Marketing Status and Brand-name Drug Prices: Evidence from Rx-to-OTC Switch

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Abstract

This study examines the impact of marketing status on brand-name pricing by exploiting Prescription to Over-the-Counter (Rx-to-OTC) switches between 2001 and 2016. Using a Stacked Difference-in-Differences design, we find that both the retail and net prices of brand-name drugs reduce substantially following an Rx-to-OTC switch, while accounting for potential confounding factors related to patent expiration. We show that the reduction in brand prices is primarily driven by increased patient price elasticity in the OTC market. The findings presented in this paper not only emphasize the significance of increasing patient price sensitivity to tackle the problem of high brand-name prescription drug prices in the United States but also hold valuable policy implications for prescription drug policies worldwide.

Key Words: Pharmaceutical cost, Brand-name drug price, Marketing status, Rx-to-OTC Switch, Stacked difference-in-differences

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1 Introduction

The United States has spent more on prescription drugs than other countries[1] mostly due to high expenditure on brand-name prescription drugs[2], which is widely considered a result of manufacturers pricing brand-name prescription drugs at high levels (Kanavos and Vandoros, 2011; Kanavos et al., 2013; Kesselheim et al., 2016; Papanicolas et al., 2018; Anderson et al., 2019), especially for the newly-introduced specialty drugs. In particular, comparing the prices of 68 top-selling branded drugs in 2010, Kanavos et al. (2013) show that the U.S. prices of brand-name prescription drugs were on average 5 to 198 percent greater, echoing the evidence presented in Mulcahy et al. (2021) that the 2018 U.S. brand-name prescription prices were 3.4 times higher than the comparison countries.

Recent research has gained much progress in understanding the causes behind the high prices of brand-name prescription drugs in the United States. One branch of literature focuses on the role of competition in brand-name pricing but has mixed findings. For example, Wiggins and Maness (2004) find that generic competition after patent expiry leads to lower brand-name prices, while Lexchin (2004) and Vandoros and Kanavos (2013) find that generic competition increases brand-name prices, known as the Generic Competition Paradox. Although this branch of literature has yet to reach a consensus on whether and to what extent patent protection and insufficient generic competition could explain the high prices of brand-name prescription drugs, the mixed evidence suggests a limited responsibility of competition, if any. Dafny et al. (2017) shed light on the strategies exploited by drug manufacturers to maintain high brand-name pricing in the face of generic competition. They find that brand-name manufacturers use coupons to reduce the sales of bioequivalent generics and increase branded sales, thereby gaining advantageous positions in price negotiations with pharmacy benefit managers. Moreover, government price regulations, particularly reference pricing, are shown to be effective in reducing high brand-name prices (Brekke et al., 2011; Kaiser et al., 2014)[3], while

[1] In 2013, the U.S. prescription drug spending per capita was $858, much higher than the $400 average in other OECD countries (OECD, 2015).

[2] Although brand-name drugs comprise only 11% of all dispensed prescriptions in the United States, they account for 74% of drug spending (Generic Pharmaceutical Association, 2017).

[3] In particular, Brekke et al. (2011) find that brand-name prices drop by 33 percent when the price regulation regime in

payment policy of public insurance programs could drive up the pharmaceutical price (Ridley and Lee, 2020).

We complement the literature by examining an understudied factor of brand-name prescription drug prices-the marketing status of brand-name drugs. Pharmaceutical products can be distributed through two broad channels: prescription (Rx) or nonprescription, which includes over the counter (OTC) and behind the counter (BTC). Theoretically, it is reasonable to expect that the ways in which brand-name drugs are dispensed could have varying implications on the prices, as different marketing channels may exhibit different degrees of patient price sensitivity. In recent years, the U.S. Food and Drug Administration (FDA) has approved a number of Rx-to-OTC switches at an accelerated rate. In this study, we leverage the occurrence of 18 Rx-to-OTC switches between 2001 and 2016 to investigate how the prices of brand-name prescription drugs are affected when the brand-name drugs are switched from the prescription market to the OTC market. Besides promoting the understanding of the effect of marketing status on brand-name prescription prices, our study also provides economic arguments for or against the recent administrative effort toward facilitating Rx-to-OTC switches.

To study the effect of marketing status on brand-name prescription drug prices, we obtain drug-level payment data from Medical Expenditure Panel Study (MEPS) Prescribed Medicine Files and other drug product information from the National Drug Code (NDC) directory. A prescription drug is defined based on the unique New Drug Application (NDA) number granted by FDA during its application for marketing approval, its dosage form, and the strength(s) of its active ingredient(s), because the Rx-to-OTC switch typically occurs at the levels of dosage form and strength of a drug product.[4] Compared with the NDC drug identifier used in MEPS, which is susceptible to changes over time, our drug identifier has the advantage of consistently tracking the same prescription drug over a long period of time. Among the sample of prescription drugs, we further identify brand-name prescription drugs

Norway changes from price cap to reference pricing in 2003, and Kaiser et al. (2014) show that in Denmark, reference pricing based on minimum domestic price is more effective in reducing brand-name prices than that based on average European Union price. It is noteworthy that not all price regulations have the same effectiveness. In particular, Li and Wu (2022) show that price ceilings could have the perverse effect of increasing the prices of some pharmaceuticals.

[4] To ensure safety, drug products with lower therapeutic strength are allowed to be sold as OTC drugs, while the versions with higher potency are typically reserved for the prescription market.

as prescription drugs with any patenting history. To estimate the effect of Rx-to-OTC switch on retail prices of brand-name prescription drugs, we use a stacked difference-in-difference (SDID) model as the preferred specification. In our setting, brand-name drugs could be switched from prescription-only to over-the-counter status at different times, and the effects of the switch could show heterogeneous dynamics. When the Rx-to-OTC switching is staggered, a conventional generalized difference-in-difference model may produce biased estimates if the estimated effects vary over time (Goodman-Bacon, 2021). Therefore, we use stacked DID as the preferred specification, which was first introduced by Cengiz et al. (2019) and Deshpande and Li (2019) as an effective solution for the problem. The treatment group consists of brand-name prescription drugs that are ever switched to OTC during our sample period, and the control group consists of the brand-name prescription drugs in the same therapeutic class of switchers that are sold in the prescription market from start to end.

Our results show that marketing status plays a significant role in brand-name pricing to the extent that we have sufficiently controlled for the confounding factors. On the one hand, switching brand-name drugs from prescription-only to OTC sales reduces the retail prices by 29.6 log points (25.6 percent) on average during our sample period. Annual treatment effect estimates show that while the effect is minor during the first two years, the retail prices experience a sharp decline of 80 log points (55 percent) in the third and fourth years, followed by a dramatic plunge of 141 log points (76 percent) in the fifth year and subsequent years. On the other hand, switching to the OTC market with more elastic demand also lowers the net price of brand-name drugs. Given that the pre-switch rebate levels for switchers range from 23% to 40%, and that the retail price effects are -55% and -76% during the third and fourth post-switch years and at the fifth year and beyond, respectively, the net price effect of the Rx-to-OTC switch is estimated to be between -22% and -15% during the third and fourth year, and between -53% to -36% in the fifth year and beyond. We present several pieces of empirical evidence in support of the price-sensitivity mechanism. First, we show that consistent with the price effect dynamics that brand-name prices decline as time progress, we find patient cost sharing increases gradually over time, suggesting that increasing patient

cost sharing and price sensitivity may be the main forces driving the price decline. Second, we estimate the heterogeneous price effects of Rx-to-OTC switch by several dimensions of patient price sensitivity: patient cost sharing, Medicaid market share (the proportion of prescriptions by Medicaid patients), cash market share (the proportion of prescriptions paid for at the full price), and brand competition (the number of brand competitors). We find that the price effect depends negatively on patient cost sharing, cash market share, brand competition, and positively on Medicaid Medicaid share. These results provide strong empirical support for the hypothesis that increased price elasticity in the OTC market induces brand-name manufacturers to lower the prices of the brand-name drugs. Our finding implies that policymakers, who attempt to combat the high brand-name pharmaceutical expenditures, should enhance information transparency in brand-name pricing in the prescription market and, whenever possible, should promote qualified prescription drugs that are potentially large in price elasticity to be sold in the OTC market.

This study builds upon existing literature that highlights the potential downside of insurance to create inelastic demand and therefore stimulate higher prices from brand-name drugs with market power. Early research works by Feldstein (1970, 1971, 1973) identify the adverse welfare effects associated with health insurance, illustrating how it reduces price elasticity and leads to increased healthcare prices. Chiu (1997) and Vaithianathan (2006) further formalize this idea in theoretical models, demonstrating that a high level of insurance coverage results in a high-priced healthcare industry when healthcare markets are imperfectly competitive, which is substantiated by subsequent empirical studies. Pavcnik (2002) shows that brand-name prescription prices in Germany are highly sensitive to patient cost sharing. Duggan and Scott Morton (2006) focus on the Medicaid program in the United States and show that its implementation increases pharmaceutical prices due to a zero copay policy that significantly lowers the price elasticity of Medicaid recipients. In a subsequent study, Duggan and Morton (2010) examine the impacts of the Medicare Part D program and find a decrease in average pharmaceutical prices. However, the magnitude of these average effects varies across drugs with different market power, suggesting that while the insurance-induced reduction in patient price elasticity is still at work, it is outweighed by insurance negotiation power in

this case. More recently, pharmaceutical companies have been observed employing strategies to circumvent insurance negotiation constraints. Dafny et al. (2022) show that branded prescription drug manufacturers use coupons to reduce patient price sensitivity and maintain high prices. Against this backdrop, our study offers new insights into the increasingly important role of patient price elasticity in influencing brand-name pricing.

Our study also contributes to the existing literature on the economic effects of the Rx-to-OTC switch, which primarily focuses on estimating the effects of Rx-to-OTC switch on physician visits (Temin, 1992; Gurwitz et al., 1995), prescription drug utilization (Pierce and Gilpin, 2002; Reed et al., 2005; Sullivan et al., 2005; Sood et al., 2012; Stomberg et al., 2013), or a combination of both (Gurwitz et al., 1995; Kunz et al., 1996).[5] Most studies in this line of research focus on examining one or two cases of Rx-to-OTC switch, with the exception of Stomberg et al. (2013), which analyzes all Rx-to-OTC switches that took place between 1999 and 2010. Notably, the aforementioned studies do not employ quasi-experimental designs. Our study contributes to this literature by considering all Rx-to-OTC switches that occurred from 2001 to 2016, and estimating the treatment effect of the Rx-to-OTC switch on brand-name prices.

