Patient Cost Sharing and Prescription Drug Trends: Evidence from Japan

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PRELIMINARY WORK. PLEASE DO NOT CIRCULATE.

Abstract

This paper studies the impact of a change in patient cost sharing on total prescription drug spending. I exploit a feature of the Japanese health care system, where an individual's coinsurance rate is determined primarily by their age. I contribute to the existing literature by investigating heterogeneous effects by patient sex and drug therapeutic class (focusing on cardiovascular drugs, antibiotics, vitamins, antihistamines, and psychotropic drugs). I find that for the whole sample, price elasticity for spending ranges from -0.12 to -0.23. This is comparable to previous estimates of price elasticity of spending for general medical services (-0.2). I find no evidence of heterogeneous effects by sex over the whole sample of prescriptions, but I do find statistically significant differences between women and men within therapeutic drug classes. I also conduct exploratory analysis on the effect of changes in patient cost sharing on the volume of prescriptions. I estimate a price elasticity of demand between -0.33 and -0.69, which is larger than previous estimates of demand elasticity for general medical services (-0.16 to -0.2). I also find evidence that physicians do not respond on the intensive margin by prescribing more expensive medications. Although Japanese patients are more likely to be prescribed brand-name drugs, patients on generics may be more price sensitive to changes in patient cost sharing. Overall, the findings suggest that physicians respond by prescribing a greater quantity of medications, either on the extensive or the intensive margin.

1 Introduction

Over the past several decades, health care spending has risen dramatically. From 2000 to 2019, global health care expenditure as the share of GDP has increased from 8.6% to 9.8%,

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and global per capita health expenditure has increased from $479 to $1,122 (World Health Organization, 2022). With the rise in health care expenditure, patients' financial burden of out-of-pocket spending — how much individuals pay directly for their medical care — has also increased (World Health Organization, 2022). This has been driven in part by an increase in patient spending on pharmaceutical drugs. In the United States, which has the largest prescription drug market in the world (Daemmrich, 2007), per capita spending on prescription drugs has increased from around $100 in 2000 (about 2% of per capita health care spending) to just over $1000 in 2015 (10% of per capita spending) (Sarnak et al., 2017; The Organization for Economic Cooperation and Development, 2021)[1]. In Japan, which has the second largest pharmaceutical market (Daemmrich, 2007), drug spending increased from 1.4% of total national health care expenditures in 1980 to 9.2% in 2000 and 18.8% in 2017 (Ibuka et al., 2016; Ministry of Health, Labor and Welfare, 2018).

The out-of-pocket spending — also referred to as patient cost sharing — component of health care system financing is determined through copays (a lump-sum payment for the medical service), coinsurance rates (a percentage of the service cost), or both. Governments and insurance companies can use these tools to regulate overall spending. Lower copays and coinsurance rates can make health care more accessible and increase the demand for care (Newhouse and the Insurance Experiment Group, 1993; Gaynor et al., 2007; Shigeoka, 2014), but this does not necessarily improve health outcomes (Shigeoka, 2014). The unnecessary utilization of medical services and overall costs could be reduced by increasing patient cost sharing, but the trade-off is a greater financial burden on sicker and lower income individuals as well as a potential reduction in necessary medical care. Studying how changes in patient cost sharing affect prescription drug spending and utilization as well as health outcomes can inform the design of an effective government policy to contain costs without resulting in adverse health outcomes.

This paper investigates how a change in patient cost sharing impacts prescription drug

[1]Prescription drug spending as a share of total health care spending in the United States in 2000 was calculated using approximate prescription drug spending from Sarnak et al. (2017) and total per capita health care spending from The Organization for Economic Cooperation and Development (2021) for the year of interest.

spending. I exploit an institutional feature of the Japanese health care system, where coinsurance rates are determined primarily by age. Individuals under 70 years old (except those younger than 6 years old) face a coinsurance rate of 30%, while those 70 years and older face coinsurance rates between 10% and 30%, depending on age and income[2]. During the study period (2014-2016), the coinsurance rate was set to decrease to 20% at age 70 and then to 10% at age 75. The discontinuity in coinsurance rates without changes in other benefits or life circumstances as well as additional features of the Japanese health care system make this an attractive setting to study the effect of patient cost sharing. These are discussed in more detail in Section 2.

