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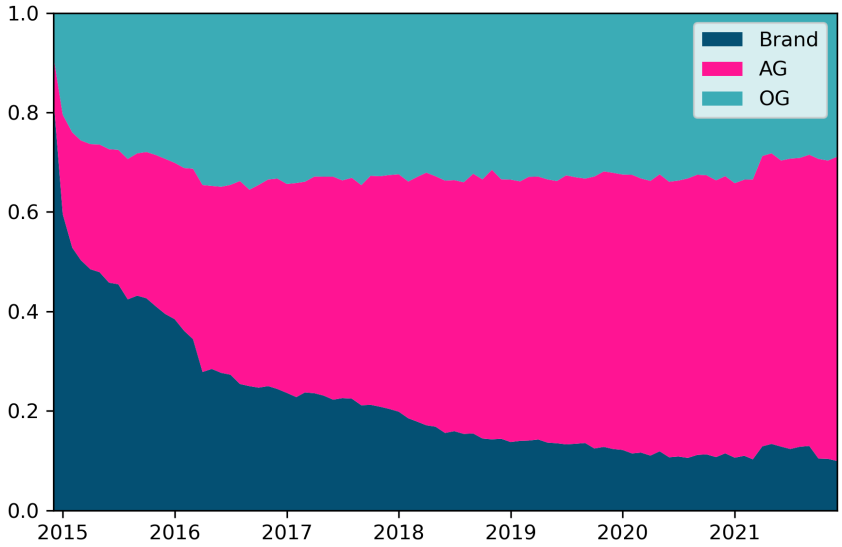
1 Introduction

Understanding the sources of preferences for pharmaceutical health products is crucial for promoting cost-effective policies. The literature shows that even when brand-name drugs are sold at higher prices, consumers often exhibit a greater willingness to pay, reflecting their brand preference (Bronnenberg et al., 2015; Janssen, 2023). Early work focused on consumer-specific attributes (e.g., education, health literacy) as key determinants of brand preference (Bronnenberg et al., 2015), whereas recent studies have highlighted external, context-dependent factors–such as nutrition labeling and peer signals–that can significantly shift purchasing behavior (Fichera and von Hinke, 2020; Carrera and Villas-Boas, 2023; Evdokimova, 2024). In both strands, these findings imply that if brand and nonbrand products are priced equally, consumers will consistently favor the brand due to brand preferences.

Contrary to this expectation, however, our data reveal a puzzle: some consumers persistently choose nonbrand products even when a brand-identical option is available at the same price. Within Japan's generic drug market—the third largest globally—brand companies market authorized generics (AGs), which are identical to their brand-name counterparts. These AGs are sold in the same market segment as ordinary generics (OGs), which are equivalent in efficacy and safety but not identical. The Japanese government sets the same prices for AGs and OGs to encourage substitution away from costly brand-name drugs, yet the only difference is their perceived brand premiums. Despite extensive literature indicating a strong consumer brand preference–and thus implying that AGs should dominate the market by displacing OGs–many patients continue to opt for OGs. Figure 1 shows that while AGs have gradually replaced brand-name products over time, for *levofloxacin*, the antibiotic drug analyzed in this paper, a subset of consumers still select the same-priced OGs.

Our study empirically demonstrates how consumers' brand preferences are related to professional experts' behavior by examining the role of pharmacists. Although pharmacists are recognized as healthcare experts worldwide, Japan has broadened their responsibilities. They can adopt either AGs or OGs independently of physicians' prescriptions, indicating a substantial influence on patients' choices. Figure 2 illustrates that pharmacies with a higher prescription shares by family pharmacists—qualified practitioners who have access to patient health records and provide tailored

Figure 1: Prescription Share of Antibiotics.

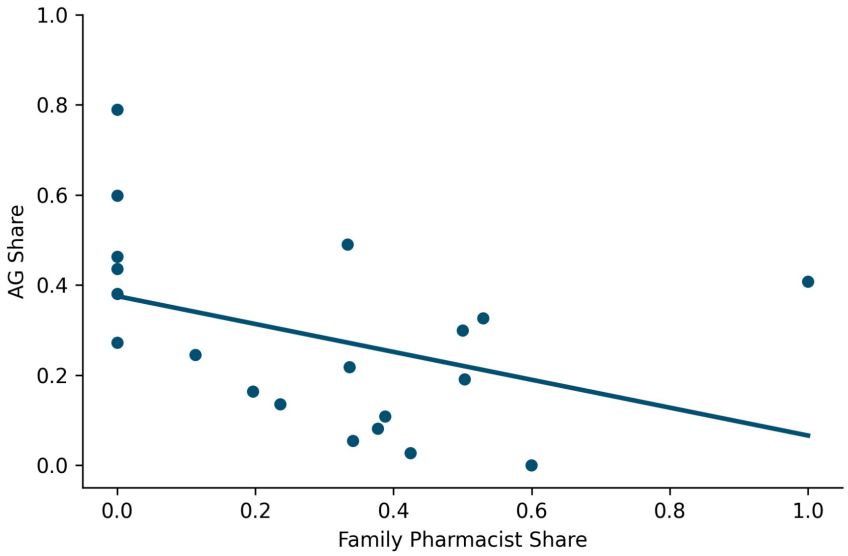


Notes: This figure shows the transition of share regarding brand-name, OG, and AG drugs for the antibiotic levofloxacin (its brand name is *Cravit*) after brand-name drug's patent expires. The data is from monthly claim data and data period is from January 2015 to December 2021 and aggregated at the month level. The data used in the analysis are limited to out-of-hospital prescriptions.

counseling—tend to exhibit lower AG dispensing. This pattern implies that pharmacists' involvement may explain why some consumers still choose OGs over brand-identical AGs. By drawing on these institutional features, our study shows how pharmacists' behavior works as external, context-dependent information that shapes heterogeneous brand preferences.

We model consumers' generic choices and pharmacy adoption decisions to explore both demand (patients) and supply (pharmacists) roles in antibiotic markets. We define the demand for brand-name drugs, AGs, and OGs and find that preferences vary across pharmacies given the prominent role of pharmacists. Each pharmacy then chooses whether to adopt AGs or OGs to maximize profits, which influences its generic dispensing share. To estimate brand preferences, we adapt the three-period correlated random coefficient (CRC) model—originally from the development literature (Suri, 2011; Cabanillas et al., 2018; Michler et al., 2019)—to our pharmaceutical demand setting. Under our regulatory framework, this approach leverages cross-sectional differences in pharmacies' AG adoption histories to identify patients' brand preferences while accounting for both patients' and pharmacists' incentives.

Figure 2: AG Shares and Family Pharmacist Shares.



Notes: This figure shows the relationship between family pharmacists' share and AG prescription share for the antibiotic levofloxacin (its brand name is *Cravit*). The data is the medical claim data aggregated into pharmacy-level from April 2016 to December 2021, and each dot shows the representative 20 pharmacies during the data period using binscatter plot (Cattaneo et al., 2024).

Our empirical findings show that patients generally prefer AGs over OGs, increasing generic substitution rates by approximately 1.00–1.56%. We also uncover significant cross-pharmacy variation in brand preferences, explaining roughly one-third of the average AG preference; moreover, even brand-name products and AGs elicit different responses from patients. These results highlight the substantial heterogeneity of patient preferences across pharmacies.

Finally, we focus on the role of family pharmacists in shaping these heterogeneous preferences. Although patients typically favor AGs, family pharmacists often guide them toward OGs by providing key pharmaceutical details about their efficacy, dosage, and potential side effects. Our findings thus emphasize that pharmacists' personalized counseling fosters patient confidence in generics. Therefore, the successful promotion of generic drugs depends on pharmacists providing personalized counsel that addresses each patient's concerns and needs for generic options.

This paper joins the growing empirical literature on brand premiums, which has investigated drivers such as consumer 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 work in health markets shows that product information—e.g., nutrition labels (Fichera and von Hinke, 2020), sales rankings (Carrera and Villas-Boas, 2023), and labeling design (Evdokimova, 2024)—significantly shapes choices in over-the-counter drugs[1]. Our study suggests that brand premiums also hinge on professional experts' behavior mandated by the government, thereby affecting consumers' brand preferences.

This paper is also a part of the literature exploring healthcare provider behavior. Many previous studies have targeted physicians (Chalkley and Tilley, 2005; Iizuka, 2007, 2012; Clemens and Gottlieb, 2014; Epstein and Ketcham, 2014; Chan et al., 2022), but given the growing attention to generic drugs (Appelt, 2015; Ito et al., 2020; Janssen and Granlund, 2023) and 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 examined the financial incentives behind physicians' prescriptions of generic drugs in Japan, stated that *In fact, the role of the pharmacist as another key agent for the patient is seriously understudied*. The study most closely related to ours is Brekke et al. (2013), which conducted 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 explicitly incorporate heterogeneous brand preferences using AGs. Second, we employ pharmacy-level dispensing data—including family pharmacist qualifications—to analyze generic substitutions, leveraging policy reforms introduced in 2016 to investigate how pharmacists affect patients' pharmaceutical choices.

This paper proceeds as follows. Section 2 overviews the Japanese healthcare market, and Section 3 describes the data. Section 4 introduces a model covering both patient demand and pharmacy adoption decisions. Section 5 outlines the empirical approach and identification assumptions. Section 6 presents the estimation results, with a focus on patients' AG preferences and heterogeneity. Section 7 examines the pharmacist-related factors behind heterogeneous brand preferences. Section 8 concludes the study.

[1] See Handel and Schwartzstein (2018) for a comprehensive review of information provision.

2 Institutional Background

This section explains the supply side of the Japanese pharmaceutical system, covering prescribing and dispensing processes, particularly focusing on pharmacists' roles. It summarizes the government's policies to promote generic drugs and introduces *AGs*, which are identical to their brand-name equivalents and produced by the original manufacturer.

2.1 Japan's Pharmaceutical Supply System

Prescription drugs fall under universal health insurance, ensuring that every individual has some form of coverage in Japan. Historically, Japanese medical care was dominated by physician-led prescribing and dispensing within hospitals and was influenced by traditional Eastern medicine (Iizuka, 2012). Since the 1940s, the government has separated physicians' services and pharmacists' dispensing to ensure high-quality care, making pharmacists central to understanding the system.

Following these policy transitions, pharmacists have expanded their influence on patient medication choices. First, the introduction of nonproprietary name prescribing in 2012 allowed patients and pharmacists to choose between brand-name or generic drugs[2]. Before 2012, proprietary name prescriptions dominated, often leading to brand-name dispensing[3]. However, the implementation of nonproprietary name prescriptions enabled generic and brand choices from physicians to pharmacists.

Second, most patients receive pharmaceutical dispensing outside hospitals under the Uniform Drug Pricing Policy, where the Ministry of Health, Labour, and Welfare revises drug prices on the basis of market data (Ito et al., 2020)[4]. Physicians previously profited from in-hospital dispensing through large price-cost margins[5], but margins dropped below 10% (Ministry of Health, Labour and Welfare, 2021), making in-hospital dispensing less profitable[6]. Consequently, out-of-

[2]Physicians have two methods: *proprietary name* prescriptions, which specify a brand name, or *nonproprietary name* prescriptions by the active ingredient name. Pharmacists can select generics for both prescriptions in many cases.