The paper proceeds as follows. Section 2 discusses the institutional background relevant to the Rx-to-OTC switch. Section 3 and section 4 describe the data and the empirical methodology, respectively. Section 5 presents the estimated effects of Rx-to-OTC switch on both the retail price and net price of brand-name drugs as well as addresses major identification concerns. Section 6 explores the underlying mechanisms through which the price of brand-name drugs may respond to the Rx-to-OTC switch. Section 7 concludes and discusses some limitations of this study.

2 Background

When a brand-name drug is launched into the market, it initially enters as a prescription drug, requiring a doctor's prescription for purchase. After certain period of time, when the brand-name drug has accumulated sufficient records to demonstrate

[5] See Cohen et al. (2013) for a more comprehensive review.

its safety for over-the-counter (OTC) use, without the involvement of a learned intermediary like physicians, the manufacturer may opt to sell the drug directly to consumers in retail pharmacies over the counter. To accomplish this, the manufacturer must submit a new drug application supplemental to the FDA, specifically requesting an Rx-to-OTC switch. The FDA thoroughly evaluates the drug's safety and efficacy for use without a prescription and subsequently approves or denies the application based on their assessment.

The universe of brand drugs suitable for an Rx-to-OTC switch is largely determined by the nature of the drugs, such as their specific ingredients, strengths, and formulations. Although there are no specific rules determining if a brand prescription drug can be sold in the OTC market, qualified candidates must demonstrate the characteristics of low toxicity, minimal potential for misuse or abuse, absence of significant drug interactions, and ease of self-diagnosis and self-medication.

These requirements may result in different qualification statuses for two similar drugs that only differ in ingredient safety margins or indications. For instance, despite demonstrating comparable effectiveness to second-generation antihistamines (SGAs) in relieving allergy symptoms, such as nasal congestion, runny nose, sneezing, and itching, the antihistamine montelukast sodium (Singulair Allergy) was rejected for an Rx-to-OTC switch by the FDA in 2014. In contrast, the FDA approved the Rx-to-OTC switches of three SGAs—Claritin, Zyrtec, and Allegra—in 2002, 2007, and 2011, respectively. The FDA's decision was influenced by concerns that despite being marketed as a prescription medication since 1998, montelukast sodium (Singulair Allergy) could lead to adverse events, including depression, aggression, and even suicide if misused.

Although the decision of Rx-to-OTC switches initiated by third parties can be considered exogenous, the timing of the switch is endogenous because manufacturers can manipulate when to conduct the switch. [6] Manufacturers can use various strategies to influence the timing of Rx-to-OTC switching. The process requires a New Drug Application (NDA) that includes efficacy and safety data to demonstrate

[6] For example, after reviewing WellPoint's petition to move Claritin, Zyrtec, and Allegra into OTC use, the FDA recommended the manufacturers make the switch in 1998. Initially opposed to the idea, Schering-Plough announced in 2002 that Claritin would be made available over the counter for the treatment of seasonal allergies without a prescription, just one year before its patent expiration.

the drug's suitability for nonprescription use. These data may encompass information from randomized controlled clinical trials submitted during the original NDA, as well as new randomized controlled trials. Since manufacturers collect most of this data, they have the ability to manipulate the time required to prepare the supplemental NDA, thereby influencing the timing of FDA approval for the Rx-to-OTC switch. To legitimately account for the confounding effects from patent expiration, we control for the number of generic and brand competitors in the baseline model, as well as other variables measuring generic and brand competition in flexible forms in alternative specifications.

Following an Rx-to-OTC switch, manufacturers often encounter an OTC market where patients exhibit greater price elasticity. On the one hand, patients typically experience increased cost sharing when a brand-name drug transitions from prescription to the nonprescription OTC market, primarily due to the fact that most insurance plans offer little or restrictive coverage for OTC drugs. The heightened cost sharing contributes to greater price sensitivity among patients, incentivizing manufacturers to choose a lower optimal price (Pavcnik, 2002). On the other hand, patients in the OTC market are less likely to be influenced by physicians who have insufficient responsiveness to brand prices. In the prescription market, ideally a doctor would act as a perfect agent for the patient and prescribe the product that maximizes the patient's well-being. However, in reality, physicians are often unresponsive to brand-name prices due to the costs associated with gathering information about product prices and other characteristics. Furthermore, the well-known physician agency problem can manifest in various scenarios, leading to less sensitivity to brand-name prices among physicians who dispense drugs. Habit persistence in prescribing branded drugs (Crea et al., 2019), limited use of information technology (Epstein and Ketcham, 2014), motivations such as profit-seeking (Liu et al., 2009; Iizuka, 2012) and risk avoidance (Frank and Salkever, 1992, 1997) contribute to this phenomenon. Therefore, switching a drug from prescription to OTC status would enhance consumer price sensitivity by mitigating the physician agency problem. The appendix section A provides more discussion on the potential price-raising factors associated with the Rx-to-OTC switch.

3 Data

3.1 Data Construction

Our main data source is Medical Expenditure Panel Study Prescribed Medicine Files (MEPS-PMF) from 1999 to 2016, a nationally representative survey of US households about prescription use and payment. In particular, MEPS-PMF documents prescription records for survey respondents and their family members, including detailed payment information for each prescription and the quantity or package size dispensed. Detailed payment data include total payment per prescription, out-of-pocket (OOP) payment, and payment by each insurer. The payment data in MEPS measures the amount paid at the point of purchase, excluding pharmacy discounts and consumer coupons that are applied before the payment is made. However, MEPS payment data does not exclude rebate amounts, if applicable, that are returned to insurers after the transaction. We thus use total payment per unit to measure pre-rebate prices of brand-name drugs, which can also be interpreted as the retail price that is paid to pharmacy stores at the point of purchase. Patient demographic characteristics come from MEPS Consolidation Files, including age, sex, education, race, income, and insurance status.

The MEPS-PMF dataset provides comprehensive information on prescription records in the United States from 1999 to 2016, comprising a total of 5,418,563 records. Among these records, 1,316,784 (24.3%) are brand-name prescriptions. We first follow the sample reduction steps outlined in Appendix section **??** and then collapse the prescription-drug-year observations into a drug-year dataset, leading to a sample of 9,364 brand-drug–year observations. This dataset comprises 1,117 brand-name prescription drugs, which encompass 433 unique active ingredients. To construct the control group, we focus on brand-name prescription drugs with comparable product life spans to the switchers. In particular, we keep brand-name drugs that were first launched between the earliest observed launch date in 1993 and the latest observed launch date in 2006 among the switchers. Additionally, we limit our analysis to the five therapeutic categories that encompass the Rx-to-OTC switchers. Therefore, the brand prescription drugs in the control group are similar to the switchers in terms of product life and therapeutic efficacy. Our final

sample consists of 3,823 brand-name drug years, encompassing 421 brand-name prescription drugs and 198 active ingredients.

3.2 Data Description

Table 1 presents an overview of the characteristics of brand-name switchers compared to non-switchers. Prior to the Rx-to-OTC switch, switchers exhibit similarities to non-switchers in various consumer characteristics, including the proportion of female consumers (60.7% vs. 66.7%), married consumers (45.5% vs. 49.5%), white consumers (86.6% vs. 83.8%), consumers with at least a high school education (47.9% vs. 47.0%), and the average family income of consumers ($69,100 vs. $68,900). However, brand-name switchers display distinct attributes compared to non-switchers in several aspects. Firstly, they tend to be high-value drugs with higher annual total spending ($291 million vs. $195.9 million), greater utilization, and wider popularity (e.g., 1.51 million vs. 0.28 million consumers and 4.38 million vs. 1.15 million prescriptions). Secondly, brand-name switchers are more popular among non-elderly individuals, with a higher proportion of young consumers under the age of 25 (28.9% vs. 16.8%) and a lower proportion of elderly consumers above the age of 65 (18.2% vs. 30.9%). Thirdly, brand-name switchers are launched, on average, 2.2 years later than non-switchers. Notice that we cannot determine whether the price of non-switchers' prescription drugs is higher or lower than that of switchers, because the retail prices of medicines cannot be directly compared due to variations in units of measurement across different medications.

Despite these differences, the pricing dynamics exhibit similar patterns between switchers and non-switchers before the Rx-to-OTC switch. Figure 1 depicts the weighted average of retail prices separately for switchers and non-switchers over a five-year period before and after each Rx-to-OTC switch. The red line with triangles represents the price trend of non-switchers, which shows a steady increase over the study period. The average inflation-adjusted price of brand-name non-switchers in the five therapeutic classes rises from $19.6 to $23.7 (a 21% increase) in 2016 dollars during the ten-year window. It is worth noting that this price growth rate is lower than the 55% inflation-adjusted price growth observed for the most

commonly used brand-name drugs between 2014 and 2019, as documented in Express Scripts (2016).[7] Such discrepancy in price growth rates may be attributed to differences in sample composition. Our analysis excludes expensive new drugs introduced after 2006 and focuses exclusively on brand-name drugs within the five specified therapeutic classes.

Second, the average price of brand-name switchers, represented by the blue line with diamond markers in Figure 1, exhibits a similar trend over time as non-switchers before the Rx-to-OTC switch. This co-movement in prices between switchers and non-switchers can be attributed to several factors. Firstly, prior to the switch, switchers and non-switchers share many similarities in terms of various characteristics, as evidenced in Table 1. Moreover, as they belong to the same therapeutic class, they are subject to similar demand and supply dynamics at the drug class level. On the other hand, to the extent that switchers and non-switchers differ in terms of popularity and suitability for self-administered use by consumers, these differences are unlikely to cause divergences in pricing between switchers and non-switchers absent the Rx-to-OTC switch. In particular, The amenability of a drug to self-care by consumers is a drug-specific characteristic determined by its ingredients, strength, and dosage form, which are unlikely to change over time. Additionally, while utilization and popularity of a brand-name drug can fluctuate over time due to changes in patient demand and competition from therapeutic substitutes, there is no reason to expect these effects to differ significantly across brand-name switchers before the Rx-to-OTC switch. The reason is that brand-name switchers and non-switchers are in the same therapeutic drug class, have similar product life spans, and have similar competition level in the prescription market. The event study estimates in section 5.1 provide more rigorous supporting evidence for the common trends assumption.

[7] In particular, Express Scripts (2016) shows that the prices for the most commonly used brand-name drugs increase by 62.1% from 2014 to 2019, and the consumer price index increases by 7.2% during the same period. We approximate the increase in deflated prices by simply subtracting the raw increase from the inflation rate.