I use regression discontinuity (RD) analysis to identify the impact of a change in patient cost sharing on prescription drug spending. While elderly Japanese patients face two decreases in the coinsurance rate, because of the aggregate structure of the data, I estimate the average effect of a decrease in the cost sharing rate from 30% to 20% at age 70 and a decrease in the cost sharing rate from 20% to 10% at age 75. I investigate how the effect differs between brand-name and generic medications as well as by patient sex. In addition to the full sample, I also analyze the impact for five therapeutic drug classes: cardiovascular drugs (within this class looking at all drugs and separately at drugs that treat high blood pressure), antibiotics, vitamins, antihistamines[3], and psychotropic drugs[4]. The data and the methodology are discussed in more detail in Sections 3 and 4, respectively.

I find that the average of the two decreases in the coinsurance rate leads to an increase in total prescription drug spending. Spending for an average individual on any drug increases by 5% (which corresponds to a price elasticity of spending of -0.12), and that for an average man using a generic drug increases by 9.6% (price elasticity of spending: -0.23). These price elasticities are comparable to those estimated in previous studies: spending elasticity for general medical services in the US has been estimated to be around -0.2 (Newhouse and

[2]High-income individuals in Japan face a higher coinsurance rate, but previous studies have identified that this group makes up a relatively small share of the population. As I cannot identify these individuals in my data, I do not condition changes in prescription drug outcomes on patient income, only on age.

[3]Antihistamines are typically used to relieve symptoms of allergies and reactions to insect bites or stings.

[4]Psychotropic drugs (e.g., antidepressants, mood stabilizers, stimulants, etc.) can be used to treat various conditions such as depression, anxiety, mania, sleep disorders, and others.

the Insurance Experiment Group (1993); Aron-Dine et al. (2013). Over the whole sample of drugs, there are no significant heterogeneous effects due to sex.

Analyzing the data by therapeutic class, I find that women's spending on cardiovascular drugs and high blood pressure drugs is statistically significantly less than men's spending on the same classes of medications. I find no statistically significant response at the age threshold for men using generics for any of the classes except psychotropic drugs. For these individuals, spending increases by 74.5 percent. For women, spending on cardiovascular drugs, high blood pressure drugs, and vitamins increases by 13.7%, 25.2%, and 10.1% at the age threshold, respectively. Conversely, spending on antibiotics for women over the age of 70 decreases by 11.1 percent, even though prior to the decrease in the coinsurance rate there was no statistically significant difference between women and men's spending on this drug class. Shigeoka (2014) does not find any discontinuities in the incidence of health conditions at the coinsurance age threshold, so these results suggest that patients are being either under-treated or over-treated. Results are discussed in more detail in Section 5.

In addition to examining the impact on spending, I also study how the number of prescriptions — the demand for pharmaceuticals — responds to changes in patient cost sharing. As data is aggregated beyond individual level, this analysis is primarily exploratory. I estimate a price elasticity of demand for all patients for all drugs of -0.33 and a price elasticity of demand for men for generics of -0.69. Previous studies have estimated a demand elasticity for general medical services in Japan between -0.16 (Fukushima et al., 2016) to -0.2 (Shigeoka, 2014). This suggests that patients may have a higher elasticity for prescription drugs compared to that of other types of health care spending. See Section 6.1 and Appendix B for more discussion.

Finally, I also conduct a robustness check that sets the age threshold at 75 years instead of 70 years. In the full sample, I cannot reject that there is no statistically significant change in the level of either prescription spending or volume at 75 years. As with the primary specification, there is no evidence of heterogeneity by sex within the full sample of all drugs. See Section 6.2 and Appendix C for more details.