[3]Before 2006, nonprescription generic sales were prohibited. Until 2012, only proprietary name prescriptions were available, although brand-to-generic substitution was sometimes allowed (Iizuka, 2012).

[4]Until 2018, revisions were biennial, after which they became annual.

[5]Prescriptions occur *in-hospital* or *out-of-hospital*; in-hospital dispensing can be performed by both pharmacists and physicians, whereas only pharmacists dispense out-of-hospital.

[6]The Ministry of Health, Labour and Welfare's *drug survey* reports margins between regulated retail and wholesale

hospital dispensing has increased to nearly 80% (Ministry of Health, Labour and Welfare, 2023b), magnifying the impact of pharmacists on patients.

Third, pharmacists' responsibilities has grown beyond basic dispensing to include comprehensive medication management and patient education[7]. In 2016, the family pharmacist system granted qualified pharmacists access to patients' health information for more tailored counseling. These family pharmacists build ongoing relationships, review medications, prevent polypharmacy and adverse interactions, monitor adherence, provide personalized advice, and shift pharmacy services toward patient-centered care while still facing transparency challenges.

2.2 Generic Drug Promotion Policies in Japan

Promoting the use of generic drugs is an effective way 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 rely on financial incentives. For instance, pharmacies achieving a specified generic prescription rate receive a generic dispensing subsidy (referred to as a generic dispensing add-on)[8]. Since drug price-cost margins have remained low in recent years, approximately 1.52–2.84% of the generic subsidy (Ministry of Health, Labour and Welfare, 2021), dispensing generics and receiving generic add-ons can be more profitable[9]. Patients also benefit financially, as uniform drug prices for generic drugs are set at 40–50% of the cost of the original brands.

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 pharmacists and patients to choose between brand and generic drugs at the pharmacy, encouraging

prices. In 2020, the average margin was 8%.

[7]Known as the *Shinryo Houshu Seido*, Japan's reimbursement system rewards pharmacists for (1) offering detailed consultations to ensure that patients understand proper medication use; (2) providing comprehensive information on potential side effects, drug interactions, and safe medication practices; (3) proactively monitoring, documenting, and reporting adverse drug reactions to improve medication safety; and (4) collaborating closely with physicians to optimize prescriptions, especially for high-risk patients.

[8]Physicians also gain financial incentives for nonproprietary name prescriptions, known as a prescription add-on.

[9]We calculate the ratio between margins and generic subsidies using the average price-cost margins in the Drug Price Survey in 2021.

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.

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 be legally manufactured and sold by other companies[10]. However, their manufacturing processes and additives often differ, due primarily to different production methods or cost-saving measures. In contrast, *AGs* are essentially brand-name drugs repackaged and sold under generic names by the original manufacturer[11]. Therefore, AGs are *identical* to their brand-name counterparts in terms of the quality, strength, additives, manufacturing process, and dosage form[12].

There are specific reasons why Japanese pharmaceutical companies choose to sell AGs. First, since AGs are identical to brand-name drugs in terms of the quality and manufacturing processes, they can maintain patient loyalty and potentially capture a greater market share than 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[13]. 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[14]. Consequently, only some new generics are sold as AGs in Japan.

Table B1 lists major oral AGs from 2014 to 2021. Among the 775 newly marketed generics, 74 (9.54%) had AGs by December 2020. Pharmacies typically carry either an OG or an AG

[10]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 expiration date of the patent or other exclusive rights."

[11]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."

[12]The only difference between the brand name product and AG is the company name displayed on the package, which is the name of a subsidiary of the brand-name company.

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

[14]In the U.S., an advantage in launching AGs six months before patent expiry (Federal Trade Commission, 2011), allowing large revenues. In Japan, re-evaluation periods can delay AG sales to the same time as OG launches.

for each active ingredient to minimize inventory costs; only 0.36% keep both three years after release. Despite being few in number, AGs maintain high market shares; for example, Table B1 shows that the levofloxacin AG had 37.57% of the market share within one year of its release, which increased to 38.08% after three years, although 30 other generic companies sell levofloxacin OGs. In addition, brand companies focus mainly on introducing AGs in major and profitable drug categories, such as hypertension, antiplatelet, and endometriosis, suggesting that AGs play a substantial role in the pharmaceutical market.

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 individual-monthly level 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 healthcare facilities, the names of ailments and injuries, and prescription drugs dispensed by pharmacies[15] [16]. During the study period, 114,121,902 claims were observed, representing 7,839,803 patients[17]. The sex ratio was 90.47, indicating that there were 90.47 females for every 100 males. The average ages were 38.5 and 39.08 years for males and females, respectively. In the main analysis, we aggregate the data at the pharmacy-monthly level.

3.2 Antibiotics

We explore the dispensing decisions of pharmacies regarding the antibiotic levofloxacin, marketed under the brand name *Cravit*[18]. This drug is prescribed for various infections, including pharyngitis, tonsillitis, pneumonia, otitis media, chlamydia, and gonorrhea. We focused on the 250 mg

[15] While our data capture detailed dispensing records from pharmacies, we cannot observe the original prescriptions issued by physicians, only the medications ultimately dispensed.

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

[17] As of the end of fiscal year 2021, according to the Ministry of Health, Labour and Welfare, there were 61,791 pharmacies in Japan, and this data covers 56,260 of them. The coverage rate is 91.0%.

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

and 500 mg doses of levofloxacin for the following reasons: (1) the introduction of their generics within our data period, (2) the availability of AGs, and (3) the consistent demand for the two doses of the drug, given that no new alternatives were introduced during this 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.

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 coverage of Ministry of Health, Labour, and Welfare'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 sexes(Statistics Bureau of Japan, 2020)[19]. 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 sex and age groups, which suggests that the JAST data are reasonably representative of the broader population regarding levofloxacin prescriptions.

3.3 Pharmacists Survey

To better understand the motivations behind Japanese pharmacists' antibiotic dispensing behavior, we conducted a survey focusing on levofloxacin[20]. This survey targeted 100 supervising pharmacists who are responsible for drug procurement and have experience dispensing the AG levofloxacin. The sample consisted of pharmacists from three types of retail pharmacies: independent pharmacies, near-hospital pharmacies, and retail pharmacy chains, excluding in-hospital pharmacies[21]. The survey explored not only workplace characteristics and professional attributes but also specific questions related to dispensing practices, such as the rationale for AG adoption, procurement strategies, and communication with patients. For detailed survey results, refer to Appendix

[19]The NDB managed by the Ministry of Health, Labour, and Welfare 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.

[20]These surveys were conducted in partnership with MCI Co., Ltd., a consulting firm specializing in the healthcare industry. The surveys were implemented in two waves: October 2023 and November 2024. The first wave in 2023 served as a preliminary investigation into the basic dispensing behavior of pharmacists. In contrast, the 2024 survey focused specifically on dispensing practices related to the antibiotic levofloxacin, which was the primary focus of our analysis. The results presented in this section and in the Appendix A are based on the 2024 survey.

[21]In Japan, near-hospital pharmacies predominantly serve patients from adjacent medical facilities by dispensing prescriptions issued by that facility.

A.

To summarize our survey analysis, our findings reveal several key patterns in pharmacists' decision-making regarding antibiotic generic drugs. First, pharmacists prioritize demand-side factors, particularly patients' preferences, in their generic drug dispensing decisions. This emphasis stems from the professional role of pharmacists in explaining drug efficacy and safety to patients. Second, while supply-side factors such as contract management and system adjustments are secondary concerns, they remain relevant considerations in pharmacists' decisions on generic drug dispensing. Third, these patterns vary notably across pharmacy types: independent pharmacies place greater emphasis on patient factors, whereas near-hospital pharmacies and retail pharmacy chains place greater weight on transaction costs, including search costs and fixed costs. Fourth, pharmacists employ different explanatory approaches when counseling patients: when explaining AGs to patients, they emphasize both therapeutic properties and physical identity with brand-name products, whereas their explanations of OGs focus primarily on efficacy and safety. On the basis of these findings, we develop a theoretical model that captures both the demand and supply sides of the generic drug market, incorporating heterogeneous patient preferences and pharmacies' strategic inventory decisions.

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 in which patients receive a brand-name drug, an OG, or an AG, contingent on their preferences and subject to the limitations imposed by the pharmacy's available stock.

Our model relies on two key institutional features of the Japanese pharmaceutical system. First, we assume that physicians play a minimal role in patients' drug choices[22]. In most cases, physicians issue antibiotic prescriptions using nonproprietary name prescriptions, specifying the active ingredient name (i.e., levofloxacin) rather than the brand name (i.e., *Cravit*). Even when physicians

[22]While our model assumes that physicians' influence on patients' preferences is negligible, we discuss in section 5.2 the possibility that physicians might affect both patients' drug preferences and pharmacy choices.

prescribe medications using brand names, patients and pharmacists can generally choose generics, except in rare cases[23]. Second, pharmacists have a professional obligation to provide detailed explanations when dispensing medications to patients. This responsibility includes explaining what the medication is, how to take it properly, and potential side effects, regardless of whether it is a brand-name drug, OG, or AG[24].

Building on these institutional features, we first define patients' preferences for brand-name and generic drugs, which are crucial in shaping patients' demand-side decisions. We subsequently 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 to maximize their profits.

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 the patient chooses the generic option, then they are 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 on the basis of static utility maximization rather than dynamic utility maximization when selecting an antibiotic type. As such, our analysis does not consider the learning effect, variety-seeking behavior, or inertia concerning the choice of medications given the pharmaceutical properties of the antibiotic levofloxacin[25]. The data corroborate that patients do not use antibiotics frequently in a short period[26].

[23] Specifically, nonproprietary prescriptions account for 53% of all prescriptions. Moreover, only 4% of all prescriptions are brand-name prescriptions that prohibit substitution with generic drugs (Ministry of Health, Labour and Welfare, 2023b).

[24] This obligation is explicitly mandated by the *Act on Securing Quality, Efficacy and Safety of Products Including Pharmaceuticals and Medical Devices*, a regulation issued by the Ministry of Health, Labour and Welfare.

[25] Iizuka (2012) and Ito et al. (2020) focused on chronic diseases such as hypertension and dyslipidemia, demonstrating that brand-name drug inertia plays a significant role in consumer choices of generic pharmaceuticals. In contrast, our study focuses on antibiotics, analyzing the short-term choices between brand-name and generic drugs.

[26] 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, whereas the majority of the average prescription days reported in Ito et al. (2020), which examines the inertia of brand-name drugs in chronic dyslipidemia,

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.

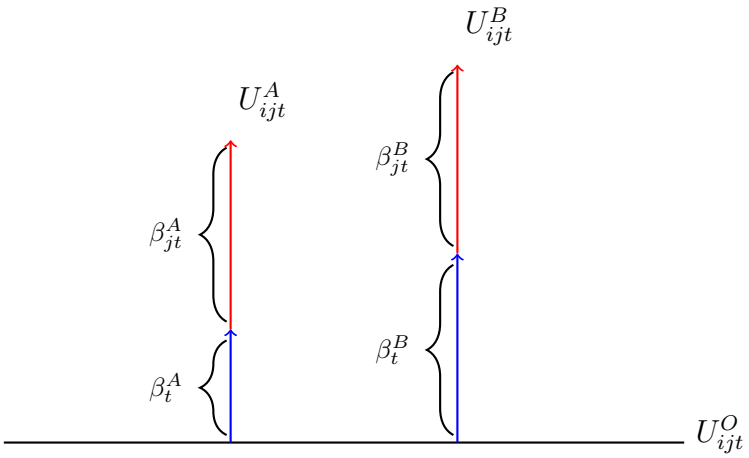
The parameters β_t^B and β_t^A encapsulate the *drug-specific (context-independent)* components of patient preferences, reflecting the brand premium associated with brand-name drugs and AGs. Despite the biosimilarity between brand-name drugs and OGs, patients generally prefer brand-name drugs because of their extensive clinical trials and established safety and efficacy records. Similarly, AGs, which are produced by the same manufacturers as brand-name drugs, are perceived more favorably than OGs are, contributing to their brand premium. This preference stems from the consistent trust patients place in both brand-name drugs and AGs due to their proven reliability and well-documented effectiveness.

