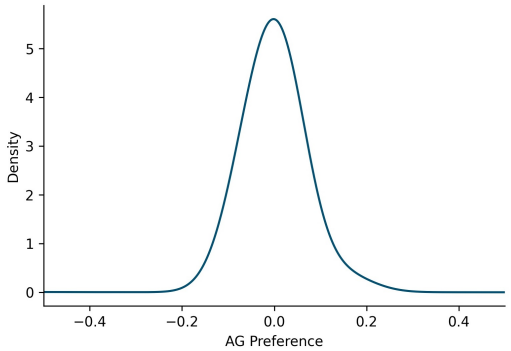
(a) 4th Polynomial



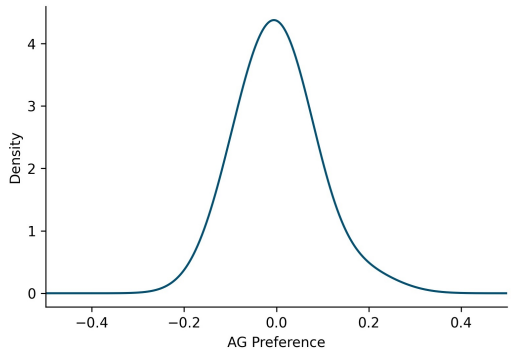
(b) 5th Polynomial



(c) 6th Polynomial



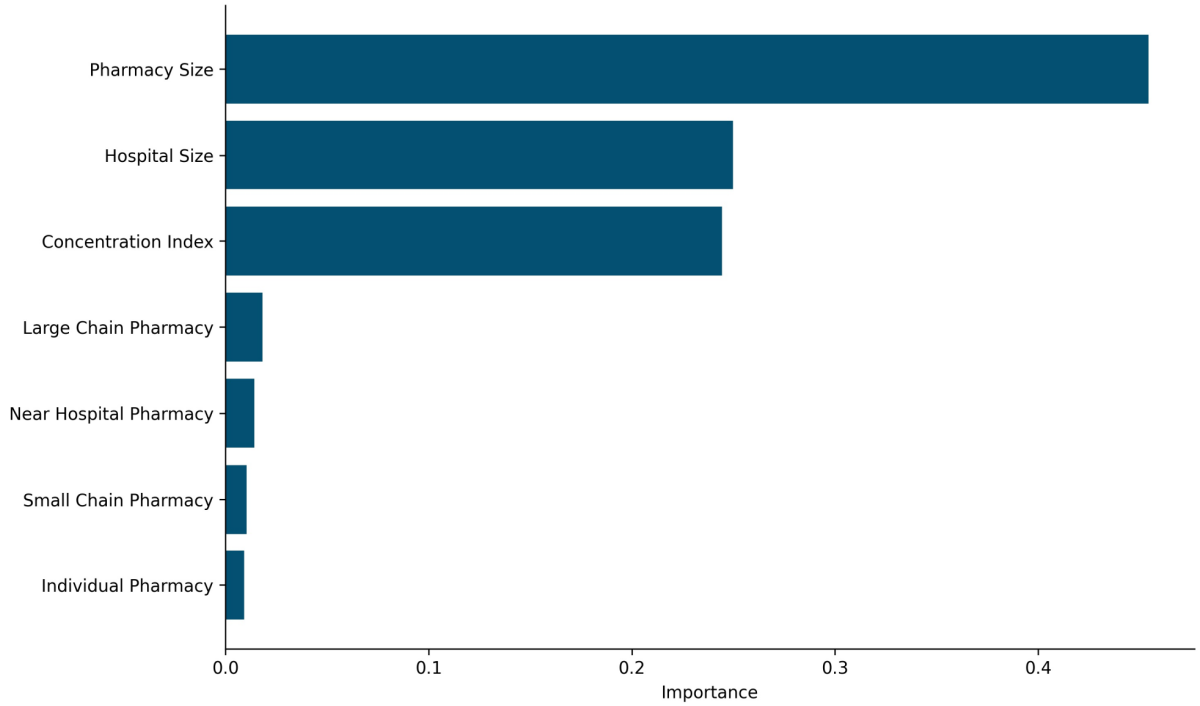
(d) Xgboost



(e) Lasso

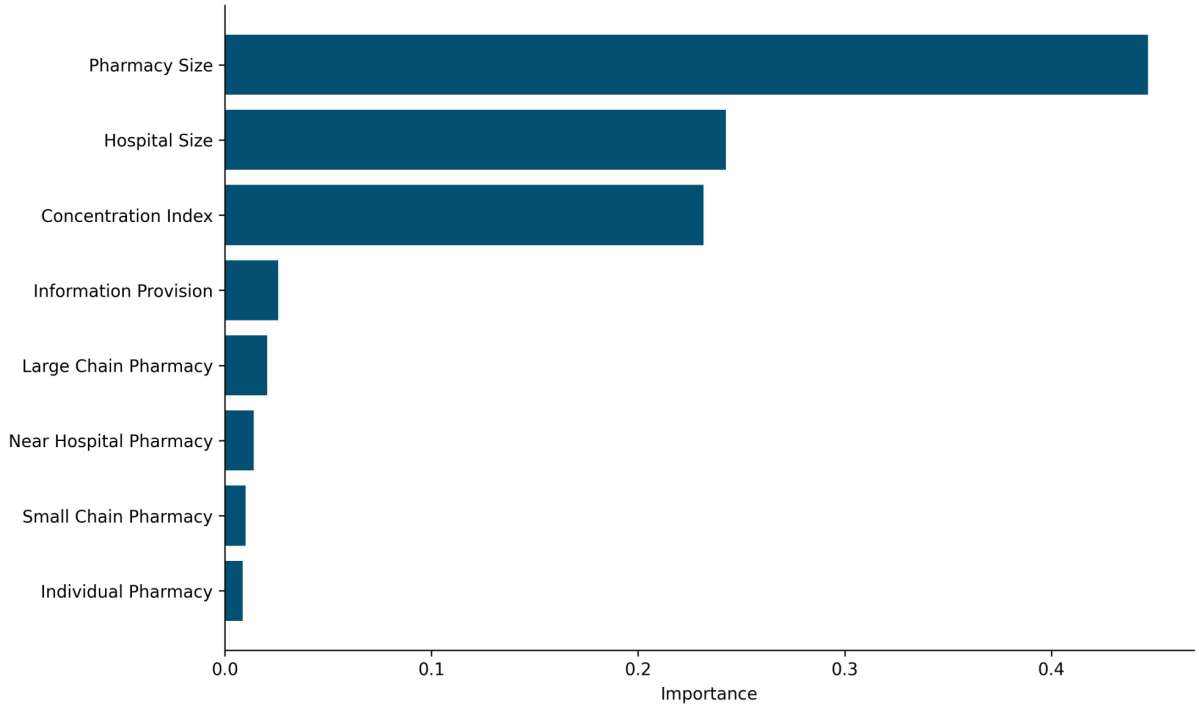
Figure D1: The Recovered Patient's Heterogeneous Preferences

E Pharmacy Characteristics Importance



Notes: This table reports the importance estimated in our random forest. The dependent variables represent recovered AG preferences as shown in Table 8. Pharmacy size is the number of prescriptions in each pharmacy. Hospital size is the number of beds in hospitals where prescription is issued. The Concentration Index is the Herfindahl-Hirschman index of prescriptions in each pharmacy. Large chain, Near Hospital, Small Chain, and Individual Chain are dummy variables.

Figure E1: The Importance of Cost Factors in Random Forest



Notes: This table reports the importance estimated in our random forest. The dependent variables represent recovered AG preferences as shown in Table 8. Pharmacy size is the number of prescriptions in each pharmacy. Hospital size is the number of beds in hospitals where prescription is issued. The Concentration Index is the Herfindahl-Hirschman index of prescriptions in each pharmacy. Information Provision is the prescription share by family pharmacists in each pharmacy. Large chain, Near Hospital, Small Chain, and Individual Chain are dummy variables.

Figure E2: The Importance of Cost and Information Factors in Random Forest

F Estimation in Three-Period Model

Following Suri (2011), we rearrange the Equation (14),

$$y_{jt} = \alpha \Delta P_t - \beta_t^B + (\beta_t^A + \varphi\theta_j) h_{jt}^A + \theta_j - \tau_j + \nu_{jt}, \tag{26}$$

where $\theta_j = -\phi\theta_j^A$ and $\varphi = -\frac{1}{\phi}$.