This paper contributes to several strands of literature. The first strand of literature is the work on the impact of changes in patient cost sharing on health care utilization and medical spending. The most well-known study of patient cost sharing is the RAND Health Insurance Experiment (RAND HIE), which found that health care utilization decreases in response to higher patient cost sharing (Newhouse and the Insurance Experiment Group, 1993). However, the experiment suffers from threats to validity such as selection in experiment participation and reporting (Aron-Dine et al., 2013), and does not consider elderly individuals over 62 years of age. (Card et al., 2008) find that Medicare eligibility increases health care utilization. However, many individuals in the United States do not have complete health insurance prior to age 65: the Affordable Care Act alone expanded insurance coverage to an additional 20 million people who did not have insurance previously (Sarnak et al., 2017). The lack of completely coverage for individuals before they reach 65 makes it difficult to determine whether the effect is due to changes in cost sharing or insurance coverage.

Several studies have addressed this challenge of the US health care setting by exploiting the sharp discontinuity in patient coinsurance rates in Japan. Shigeoka (2014) uses survey data to study the impact of an earlier policy where the coinsurance rate only decreased once for elderly individuals, from 30% to 10% at age 70. He finds that despite no change in the incidence of health conditions and overall mortality at age 70, total spending and outpatient visits for various health conditions see a discrete increase at the age threshold. On the other hand, out-of-pocket spending *decreases*, as the decrease in the coinsurance rate more than offsets the increase in the volume of services received by the patients. Shigeoka (2014) does not look at pharmaceuticals as a separate category of medical services. Also in this space, Fukushima et al. (2016) use longitudinal individual-level claims data to analyze the effect of the same earlier policy on various medical procedures by treatment type. The authors find that total outpatient visits and inpatient admissions and spending specifically on orthopedics, mental health specialty, diagnostic imaging, and select other services increase. They also compare changes in prescription spending for brand-name vs. generic medications.

While spending on both increases at the age threshold, the authors find that the increase in spending on generics is largely transitory and is primarily due to intertemporal substitution around the threshold: patients strategically shift their spending from the months right before their 70th birthday to the months right after. In contrast to this, spending on brand-name drugs increases permanently in response to a decrease in patient cost sharing. The authors do not conduct additional heterogeneity analysis. I extend the work in these papers by considering how prescription volume and spending may differ not only between brand-name and generic drugs but also by patient sex and by drug therapeutic class.

This paper also contributes to the literature on the relationship between patient sex and health care use and expenditure. Cylus et al. (2011) find that in the United States, boys are more likely to have higher per capita drug expenditures than girls, while working age and elderly women have higher per capita expenditures than men in the same age group. The authors argue that this is primarily due to the incidence of various illnesses and health conditions across populations of different age groups. Lassman et al. (2014) find that while women filled 4.6 more prescriptions per capita than men in 2011, men were experiencing a faster growth in drug spending compared to women. This was true for men ages 65 and older, and was in part driven by increasing life expectancy and increasing prevalence of heart disease, prostate cancer, and leukemia for men. These studies are primarily descriptive and attribute differences by sex to disease incidence. However, variable expenditures by men and women can also arise due to physician bias and/or differences in patient behavior and agency, as has been shown in studies of patients with chronic diseases (Lorig et al., 2001). The goal of the paper is to determine whether there is a heterogeneous response by sex and drug class that should be examined further.