In contrast, β_{jt}^B and β_{jt}^A capture the *pharmacy-specific (context-dependent)* patient preferences, which vary across pharmacies and are influenced by factors such as pharmacists' explanations, the drug information they provide, and how the drug is prescribed. As discussed in Section 2.1, pharmacists, fulfilling their professional responsibility to recommend the most appropriate medication, influence patients' preferences by providing comprehensive explanations of drug efficacy, dosage, and potential side effects. Consequently, patients' evolving understanding and receptiveness—guided by these tailored explanations—play a significant role in determining these preferences.

Figure 3 shows how these brand premiums differ. 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

is 28 days.

Figure 3: Brand Preferences.



Notes: This figure shows that the patients receive utility from two different sources, which are context-independent factors β^B_t and β^A_t and context-dependent factors β^B_{jt} and β^A_{jt}. 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 preferences across patients of identical products, namely, AGs and brand-name products.

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 $\varepsilon^O_{ijt}, \varepsilon^A_{ijt}$, and ε^B_{ijt} 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^ℓ_{jt} 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 drug is given by $Y^B_{jt} = 1 - Y^\ell_{jt}$ for $\ell \in \{O, A\}$, where O and A are the OG and the AG, respectively. $y^\ell_{jt} = ln(Y^\ell_{jt}) - ln(Y^B_{jt})$ 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 $(\varepsilon^O_{ijt}, \varepsilon^A_{ijt}, \varepsilon^B_{ijt})$ 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:

$$\begin{aligned} y^A_{jt} &= \alpha \Delta P_t + (\beta^A_t - \beta^B_t) + (\beta^A_{jt} - \beta^B_{jt}) \\ y^O_{jt} &= \alpha \Delta P_t - (\beta^B_t + \beta^B_{jt}). \end{aligned} \tag{2}$$

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

4.2 Pharmacy 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 types at time t. We assume that the primary determinant of a pharmacy's revenue from the sale of antibiotics is the generic dispensing subsidy, denoted by $subsidy_{jt}^{\ell}$, since the price–cost margins of brand-name and generic antibiotics are negligibly small relative to the generic subsidy.

This subsidy is determined by the total sales volume, encompassing the sales of other generic and brand-name drugs[27]. 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 drug and type ℓ generic antibiotic drugs, respectively. We assume, from the regulatory perspective, 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[28].

We assume that fixed costs f_j^B and f_j^{ℓ} vary across pharmacies and may influence their profit and drug selection, whereas the marginal cost of pharmaceuticals is minimal. As revealed in our survey of pharmacists, these fixed costs encompass transition costs for introducing generic antibiotics: operational costs for drug supply, search costs for finding wholesale companies, and negotiation costs associated with contracts[29]. In contrast to these significant fixed costs, the marginal costs of

[27] In practice, the subsidy rule is more complex and consists of a threshold determined by the government every two years. However, we assume a linear subsidy for simplicity and without loss of generality in the subsequent analysis of the comparative advantage. For the pharmacy's behavior based on the threshold-based generic subsidy, see Appendix D.2.

[28] In Japan, pharmacies are prohibited from advertising and promoting their own pharmaceutical products. Hospitals are independent of pharmacies, and in any form, physicians are prohibited from referring patients to specific pharmacies. In addition, our data show that 77.3% of all patients receive a prescription for levofloxacin only once. Therefore, we assume that patients do not know ex ante which pharmacies have AGs and which have OGs.

[29] In Japan, pharmacies often engage in bundled pricing negotiations (*Souka-Torihiki* in Japanese) with wholesalers,

pharmaceuticals are negligible compared with the generic subsidy. While wholesale prices for OG drugs are approximately 15

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_j, which is also exogenous to the number of patients n_{jt}. We calculate the total generic share as $Y_{jt}^{\ell} r_j + g_{jt}$, with g_{jt} being the overall generic share of drugs excluding antibiotics[30]. Consequently, the generic dispensing subsidy is given as follows:

$$subsidy_{jt}^{\ell} = s_t \left(Y_{jt}^{\ell} r_j + g_{jt} \right), \tag{4}$$

where s_t represents the amount of the subsidy. Note that although the amount of subsidy s_t fluctuates over time, it remains constant across all pharmacies[31].

4.3 Pharmacies' Comparative Advantage

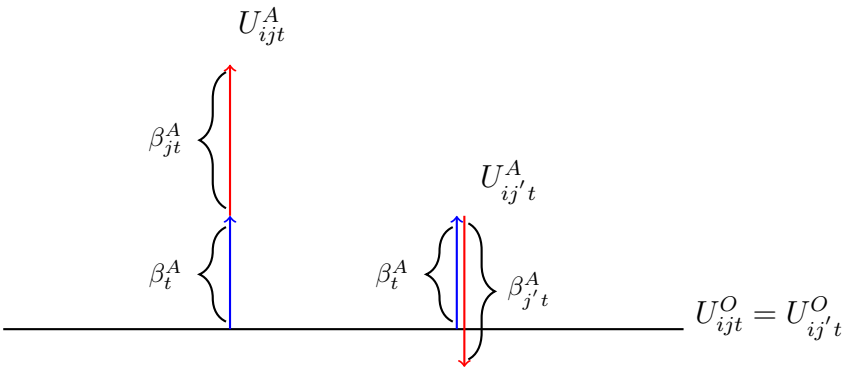
Assume that each pharmacy, aware of patient preferences for antibiotics, optimizes its generic drug inventory to maximize its generic dispensing share. In period t, pharmacy j faces two potential choices, to select an AG or to select an OG, associated with the potential generic shares Y_{jt}^{A} and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

where the prices of multiple pharmaceuticals are negotiated together (Ministry of Health, Labour and Welfare, 2024). Owing to fierce price competition among OGs, OGs are frequently used as bargaining chips in these negotiations, unlike brand-name drugs and AGs, which are sold exclusively by originator companies. When antibiotics are procured through bundled pricing, OGs may be grouped with other drugs for bulk negotiation, resulting in uniform price discounts. This makes the procurement cost of generic drugs a fixed expense, independent of the quantity purchased. These fixed costs can vary depending on whether OGs or AGs are included in the bundle.

[30] To elaborate, suppose that there are K drugs other than antibiotics, with r_{jk} being the share of drug k at pharmacy j during period t; thus, $r_j + \sum_{k=1}^{K} r_{jk} = 1$ 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 $Y_{jt}^{\ell} r_j + \sum_k G_{jkt} r_{jk} = Y_{jt}^{\ell} r_j + g_{jt}$, where we define $g_{jt} = \sum_{k=1}^{K} G_{jkt} r_{jk}$.

[31] While subsidies are the primary source of profit in Japan, similar financial incentive structures exist elsewhere, where a higher generic share increases pharmacists' profits. For example, reference-pricing systems in France and PBM-driven reimbursement schemes in the United States both motivate pharmacists to dispense more generics due to financial incentives.

Figure 4: 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 .

in the potential shares in logs is connected to the AG premiums perceived by patients.

$$\ln(Y^A_{jt}) - \ln(Y^O_{jt}) = y^A_{jt} - y^O_{jt} = \beta^A_t + \beta^A_{jt}. \tag{5}$$

Equation (5) 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 $\beta^A_t + \beta^A_{jt}$[32].

While context-independent preferences β^A_t are assumed to be positive, individual pharmacies may face positive or negative context-dependent patient preferences β^A_{jt}. Survey responses from pharmacists demonstrate substantial variation in how they prioritize different aspects—efficacy, safety, and stable supply—when explaining AGs and OGs to patients. Such differences in pharmacists' explanations contribute to variations in context-dependent patient preferences. In other words, these differences in pharmaceutical information provision influence patients' satisfaction with and confidence in their medications.

Comparative advantage plays a key role in driving the AG adoption choices of pharmacies. Pharmacies with higher β^A_{jt} values are better positioned to sell AGs, whereas those with lower β^A_{jt}

[32]In Appendix D.1, we demonstrate that the difference in logarithmic shares between AG and OG is positively related to the difference in their actual shares. In other words, we show that the sign of $y^A_{jt} - y^O_{jt}$ corresponds to the sign of $Y^A_{jt} - Y^O_{jt}$.

values may favor OGs. For example, consider pharmacies j and j', where $\beta_{jt}^A > 0 > \beta_{j't}^A$. A higher β_{jt}^A indicates a *comparative advantage* for pharmacy j in selling AGs, whereas a lower $\beta_{j't}^A$ suggests that pharmacy j' has a sales advantage in OGs. Figure 4 illustrates how comparative advantage influences AG adoption. The context-independent preferences β_t^A (blue lines) remain consistent across pharmacies, whereas the context-dependent preferences β_{jt}^A and $\beta_{j't}^A$ (red lines) vary, reflecting the differing comparative advantages of pharmacies j and j'.

4.4 Pharmacy's Decision

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:

$$Y_{jt}^A - Y_{jt}^O \geq \frac{F_j^A}{s_t r_j n_{jt}}, \tag{6}$$

where $F_j^A = f_j^A - f_j^O$ represents the relative fixed cost for pharmacy j when stocking AGs, defined as the difference between the fixed costs associated with the AG inventory and those associated with the OG inventory.

Equation (6) shows how the pharmacy's AG inventory is determined. The left-hand side, $Y_{jt}^A - Y_{jt}^O$, represents the difference between potential AG and OG shares relative to the brand-name drug at pharmacy j. Since pharmacies stock either AG or OG exclusively, this difference in shares is counterfactual and cannot be directly observed. However, we assume that pharmacies have complete knowledge of patients' generic drug preferences and can anticipate the demand for both AGs and OGs even if they were to stock either one. As explained in the previous section, pharmacies have varying levels of comparative advantage in dispensing AGs versus OGs on the basis of their patients' preferences. Therefore, while some pharmacies may achieve higher sales shares with AG, others may perform better with OG, making the difference in sales shares between AG and OG positive for some pharmacies and negative for others.

The right-hand side consists of several terms: the relative fixed costs F_j^A associated with the AG inventory at pharmacy j, the number of patients n_{jt}, the antibiotic prescription rate r_j, and the

generic subsidy s_t. Since all pharmacy-specific and time-specific characteristics in the denominator are positive, the sign of the right-hand side ultimately depends on the relative fixed cost F_j^A. Our survey results indicate that these fixed costs, reflecting time-invariant operational expenses associated with maintaining generic inventory, vary substantially across pharmacies, particularly across different management types. Consequently, F_j^A can be either positive or negative, suggesting considerable heterogeneity across pharmacies. Therefore, from a cost perspective, the sign of the right-hand side may vary across pharmacies.