4 Empirical Framework

4.1 Effect on Retail Price

Traditional Difference-in-Difference in a staggered adoption design produces biased estimates when treatment effects vary over time (Goodman-Bacon, 2021). We thus estimate the effect of Rx-to-OTC switch on brand-name drug payment using a Stacked DID (SDID) model as our preferred specification, the idea of which initially appears in Cengiz et al. (2019) and Deshpande and Li (2019). We choose an event window of up to 5 years before and after the Rx-to-OTC switch. Switchers switching to OTC in the same year form the treatment group of a sub-experiment, and the control group is non-switchers. For each sub-experiment, we construct a sub-dataset containing observations in the event window of the switchers and non-switchers associated with the sub-experiment. Finally, we stack all the sub-datasets to form the main stacked dataset for analysis. Let i denote a brand-name drug, t denote calendar year, and s denote a sub-experiment. The SDID model can be represented by the following equation:

$$\begin{aligned} \ln p_{its} = \quad & \alpha + \beta \text{post}_{ts} \cdot \text{switch}_{is} + \gamma \text{generic competition}_{its} \\ & + \delta \text{brand competition}_{its} + \Gamma X_{its} + \Theta_{m(i)ts} + \Theta_{cits} + \Theta_{d(i)ts} + \epsilon_{its} \end{aligned} \tag{1}$$

The dependent variable, $\ln p_{idts}$, is the logarithmic retail price of brand-name drug i at year t of sub-experiment s. switch_{is} is an indicator for switchers that equals to 1 when brand-name drug i is ever switched to over the counter in sub-experiment s. post_{ts} indicates years after the Rx-to-Switch in sub-experiment s, which equals to 0 for years before the switch. For brand-name non-switchers, $\text{Post}_{ts} \times \text{switch}_{ds}$ takes the value of 0 for all years. $\text{generic competition}_{its}$ and $\text{brand competition}_{its}$ measure the generic and brand competition faced by drug i at year t, respectively, which are included to control for the simultaneous changes in competition associated with the Rx-to-OTC switch. For example, because manufacturers often choose to make the Rx-to-OTC switch near patent expiration, one would expect that the effect of the switch is confounded by patent expiration and generic competition. Appendix Figure B1(a) confirms such concerns that pharmaceutical firms strategically make

the Rx-to-OTC switch close to patent expiry: the number of generic competitors for switchers increases sharply in the year following the switch, while non-switchers on average have about two generic competitors before and after the switch. The same concern exists for brand competition (see Appendix Figure B1(b)).

β represents the effect of interest, which captures changes in the retail price dynamics of brand-name drugs before and after Rx-to-OTC, after controlling for generic and brand competition, as well as other confounding effects at the therapeutic class and manufacturer level. Assuming that the switchers and non-switchers, which share the same manufacturer, have the same dosage from belonging to the same therapeutic class, and share similar dynamics in retail price, the parameter of interest, β, can be identified as the average treatment effect on the treated and be interpreted as the change in the retail price of a branded drug caused by the Rx-to-OTC switch. The validity of the common trend assumption will be examined in an event study in Panel A of section 5.1. Regressions are weighted by the prescription volumes of each drug. Standard errors are clustered at the drug level. To shed light on the bias from estimating a traditional DID specification with staggered adoption using the original and unstacked data, we also compare our estimates from the preferred SDID model to those from a traditional DID model.

4.2 Effect on Net Price

As mentioned previously, the most ideal approach for estimating the net price effect would involve using SSR Health net drug pricing data, which is widely used in pharmaceutical rebate-related studies. However, if we were to utilize SSR Health data starting from 2007, the number of treated drugs in our study would decrease by 56 percent (10 out of 18 drugs). This reduction in the number of treated drugs would lead to a less representative sample in our analysis. Given this limitation, we adopt an alternative approach in our study. We adjust the estimated retail price effect using the derived bias to recover the net effect. (See online Appendix for more details)

5 The Effect of Rx-to-OTC Switch on Brand-name Prices

5.1 Effects on retail price

We begin by examining the impact of the Rx-to-OTC switch on the brand-name switcher's retail price, which refers to the payment per unit paid by all parties involved before subtracting the manufacturer rebate. Retail price matters for both insured and uninsured patients. Insured patients' cost sharing is determined based on a percentage of the retail price, while uninsured patients are typically required to pay the full retail price out of pocket. Regression results reveal a significant and large reduction in retail price following the Rx-to-OTC switch after accounting for brand competition and subsequent generic entry due to patent expiration. Controlling for the number of competing generic and brand-name drugs, the brand-name switchers' retail price reduces by 29.6 log points (25.6 percent) on average within five years after being switched to the OTC market (Table 2, column 1).

Analyzing the dynamics of treatment effects using a segmented Stacked DID approach, we observe notable changes in the retail price reduction. Specifically, column 2 of Table 2 demonstrates a substantial increase in magnitude over time. Initially, during the first two years following the Rx-to-OTC switch, the reduction in retail price is relatively minor and lacks statistical significance. However, as time progresses, we witness a remarkable drop in retail price. In the third and fourth years after the switch, the retail price plummets by 80 log points, equivalent to a 55 percent decrease. Importantly, this downward trend continues, with a 141 log points reduction (76 percent) occurring in the fifth year and beyond.

Albeit interpreted with caution, the presence of generic competition and the life cycle of a product have a profound impact on the retail price of brand-name drugs, leading to respective reductions of 13.8 and 19 log points. In contrast, the presence of brand competition does not demonstrate any discernible effect on the pricing of brand-name drugs. However, after removing the generic and brand competition variables in column 3, the baseline estimate remains barely unchanged, which suggests that neither generic nor brand competition serves as the primary mechanism

responsible for the price reduction observed subsequent to the Rx-to-OTC switch. Additionally, to further validate the reliability of our findings, column 4 excludes the product life variable from the baseline specification, revealing that our core estimate remains robust even in the absence of the product life variable.

Moreover, we examine the potential estimation bias that arises when employing the conventional DID specification in columns 5-7. Our findings reveal that the traditional DID design with staggered adoption leads to an overestimation of the price reduction attributed to the Rx-to-OTC switch. Specifically, columns 5-7 of Table 2 present traditional DID estimates that consistently exhibit larger magnitudes compared to the stacked DID estimates (columns 1-4). Therefore, to mitigate bias and attain more conservative estimates, we use the Stacked DID (SDID) model as our preferred specification.

A. Testing Common Trend Assumption

To assess the validity of the common trend assumption and show detailed effect dynamics, we estimate an event-study version of the baseline model of Equation 1. Figure 2 presents event-study estimates of the effect of the Rx-to-OTC switch on brand-name retail price, using one year prior to the switch as the base year. The test reveals no systematic differences in pre-trends across treated and untreated drugs, which supports the common trend assumption absent the Rx-to-OTC switch. The steady trend in retail price of switchers before the switch also indicates that pharmaceutical companies do not adjust their pricing strategy in anticipation of the upcoming switch.

B. Addressing Simultaneous and Endogenous Changes

In this study, our primary focus is to examine the impact of changes in marketing status on brand-name drug prices. We use Rx-to-OTC switch as an event that switches a brand-name drug from prescription to the OTC market. However, besides changes in marketing status, other major confounding changes may coincide with the Rx-to-OTC switch and could potentially account for the price reduction. These factors include changes in competition intensity and pricing strategies for

the switched drugs. It is possible that the estimated price reduction after the Rx-to-OTC switch may be driven by these simultaneous changes in competition and pricing strategy, rather than solely by the changes in marketing status. We ignore other minor changes associated with the switch, such as potential increases in patient demand [8] and marketing expenditure[9]. The reason for disregarding these minor changes is that, in theory, these changes would lead to price increases rather than reductions. Therefore, they do not confound the estimated price reduction but rather serve as an indication that our estimated price reduction is quite conservative.

Simultaneous change in competition The first concern we address relates to the confounding effects arising from changes in competition after the Rx-to-OTC switch. Pharmaceutical companies typically choose to make the switch near patent expiration. As a result, an Rx-to-OTC switch is often accompanied by increased competition from either generic or brand entry, which could potentially result in an overestimation of the price-reducing effect of the Rx-to-OTC switch. To address this concern, the main approach we rely on is to carefully control for the confounding competition effects. First, in the baseline regression, we have controlled for the logarithmic numbers of generic and brand competitors (see column 1 of Table 2). Second, in response to the concern that the number of generic and brand competitors included in the baseline model may ignore the non-linear effects of competition, we also control for the logarithm of the number of generic and brand competitors each year as well as the squared terms in column 2 of Table 3. We observe that brand-name retail price decays more quickly with more generic competitors entering the market. However, controlling for this non-linear effect from generic competition (column 2) produces an estimate close to the baseline estimate (column 1).

Third, we also allow the price effect of competition to be different across switchers and non-switchers in column 3, leading to an estimate that is slightly larger in

[8] In particular, allergy drugs, the major class of switchers in our study, experience substantial growth in consumer demand due to convenient access to the drugs. According to Consumer Healthcare Products Association, the number of allergy sufferers who use OTCs has gone up from 66 percent in 2009 to 75 percent in 2015. See https://www.chpa.org/about-consumer-healthcare/research-data/otc-sales-statistics

[9] It is difficult to generalize which type of drug incurs higher marketing costs. In some cases, a prescription drug may require significant marketing efforts to promote the product to healthcare providers and persuade them to prescribe it to their patients. This can involve expensive sales representative visits, direct mail campaigns, and other promotional activities. On the other hand, OTC drugs may require more consumer-oriented marketing efforts, such as TV commercials, print ads, and social media campaigns. These marketing activities may be targeted towards a broader audience and may involve different marketing strategies compared to those used for prescription drugs. Nevertheless, according to some statistics, OTC drugs typically spend more on marketing than prescription drugs.

size than the baseline. Finally, we capture the threshold effect from generic and brand competition by including generic and brand entry dummy in column 4 as well as their interaction terms with the OTC status dummy in column 5. Our estimates remain robust even after controlling for the competition effect using these generic and brand entry dummy variables.

Simultaneous changes in pricing strategy: price penetration and price skimming One may concern that our estimated price reduction following the Rx-to-OTC switch might be influenced by changes in pricing strategy associated with the switch. This is because pricing strategies for OTC drugs are inherently distinct from those for prescription drugs. In one possible scenario, pharmaceutical firms that have made an Rx-to-OTC switch may adopt a penetration pricing strategy to increase OTC sales, whereby they initially offer lower prices, sometimes at a steep discount, to establish brand awareness and loyalty, and then gradually raise prices over time. In this case, the observed price reduction is not a genuine response to increased patient price sensitivity but a short-term price strategy to establish brand awareness. We examine whether the penetration pricing strategy can explain the estimated price reduction following the Rx-to-OTC switch. The treatment effect dynamic diagram of Figure 2 shows that the price reduction deepens over the five-year period following the switch, which contradicts the price patterns in a penetration pricing strategy where the price would increase ultimately.