Finally, this paper contributes to the literature that studies how the effect of patient cost sharing on prescription drug spending and demand differs based on drug characteristics such as therapeutic class or the type of condition that the medication treats. Drugs that treat more acute episodes like infections (e.g., antibiotics) may not see any discontinuous changes in demand at the age threshold, although physicians may choose to prescribe more expensive medications once the patient's cost sharing decreases. The same can be hypothesized for drugs that treat serious conditions that require a strict treatment regimen, such as various cardiovascular medications. On the other hand, for drugs that may be primarily for symptomatic relief (e.g., antihistamines) or where the exact treatment regimen is more subject to the doctor's judgment (e.g., vitamins, psychotropic drugs), the volume of prescriptions and the total spending (driven either by higher volume or the prescribing of more expensive drugs) may increase once drugs become cheaper for patients. Goldman et al. (2007) highlight in their survey of the literature that the empirical evidence on how patient cost sharing affects prescriptions of "essential" drugs (e.g., anti-hypertensive agents) vs. "non-essential" drugs (e.g., antihistamines) is largely inconclusive[5]. Mann et al. (2014), in a survey of studies looking at the impact of increases in patient cost sharing on medication adherence for chronic conditions (i.e., diabetes, hypertension, coronary artery disease, and others) likewise found that effects varied from none to lower adherence. Studying the prescription of anti-hypertension drugs in Japan, Iizuka (2007) finds that although physicians' decisions are influenced by drug markups, they also prefer to dispense drugs that are less expensive for the patients, possibly because of reputation concerns or altruism. I contribute to this literature by studying the impact of changes in patient cost sharing in a health care setting with uniform access to medical services, price transparency, and no selection into insurance plans, and expanding the analysis to more therapeutic drug classes.

2 Institutional Background

Japan's universal health insurance system covers the vast majority of individuals living in the country, such as citizens and non-citizen residents, but excluding undocumented immigrants and visitors. Individuals are enrolled in one of the several insurance schemes based on their age, employment status, and residency. Residents are covered by either one of the employer-

[5]Select papers from Goldman et al. (2007) include Fairman et al. (2003), Harris et al. (1990), and Johnson et al. (1997). The definition and classification of "essential" and "non-essential" drugs is discussed in more detail in Section 3.

sponsored health insurances[6], insurance for the elderly (late elders' health insurance, or LEHI), or a municipality-operated citizen's health insurance (CHI) (Ibuka et al., 2016). An important feature of the system is that individuals cannot select the plan in which they enroll, which mitigates concerns over self-selection. Furthermore, health insurance is comprehensive and there is no gatekeeping for treatment, meaning that all individuals are able to access all health care services available, regardless of their insurance plan or age.

While an individual's insurance provider depends on one's age, employment status, and residency, a patient's coinsurance rate depends primarily on their age. Table 1 summarizes the patient cost sharing schedule for the entire population from April 2014 to March 2016. Individuals from 6 to 69 years old face a 30% coinsurance rate[7]. The coinsurance rate first decreases to 20% once individuals turn 70, and then falls again to 10% when they turn 75 years of age[8] [9]. Patients face the same coinsurance rates for prescription drugs as for other medical procedures.

A major identification assumption in this paper is that there are no other significant changes that coincide with individuals turning 70 and 75 that may also elicit a response in either prescription drug spending or utilization. As stated above, there are no changes in the scope of insurance coverage at either of these age thresholds. The retirement age in Japan and receipt of pension likewise begin prior to age 70 and therefore do not coincide with either of the decreases in coinsurance rates. I further investigate the validity of this assumption in Section 6.3.

All fees for health care treatments are set nationally by the federal government, so pa-

[6]Employee-sponsored health insurance includes the society-managed health insurance (SMHI) for employees of large firms and the Japan Health Insurance Association (JHIA) for employees of small- or medium-sized firms. If an employee is covered by employee-sponsored health insurance, their dependents are covered under the same scheme as well.

[7]Prior to 2005, employees covered by employer-based insurance faced lower coinsurance rates (10 percent prior to 1999, and 20 percent between 1999 and 2005). Since my study period covers the prescription data from April 2014 to March 2016, during this period employees under employer-based insurance face the same coinsurance rate as other working-age individuals in the population.

[8]Although high-income earners face a 30% coinsurance rate, the threshold for income is set relatively high and only about 7 percent of the population fall into this category (Ikegami et al., 2011).