We now provide an intuition for why patient preference parameters are *not* separately identified from fixed costs. Equation (6) shows that variations in pharmacy inventory choices across pharmacies are driven primarily by two factors: patients' pharmacy-specific preference β_{jt}^A (which also reflects the pharmacy's comparative advantage) and the relative fixed cost, F_j^A. This implies that when estimating patient preferences for AGs on the basis of observed pharmacy inventory choices, these parameters cannot be separately identified from pharmacy fixed costs[33]. Section 6.3 empirically details how we separate heterogeneous patient pharmacy-specific preferences from pharmacy fixed cost variations, as reflected in the cross-pharmacy patterns of antibiotic AG adoption.

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, a patient's choice of generic drug type depends not only on their preferences (demand side) but also on the availability of the generic drug at the pharmacy (supply side). Since pharmacies make dispensing decisions on the basis of 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

[33]This nonseparable identification between comparative advantage factors and fixed cost factors can also be found in Suri (2011), who first proposed structural estimation using the CRC model. In her framework, where farmers facing a decision regarding whether to adopt a new technology are studied, the comparative advantage parameter reflects how well each farmer is suited to the technology, influencing the relative gains from adoption, whereas the fixed cost parameter captures the enduring, farmer-specific costs needed to implement the technology. The comparative advantage parameter cannot be separated from the permanent portion of these fixed costs; both affect farmers' incentives in similarly persistent ways, rendering them indistinguishable in the estimation process.

Lemieux (1998) and Carneiro et al. (2001). Let us decompose the patient's heterogeneous preferences as follows:

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

where θ_j^B and θ_j^A represent a patient's *permanent* preferences for brand-name drugs and AG 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[34]. 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 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 that both types of drugs produced by the same company are identical in terms of their appearance and content.

By reformulating these decomposition outcomes into log odds equations, as specified by Equa-

[34]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.

tion (2), we obtain the following:

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

Then, the difference in the log odds, given by Equation (5), can be expressed as follows:

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

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 the generic antibiotics share 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.

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

By substituting Equation (10) into Equation (12) and rearranging the above equation, we obtain the following empirical specification:

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

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

Equation (13) 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:

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

where τ_j' denotes individual fixed effects. The relationships between the estimated and original parameters are $\tau_j' = \tau_j + \phi \theta_j^A$ and $\nu_{jt}' = \nu_{jt} + \theta_j^A h_{jt}^A$. The term $\theta_j^A h_{jt}^A$ is part of the composite error,

as it is unobservable and varies across pharmacies and time. In the special case where $\theta_j^A = 0$, the CRC model reduces to the fixed effects model. Otherwise, the endogeneity issue remains due to the inherent correlation between h_{jt}^A and the composite error ν'_{jt}. Therefore, using the fixed effects model generally yields a biased estimate of overall AG premiums β_t^A and fails to identify the projection coefficient ϕ related to brand and AG premiums.

5.1 Estimation Method

To estimate the structural parameters $(\beta_t^A, \theta_j^A, \phi)$ specified in Equation (13), 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_j^A, as captured by linearly projecting θ_j^A, representing the AG preference associated with pharmacy j, onto the history of its inventory decisions h_{jt}^A. By embedding the projection equation in the estimation strategy, we aim to mitigate the endogeneity problem caused by the correlation between θ_j^A and h_{jt}^A.

For clarity, we outline the two-period estimation method; a three-period approach is detailed in Appendix G. Aligned with the approach of Chamberlain (1984), the linear projection in the two-period case is given as follows[35]:

$$\theta_j^A = \lambda_0 + \lambda_1 h_{j1}^A + \lambda_2 h_{j2}^A + \lambda_3 h_{j1}^A h_{j2}^A + \upsilon_j. \tag{15}$$

Substituting Equation (15) into Equation (13), we derive the following two reduced-form equations from the above equations :

$$\begin{aligned} y_{j1} &= \delta_1 + \kappa_1 h_{j1}^A + \kappa_2 h_{j2}^A + \kappa_3 h_{j1}^A h_{j2}^A + \zeta_{j1} \\ y_{j2} &= \delta_2 + \kappa_4 h_{j1}^A + \kappa_5 h_{j2}^A + \kappa_6 h_{j1}^A h_{j2}^A + \zeta_{j2}, \end{aligned} \tag{16}$$

[35]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 $h_{j1}^A h_{j2}^A$ is omitted from the projection equation, Equation (15), 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 (16).

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:

$$\begin{aligned} \kappa_1 &= (1-\phi)\lambda_1 + \beta_1^A + \lambda_0, & \kappa_4 &= -\phi\lambda_1, \\ \kappa_2 &= -\phi\lambda_2, & \kappa_5 &= (1-\phi)\lambda_2 + \beta_2^A + \lambda_0, \\ \kappa_3 &= (1-\phi)\lambda_3 + \lambda_2, & \kappa_6 &= (1-\phi)\lambda_3 + \lambda_1 \end{aligned} \tag{17}$$

There are six reduced-form parameters $(\kappa_1, \kappa_2, \kappa_3, \kappa_4, \kappa_5, \kappa_6)$ and six structural parameters $(\lambda_1, \lambda_2, \lambda_3, \beta_1^A, \beta_2^A, \phi)$ [36]. 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 $\lambda_0 = -\lambda_1\bar{h}_1^A - \lambda_2\bar{h}_1^A - \lambda_3\bar{h}_1^A\bar{h}_2^A$, where $\bar{h}_1^A$ and $\bar{h}_2^A$ 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 (16). We obtain the reduced-form parameters and the variance-covariance matrix from this estimation. Second, we estimate the structural parameters using optimal minimum distance (OMD) estimates on the basis of first-stage estimates under an appropriate restriction matrix that embodies the parameter restrictions given by Equation (17)[37].

5.2 Identification

This section discusses the identification of structural parameters $(\beta_t^A, \theta_j^A, \phi)$ presented in our empirical specification. Building upon Equation (6), which characterizes the relationship between pharmacy inventory decisions and patient preferences, the identification of patient preferences follows from the AG adoption profiles h_{jt}^A across pharmacies and time periods. Specifically, the context-independent AG preference β_t^A is identified through temporal variation in the average AG adoption rate $\bar{h}_t^A$, whereas the context-dependent preferences θ_j^A are identified through cross-pharmacy variation in AG adoption profiles h_{jt}^A, as formalized in Equation (15).

The correlation between AG and brand preferences, captured by ϕ, is identified through both the AG adoption profiles h_{jt}^A and variation in the log odds of generic drugs y_{jt} across pharmacies. This identification mechanism is formally established through the relationships in Equations (16)

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

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

and (17). Intuitively speaking, patients' substitution patterns between brand-name drugs and AGs manifest in the odds of generic sales shares at pharmacies–higher brand-name drug preference relative to AG preference results in lower average generic sales shares.

While the structural parameters of patient preferences can be identified through variations in pharmacies' log odds of generic drug y_{jt} and AG adoption profiles h_{jt}^A, the context-dependent preferences θ_j^A potentially incorporate pharmacy-specific fixed cost factors F_j^A. As discussed in the previous section, this presents a nonseparable identification challenge for β_{jt}^A, which extends to its time-invariant component θ_j^A.

From an econometric perspective, all structural parameters are estimated using the CRC model formalized in Equation (13). This specification requires the conditional mean zero assumption for the composite error term $\tau_j + \nu_{jt}$, given the patient's heterogeneous preference θ_j^A and the pharmacy's historical adoption patterns $(h_{j1}^A, h_{j2}^A, h_{j1}^A h_{j2}^A)$ in the two-period model.

$$\mathrm{E}(\tau_j + \nu_{jt} | \theta_j^A, h_{j1}^A, h_{j2}^A, h_{j1}^A h_{j2}^A) = 0. \tag{18}$$

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[38].

On the basis of 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 (18) holds.

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

However, if certain time-variant factors influence both patients' transitory preferences and pharmacies' inventory decisions, the identification assumption in our CRC model may be compromised. For example, physician-provided information might simultaneously affect patients' preferences and pharmacy choices, creating a potential correlation between patients' preferences and pharmacies' inventory decisions. Similarly, regional demographic or environmental factors could create similar short-term drug preferences among patients in specific areas. If pharmacies adjust their inventory on the basis of such time-varying regional characteristics, transitory patients' preferences and pharmacies' inventory decisions could also be correlated.

To address these concerns—physician influence on pharmacy selection and regional factors affecting drug preferences—we provide evidence and alternative assumptions to mitigate their potential impact on our identification strategy. Regarding the first concern, regulations in Japan prohibit medical institutions and physicians from directing patients to specific pharmacies[39]. These rules ensure patients' freedom to choose pharmacies and uphold the separation of medical and pharmaceutical services. Thus, this concern seems mitigated. For the second concern related to region-specific factors, we address the potential influence of time-varying regional characteristics by estimating the model under an alternative assumption as follows:

$$\mathrm{E}(\tau_j + \nu_{jt} | \theta_j^A, h_{j1}^A, h_{j2}^A, h_{j1}^A h_{j2}^A, M_{jt}) = 0, \tag{19}$$

where M_{jt} represents a vector of local regional 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 regional 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 (19), we conduct empirical analysis by incorporating the regional characteristics into a reduced-form equation.

[39] *The Rules for Health Insurance-covered Dispensing Pharmacies and Pharmacists*, established by the Ministry of Health, Labour and Welfare, prohibit (1) medical institutions from instructing patients to use specific pharmacies and (2) medical institutions from receiving financial or other benefits from pharmacies to direct patients to them.

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 following 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 correlation case, $\phi = 1$, then patients perceive 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 (15). To confirm the validity of this relationship, the significance of parameters $(\lambda_1, \lambda_2, \lambda_3)$ should be confirmed through a joint test[40]. 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, which is consistent with our model assumptions. We calculate this heterogeneous preference using Equation (15) with the structural parameters $(\hat{\lambda}_0, \hat{\lambda}_1, \hat{\lambda}_2, \hat{\lambda}_3)$ and set ν_{jt} 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_t^A.

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

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 dispense both OG and AG forms of levofloxacin. Furthermore, small pharmacies with extremely low numbers of prescriptions were 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, the 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 empirical 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 between 0 and 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 (13), 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; thus, the value h_{jt}^A representing whether phar-

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 pharmacy 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.

macy j holds an inventory in period t cannot be determined[41]. 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 in period $t-1$, then we derive h_{jt}^{A} from the observed generic types in $t-1$. 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 from hospitals to pharmacies) for each period. The number of prescriptions refers to the number of

[41]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 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.

all prescriptions, including antibiotics and other pharmaceuticals, dispensed by each pharmacy[42]. 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 pharmacy. 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 pharmacy characteristics. For pharmacy size, we categorize pharmacies on the basis of 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 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 on the basis of 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}^{A} on the basis of the predominant generic

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

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 (14). 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 5 displays our model estimation results from Equation (15) 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 (15). 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}^A than the three-period model does, it is plausible that the two-period model is insufficient for extracting heterogeneous preference θ_j^A from adoption history h_{jt}^A. In the following analysis, our primary empirical approach employs the

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 × Regional 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.

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 than for OGs in terms of scientific efficacy, color, and additives. While β_t^A varies across periods, the magnitude of the preference remains 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 generic share, benefiting from patients' overall positive preference for AGs.