Besides penetration pricing strategy, manufacturers may also adopt a price skimming/milking strategy, where they initially set a higher price and then gradually lower it as competitors begin to offer similar products or alternatives. As a result, it is reasonable to be concerned that the estimated price reduction following the Rx-to-OTC switch might be simply a pre-determined, natural response over the product life cycle, and that the price reduction following the Rx-to-OTC switch is indeed a strategy responding to the patient expiration subsequent to the switch. If this concern is true, we should observe that generic competition can explain our estimates, which is not the case: columns 1 and 2 in Table 2 show that our baseline estimate is robust regardless of whether we include or exclude generic and brand competition.

C. Examining Reverse Causality

Our estimation also subjects to the concern of the reverse causality problem: the brand-name price reduction following the Rx-to-OTC switch is not a result of the switch. Instead, pharmaceutical manufacturers, who want to change their pricing and marketing strategy, refer to the Rx-to-OTC switch as a means to lower prices and expand their consumer base. To examine the severity of the reverse causality problem, we distinguish between Rx-to-OTC switches that are petitioned by third parties and those voluntarily initiated by the manufacturers. Of the eighteen Rx-to-OTC switches (see Appendix Table B1), only three brand-name drugs –Nexium 24 Hour tablet, Flonase Allergy Relief spray, and Oxytrol for Women, are switched voluntarily by the manufacturers. The petition for the remaining fourteen Rx-to-OTC switches of SGAs (mainly Second Generation Antihistamines) is initiated by the insurer of the Wellpoint company, aiming to reduce pharmaceutical spending on these drugs. On the other hand, the switch of Plan B is initiated by the Center for Reproductive Rights, driven by considerations of public interest. Given that the Wellpoint company's request is motivated by its own benefit, while the Center for Reproductive Rights acts in the public interest, the fifteen Rx-to-OTC switchers can be considered exogenous and are less susceptible to the issue of reverse causality. Therefore, we exclude the three voluntary switchers, as they are more inclined to utilize the Rx-to-OTC switch as a strategy to lower price, and examine whether the price-reducing impact of the Rx-to-OTC switch persists in the absence of these cases. As presented in Table B2, employing exclusively exogenous switchers as the treatment group still yields substantial price reductions subsequent to the Rx-to-OTC switch across all specifications. This finding indicates that the price-reducing effect of the Rx-to-OTC switch in our context is not influenced by reverse causality.

D. Controlling for Spillover Effects to Non-switchers in the Control Group

Another test we perform is to examine whether the effects of the Rx-to-OTC switch spill over to the brand drugs in the control group, particularly for the drugs in the same therapeutic subclass. Specifically, we create an indicator variable, switch_sub, which equals to 1 if a brand-name drug in the control group is a neighbor of switchers (i.e., located in the same therapeutic sub-class as that of switchers). We estimate

the following specification.

$$\begin{aligned}\ln p_{its} = {} & \alpha + \beta_{11}\text{post years(1-2)}_{ts} \times \text{switch}_{is} + \beta_{12}\text{post years(3-4)}_{ts} \times \text{switch}_{is} \\ & + \beta_{13}\text{post years}(\geq 4)_{ts} \times \text{switch}_{is} + \beta_2 \text{post}_{ts} \times \text{switch\_sub}_{is} + \Gamma \text{generic competition}_{its} \\ & + \Delta \text{brand competition}_{its} + \Theta_{m(i)ts} + \Theta_{cits} + \Theta_{f(di)ts} + \epsilon_{its}\end{aligned} \tag{2}$$

β_2 indicates whether and to what extent the price effects of the Rx-to-OTC switch spill over to the non-switchers in the same therapeutic sub-class. Table B3 shows the baseline estimate (column 1), and estimates from other specifications (columns 2-6) that does not control for generic and brand competition, includes logarithm of the number of generic and brand competitors and their squared terms, allows for competition effect to differ across switchers and non-switchers, and drops voluntary switchers, respectively. As shown in columns 1-5 of Appendix Table B3, the coefficients of the interaction term, switch_sub×post, is significantly positive across all specifications, which suggests that switching a brand-name drug from prescription to over the counter increases the retail price of close prescription substitutes. This is because insurance plans often increase cost-sharing of close prescription substitutes to encourage their beneficiaries to use the OTC drugs that are removed from coverage (Sullivan et al., 2005).[10] However, it is noteworthy that our estimates of the price effect of the Rx-to-OTC switch remain large and significant after accounting for the positive spillover effects across all specifications.

E. More Robustness Checks

In this subsection, we explore the sensitivity of the baseline results to various settings. First, we examine whether our estimates are sensitive to the sample composition of survey participants following the Rx-to-OTC switch. Since surveys only capture data on prescription drug use, the MEPS dataset contains fewer observations for switchers when they are sold as OTC drugs, leading to a change in the sample composition of surveyed individuals associated with the Rx-to-OTC switch.[11] We show that the change in consumer sample composition cannot explain

[10] For example, a majority of health plans have initiated policies to encourage the use of OTC loratadine by raising copayments for prescription SGA, fexofenadine, cetirizine, and move loratadine to the third tier range.

[11] Although most insurance plans remove OTC drugs from their formulary list, some generous private insurance plans and government programs such as Medicaid still provide limited coverage benefits for OTC drugs.

our baseline estimate. Column 2 of Appendix Table B4 removes the time-varying basic controls of consumer characteristics from the baseline model, which include average income, female percentage, race composition, and education level of the consumers for each drug, and shows that the estimate is barely the same to the baseline estimate in column 1 in Appendix Table B4. Moreover, we show that our baseline estimates are robust to using all other brand-name drugs as control groups in addition to those within the same therapeutic categories as the switchers, as well as to dropping weights in the regressions (columns 3-4 in Appendix Table B4).

In columns 5-6, we examine the importance of absorbing yearly variations at the levels of drug class and manufacturers. On the one hand, failing to absorb yearly variations across drug classes would overestimate the size of price reduction: column 5 shows that dropping the class by year fixed effect would overestimate the effect size by 35 log points. On the other hand, it is important to control for applicant-by-year fixed effect in the baseline model because manufacturers could adopt different pricing strategies over time. Column 6 reports a larger reduction after removing applicant-by-year fixed effects, suggesting that distributors of OTC drugs tend to adopt a lower pricing strategy compared to prescription brand-name drugs.

5.2 Effects on Net Price

Thus far, we have demonstrated that the Rx-to-OTC switch leads to a decrease in retail price, while sufficiently controlling for generic and brand competition. The estimated reduction in retail price has been shown to be robust to various settings. Now, we shift our focus to investigating the effect of the Rx-to-OTC switch on net price, which is of particular interest from a public policy perspective as it considers the rebates returned to the manufacturer after the transaction.

Recall the relationship between the estimated retail price effect and the estimated net price effect shown in Equation (**??**), where $\widehat{\beta}_{\text{net}} = \widehat{\beta}_{\text{retail}} + \widehat{\text{E}}[\text{r}_{i,t}|\text{post}_t = 0, \text{switch}_d = 1]$. The retail price effect $\widehat{\beta}_{\text{retail}}$ has been estimated in Table 2. The bias term $\widehat{\text{E}}[\text{r}_{i,t}|\text{post}_t = 0, \text{switch}_i = 1]$ can be estimated as the average rebate of switchers before Rx-to-OTC switching. On the one hand, the lower bound of the

pre-switch rebate can be set at 23% of retail price prior to the switch, which corresponds to the lower bound of rebates set by Medicaid for brand-name drugs (Dolan, 2019).[12] On the upper end, we choose 40% of the retail price for the pre-switch rebates for two reasons. Firstly, Medicaid recouped between 29% and 38% of its expenditures for prescription drugs annually from 2006 to 2009 (Levinson, 2011). Secondly, in terms of rebate levels for switchers, Sullivan et al. (2005) use rebate levels of 30% to 40% for second-generation antihistamines, which are the major switchers in our treatment group. It is important to note that our selection of lower and upper bounds for the rebate levels is rather conservative: we use the rebate level provided to Medicaid as a reference, the highest level of rebate that manufacturers must return as compared to other insurers.

Finally, we recover the effect of the Rx-to-OTC switch on the net price of brand-name switchers based on the estimated lower bound and upper of bias term, as well as the retail price effects estimated in Table 2. Given that the bias term, or pre-switch rebate for switchers, ranges from 23% to 40%, and the retail price effects (shown in Table 2) are -55% and 76% during the third and fourth post-switch years, and from the fifth year and above, respectively, following Equation (**??**) would lead to an estimate of net price effect of the Rx-to-OTC switch to be between -22% and -15% during the third and fourth year, and between -53% to -36% since the fifth year.

6 Mechanism Analysis

Given that competition is properly controlled during the Rx-to-OTC switch, the observed price reduction following the switch can be seen as the manufacturer's optimal response to the new OTC market. Patients in the OTC market are more sensitive to pharmaceutical prices compared to the prescription market, mainly because most insurance plans offer no or more restrictive coverage if any, for OTC drugs. Consequently, when a brand-name drug is switched from prescription-only

[12] Medicaid sets a formula for rebates that varies by brand and generic drugs. According to Dolan (2019), for brand name drugs, the rebate is 23.1% of the Average Manufacturer Price (AMP) or the difference between AMP and "best price," whichever is greater. AMP is defined as the average price paid to drug manufacturers by wholesalers and retail pharmacies, which is close to retail price documented in MEPS. For generic drugs, the rebate amount is 13% of AMP, and there is no best price provision.

to over the counter, consumer price sensitivity to the drug is also raised. Theoretically, the heightened price sensitivity among patients would result in a lower optimal price for the manufacturer (Pavcnik, 2002; Ferrara and Kong, 2008). The price elasticity force described above is a widely recognized problem inherent in insurance coverage (Duggan and Morton, 2010) and patient behavior (Feng, 2022)[13]. In this section, we provide several empirical pieces of evidence to support the hypothesis that in the context of Rx-to-OTC switch, the higher price elasticity in the OTC market drives the price reduction following the switch, while holding the competition level constant.