[9]Prior to April 2014, the coinsurance rate for all regular residents over 70 was 10%, but in light of increasing health care costs the government increased the coinsurance rate for those aged 70-74 to 20 percent.

tients, conditional on the coinsurance rate, face the same out-of-pocket prices for a given visit, treatment, or prescription, regardless of age, health condition, or insurance. The prescription drug retail prices are determined and published by the government every two years in the *Standardized Drug Cost* tables (*Yakka Kijun*). The formula for the retail price takes into account the average wholesale price across the country and the previous schedule's retail price, scaled by a term called the "reasonable zone" that is intended to cover technical fees and transaction costs to dispense the drug.

Physicians who write prescriptions are also able to fill drug scripts through the hospital pharmacy. While hospitals purchase drugs from pharmaceutical companies at wholesale prices, drug claims are reimbursed at the higher retail prices. Hospitals that dispense the drugs are able to keep the mark-up between the wholesale and retail prices. Since the mark-ups for brand-name drugs are typically higher than those for their generic counterparts[10], physicians have incentive to prescribe the more expensive brand-name pharmaceuticals to their patients. Iizuka (2007) showed that while a physician's prescribing is influenced by the mark-up, they are also sensitive to patient out-of-pocket costs. He finds that patients are prescribed drugs that they do not need, and patients who are already on treatment are prescribed drugs different from the ones that they would have received otherwise. However, due to the decrease in the coinsurance rate after the patients turn 70, it is still possible for their out-of-pocket expenses to stay the same or even decrease while they use more prescription drugs or more expensive drugs and increase the physicians' profits.

3 Data

Data on prescription drug quantity and spending come from the National Database of Health Insurance Claims and Specific Health Checkups of Japan (NDB) collected by the Ministry of Health, Labor and Welfare (2017). I use the publicly available data on the total number of prescriptions for drugs approved for government reimbursement, by sex (women and men)

[10] Retail prices of generics are set at 60% of the corresponding brand-name drug (Fukushima et al., 2016).

by 5-year age groups (0-4 years old, 5-9 years old, ..., 85-89 years old, and over 90 years old). Age is coded as the starting age for each group (i.e., 0 years, 5 years, etc.). Prescription data is aggregated at the national level and is available for two Japanese fiscal years, from April 2014 to March 2015 and from April 2015 to March 2016. The NDB also contains data on the government retail prices for pharmaceuticals in yen. The government updates drug prices every two years, and the price schedule remained unchanged in my study period from April 2014 to March 2016.

The MHLW categorizes prescription drugs into five *types*, by modality (i.e., how the drug is administered) and the setting of drug administration: (1) administered internally in an in-hospital outpatient setting; (2) internally administered in an outpatient out-of-hospital setting; (3) internally administered in an inpatient setting; (4) externally administered (no specific setting); and (5) injection (no specific setting). The same drug can appear in the data under more than one type depending on the circumstances of the prescription. For example, the 20 mg capsule formulation of Cymbalta (a drug used to treat depression and anxiety, among other conditions) appears separately as being administered internally in an outpatient in-hospital setting, internally in an outpatient out-of-hospital setting, and internally in an inpatient setting. Because the retail price of the drug is the same regardless of this categorization, for each individual drug-formulation I calculate the total number of annual prescriptions for each sex by 5-year age group by summing over all five categories.

To control for the differences in the number of individuals in each age group, I use as the main outcome variable total spending per 1000 individuals. For the secondary outcome, I use the total number of prescriptions per 1000 individuals. Because I do not observe the number of individuals receiving a prescription, the denominator is the number individuals in the general population. Monthly population data by sex by 5-year age groups comes from the Statistics Bureau of the Ministry of Internal Affairs and Communications (2018). I average the monthly data to get annual population for the corresponding fiscal year.