Columns (3)–(6) investigate the robustness of our primary findings. In Column (3), we consider all pharmacies, omitting the exclusion of the bottom 5% on the basis of 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}^A for pharmacies that do not dispense generic drugs. We posit that if a pharmacy does not dispense

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]
Regional 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 (15). 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.

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 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[43]. 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 share. As Table 7 illustrates, the prevalence of generic drug adoption is already high in every

[43]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 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
Regional 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}^A is sourced from the previous year for each period.

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
Actual 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.

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 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}^A, the recovered preference $\hat{\theta}_j^A$ depends on the adoption patterns, as shown in Table 3. The results suggest that a sub-

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.

stantial 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 on the basis of their 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 (6) shows that the adoption decision h_{jt}^A 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). Consequently, the recovered $\hat{\theta}_j^A$ from the linear projection in Equation (15) may conflate demand factors such as patient preferences with supply factors such as adoption costs. To isolate these conflated demand and supply factors, we regress $\hat{\theta}_j^A$ on a nonlinear function of pharmacy-specific, time-invariant characteristics F_j^A, related mainly to the cost of dispensing generics.

The residual from the regression is considered the "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[44]. Our main analysis employs a random forest for nonlinear functions. Even when other methods, including lasso, Xgboost, and polynomial functions, are utilized as alternative specifications, the magnitude of the residual remains consistent.

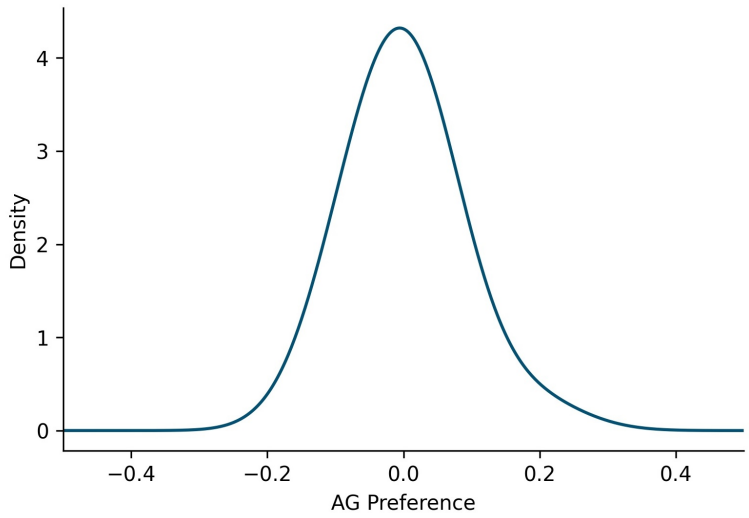
In Appendix F, we detail the estimation procedures and confirm the robustness of the results across various specifications. In addition, we investigate which cost factors at pharmacies are associated with recovered context-dependent preferences $\tilde{\theta}_j^A$. Figure E1 uses the feature importance measures from our baseline random forest to show which cost factors are related to $\hat{\theta}_j^A$[45]. The 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 5 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 across pharmacies.

[44] Our choice of these covariates as proxies for pharmacy fixed costs is supported by two sources of evidence. First, our survey of pharmacists indicates that supply-side considerations, particularly operational costs and contractual arrangements, vary systematically by pharmacy type, with chain and near-hospital pharmacies placing greater emphasis on fixed costs than independent pharmacies do. Second, Ministry of Health, Labour and Welfare (2023a) reported that price negotiation structures differ on the basis of a pharmacy's size and management system.

[45] We evaluate feature importance in the random forest model on the basis of Gini importance, which measures the importance of each feature by the total decrease in Gini impurity that it brings about across all the trees in the forest.

Figure 5: 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.

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' 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 greater than $\mathrm{Var}(\theta_j^A)$, or that patients' preference for brand-name drugs is more widely distributed across pharmacies than their preference for AGs.

Further analysis is needed to understand why the distribution of patient preferences differs between brand-name drugs and AGs. One possible explanation lies in pharmacists' provision of detailed pharmaceutical information. As discussed in Section 2, Japanese pharmacists are responsible for comprehensive medication management and counseling about drug efficacy, safety, and

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
Regional 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}^A is sourced from the previous year for each period.

proper usage when dispensing medications. As our survey reveals, pharmacists employ various communication strategies to gain patient trust in dispensing decisions and build reassurance around generic medications. These pharmacists provide detailed explanations of the therapeutic properties of generic drugs compared with brand-name drugs, enabling patients to gain more accurate knowledge about AGs. Compared with brand-name drugs, this enhanced information flow from qualified healthcare professionals may result in more consistent and therefore smaller variance in patient preferences for AGs across pharmacies.

In the next section, to further examine the role of pharmacists in shaping patients' preferences, we investigate how pharmacists' qualifications as medication specialists influence patients' preferences for generic drugs.

7 Family Pharmacists and Patient Preferences

Our analysis revealed substantial heterogeneity in patients' context-dependent AG preferences across pharmacies, which can be interpreted as pharmacists' comparative advantages in dispensing different types of generics. Given these findings, we examine how the presence of family pharmacists affects patient preferences, focusing on this specialized qualification that enables personalized

medication management[46].

Table 10: Family Pharmacist and AG Preference

	Three Period			
	(1)	**(2)**	**(3)**	**(4)**
Family Pharmacist: Presence	-0.0216	-0.0163	-0.0160	-0.0128
	(0.0033)	(0.0043)	(0.0031)	(0.0042)
Family Pharmacist: Prescription Share		-0.0613		-0.0376
		(0.0293)		(0.0292)
Observations	9818	9818	9818	9818

Notes: Standard errors are in parentheses. The table shows the relationship between a patient's AG brand preference and family pharmacist presence and prescription share at each pharmacy. 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 5. 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 presents the relationship between the recovered AG preference and the role of family pharmacists in each pharmacy. We employ two indicators to measure this relationship: a dummy variable indicating the presence of family pharmacists in the pharmacy and the proportion of prescriptions handled by family pharmacists. In Columns (1)(2), the dependent variable is the recovered AG preference, $\hat{\theta}_j^A$, as reported in Table 8. In Columns (3)(4), the dependent variable is the "partialled-out" AG preference, $\tilde{\theta}_j^A$, as depicted in Figure 5. Column (1) reveals that patients are less likely to exhibit a preference for AGs when they obtain medications from pharmacies where family pharmacists are present. Column (2) examines the extent to which the proportion of prescriptions dispensed by family pharmacists correlates with patients' AG preferences. The results indicate that a greater share of drugs dispensed by family pharmacists is associated with a reduced tendency for patients to exhibit AG preference. The results in Columns (3)(4) show a consistent

[46]Focusing on family pharmacists in the analysis is consistent with our survey findings presented in Appendix A, which highlight significant differences in how family pharmacists explain generic drugs to patients compared with other pharmacists. Table A4 illustrates that when explaining AGs, family pharmacists tend to emphasize physical attributes such as shape, color, and packaging as being identical to the brand-name drug, whereas nonfamily pharmacists focus primarily on explaining the efficacy of AGs. Moreover, previous studies have shown that patients receiving medications from family pharmacists are more likely to experience pharmacist-initiated prescription changes (Nishikawa et al., 2023). These findings suggest that family pharmacists play a critical role in guiding patient preferences.

pattern[47].

These results clearly demonstrate that family pharmacists hold a comparative advantage in promoting OGs, whereas nonfamily pharmacists are more likely to encourage AG adoption. As shown in Table 2, pharmacies with family pharmacists present an AG adoption rate that is approximately 20% lower than that of pharmacies without family pharmacists. While part of this difference may be attributed to supply-side factors, such as pharmacy-level fixed cost variations, the analysis indicates that a significant relationship persists even after controlling for cost-related factors in columns (3)(4). This implies that differences in AG dispensing across pharmacies are significantly influenced by variations in patients' pharmacy-specific preferences, shaped by the comparative advantages of the pharmacists themselves.

As discussed in Section 2.1, family pharmacists assess patients' medication histories and make tailored recommendations. Although patients generally show a preference for AGs over OGs, family pharmacists can strengthen patients' understanding and trust in their medication therapy involving OGs by thoroughly explaining key pharmaceutical details, such as efficacy, dosage, and potential side effects. By combining these explanations with their comprehensive knowledge of patients' medication profiles, family pharmacists may shift patient preferences toward OGs, increasing their acceptance despite the widespread preference for AGs.

Why do family pharmacists tend to reduce patients' relative preference for AGs compared with OGs through personalized medical management, encouraging patients to prefer OGs? One reason is that OGs are *not* necessarily inferior in quality to brand-name drugs or AGs. They are often produced with unique methods and incorporate pharmaceutical innovations that enhance medication adherence, such as smaller tablet sizes or improved taste[48]. Given that family pharmacists recommend medications on the basis of patients' needs, it is not surprising that patients' preference for

[47] In Appendix F, we examine the relationship between family pharmacist presence 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 family pharmacist presence to context-dependent preferences is considerable, ranking as the third most influential factor after pharmacy size and the characteristics of hospitals issuing prescriptions.

[48] Generic drug manufacturers differentiate their OGs from brand-name drugs by employing innovations beyond basic cost reduction. These include developing unique formulations unavailable in brand-name drugs, improving sustained-release performance, and printing drug names on tablets to minimize medical errors (Technical Information Institute, 2016). In contrast, brand-name drugs generally maintain their original manufacturing process from initial production to patent expiration, with modifications limited to additional indications or formulations. Since AGs are identical to brand-name drugs in composition and form, OGs may provide added benefits in areas such as pharmaceutical technology and safety, making them preferable for certain patients.

AGs might decline when they provide balanced explanations about the features and trade-offs of each option. Instead of defaulting to AGs owing to their identical nature to brand-name drugs, family pharmacists may highlight the unique advantages of OGs, fostering patient confidence in these alternatives[49].

Therefore, our estimation results therefore highlight the critical role of pharmacists in enhancing patient confidence through personalized medical management, which must be tailored to each patient's level of comprehension and receptiveness. While patients often exhibit an inherent preference for brand-name drugs, encouraging the adoption of generics necessitates individualized guidance that addresses specific concerns and needs. By focusing on this personalized medical management, pharmacists can build trust in generic medications and support their broader acceptance in practice.

8 Conclusions

This paper examines how pharmacists influence patients' brand preferences, focusing on AGs that are identical to original brand-name drugs. Our model and empirical results reveal significant heterogeneity in patients' AG preferences across pharmacies. This variation appears to be strongly linked to the qualifications and expertise of pharmacists, particularly family pharmacists, who provide comprehensive medication management. While patients generally prefer AGs over OGs, we find that family pharmacists hold a comparative advantage in promoting OGs through their specialized knowledge and patient relationships. In contrast, standard pharmacies demonstrate greater success with AG adoption, suggesting that different types of pharmacists develop distinct comparative advantages in generic drug dispensing. These findings challenge the conventional understanding that consumers consistently prefer brand products when prices are equal, highlighting how professional expertise can create context-dependent variations in brand preferences that explain why some consumers choose nonbrand alternatives even when brand-identical options are

[49] In addition to the abovementioned reasons, cost factors may influence the willingness of pharmacies with family pharmacists to promote OGs. As discussed in footnote 29, OGs are often used as leverage in bundled pricing negotiations between pharmacies and wholesalers. Because OGs are negotiated collectively with other generics, procuring them can result in greater fixed-cost savings for pharmacies than AGs. If acquiring OGs is more cost-effective, family pharmacists may strategically emphasize their innovative features to patients, reducing their preference for AGs in favor of OGs.

available at the same price.