Firstly, we estimate the annual treatment effects of the Rx-to-OTC switch on patient cost sharing to examine the timing of changes in patient cost sharing. Recall that the price reduction caused by Rx-to-OTC switch increases in size over time in Figure 2. If changes in patient price sensitivity can explain this pattern, the annual treatment effect on patient cost sharing (which reflects patient price sensitivity) should grow over time. Appendix Figure B2 shows the annual event study estimates of the effect of Rx-to-OTC switch on patient cost sharing, measured as the ratio of OOP expenditure to total drug expense for a drug. We observe that patient cost sharing grows gradually after the Rx-to-OTC switch as insurance plans impose more restrictive benefit or even remove coverage of the switcher. The evidence that patient price sensitivity grows over time is consistent with the fact that the price effect decreases over time in Figure 2.

Secondly, we estimate the heterogeneous treatment effect by patient cost sharing based on the following equation.

$$\begin{aligned} \ln p_{its} &= \alpha + \beta_0 \text{post}_{ts} \cdot \text{switch}_{is} + \beta_1 \text{post}_{ts} \cdot \text{switch}_{is} \cdot \text{patient cost sharing}_{its} \\ &+ \beta_2 \text{patient cost sharing}_{its} + \gamma \text{generic competition}_{its} + \delta \text{brand competition}_{its} \\ &+ \Gamma \mathbf{X}_{its} + \Theta_{m(i)ts} + \Theta_{cits} + \Theta_{d(i)ts} + \epsilon_{its} \end{aligned} \tag{3}$$

where patient cost sharing$_{its}$ represents the share of OOP expense for drug i at year t of sub-experiment s. β_1, the coefficient of an interaction term between patient cost sharing and Rx-to-OTC switch, measures the relationship between a drug's average

[13] Feng (2022) shows that history-dependence in demand can lead to higher prices of brand-name drugs.

patient cost sharing and its price. If higher price sensitivity in the OTC market is the driving force behind the price reduction, we would expect β_1 to be negative. Columns 1-4 in Table 4 report the estimates of β_1 based on Equation (3) and its variants that flexibly control for generic and brand competition. As expected, the estimates of the interaction term are negative and large in size. This suggests that switchers with a larger increase in patient cost sharing experience a greater increase in price sensitivity, resulting in a more significant price reduction.

Another hypothesis test we perform is on the heterogeneous effects based on the Medicaid market share of a brand-name drug. Duggan and Scott Morton (2006) have shown empirically that prescription drugs with a larger share of Medicaid patients experience lower price sensitivity due to the program's zero co-pay policy, and thus charge higher prices. If higher price sensitivity in the OTC market is the force that drives the price reduction following the Rx-to-OTC switch, switchers with a higher Medicaid market share should experience a smaller price reduction. We estimate the relationship between the price effect of Rx-to-OTC switch and Medicaid market share using a variant model of Equation (3) that replaces the variable of patient cost sharing with Medicaid market share (e.g., the ratio of the number of prescriptions by Medicaid patients to the number of all prescriptions). Columns 5-8 in Table 4 report the heterogeneous price effect by Medicaid market share: across all specifications that control for generic and brand competition in flexible forms, switchers with a larger Medicaid market share indeed experience a significantly smaller price reduction following the Rx-to-OTC switch.

To provide more evidence that higher patient price sensitivity in the OTC market is responsible for the price reduction following the Rx-to-OTC switch, we examine the heterogeneous effects by patient price sensitivity from two additional dimensions: the market share of cash prescriptions (i.e., prescriptions paid by patients alone), and the level of brand competition (i.e., the number of brand competitors). On the one hand, switchers with more cash purchases are more price sensitive and likely to experience a larger price reduction, the hypothesis of which is supported by the negative coefficient of the triple interaction term post$\times$switch$\times$cash market share Appendix Table B5. On the other hand, since greater brand competition means more substitutes and higher price sensitivity, switchers facing more brand competi-

tors would undergo a larger price reduction, which is also supported by the negative coefficient of the triple interaction term post×switch×ln(brand number) in Appendix Table B5. Although the coefficients of the two interaction terms may not be statistically significant, the signs are in line with the hypothesis that increased price sensitivity following the Rx-to-OTC switch explains the subsequent price reduction.

7 Conclusion

Prescription drug markets and nonprescription markets exhibit differences in patient price sensitivity, and economic theory suggests that changes in marketing status can affect drug pricing. By exploiting recent Rx-to-OTC switches that occurred between 2001-2016, we find that marketing status affects both the retail and net price of brand-name drugs: manufacturers generally decrease the prices of brand-name drugs following an Rx-to-OTC switch. The results are robust to flexibly controlling for possible confounders such as brand competition and generic competition after patent expiry, as well as to excluding the voluntary switchers that are more prone to reverse causality issues. Further analysis reveals that the primary driver behind the observed price reduction is the increased consumer price sensitivity resulting from the marketing status switch. These findings have important implications. To address the issue of high brand-name drug prices, we recommend that policymakers in the United States implement measures aimed at enhancing the price elasticity of brand-name drugs. Such actions could involve improving information transparency of prices and alternative options in the prescription market, increasing patient cost sharing for high-cost brand-name drugs, and promoting Rx-to-OTC switches for brand-name drugs with potential high price elasticity that are safe to use without surveillance.

When interpreting the results in this paper, a number of caveats should be mentioned. Firstly, the small sample size of switcher drugs that transitioned from Rx to OTC between 2001 and 2016 restricts the generalizability of our results to brand-name drugs that share similar characteristics with the switchers. Specifically, our findings can be most applicable to brand-name drugs with a substantial customer

base that are sensitive to drug prices. For high-priced specialty brand drugs, the transition from prescription to over-the-counter (OTC) status may lead to an increase in price. This is primarily due to the fact that the role of insurer negotiation is a dominating factor in determining the price of these drugs, surpassing the impact of consumer price elasticity. Thus, the interplay between consumer demand and insurer negotiation dynamics may result in distinct pricing outcomes for different types of brand-name drugs following an Rx-to-OTC switch, particularly those in the high-priced specialty category. Secondly, due to data limitations, we were unable to estimate the effects of the Rx-to-OTC switch on additional variables of interest. For instance, we could not address inquiries such as the impact on drug utilization and individuals' health status. The scope of this paper does not encompass exploring whether manufacturers actually benefit from the observed price reduction through increased sales volume. Exploring these topics serves as an important avenue for future research.

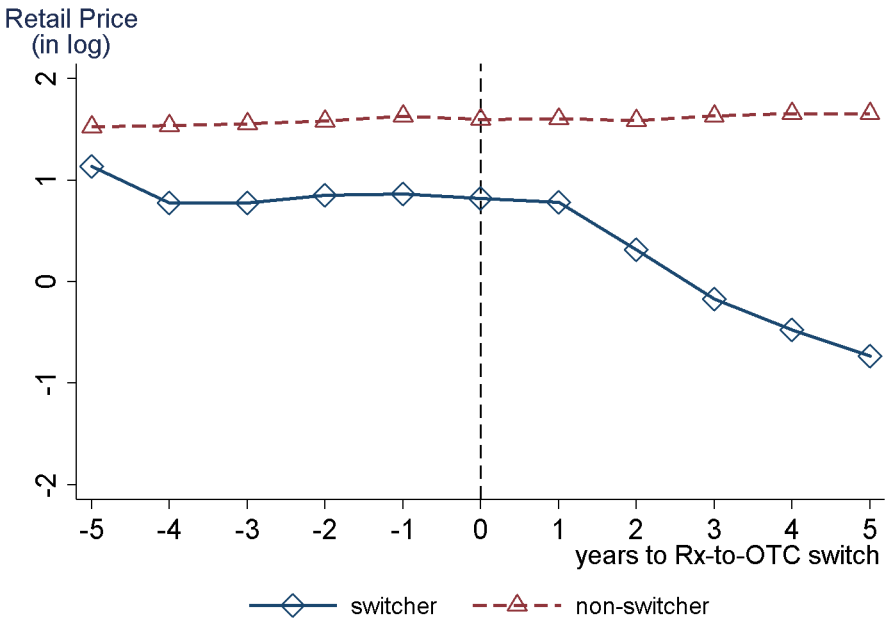

Figure 1: Time Trends in Brand-name Retail Prices for Switchers and Non-switchers

Notes: The retail prices of brand-name drugs, both for switchers and non-switchers, are computed as simple weighted averages of unit payments in logarithmic form and are adjusted to 2016 dollars using a deflation method. The treated group, consisting of switchers, encompasses all brand-name drugs that underwent a transition from prescription to OTC status during the sample period. The non-switchers serve as control groups, comprising brand-name prescription drugs within the same therapeutic class and possessing similar product life as the switchers. We stack the data set of each sub-experiment denoted by year of switch (See Section 3 for details). Source: MEPS Prescribed Medicine File, National Drug Code Directory, and Orange Book.

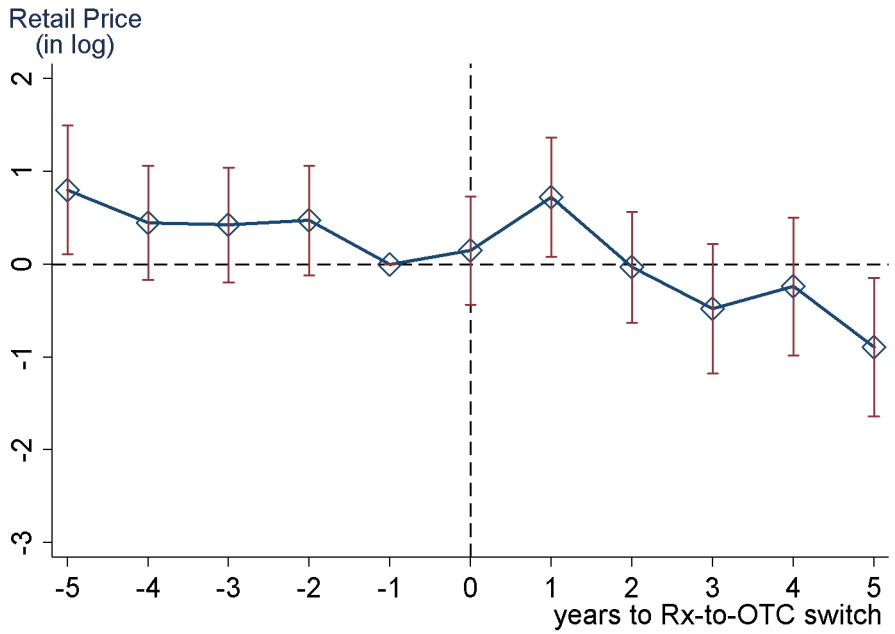

Figure 2: Event Study Estimates of the Effect of Rx-to-OTC Switch on Brand-name Retail Price

Notes: The figure shows the event-study estimates along with their corresponding 95 percent confidence intervals. The retail price of brand-name drugs, prior to any rebates, is represented in logarithmic form and adjusted for inflation to 2016 dollars. The treated group consists of switchers, which includes all brand-name drugs that underwent an Rx-to-OTC switch between 2001 and 2016. The control group comprises non-switchers, which are brand-name prescription drugs within the therapeutic classes of the switchers. We stack the data set of each sub-experiment denoted by year of switch (See section 3 for details). The reference year used is one year prior to the Rx-to-OTC Switch. Source: MEPS Prescribed Medicine File, National Drug Code Directory, and Orange Book.