I restrict the sample to only drugs for which prescriptions were filled in both fiscal years. I also restrict the sample to all age groups 40 years and older, since the types of drugs that are prescribed and drug prescription trends for the older population may vary greatly from those for younger individuals. Shigeoka (2014) and Fukushima et al. (2016) are much more conservative in their choice of age window around the threshold, looking at individuals aged 65 to 75 years old. To ensure a reasonable model fit given the aggregate structure of the data, I use the larger window around the threshold.

For drug j in therapeutic class k, for 5-year age group a of sex $s \in \{\text{female, male}\}$ in fiscal year t, I define the total number, or volume, of prescriptions as Vol_{ajkst}, the real price of drug j as P_{jkt} in thousands of yen[11], and the average annual population as Pop_{ast}. I calculate the following:

$$TotalVol_{ajkst} = \frac{1}{1000} \times \frac{Vol_{ajkst}}{Pop_{ast}} \tag{1}$$

$$Cost_{ajkst} = TotalVol_{ajkst} \times P_{jkt} \tag{2}$$

The spending outcome is total health care costs, not patient out-of-pocket costs. Both $TotalVol_{ajkst}$ and $Cost_{ajkst}$ take non-negative values only and are heavily skewed to the right, so I use log transformation of the variables.

Aside from the categorization by type (modality and administration setting) discussed above, MHLW assigns each drug to a *drug group* based on its treatment function (e.g., vasodilators, anti-hypertensive drugs, Vitamin A and D combinations, Vitamin B combinations, etc.). I further aggregate drug groups into *therapeutic classes* (e.g., cardiovascular drugs, vitamins, etc.). In addition to looking at the impact of a change in cost sharing across all drugs, I also compare the effect across five therapeutic classes: cardiovascular drugs, antibiotics, vitamins, antihistamines, and psychotropic drugs. Within cardiovascular drugs, which can be used to treat a wide range of heart-related conditions, I also separately focus on drugs that treat high blood pressure. Antihistamines are primarily used to alleviate allergy or insect bite symptoms, and psychotropic drugs are used to treat a variety of mood

[11] I use the real price of drug j in yen. I index the 2015-2016 fiscal year prices to 2014-2015 fiscal year prices using the inflation rate.

and sleep disorders. The full list of drug groups categorized under the select therapeutic classes can be found in Table A.1.

Outcome heterogeneity across drug classes can be attributed to a number of drug characteristics, and the classes in this study have been selected with these in mind. One dimension on which outcome response may differ is whether the drug is designated to treat a chronic condition or an acute episode. Patients with chronic conditions are likely to face higher medical costs and can be expected to be more sensitive to changes in drug prices. In the case of one-time, acute episodes, the average cost of medical treatment is relatively small over one's lifetime, so patients are unlikely to be very sensitive to the prices of associated medications. While the purpose of the treatment is not evident in the aggregate data, antibiotic treatment for infections can typically be classified as treatment for acute episodes. While cardiovascular drugs can be used to treat either acute episodes and or chronic conditions, this distinction for this class is not considered here.

Another dimension is the classification of drugs as either "essential" or "non-essential". The World Health Organization defines "essential" medications as "those that satisfy the priority health care needs of the population" (World Health Organization, 2017). Harris et al. (1990) define "essential" drugs as those "whose withdrawal could have important effects on health status". "Non-essential" (or, as the authors refer to them, "discretionary") drugs are "prescribed primarily for symptomatic relief, often on an as-needed basis for self-limiting conditions". Spending on and demand for non-essential drugs may respond more strongly to changes in patient cost sharing than the same measures for essential classes. Referring to previous literature on the topic (Harris et al., 1990), to the World Health Organization (2017) list of "essential" and "non-essential" drugs, and to the World Health Organization (2018) database of therapeutic classes, I classify cardiovascular drugs, antibiotics, and psychotropic drugs as "essential" and vitamins and antihistamines as "non-essential" medications.