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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Supplemental Appendix

A Pharmacists Survey Results

A.1 Survey Design and Methodology

Two waves of surveys were conducted in collaboration with MCI Co., Ltd., a consulting firm specializing in healthcare industry research. The first wave, conducted in October 2023, served as a preliminary investigation into the general dispensing behaviors of Japanese pharmacists. The second wave, conducted in November 2024, focused specifically on dispensing practices related to levofloxacin. This study primarily analyzes data from the 2024 survey, which targeted 100 supervising pharmacists responsible for drug procurement and experienced in dispensing AG levofloxacin.

Participants were randomly drawn from MCI's panel of 7,481 pharmacists, excluding those working in hospital pharmacies. The final sample included pharmacists working in three main types of retail pharmacies: independent pharmacies, near-hospital pharmacies, and pharmacy chains. Pharmacists could select multiple pharmacy types, allowing for cases where pharmacies were classified as both near-hospital pharmacies and pharmacy chains. Consequently, the total sample size of pharmacy types exceeds 100. The survey explored workplace characteristics, professional attributes, procurement practices, and dispensing preferences for both AG and OG versions of levofloxacin. Key areas of focus included pharmacists' rationale for selecting AG over OG, challenges faced when switching manufacturers, and strategies for explaining these choices to patients.

A.2 Primary Reasons for AG Dispensing Among Pharmacists

Table A1 presents the primary reasons pharmacists selected AG levofloxacin instead of OG alternatives. Respondents were asked to choose multiple reasons and rank their top three in order of priority. Table displays the percentages of respondents identifying each factor as their most important consideration.

The results indicate that the most significant reason for choosing AG was pharmacists' con-

fidence in its identical composition to the brand-name product, allowing them to provide authoritative explanations about efficacy and safety. This factor aligns with pharmacists' professional responsibility to ensure patient confidence. The second most cited reason was patient reassurance, as pharmacists believed patients felt more secure receiving a product identical to the brand version. Stable supply also emerged as a key concern, as pharmacists emphasized the importance of uninterrupted availability for patient care.

Conversely, cost considerations had a limited impact on decision-making. Few pharmacists identified cost as a primary factor, which aligns with both our survey results and national statistics on generic drug pricing. According to our survey's procurement price data, OGs are typically only 10% to 20 % less expensive than AGs (see Table A5), a finding that mirrors broader national trends. This modest price differential is further offset by substantial subsidies that incentivize the dispensing of generic drugs.

Table A1: Most Important Reasons for Choosing AG Products, Categorized by Pharmacy Type

	Independent	**Near-Hospital**	**Chains**
Cost (affordability and procurement ease)	3.12%	8.00%	4.35 %
Stable supply (availability ensured)	9.38%	16.00%	30.43%
Pharmacist confidence (identical composition)	50.00 %	44.00%	32.61%
Patient reassurance (identical composition)	37.50%	30.00%	30.43%
Other	0.00 %	2.00%	2.17%
N	32	50	46

A.3 Primary Challenges in Switching Between AG and OG Manufacturers

Table A2 summarizes pharmacists' challenges when switching between AG and OG manufacturers. Table identifies the most important challenge Patient education emerged as the most significant concern for pharmacists, cited by over 85% of respondents. Explaining changes in drug appearance, packaging, or manufacturer identity posed communication challenges, reflecting the importance of maintaining patient trust during transitions.

Supply-side factors were also noteworthy, particularly contract management challenges. These concerns reflect transaction costs, such as identifying new suppliers, renegotiating agreements, and

managing supply chain adjustments. Fixed costs related to staff training and system reconfiguration also added operational burdens.

Table A2: Most Important Challenge in Switching Between Generic Drug Manufacturers

	Independent	**Near-Hospital**	**Chains**
Patient education needs	93.75 %	90.00 %	73.91%
Wholesaler contract management	3.12 %	6.00 %	13.04 %
Staff training requirements	3.12%	4.00%	2.17%
Dispensing system adjustments	0.00%	0.00%	6.52%
Other	0.00%	0.00%	4.35%
N	32	50	46

A.4 Pharmacists' Key Information Points When Explaining Generic Drugs to Patients

The survey also explored pharmacists' communication strategies when explaining AG and OG medications to patients. Table A3 highlights the percentage of pharmacists prioritizing each information point. For AG drugs, pharmacists focused heavily on physical similarities to the brand-name product (e.g., shape, color, and manufacturer identity) to reassure patients of equivalence. For OG drugs, emphasis shifted to therapeutic properties like efficacy and safety.

Communication strategies also differed based on pharmacy type. Independent pharmacists placed greater emphasis on brand-name identity, reflecting their personalized care model. Conversely, retail pharmacy chains and near-hospital pharmacies adopted broader priorities, particularly for OG medications, by highlighting therapeutic properties over physical similarities.

Table A4 further compares key information points based on whether pharmacists identified as *family pharmacists* or *non-family pharmacists*. Significant differences were observed, particularly when explaining AG medications. Family pharmacists emphasize the physical similarity to the brand-name product (shape, color, and packaging) to reassure patients, reflecting their closer patient relationships and trust-building strategies. In contrast, non-family pharmacists prioritized efficacy when explaining AG drugs.

Table A3: Pharmacists' Key Information Points When Explaining Generic Drugs to Patients

(a) Information Priorities When Explaining AG			
	Independent	**Near-Hospital**	**Chains**
Efficacy	18.75%	16.00%	21.74%
Safety	15.62%	10.00%	2.17%
Identity to the brand-name product (shape and color)	46.88%	40.00%	43.48%
Identity to the brand-name product (packaging)	0.00%	2.00%	2.17%
Identity to the brand-name product (manufacturer)	15.62%	28.00%	28.26%
Stable supply	3.12%	4.00%	2.17%
Other	0.00%	0.00%	0.00%
N	32	50	46
(b) Information Priorities When Explaining OG			
	Independent	**Near-Hospital**	**Chains**
Efficacy	59.38%	46.00%	54.35%
Safety	15.62%	30.00%	28.26%
Identity to the brand-name product (shape and color)	6.25%	8.00%	6.52%
Identity to the brand-name product (packaging)	0.00%	6.00%	2.17%
Identity to the brand-name product (manufacturer)	6.25%	4.00%	0.00%
Stable supply	6.25%	2.00%	0.00%
Other	6.25%	4.00%	8.70%
N	32	50	46

Table A4: Pharmacists' Key Information Points by Family and Non-Family Pharmacists

(a) Information Priorities When Explaining AG		
	Family Pharmacists	**Non-Family Pharmacists**
Efficacy	17.05%	41.67%
Safety	9.09%	8.33%
Identity to the brand-name product (shape and color)	43.18%	25.00%
Identity to the brand-name product (packaging)	2.27%	0.00%
Identity to the brand-name product (manufacturer)	25.00%	25.00%
Stable supply	3.41%	0.00%
Other	0.00%	0.00%
N	88	12
(b) Information Priorities When Explaining OG		
	Family Pharmacists	**Non-Family Pharmacists**
Efficacy	53.41%	50.00%
Safety	25.00%	25.00%
Identity to the brand-name product (shape and color)	5.68%	16.67%
Identity to the brand-name product (packaging)	3.41%	0.00%
Identity to the brand-name product (manufacturer)	2.27%	8.33%
Stable supply	3.41%	0.00%
Other	6.82%	0.00%
N	88	12

A.5 AG and OG Procurement Price Differences

Table A5 illustrates the distribution of the percentage by which OG procurement prices are lower than AG procurement prices, categorized by pharmacy type. The calculations are based on responses from pharmacists who indicated they were familiar with procurement prices.

Table A5: Distribution of whole sale price differences by Pharmacy Type

OG discount on AG wholesale price	**Total**	**Independent**	**Near-Hospital**	**Chains**
Below 0%	0.00%	0.00%	0.00%	0.00%
0% to less than 10%	27.78%	28.57%	26.67%	28.57%
10% to less than 20%	23.61%	38.10%	26.67%	4.76%
20% to less than 30%	31.94%	19.05%	36.67%	38.10%
30% to less than 40%	12.50%	9.52%	10.00%	19.05%
40% to less than 50%	4.17%	4.76%	0.00%	9.52%
50% and above	0.00%	0.00%	0.00%	0.00%
Mean	15.18%	18.43%	13.43%	14.13 %
Median	15.00%	20.00%	10.00 %	14.00%
N	72	21	21	30

Overall, the table shows that OG prices are consistently lower than AG prices, with the majority of discounts falling between 10% and 30%. Extremely large reductions (over 50%) do not occur. The overall mean and median discounts both hover around 15%, suggesting that, on average, OG wholesale prices are roughly 15% lower than AG wholesale prices. Independent pharmacies tend to secure slightly higher average discounts than others, while near-hospital and chain pharmacies generally experience more moderate reductions.

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:

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

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

where M_{jt} is regional characteristics. 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,

$$\Delta\widehat{Y_{gt}} = \frac{1}{J_g} \sum_{j=1}^{J_g} \frac{\widehat{Y_{jt}^A} - \widehat{Y_{jt}^O}}{\widehat{Y_{jt}^O}}. \tag{20}$$

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

$$\Delta\widehat{Y_g} = \frac{1}{T_g J_g} \sum_{t=1}^{T_g} \sum_{j=1}^{J_g} \frac{\widehat{Y_{jt}^A} - \widehat{Y_{jt}^O}}{\widehat{Y_{jt}^O}}. \tag{21}$$

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 Model Details

D.1 Patients' Preference and Pharmacy's Decision

The equation (6) implies the pharmacy's adoption decision depends on the patient's generic preference via generic share. From equation (2), log-generic shares in adopting AG and OG at each pharmacy j at time t are

$$y_{jt}^A = \alpha \Delta P_t + (\beta_t^A - \beta_t^B) + (\beta_{jt}^A - \beta_{jt}^B)$$
$$y_{jt}^O = \alpha \Delta P_t - (\beta_t^B + \beta_{jt}^B).$$

Since the pharmacy's decision depends on the difference of generic share $Y_{jt}^A - Y_{jt}^O$, we can rewrite it by using log-generic shares as follows

$$\begin{aligned}
Y_{jt}^A - Y_{jt}^O &= \frac{\exp(y_{jt}^A)}{1+\exp(y_{jt}^A)} - \frac{\exp(y_{jt}^O)}{1+\exp(y_{jt}^O)} \\
&= \frac{\exp(\alpha \Delta P_t + (\beta_t^A - \beta_t^B) + (\beta_{jt}^A - \beta_{jt}^B))}{1+\exp(\alpha \Delta P_t + (\beta_t^A - \beta_t^B) + (\beta_{jt}^A - \beta_{jt}^B))} - \frac{\exp(\alpha \Delta P_t - (\beta_t^B + \beta_{jt}^B))}{1+\exp(\alpha \Delta P_t - (\beta_t^B + \beta_{jt}^B))} \\
&= \frac{\exp(\alpha \Delta P_t + (\beta_t^A - \beta_t^B) + (\beta_{jt}^A - \beta_{jt}^B)) - \exp(\alpha \Delta P_t - (\beta_t^B + \beta_{jt}^B))}{(1+\exp(\alpha \Delta P_t + (\beta_t^A - \beta_t^B) + (\beta_{jt}^A - \beta_{jt}^B)))(1+\exp(\alpha \Delta P_t - (\beta_t^B + \beta_{jt}^B)))} \\
&= \frac{\exp(\beta_t^A + \beta_{jt}^A + \alpha \Delta P_t - (\beta_t^B + \beta_{jt}^B)) - \exp(\alpha \Delta P_t - (\beta_t^B + \beta_{jt}^B))}{(1+\exp(\beta_t^A + \beta_{jt}^A + \alpha \Delta P_t - (\beta_t^B + \beta_{jt}^B)))(1+\exp(\alpha \Delta P_t - (\beta_t^B + \beta_{jt}^B)))}
\end{aligned}$$