We utilize the linear projection of θ_j based on $\{h_{j1}, h_{j2}, h_{j1}h_{j2}, h_{j3}, h_{j1}h_{j3}, h_{j2}h_{j3}, h_{j1}h_{j2}h_{j3}\}$, a method that aligns with the approach of Chamberlain (1984). The following equation provides the generalized linear projection:

$$\theta_j = \lambda_0 + \lambda_1 h_{j1} + \lambda_2 h_{j2} + \lambda_3 h_{j1}h_{j2} + \lambda_4 h_{j3} + \lambda_5 h_{j1}h_{j3} + \lambda_6 h_{j2}h_{j3} + \lambda_7 h_{j1}h_{j2}h_{j3} + \upsilon_j. \tag{27}$$

To interpret β^A as the *mean* authorized premium, we adopt the normalization such that $\sum_j \theta_j = 0$ in the subsequent analysis.

Substituting the Equation (16) into the Equation (14) for each time period yields

$$\begin{aligned}
y_{j1} &= (\alpha\Delta P_1 - \beta_1^B + \lambda_0) + \left(\beta_1^A + \varphi\lambda_0 + \lambda_1(1+\varphi)\right) h_{j1} + \lambda_2 h_{j2} + \lambda_4 h_{j3} \\
&\quad + \left(\varphi\lambda_2 + \lambda_3(1+\varphi)\right) h_{j1}h_{j2} + \left(\varphi\lambda_4 + \lambda_5(1+\varphi)\right) h_{j1}h_{j3} + \lambda_6 h_{j2}h_{j3} \\
&\quad + \left(\varphi\lambda_6 + \lambda_7(1+\varphi)\right) h_{j1}h_{j2}h_{j3} + (\varphi\upsilon_j + \upsilon_j h_{j1} + \tau_j + \nu_{jt}) \\
y_{j2} &= (\alpha\Delta P_2 - \beta_2^B + \lambda_0) + \lambda_1 h_{j1} + \left(\beta_2^A + \varphi\lambda_0 + \lambda_2(1+\varphi)\right) h_{j2} + \lambda_4 h_{j3} \\
&\quad + \left(\varphi\lambda_1 + \lambda_3(1+\varphi)\right) h_{j1}h_{j2} + \lambda_5 h_{j1}h_{j3} + \left(\varphi\lambda_4 + \lambda_6(1+\varphi)\right) h_{j2}h_{j3} \\
&\quad + \left(\varphi\lambda_5 + \lambda_7(1+\varphi)\right) h_{j1}h_{j2}h_{j3} + (\varphi\upsilon_j + \upsilon_j h_{j1} + \tau_j + \nu_{jt}) \\
y_{j3} &= (\alpha\Delta P_3 - \beta_3^B + \lambda_0) + \lambda_1 h_{j1} + \lambda_2 h_{j2} + \left(\beta_3^A + \varphi\lambda_0 + \lambda_4(1+\varphi)\right) h_{j3} \\
&\quad + \lambda_3 h_{j1}h_{j2} + \left(\varphi\lambda_1 + \lambda_5(1+\varphi)\right) h_{j1}h_{j3} + \left(\varphi\lambda_2 + \lambda_6(1+\varphi)\right) h_{j2}h_{j3} \\
&\quad + \left(\varphi\lambda_3 + \lambda_7(1+\varphi)\right) h_{j1}h_{j2}h_{j3} + (\varphi\upsilon_j + \upsilon_j h_{j1} + \tau_j + \nu_{jt})
\end{aligned} \tag{28}$$

We derive the following two reduced-form equations from these equations that we can estimate.

$$
\begin{aligned}
y_{j1} &= \delta_1 + \kappa_1 h_{j1} + \kappa_2 h_{j2} + \kappa_3 h_{j3} + \kappa_4 h_{j1} h_{j2} + \kappa_5 h_{j1} h_{j3} + \kappa_6 h_{j2} h_{j3} + \kappa_7 h_{j1} h_{j2} h_{j3} + \zeta_{j1} \\
y_{j2} &= \delta_2 + \kappa_8 h_{j1} + \kappa_9 h_{j2} + \kappa_{10} h_{j3} + \kappa_{11} h_{j1} h_{j2} + \kappa_{12} h_{j1} h_{j3} + \kappa_{13} h_{j2} h_{j3} + \kappa_{14} h_{j1} h_{j2} h_{j3} + \zeta_{j2} \\
y_{j3} &= \delta_3 + \kappa_{15} h_{j1} + \kappa_{16} h_{j2} + \kappa_{17} h_{j3} + \kappa_{18} h_{j1} h_{j2} + \kappa_{19} h_{j1} h_{j3} + \kappa_{20} h_{j2} h_{j3} + \kappa_{21} h_{j1} h_{j2} h_{j3} + \zeta_{j3},
\end{aligned}
\tag{29}
$$