The final dimension is the extent to which treatment is standardized or needs to be personalized to the patient. Although many individuals may require tailored treatment for various conditions, this is particularly true in regards to treatment for mental health disorders. For example, “[for] reasons not yet well understood, some people respond better to some antidepressant medications than to others,” and the lack of knowledge about how and why patients may or may not respond favorably to a particular drug means that they “may need to try several medicines to find the one that works for them” (National Institute of Mental Health, 2016). This type of trial-and-error approach to find the medication that best works for the patient may be more feasible when they face lower out-of-pocket costs for the treatment. For this reason, spending on and demand for psychotropic drugs may respond to changes in patient cost sharing in the same way that these measures would respond for non-essential medications.

4 Methodology

I use regression discontinuity (RD) to estimate the effect of a change in patient cost sharing. The aggregate structure of the data creates a limitation for the model parameter estimation. As the data is aggregated at the 5-year age group level, all of the data points for individuals aged 70 to 74 years old, who face the initial decrease from 30% to 20%, correspond to only a single value of the running variable. At each level of patient cost sharing, it is possible that not only the level of prescription drug spending or volume changes, but the slope of the regression line changes as well. In a model with indicator variables at both thresholds, while it would be possible to estimate any discontinuity in the level of the outcome variable, it would not be possible to estimate a slope for the segment corresponding to the 70-74 age group from one data point.

Given the available data, one approach is to include only one threshold indicator variable for individuals 70 years or older. Patients may be more sensitive to the initial decrease in patient cost sharing, which comes a full 65 years after the last change in the individual’s coinsurance rate. This regression would estimate some local average treatment effect for individuals 70-74 years old who face a 20% coinsurance rate and those 75 years and older who face a 10% coinsurance rate. Alternatively, a regression with an indicator for those age

75 or older would estimate a more accurate fit to the right of the second threshold. At the same time, this model would assume that prescription spending and volume at age 70 fit the same regression line as spending and volume before age 70. For the primary specification, I use the first regression with the indicator at age 70. These results are presented in the next section. As a robustness check, I conduct analysis with an indicator at age 75 only (see Appendix C).

The primary specification, similar to that used by Shigeoka (2014) and Fukushima et al. (2016), is:

$$Y_{ajkst} = \beta_0 + \beta_1' f(a) + \beta_2 \times post70_{ajkst} + \beta_3' g(Price_{jkt}) + \delta_t + \epsilon_{ajkst} \tag{3}$$

where Y_{ajkst} is log of the outcome of interest for drug j in therapeutic class k per 1000 individuals of sex s in age group a in year t. $f(a)$ is a quadratic polynomial of the variable age, plus all of the corresponding interaction terms with $post70$, an indicator variable equal to unity if the outcome is for patients 70 years or older. β_2 captures any discrete jumps at the age threshold. Variable age is adjusted such that the age at the patient cost sharing discontinuity corresponds to zero. This allows me to directly interpret coefficient β_2 as the effect of decreasing patient cost sharing on the level of the outcome.

The coefficients on the interaction terms between age, age^2, and $post70$ capture changes in slope, i.e., long-term changes in prescription behavior due to the change in cost sharing. If prescription drug spending and utilization change in response to both decreases in patient cost sharing, the current model would confound discrete one-time changes in the outcome variable with long-term trend shifts, since any discontinuity in outcomes at age 75 is incorporated into the coefficient on $post70 \times age$. Similar problems of bias may arise for coefficients on other interaction terms with $post70$. Interpretations of these coefficients should be made with this in mind.

The regression also controls for price and price interacted with the $post70$ indicator variable, included in the $g(P_{jkt})$ term. The interaction term captures how patient price sensitivity changes after the decrease in the coinsurance rate. Year fixed effects are given by δ_t, and ϵ_{ajkst} is the unobserved error term. I do not include drug class or individual drug fixed effects in the regression to be able to estimate a coefficient on $brand$, which is included in subsequent specifications.

A necessary assumption for RD is that all of the other covariates that might impact the outcome variable (i.e., all predictors other than the coinsurance rate) are continuous across the threshold. If this assumption holds, it is not necessary to include additional covariates in the regression to estimate β_2. However, including additional covariates can help to reduce the sampling variability in the estimators. I can also test whether there is a heterogeneous response that depends on patient or drug characteristics.