Since $\Delta P_t - (\beta_t^B + \beta_{jt}^B)$ does not change across the choice between AG and OG, we define $C_{jt} = \Delta P_t - (\beta_t^B + \beta_{jt}^B)$ as a constant. Then, the generic share difference can be written as the function of patients' preferences $f(\beta_t^A, \beta_{jt}^A)$ such that

$$f(\beta_t^A, \beta_{jt}^A) = \frac{\exp(\beta_t^A + \beta_{jt}^A + C_{jt}) - \exp(C_{jt})}{(1+\exp(\beta_t^A + \beta_{jt}^A + C_{jt}))(1+\exp(C_{jt}))}.$$

Then, its derivative with respect to β_t^A is

$$\begin{aligned}\frac{\partial f(\beta_t^A, \beta_{jt}^A)}{\partial \beta_t^A} &= \frac{\exp(\beta_t + \beta_{jt} + C_{jt})(1 + \exp(\beta_t + \beta_{jt} + C_{jt}))(1 + \exp(C_{jt}))}{((1 + \exp(\beta_t + \beta_{jt} + C_{jt}))(1 + \exp(C_{jt})))^2} \\ &- \frac{(\exp(\beta_t + \beta_{jt} + C_{jt}) - \exp(C_{jt}))(1 + \exp(C_{jt}))\exp(\beta_t + \beta_{jt} + C_{jt})}{((1 + \exp(\beta_t + \beta_{jt} + C_{jt}))(1 + \exp(C_{jt})))^2} \\ &= \frac{\exp(\beta_t + \beta_{jt} + C_{jt})(1 + \exp(C_{jt}))^2}{((1 + \exp(\beta_t + \beta_{jt} + C_{jt}))(1 + \exp(C_{jt})))^2} \\ &= \frac{\exp(\beta_t + \beta_{jt} + C_{jt})}{(1 + \exp(\beta_t + \beta_{jt} + C_{jt}))^2} > 0\end{aligned}$$

Similarly, we can derive $\frac{\partial f(\beta_t^A, \beta_{jt}^A)}{\partial \beta_{jt}^A} > 0$. Therefore, if patients prefer AG more, $Y_{jt}^A - Y_{jt}^O$ becomes larger, which means the pharmacists are more likely to adopt AG based on financial incentives.

D.2 Alternative Model: Threshold-Based Generic Subsidy

This section shows the pharmacy's supply behavior under the different subsidy specifications: threshold-based generic subsidy. In Section 4.2, we assume that the pharmacies follow the linear generic subsidy to simplify their decision-making. In practice, however, the Japanese government employs a threshold-based generic subsidy. The government adjusts this threshold every two years, and pharmacies are eligible for the subsidy if the overall generic share exceeds the threshold.

Formally, the threshold-based generic subsidy $subsidy_{jt}^{\ell}$ is given as follows:

$$subsidy_{jt}^{\ell} = s_t \mathbb{1}\left(Y_{jt}^{\ell} r_j + g_{jt} \geq c_t\right), \tag{22}$$

where $\mathbb{1}(\cdot)$ is an indicator function, $Y_{jt}^{\ell} r_j + g_{jt}$ is the total generic share, including other generic and brand drugs, 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. Note that the threshold c_t remains constant across all pharmacies while fluctuating over time.

Based on the definition of the subsidy, we can derive the condition under which pharmacies adopt AG, similar to equation 6, as follows:

$$\mathbb{1}\left(Y_{jt}^A \geq c_{jt}\right) - \mathbb{1}\left(Y_{jt}^O \geq c_{jt}\right) \geq \frac{(f_j^A - f_j^O)}{s_t n_{jt}}, \tag{23}$$

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 $(c_t - g_{jt})/r_j$.

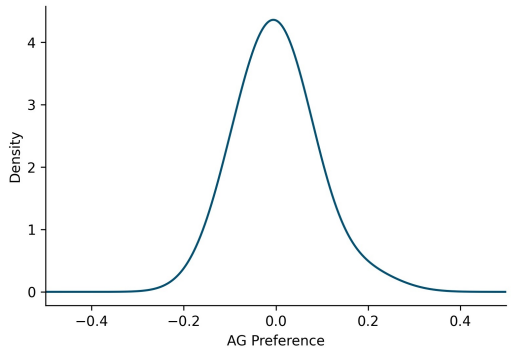
If we consider the indicator function $\mathbb{1}(Y_{jt}^{\ell} \geq c_{jt})$ to be a nondecreasing function of Y_{jt}^{ℓ} and the threshold c_{jt} to be common on the left-hand side of Equation (23), then the profit difference $\pi_{jt}^{A} - \pi_{jt}^{O}$ also becomes a nondecreasing function of the log share difference $\ln(Y_{jt}^{A}) - \ln(Y_{jt}^{O})$. Then, the share of generic antibiotics Y_{jt}^{ℓ} is still the key factor in a pharmacy's decision to stock either an AG or an OG. Therefore, our analysis of comparative advantages and pharmacy decision-making remains applicable even under the threshold-based generic subsidy.

E Recovered Heterogeneous Preference

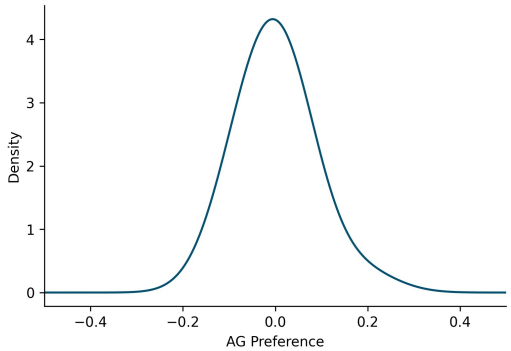
As discussed in section 5.3, we regress $\hat{\theta}_j^A$ on a nonlinear function of pharmacy characteristics $f(F_j)$ to estimate the patient AG preferences denoted as $\tilde{\theta}_j^A$. Formally, we estimate the following Equation,

$$\hat{\theta}_j^A = f(F_j) + \varepsilon_j \tag{24}$$

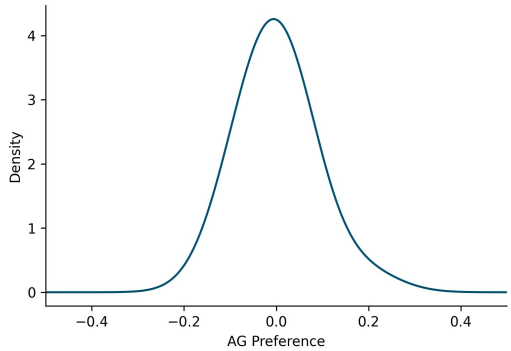
where ε_j is the error term. The primary analysis in figure 5 employs a fifth-degree polynomial of the cost-associated variable F_j. Figure D1 shows the AG preference estimated by various nonlinear functions. Panels (a) and (b) illustrate the AG preference estimations using fourth and sixth-degree polynomials, 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.