Table 1: Summary Statistics: Switchers vs. Non-switchers

	Non-switchers (all years)		Switchers (years before switch)	
Variables	mean	sd	mean	sd
Payment (in 2016 dollars)				
Annual payment per drug (millions)	195.9	624.1	291.0	343.7
Retail price (payment per unit)	23.4	150.9	4.6	7.2
Market size (per drug per year)				
Consumers (millions)	0.28	0.54	1.51	1.73
Prescriptions (millions)	1.15	2.50	4.38	5.03
Characteristics of Patients				
product life (years)	9.2	4.7	7.0	3.8
Age < 25 (%)	16.8	28.3	28.9	25.9
Age > 65 (%)	30.9	30.5	18.2	19.5
Female (%)	66.7	30.2	60.7	15.1
Married (%)	49.5	29.8	45.5	20.8
White (%)	83.8	20.4	86.6	7.3
High School (%)	47.0	28.6	47.9	14.9
Average Income ($1000)	68.9	36.8	69.1	14.8

Notes: Retail price levels are not directly comparable across medications that are measured in different units, such as tablets, milliliters (ml), capsules, and ounces (oz). The number of consumers refers to a weighted sum of surveyed participants with prescription records per year, while the prescription number represents a weighted sum of prescriptions for a specific medication per year. Due to the absence of a uniform post-switch year indicator because switchers could make the Rx-to-OTC switch at different years during our sample period, we present summary statistics for non-switchers using data from all years in the sample. For switchers, summary statistics are based on pre-switch data years only. Source: MEPS, National Drug Code Directory, and Orange Book.

Table 2: The Effect of Rx-to-OTC Switch on Brand-name Retail Price

Dependent Variable:	Stacked DID				Conventional DID		
ln (retail price)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
switch×post	-0.296		-0.285	-0.250	-0.326	-0.369	-0.329
	(0.1358)		(0.1356)	(0.1390)	(0.1553)	(0.1565)	(0.1542)
switch×post years (1-2)		-0.033					
		(0.1409)					
switch×post years (3-4)		-0.800					
		(0.2273)					
switch×post years (≥5)		-1.412					
		(0.2799)					
ln (generic number)	-0.138	-0.135		-0.136	-0.166		-0.165
	(0.0634)	(0.0633)		(0.0660)	(0.0583)		(0.0583)
ln (brand number)	0.042	0.035		0.023	0.153		0.154
	(0.1188)	(0.1176)		(0.1240)	(0.1285)		(0.1307)
ln (product life)	-0.190	-0.217	-0.176		0.012	0.013	
	(0.1016)	(0.0999)	(0.1011)		(0.0830)	(0.0841)	
Basic fixed effects	Y	Y	Y	Y	Y	Y	Y
Basic controls	Y	Y	Y	Y	Y	Y	Y
Observations	11,736	11,736	11,736	11,736	3,440	3,440	3,440
R-squared	0.962	0.962	0.961	0.962	0.951	0.950	0.951

Notes: Standard errors in parentheses. The retail price of brand-name drugs includes the manufacturer rebate, which is adjusted for inflation and presented in logarithmic form using 2016 dollars. Our treated group comprises all brand-name drugs that underwent an Rx-to-OTC switch between 2001 and 2016. The control group, or non-switchers, consists of brand-name prescription drugs within the same therapeutic class and with similar product life as the switchers. Column 1 reports baseline estimates based on the specification in Equation (1). Generic drugs are defined as ANDA drugs with the same ingredients, strength, and dosage form as corresponding brand-name drugs. Brand-name competitors are identified as other brand-name drugs, prescription or nonprescription, in the same therapeutic sub-class. Column 2 presents the dynamics of the treatment effect during the first two years, the 3rd-4th years, and beyond the fifth year following the Rx-to-OTC switch. Column 3 removes the effects of generic and brand competition from the baseline specification, while column 4 removes the influence of product life. Columns 5-7 report the results from estimating the traditional DID model using unstacked data. The basic fixed effects in the traditional DID model include drug fixed effects, therapeutic class by year fixed effects, manufacturer by year fixed effects, and dosage form by year fixed effects. In the SDID model, each of these fixed effects is interacted with the sub-experiment indicator. The basic controls include average consumer income, sex ratio, marriage rate, proportion of elderly individuals (aged 65 and above), and proportion of young individuals (aged 25 and below). Source: MEPS, National Drug Code Directory, and Orange Book.

Table 3: Addressing Endogenous Change in Generic and Brand Competition

Dependent Variable:	Baseline	Alternative Specifications			
ln (retail price)	(1)	(2)	(3)	(4)	(5)
post×switch	-0.296	-0.294	-0.352	-0.306	-0.325
	(0.1358)	(0.1413)	(0.1505)	(0.1386)	(0.1379)
ln (generic number)	-0.138	-0.030	-0.182		
	(0.0634)	(0.1206)	(0.0722)		
ln (generic number) squared		-0.048			
		(0.0631)			
ln (brand number)	0.042	0.015	-0.001		
	(0.1188)	(0.1799)	(0.1132)		
ln (brand number) squared		0.007			
		(0.0332)			
ln (product life)	-0.190	-0.199	-0.163	-0.168	-0.167
	(0.1016)	(0.1013)	(0.1000)	(0.1021)	(0.1025)
ln (generic number)×switch			0.295		
			(0.1065)		
ln (brand number)×switch			0.520		
			(0.5024)		
generic entry dummy				-0.139	-0.148
				(0.0673)	(0.0706)
brand entry dummy				0.064	0.065
				(0.2687)	(0.2683)
generic entry dummy×switch					0.098
					(0.2201)
brand entry dummy×switch					0.000
					(0.0000)
Basic fixed effects	Y	Y	Y	Y	Y
Basic controls	Y	Y	Y	Y	Y
Observations	11,736	11,736	11,736	11,736	11,736
R-squared	0.962	0.962	0.962	0.962	0.962

Notes: Standard errors in parentheses. Column 1 reports baseline estimates based on the specification in Equation (1). The basic fixed effects include drug fixed effects, therapeutic class by year fixed effects, manufacturer by year fixed effects, and dosage form by year fixed effects. Each of these fixed effects is interacted with the sub-experiment indicator. The basic controls include average consumer income, sex ratio, marriage rate, proportion of elderly individuals (aged 65 and above), and proportion of young individuals (aged 25 and below). Columns 2-5 control for competition effects in flexible forms. Source: MEPS, National Drug Code Directory, and Orange Book.

Table 4: The Heterogeneous Effects of Rx-to-OTC Switch on Price by Patient Price Sensitivity

	by patient cost sharing				by Medicaid patient share			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
post×switch	-0.166	-0.165	-0.171	-0.159	-0.728	-0.670	-0.733	-0.700
	(0.1324)	(0.1319)	(0.1319)	(0.1506)	(0.2583)	(0.2569)	(0.2562)	(0.2651)
post×switch×patient cost sharing	-0.394	-0.458	-0.373	-0.396				
	(0.2336)	(0.2440)	(0.2434)	(0.2453)				
patient cost sharing	-0.189	-0.185	-0.184	-0.189				
	(0.0656)	(0.0660)	(0.0647)	(0.0656)				
post×switch×Medicaid prescription share					0.597	0.493	0.609	0.620
					(0.3013)	(0.2975)	(0.2982)	(0.3042)
Medicaid prescription share					-0.052	-0.044	-0.046	-0.051
					(0.0784)	(0.0775)	(0.0779)	(0.0785)
ln (generic number)	-0.124		-0.001	-0.125	-0.128		0.005	-0.125
	(0.0631)		(0.1212)	(0.0654)	(0.0642)		(0.1228)	(0.0666)
ln (generic number) squared			-0.065				-0.070	
			(0.0675)				(0.0682)	
ln (brand number)	0.023		0.152	0.021	0.012		0.162	0.010
	(0.1116)		(0.1893)	(0.1119)	(0.1115)		(0.1890)	(0.1119)
ln (brand number) squared			-0.034				-0.039	
			(0.0392)				(0.0396)	
ln (generic number)×switch				0.012				-0.051
				(0.1484)				(0.1465)
ln (brand number)×switch				0.158				0.116
				(0.3567)				(0.3217)
ln (product life)	-0.020	-0.019	-0.022	-0.019	-0.008	-0.008	-0.011	-0.009
	(0.0814)	(0.0815)	(0.0821)	(0.0817)	(0.0817)	(0.0818)	(0.0824)	(0.0821)
Basic fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Basic controls	Y	Y	Y	Y	Y	Y	Y	Y
Observations	11,626	11,626	11,626	11,626	11,626	11,626	11,626	11,626
R-squared	0.958	0.958	0.958	0.958	0.958	0.957	0.958	0.958

Notes: Standard errors in parentheses. Columns 1-4 present the baseline estimates derived from an augmented specification of Equation (3), wherein patient cost sharing is incorporated as an interaction term. On the other hand, columns 5-8 are based on a modified version of Equation (3), wherein the interaction variable is replaced with Medicaid market share. The basic fixed effects include drug fixed effects, therapeutic class by year fixed effects, manufacturer by year fixed effects, and dosage form by year fixed effects. Each of these fixed effects is interacted with the sub-experiment indicator. The basic controls include average consumer income, sex ratio, marriage rate, proportion of elderly individuals (aged 65 and above), and proportion of young individuals (aged 25 and below). Source: MEPS, National Drug Code Directory, and Orange Book.