where $\delta_1 = \alpha \Delta P_1 - \beta_1^B + \lambda_0$, $\delta_2 = \alpha \Delta P_2 - \beta_2^B + \lambda_0$, $\delta_3 = \alpha \Delta P_3 - \beta_3^B + \lambda_0$ and ζ_{j1}, ζ_{j2}, and ζ_{j3} are composite error term in the estimation. The association between the reduced form parameters

and the structural parameters is illustrated as follows:

$$
\begin{aligned}
\kappa_1 &= \beta_1^A + \varphi\lambda_0 + \lambda_1(1+\varphi) \\
\kappa_2 &= \lambda_2 \\
\kappa_3 &= \lambda_4 \\
\kappa_4 &= \varphi\lambda_2 + \lambda_3(1+\varphi) \\
\kappa_5 &= \varphi\lambda_4 + \lambda_5(1+\varphi) \\
\kappa_6 &= \lambda_6 \\
\kappa_7 &= \varphi\lambda_6 + \lambda_7(1+\varphi) \\
\kappa_8 &= \lambda_1 \\
\kappa_9 &= \beta_2^A + \varphi\lambda_0 + \lambda_2(1+\varphi) \\
\kappa_{10} &= \lambda_4 \\
\kappa_{11} &= \varphi\lambda_1 + \lambda_3(1+\varphi) \\
\kappa_{12} &= \lambda_5 \\
\kappa_{13} &= \varphi\lambda_4 + \lambda_6(1+\varphi) \\
\kappa_{14} &= \varphi\lambda_5 + \lambda_7(1+\varphi) \\
\kappa_{15} &= \lambda_1 \\
\kappa_{16} &= \lambda_2 \\
\kappa_{17} &= \beta_3^A + \varphi\lambda_0 + \lambda_4(1+\varphi) \\
\kappa_{18} &= \lambda_3 \\
\kappa_{19} &= \varphi\lambda_1 + \lambda_5(1+\varphi) \\
\kappa_{20} &= \varphi\lambda_2 + \lambda_6(1+\varphi) \\
\kappa_{21} &= \varphi\lambda_3 + \lambda_7(1+\varphi)
\end{aligned}
\tag{30}
$$

There are 21 reduced form parameters $(\kappa_1, \ldots, \kappa_{21})$ and 11 structural parameters $(\lambda_1, \ldots, \lambda_7, \beta_1^A, \beta_2^A, \beta_3^A, \varphi)$. Considering the normalization $\sum \theta_j = 0$, we can express λ_0 in terms of $\lambda_1, \ldots, \lambda_7$. Specifically, λ_0 can be represented as $\lambda_0 = -\lambda_1\bar{h}_1 - \lambda_2\bar{h}_2 - \lambda_3\bar{h}_1\bar{h}_2 - \lambda_4\bar{h}_3 - \lambda_5\bar{h}_1\bar{h}_3 - \lambda_6\bar{h}_2\bar{h}_3 - \lambda_7\bar{h}_1\bar{h}_2\bar{h}_3$, where $\bar{h}_1$, $\bar{h}_2$, and $\bar{h}_3$ represent the average AG adoption rate across pharmacies in each period.

Once we estimate θ_j and φ, we can calculate θ_j^A and ϕ as $\frac{\theta_j}{-\phi}$ and $-\frac{1}{\varphi}$, respectively. Therefore, we obtain $\hat{\theta}_j^A$ as

$$\hat{\theta}_j^A = \hat{\varphi}(\hat{\lambda}_0 + \hat{\lambda}_1 h_{j1} + \hat{\lambda}_2 h_{j2} + \hat{\lambda}_3 h_{j1} h_{j2} + \hat{\lambda}_4 h_{j3} + \hat{\lambda}_5 h_{j1} h_{j3} + \hat{\lambda}_6 h_{j2} h_{j3} + \hat{\lambda}_7 h_{j1} h_{j2} h_{j3}) \quad (31)$$

Now, we have the variance-covariance matrix for $(\hat{\varphi}, \hat{\lambda}_0, \ldots, \hat{\lambda}_7)$. Then, we calculate the variance-covariance matrix for $(\hat{\varphi}\hat{\lambda}_0, \ldots, \hat{\varphi}\hat{\lambda}_7)$ by the delta method.