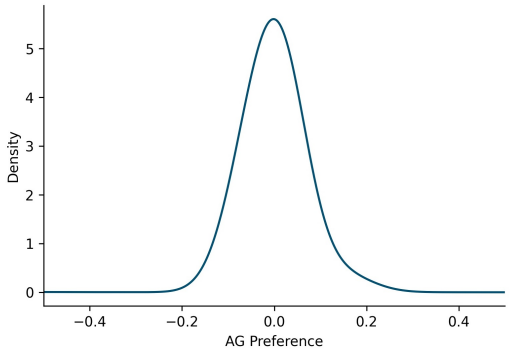
(a) 4th Polynomial



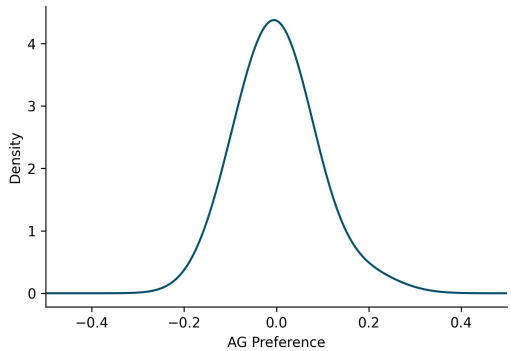
(b) 5th Polynomial



(c) 6th Polynomial



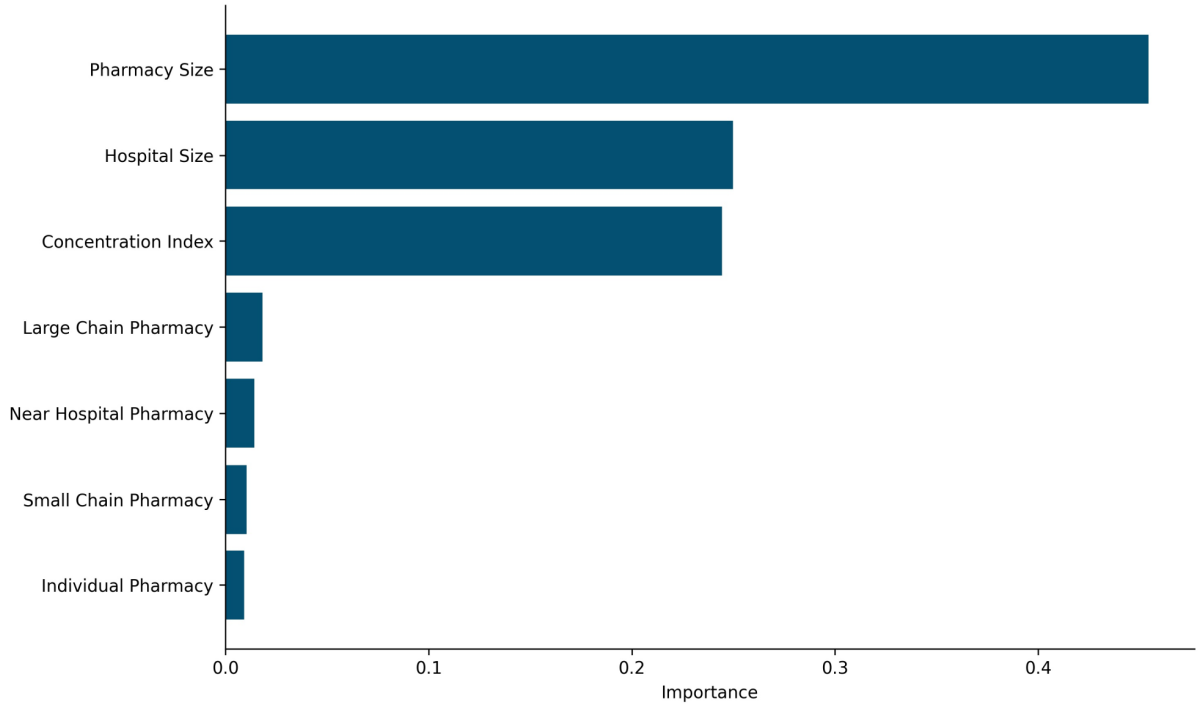
(d) Xgboost



(e) Lasso

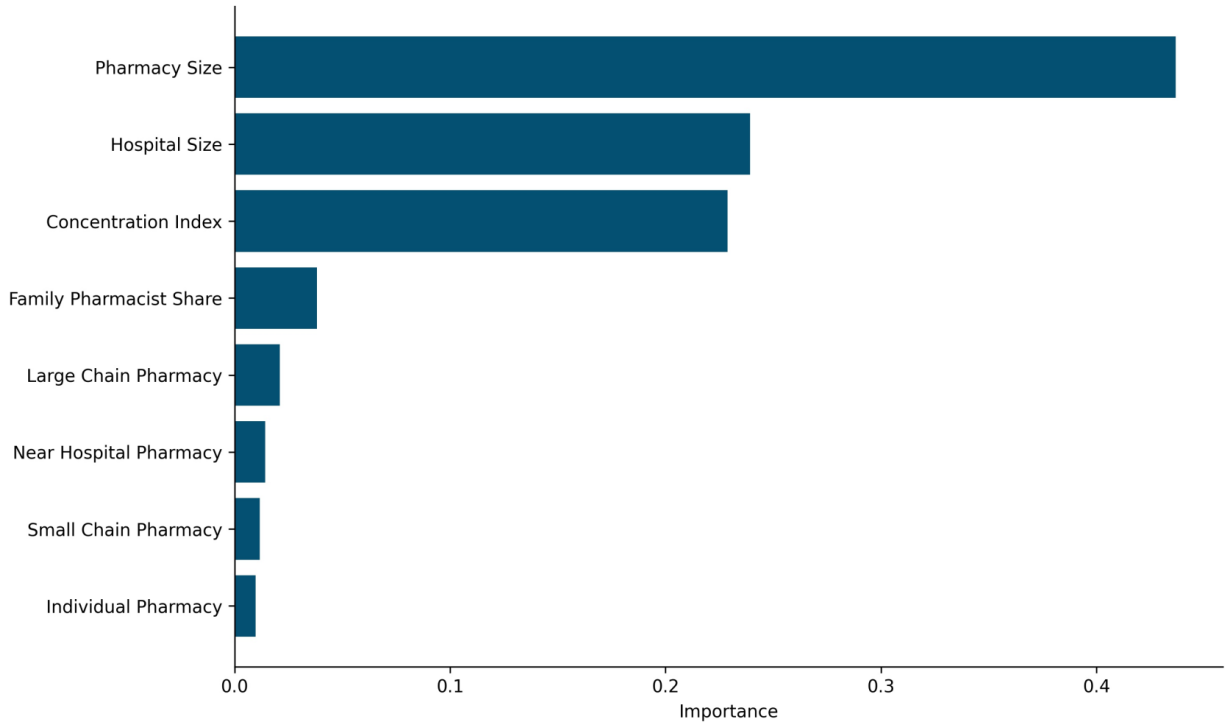
Figure D1: The Recovered Patient's Heterogeneous Preferences

F 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

G Estimation in Three-Period Model

Following Suri (2011), we rearrange the Equation (13),

$$y_{jt} = \alpha \Delta P_t - \beta_t^B + (\beta_t^A + \varphi\theta_j)h_{jt}^A + \theta_j - \tau_j + \nu_{jt}, \tag{25}$$

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

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

$$\theta_j = \lambda_0 + \lambda_1 h_{j1}^A + \lambda_2 h_{j2}^A + \lambda_3 h_{j1}^A h_{j2}^A + \lambda_4 h_{j3}^A + \lambda_5 h_{j1}^A h_{j3}^A + \lambda_6 h_{j2}^A h_{j3}^A + \lambda_7 h_{j1}^A h_{j2}^A h_{j3}^A + \upsilon_j. \tag{26}$$

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 (26) into the Equation (25) for each time period yields

$$\begin{aligned}
y_{j1} &= (\alpha\Delta P_1 - \beta_1^B + \lambda_0) + \left(\beta_1^A + \varphi\lambda_0 + \lambda_1(1+\varphi)\right) h_{j1}^A + \lambda_2 h_{j2}^A + \lambda_4 h_{j3}^A \\
&\quad + \left(\varphi\lambda_2 + \lambda_3(1+\varphi)\right) h_{j1}^A h_{j2}^A + \left(\varphi\lambda_4 + \lambda_5(1+\varphi)\right) h_{j1}^A h_{j3}^A + \lambda_6 h_{j2}^A h_{j3}^A \\
&\quad + \left(\varphi\lambda_6 + \lambda_7(1+\varphi)\right) h_{j1}^A h_{j2}^A h_{j3}^A + (\upsilon_j + \varphi\upsilon_j h_{j1}^A - \tau_j + \nu_{j1}) \\
y_{j2} &= (\alpha\Delta P_2 - \beta_2^B + \lambda_0) + \lambda_1 h_{j1}^A + \left(\beta_2^A + \varphi\lambda_0 + \lambda_2(1+\varphi)\right) h_{j2}^A + \lambda_4 h_{j3}^A \\
&\quad + \left(\varphi\lambda_1 + \lambda_3(1+\varphi)\right) h_{j1}^A h_{j2}^A + \lambda_5 h_{j1}^A h_{j3}^A + \left(\varphi\lambda_4 + \lambda_6(1+\varphi)\right) h_{j2}^A h_{j3}^A \\
&\quad + \left(\varphi\lambda_5 + \lambda_7(1+\varphi)\right) h_{j1}^A h_{j2}^A h_{j3}^A + (\upsilon_j + \varphi\upsilon_j h_{j2}^A - \tau_j + \nu_{j2}) \\
y_{j3} &= (\alpha\Delta P_3 - \beta_3^B + \lambda_0) + \lambda_1 h_{j1}^A + \lambda_2 h_{j2}^A + \left(\beta_3^A + \varphi\lambda_0 + \lambda_4(1+\varphi)\right) h_{j3}^A \\
&\quad + \lambda_3 h_{j1}^A h_{j2}^A + \left(\varphi\lambda_1 + \lambda_5(1+\varphi)\right) h_{j1}^A h_{j3}^A + \left(\varphi\lambda_2 + \lambda_6(1+\varphi)\right) h_{j2}^A h_{j3}^A \\
&\quad + \left(\varphi\lambda_3 + \lambda_7(1+\varphi)\right) h_{j1}^A h_{j2}^A h_{j3}^A + (\upsilon_j + \varphi\upsilon_j h_{j3}^A - \tau_j + \nu_{j3})
\end{aligned} \tag{27}$$

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

$$
\begin{aligned}
y_{j1} &= \delta_1 + \kappa_1 h^A_{j1} + \kappa_2 h^A_{j2} + \kappa_3 h^A_{j3} + \kappa_4 h^A_{j1} h^A_{j2} + \kappa_5 h^A_{j1} h^A_{j3} + \kappa_6 h^A_{j2} h^A_{j3} + \kappa_7 h^A_{j1} h^A_{j2} h^A_{j3} + \zeta_{j1} \\
y_{j2} &= \delta_2 + \kappa_8 h^A_{j1} + \kappa_9 h^A_{j2} + \kappa_{10} h^A_{j3} + \kappa_{11} h^A_{j1} h^A_{j2} + \kappa_{12} h^A_{j1} h^A_{j3} + \kappa_{13} h^A_{j2} h^A_{j3} + \kappa_{14} h^A_{j1} h^A_{j2} h^A_{j3} + \zeta_{j2} \\
y_{j3} &= \delta_3 + \kappa_{15} h^A_{j1} + \kappa_{16} h^A_{j2} + \kappa_{17} h^A_{j3} + \kappa_{18} h^A_{j1} h^A_{j2} + \kappa_{19} h^A_{j1} h^A_{j3} + \kappa_{20} h^A_{j2} h^A_{j3} + \kappa_{21} h^A_{j1} h^A_{j2} h^A_{j3} + \zeta_{j3},
\end{aligned}
\tag{28}
$$

where $\delta_1 = \alpha \Delta P_1 - \beta^B_1 + \lambda_0$, $\delta_2 = \alpha \Delta P_2 - \beta^B_2 + \lambda_0$, $\delta_3 = \alpha \Delta P_3 - \beta^B_3 + \lambda_0$ 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:

$$
\begin{aligned}
\kappa_1 &= \beta_1^A + \varphi\lambda_0 + \lambda_1(1+\varphi) \\
\kappa_2 &= \lambda_2 \\
\kappa_3 &= \lambda_4 \\
\kappa_4 &= \varphi\lambda_2 + \lambda_3(1+\varphi) \\
\kappa_5 &= \varphi\lambda_4 + \lambda_5(1+\varphi) \\
\kappa_6 &= \lambda_6 \\
\kappa_7 &= \varphi\lambda_6 + \lambda_7(1+\varphi) \\
\kappa_8 &= \lambda_1 \\
\kappa_9 &= \beta_2^A + \varphi\lambda_0 + \lambda_2(1+\varphi) \\
\kappa_{10} &= \lambda_4 \\
\kappa_{11} &= \varphi\lambda_1 + \lambda_3(1+\varphi) \\
\kappa_{12} &= \lambda_5 \\
\kappa_{13} &= \varphi\lambda_4 + \lambda_6(1+\varphi) \\
\kappa_{14} &= \varphi\lambda_5 + \lambda_7(1+\varphi) \\
\kappa_{15} &= \lambda_1 \\
\kappa_{16} &= \lambda_2 \\
\kappa_{17} &= \beta_3^A + \varphi\lambda_0 + \lambda_4(1+\varphi) \\
\kappa_{18} &= \lambda_3 \\
\kappa_{19} &= \varphi\lambda_1 + \lambda_5(1+\varphi) \\
\kappa_{20} &= \varphi\lambda_2 + \lambda_6(1+\varphi) \\
\kappa_{21} &= \varphi\lambda_3 + \lambda_7(1+\varphi)
\end{aligned}
\tag{29}
$$

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 $\lambda_0 = -\lambda_1\bar{h}_1^A - \lambda_2\bar{h}_2^A - \lambda_3\bar{h}_1^A\bar{h}_2^A - \lambda_4\bar{h}_3^A - \lambda_5\bar{h}_1^A\bar{h}_3^A - \lambda_6\bar{h}_2^A\bar{h}_3^A - \lambda_7\bar{h}_1^A\bar{h}_2^A\bar{h}_3^A$, where $\bar{h}_1^A$, $\bar{h}_2^A$, and $\bar{h}_3^A$ represent the average AG adoption rate across pharmacies in each period.

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

$$\hat{\theta}_j^A = \hat{\varphi}(\hat{\lambda}_0 + \hat{\lambda}_1 h_{j1}^A + \hat{\lambda}_2 h_{j2}^A + \hat{\lambda}_3 h_{j1}^A h_{j2}^A + \hat{\lambda}_4 h_{j3}^A + \hat{\lambda}_5 h_{j1}^A h_{j3}^A + \hat{\lambda}_6 h_{j2}^A h_{j3}^A + \hat{\lambda}_7 h_{j1}^A h_{j2}^A h_{j3}^A) \quad (30)$$

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.