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Marketing Status and Brand-name Drug Prices: Evidence from Rx-to-OTC Switch Online Appendix

A Background

A.1 Discussions on Pricing-increasing Effects of Rx-to-OTC Switch

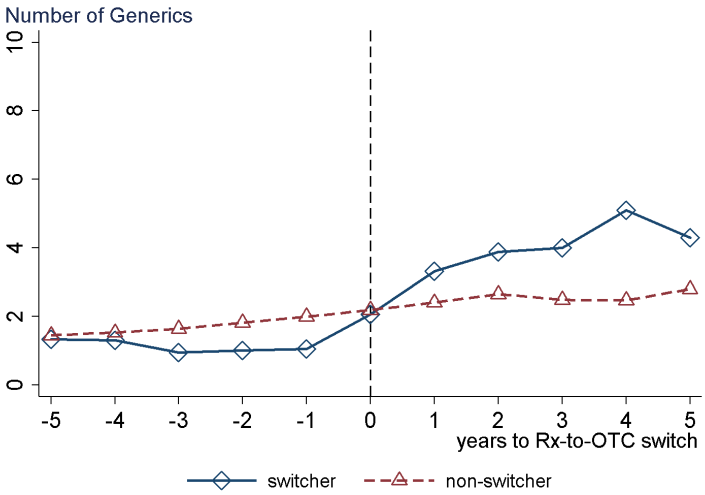
Despite the price-reducing impact resulting from having more price-sensitive consumers after an Rx-to-OTC switch as explained in section 2, manufacturers are confronted with the possibility of price increases due to the loss of insurers possessing strong negotiation power. Indeed, insurers possess the ability to exclude specific treatments from their formularies or steer their enrollees away from certain treatments in response to the prices of those treatments. This leverage enables insurers to negotiate price reductions with pharmaceutical manufacturers, which individual cash-paying consumers typically cannot achieve independently. Considering that brand manufacturers in the prescription market have devised various strategies to enhance their negotiation power and reduce patient price sensitivity (Dafny et al., 2017, 2022), it is conceivable that the classic decreases in pharmaceutical prices induced by increased patient price elasticity may outweigh the increases associated with loss of insurer negotiation, ultimately resulting in an overall reduction in brand-name prices following an Rx-to-OTC switch. However, it is important to note that for brand drugs characterized by potentially elastic patient demand, such as high-priced specialty drugs, the role of insurer negotiation becomes more significant. In such cases, switching the brand-name drug, which exhibits low price elasticity, would not lead to a reduction in the drug's price.

A.2 Multum Therapeutic Class

Multum Therapeutic Class is organized into a hierarchical system, with broad therapeutic categories at the top and more specific drug classes at lower levels. For example, the top-level therapeutic categories might include cardiovascular agents, central nervous system agents, and gastrointestinal agents, while lower-level drug classes within the cardiovascular category might include antihypertensives, antiarrhythmics, and lipid-lowering agents. The five therapeutic classes and their respective sub-classes are Gastrointestinal Agents (Antidiarrheals, H2 Antagonists, Laxatives, Miscellaneous Gi Agents, Proton Pump Inhibitors, 5-Aminosalicylates, and others), Hormones (Adrenal Cortical Steroids, Antidiabetic Agents, Miscellaneous Hormones, Sex Hormones, Thyroid Drugs, Bisphosphonates, and others), Miscellaneous Agents (Chelating Agents, Miscellaneous Uncategorized Agents, Genitourinary Tract Agents, Minerals and Electrolytes, Antidepressants), Respiratory Agents (Antihistamines, Bronchodilators, Respiratory Inhalant Products, Upper Respiratory Combinations, Leukotriene Modifiers), Topical Agents (Anorectal Preparations, Dermatological Agents, Ophthalmic Preparations, Otic Preparations, Nasal Preparations).

B Tables and Figures

(a) Generic Competitors



(b) Brand Competitors

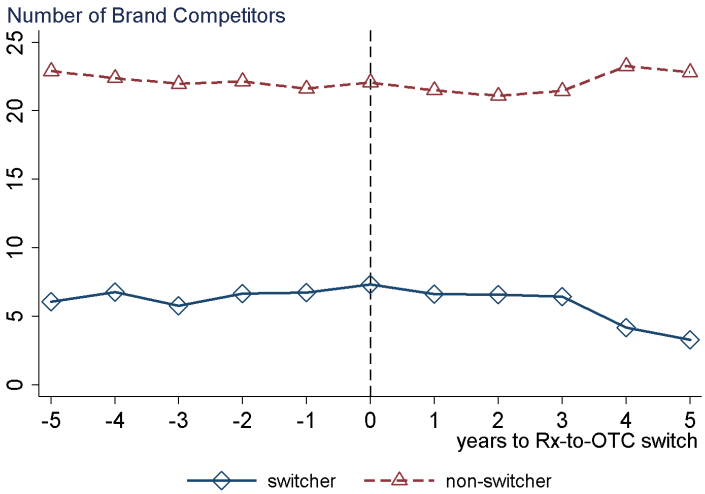


Figure B1: Time Trends in the Number of Competitors for Switchers and Non-switchers

Notes: Generic competitors are drugs that have obtained marketing approval through an Abbreviated New Drug Application (ANDA) and share the same ingredients, strength, and dosage form as the corresponding brand-name drugs, which are identified using a fuzzy matching algorithm. The date of marketing approval for generic drugs is used to determine when they enter the market. Brand competitors, on the other hand, refer to other brand-name drugs within the same Multum therapeutic sub-class. For instance, within the Gastrointestinal Agents therapeutic class, there are six sub-classes: Antidiarrheals, H2 Antagonists, Laxatives, Miscellaneous Gi Agents, Proton Pump Inhibitors, and 5-Aminosalicylates, and others. To measure brand-name competition within the Laxatives sub-class, we utilize the count of brand-name Laxatives as an indicator. We stack the data set of each sub-experiment denoted by year of switch (See Section 3 for details). Source: MEPS Prescribed Medicine File, National Drug Code Directory, and Orange Book.

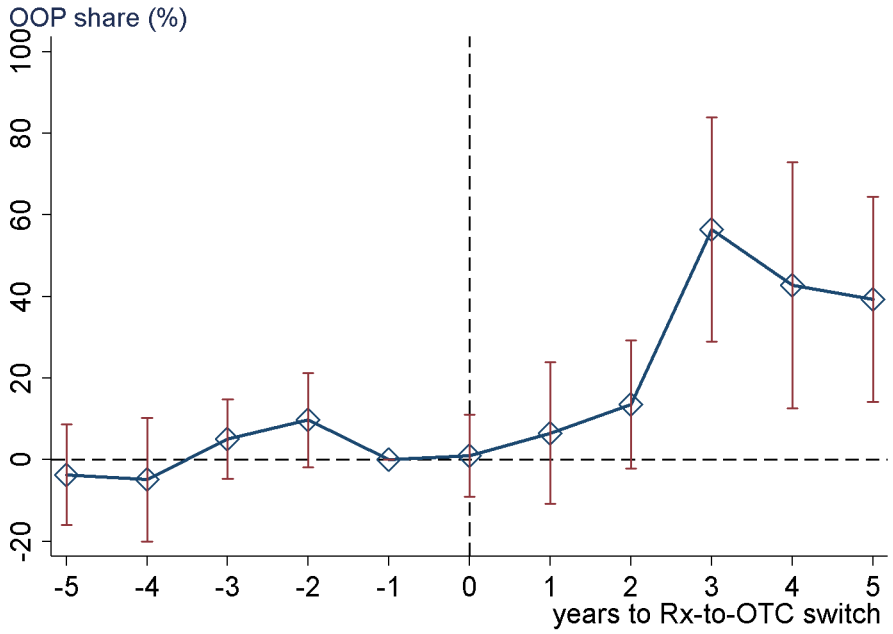


Figure B2: Event Study Estimates of the Effect of Rx-to-OTC Switch on OOP Share

Notes: The dependent variable, OOP share, is calculated by dividing the out-of-pocket payment for a medicine by its total payment. The treated group consists of switchers, which includes all brand-name drugs that have transitioned from prescription to OTC status between 2001 and 2016. The control groups consist of non-switchers, which are brand-name prescription drugs within the same therapeutic class as the switchers. We stack the data set of each sub-experiment denoted by year of switch (See section 3 for details). The reference year used is one year prior to the Rx-to-OTC Switch. Source: MEPS Prescribed Medicine File, National Drug Code Directory, and Orange Book.

Table B1: Rx-to-OTC Switch List From 2001 to 2016

NDA number	Trade Name	Strength	Dosage Form	Switch Year	Data Years (MEPS)
21153	Nexium 24hr	20mg	capsule	2014	2001-2016
20121	Flonase Allergy Relief	0.05mg/spray	spray	2014	1999-2016
21351	Oxytrol for Women	3.9mg	film	2013	2003-2013, 2015
20786	Allegra D 12 HR	60mg;120mg	tablet	2011	1999-2016
21704	Allegra 24 HR	180mg;240mg	tablet	2011	2005-2016
20872	Allegra	60mg	tablet	2011	2000-2013
20872	Allegra	180mg	tablet	2011	2000-2013,2016
21963	Children's Allegra	6mg/ml	suspension	2011	2007-11,2013-14
21150	Zyrtec-D	5mg;120mg	tablet	2007	2001-2010,2012-2015
20346	Children's Zyrtec Allergy	1mg/ml	syrup	2007	1999-2016
21621	Children's Zyrtec Allergy	10mg	tablet, chewable	2007	2004-2016
19835	Zyrtec Allergy	10mg	tablet	2007	1999-2015
21045	Plan B	0.75mg	tablet	2006	2001-2009
19658	Claritin	10mg	tablet	2002	1999-2016
20704	Claritin Reditabs	10mg	tablet	2002	1999-2016
20641	Claritin Syrup	1mg/ml	syrup	2002	1999-2016
19670	Claritin-D	5mg;120mg	tablet	2002	1999-2006,2008-2016
20470	Claritin-D 24 HR	10mg;240mg	tablet	2002	1999-2013,2015-2016

Notes: MEPS captures approximately 1 out of every 10,000 prescriptions in a typical year. Thus, brand-name drugs with small patient populations will inevitably not be included in certain years (Duggan and Morton, 2010). This list is obtained by augmenting the FDA Prescription to Over-the-Counter Switch List with drug characteristics (e.g., active ingredients, strength, dosage form) from Drugs@FDA online database.

Table B2: The Effect of Rx-to-OTC Switch on Brand-name Retail Price: Excluding Voluntary Switchers

Dependent Variable ln (retail price)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
switch post years (1-2)	0.309	0.300	0.397	0.310	0.270	0.291	0.264
	(0.2453)	(0.2518)	(0.2544)	(0.2557)	(0.2687)	(0.2432)	(0.2455)
switch×post years (3-4)	-0.646	-0.661	-0.478	-0.644	-0.818	-0.658	-0.695
	(0.2660)	(0.2645)	(0.2668)	(0.2685)	(0.2691)	(0.2640)	(0.2579)
switch×post years (>4)	-1.251	-1.322	-1.022	-1.270	-1.477	-1.251	-1.366
	(0.3176)	(0.3167)	(0.3019)	(0.3202)	(0.3304)	(0.3116)	(0.3619)
ln (generic number)	-0.135		-0.133	-0.023	-0.186		
	(0.0636)		(0.0664)	(0.1218)	(0.0736)		
ln (generic number) squared				-0.050			
				(0.0631)			
ln (brand number)	0.040		0.020	0.012	-0.007		
	(0.1177)		(0.1231)	(0.1797)	(0.1116)		
ln (brand number) squared				0.007			
				(0.0332)			
ln (generic number) # switch					0.358		
					(0.1068)		
ln (brand number)#switch					0.501		
					(0.5371)		
ln (product life)	-0.212	-0.201		-0.221	-0.184	-0.191	-0.191
	(0.0995)	(0.0985)		(0.0993)	(0.0977)	(0.0996)	(0.0999)
generic entry dummy						-0.131	-0.149
						(0.0678)	(0.0713)
brand entry dummy						0.053	0.056
						(0.2694)	(0.2686)
generic entry dummy×switch							0.188
							(0.2296)
brand entry dummy×switch							0.000
							(0.0000)
Basic fixed effects	Y	Y	Y	Y	Y	Y	Y
Basic controls	Y	Y	Y	Y	Y	Y	Y
Observations	11,713	11,713	11,713	11,713	11,713	11,713	11,713
R-squared	0.962	0.962	0.962	0.962	0.962	0.962	0.962

Notes: Standard errors in parentheses. The sample used excludes the voluntary switchers that are more likely to have the reverse causality issue, and include exogenous switches that are motivated by third-party interests. Column 1 reports baseline estimates based on the specification in Equation (1). Columns 2-3 exclude controls for competition and product life, respectively. Columns 4-7 control for competition effects in flexible forms. The basic fixed effects include drug fixed effects, therapeutic class by year fixed effects, manufacturer by year fixed effects, and dosage form by year fixed effects. Each of these fixed effects is interacted with the sub-experiment indicator. The basic controls include average consumer income, sex ratio, marriage rate, proportion of elderly individuals (aged 65 and above), and proportion of young individuals (aged 25 and below). Source: MEPS, National Drug Code Directory, and Orange Book.

Table B3: Controlling for Spillover Effects to Non-switchers

Dependent Variable ln (retail price)	(1)	(2)	(3)	(4)	(5)	(6)
switch×post years (1-2)	0.071	0.086	0.130	0.003	0.061	0.013
	(0.1526)	(0.1546)	(0.1695)	(0.2116)	(0.1547)	(0.1711)
switch×post years (3-4)	-0.738	-0.742	-0.578	-0.814	-0.746	-0.792
	(0.2222)	(0.2203)	(0.2294)	(0.2435)	(0.2217)	(0.2194)
switch×post years (>4)	-1.346	-1.406	-1.142	-1.422	-1.343	-1.468
	(0.2721)	(0.2737)	(0.2593)	(0.2995)	(0.2668)	(0.3315)
switch_sub×post	0.261	0.273	0.280	0.308	0.275	0.282
	(0.1267)	(0.1090)	(0.1288)	(0.1330)	(0.1103)	(0.1091)
ln (generic number)	-0.133		-0.041	-0.183		
	(0.0637)		(0.1229)	(0.0749)		
ln (generic number) squared			-0.040			
			(0.0650)			
ln (brand number)	0.044		0.013	-0.019		
	(0.1174)		(0.1781)	(0.1176)		
ln (brand number) squared			0.002			
			(0.0318)			
ln (generic number)×switch				0.363		
				(0.1065)		
ln (brand number)×switch				0.564		
				(0.4675)		
generic entry dummy					-0.128	-0.147
					(0.0673)	(0.0706)
brand entry dummy					0.049	0.051
					(0.2634)	(0.2625)
generic entry dummy×switch						0.190
						(0.2151)
brand entry dummy×switch						0.000
						(0.0000)
ln (product life)	-0.208	-0.196			-0.186	-0.186
	(0.0978)	(0.0967)			(0.0976)	(0.0978)
Basic fixed effects	Y	Y	Y	Y	Y	Y
Basic controls	Y	Y	Y	Y	Y	Y
Observations	11,736	11,736	11,736	11,736	11,736	11,736
R-squared	0.962	0.961	0.962	0.962	0.962	0.962

Notes: Standard errors in parentheses. The variable switch_sub is a binary indicator that takes the value 1 if brand-name prescription drugs in the control group belong to the same therapeutic sub-class as switchers, and 0 otherwise. Column 1 reports estimates based on the specification in Equation (2). The results presented in Column 1 are based on the model specified in Equation (2). Column 2 removes the controls for generic and brand competition, while columns 3-6 control for generic and brand competition in alternative specifications. The basic fixed effects include drug fixed effects, therapeutic class by year fixed effects, manufacturer by year fixed effects, and dosage form by year fixed effects. Each of these fixed effects is interacted with the sub-experiment indicator. The basic controls include average consumer income, sex ratio, marriage rate, proportion of elderly individuals (aged 65 and above), and proportion of young individuals (aged 25 and below). Source: MEPS, National Drug Code Directory, and Orange Book.

Table B4: Robustness Checks

Dependent Variable ln (retail price)	baseline (1)	drop basic controls (2)	all drugs as control groups (3)	drop weight (4)	drop class-by-year fixed effect (5)	drop manufacturer-by-year fixed effect (6)
switch×post	-0.296	-0.295	-0.365	-0.357	-0.649	-0.518
	(0.1358)	(0.1360)	(0.1359)	(0.1461)	(0.0990)	(0.1099)
ln (generic number)	-0.138	-0.135	-0.075	-0.138	-0.232	-0.120
	(0.0634)	(0.0628)	(0.0250)	(0.0622)	(0.0770)	(0.0412)
ln (brand number)	0.042	0.039	0.023	0.052	-0.158	-0.206
	(0.1188)	(0.1175)	(0.0646)	(0.0984)	(0.1333)	(0.0670)
ln (product life)	-0.190	-0.191	0.045	-0.001	-0.147	0.006
	(0.1016)	(0.1019)	(0.0601)	(0.0757)	(0.1089)	(0.0739)
Basic fixed effects	Y	Y	Y	Y	N	N
Basic controls	Y	N	Y	Y	Y	Y
Observations	11,736	11,736	30,832	11,736	11,736	12,830
R-squared	0.962	0.961	0.918	0.952	0.956	0.931

Notes: Standard errors in parentheses. Column 1 reports baseline estimates based on the specification in Equation (1). The basic fixed effects include drug fixed effects, therapeutic class by year fixed effects, manufacturer by year fixed effects, and dosage form by year fixed effects. Each of these fixed effects is interacted with the sub-experiment indicator. The basic controls include average consumer income, sex ratio, marriage rate, proportion of elderly individuals (aged 65 and above), and proportion of young individuals (aged 25 and below). Column 2 drops basic controls in the baseline model. Column 3 uses all brand-name prescription drugs that have not experienced Rx-to-OTC switch as the control group. Column 4 drops the analytical weight of the number of prescriptions used in the baseline equation. Column 5 drops the applicant-year fixed effect from the baseline model. Column 6 excludes switchers that manufacturers voluntarily switch from Rx to OTC. Source: MEPS, National Drug Code Directory, and Orange Book.

Table B5: The Heterogeneous Effects of Rx-to-OTC Switch on Price by Price Sensitivity: More Evidence

	by cash market share				by brand competition			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
post×switch	-0.280	-0.290	-0.278	-0.268	-0.111	-0.077	-0.161	-0.104
	(0.1351)	(0.1337)	(0.1332)	(0.1626)	(0.3573)	(0.3688)	(0.3524)	(0.3554)
post×switch×cash market share	-0.154	-0.228	-0.134	-0.181				
	(0.1707)	(0.1681)	(0.1842)	(0.1902)				
cash market share	-0.139	-0.137	-0.136	-0.139				
	(0.0827)	(0.0823)	(0.0827)	(0.0828)				
post×switch×ln (brand number)					-0.094	-0.118	-0.068	-0.087
					(0.1535)	(0.1571)	(0.1508)	(0.1473)
ln (generic number)	-0.122		0.007	-0.123	-0.123		0.011	-0.122
	(0.0638)		(0.1224)	(0.0660)	(0.0633)		(0.1225)	(0.0658)
ln (generic number) squared			-0.068				-0.071	
			(0.0687)				(0.0685)	
ln (brand number)	0.007		0.157	0.003	0.014		0.168	0.012
	(0.1129)		(0.1886)	(0.1133)	(0.1122)		(0.1892)	(0.1125)
ln (brand number) squared			-0.039				-0.040	
			(0.0392)				(0.0395)	
ln (generic number)×switch				0.016				-0.010
				(0.1506)				(0.1475)
ln (brand number)×switch				0.237				0.157
				(0.3708)				(0.3436)
ln (product life)	-0.019	-0.019	-0.021	-0.018	-0.013	-0.012	-0.015	-0.012
	(0.0821)	(0.0822)	(0.0828)	(0.0824)	(0.0816)	(0.0817)	(0.0824)	(0.0820)
Basic fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Basic controls	Y	Y	Y	Y	Y	Y	Y	Y
Observations	11,626	11,626	11,626	11,626	11,626	11,626	11,626	11,626
R-squared	0.958	0.958	0.958	0.958	0.958	0.957	0.958	0.958

Notes: Standard errors in parentheses. Columns 1-4 present the baseline estimates derived from an augmented specification of Equation (3), wherein the share of patients purchasing the drug all out of pocket is incorporated as an interaction term. On the other hand, columns 5-8 are based on a modified version of Equation (3), wherein the interaction variable is replaced with the level of competition from other brand substitutes. The basic fixed effects include drug fixed effects, therapeutic class by year fixed effects, manufacturer by year fixed effects, and dosage form by year fixed effects. Each of these fixed effects is interacted with the sub-experiment indicator. The basic controls include average consumer income, sex ratio, marriage rate, proportion of elderly individuals (aged 65 and above), and proportion of young individuals (aged 25 and below). Source: MEPS, National Drug Code Directory, and Orange Book.