First, physicians may respond to a decrease in patient cost sharing by switching their patients to brand-name medications to exploit the higher mark-up between wholesale and retail prices, resulting in greater profits with little, if any, additional cost to the patient. To test this, I estimate the following regression:

$$\begin{aligned} Y_{ajkst} = \alpha_0 + \alpha_1' f(a) + \alpha_2 \times post70_{ajkst} + \alpha_3' g(Price_{jkt}) + \\ + \alpha_4' h(brand_{jkt}) + \delta_t + \omega_{ajkst} \quad (4) \end{aligned}$$

where $h(brand_{jkt})$ includes the indicator $brand_{jkt}$, which equals unity if the medication is a brand-name drug, and the interaction term $brand_{jkt} \times post70_{ajkst}$, which estimates how prescribing trends for brand-name drugs change when patient cost sharing decreases. ω_{ajkst} is the unobserved error term, and all other terms are as previously defined.

Second, prescription trends may differ based on the sex of the patient, due to differences in health conditions and disease incidence, physician treatment and biases, and/or patient preferences for care. This study does not explore which of these factor(s) is (are) driving the difference in outcomes due to sex but does examine whether such heterogeneous effects are present. The corresponding equation, with additional interaction terms, is

$$\begin{aligned} Y_{ajkst} = \gamma_0 + \gamma_1' f(a) + \gamma_2 post70_{ajkst} + \gamma_3' g(Price_{jkt}) + \gamma_4' h(brand_{jkt}) \\ + \gamma_5' m(female_{ast}) + \gamma_6 brand_{jkt} \times female_{ast} + \delta_t + \varepsilon_{ajkst} \quad (5) \end{aligned}$$

where $m(female_{ast})$ includes the indicator for female age groups $female_{ast}$ and interaction for $female_{ast} \times post70_{ajkst}$. Interaction term $brand_{jkt} \times female_{ast}$ is equal to unity for brand-name drugs prescribed to female patients. ε_{ajkst} is the unobserved error term, and all other terms are as previously defined.

Regressions in eq. 3, 4, and 5 are estimated for the full sample of pharmaceutical products using robust standards errors clustered at the drug class level. I also estimate eq. 5 for each of the six selected therapeutic classes of drugs, with robust standard errors.

5 Results

Table 2 presents the total number of distinct prescription drugs (rather than the volume of prescriptions) included in the study, in the whole sample and in the therapeutic class subsamples. Table 3 provides summary statistics for the outcome variables for the full sample as well as by sex and by therapeutic class.

RD plots for total prescription drug spending show the mean spending for each age group by sex, without conditioning for other variables (Figures 1 to 7). The RD plot for total spending for all drugs by sex suggests a statistically significant increase in expenditure for both women and men (Figure 1). Breaking down spending by therapeutic class (Figures 2 to 7), I find that women have a statistically significant increase in spending for all cardiovascular drugs (an essential class) compared to men, but the same is not observed in the subset of drugs that treat high blood pressure. There is also a statistically significant increase at the threshold age for spending on vitamins (a non-essential class) for women. Although there is no evidence of statistically significant increases in spending for other groups, there is a notable change in the trend line slope after the threshold age for men's spending on psychotropic drugs.

Regression results for total spending for all drugs are presented in Table 4. Coefficients can be interpreted as a $(100 \times \beta)$ percent change in the outcome variable corresponding to a one unit change in the independent variable (here, 1,000 yen in total expenditure). The coefficient on $post70$, which captures the average effect of decreasing patient cost sharing from 30% to 20% at age 70 and decreasing cost sharing from 20% to 10% at age 75, is statistically significant in regressions (1) and (3). Spending for an average person for a medication (brand-name or generic) increases by 7.6% and spending for an average man for a generic medication increases by 9.6 percent. The respective price elasticities of spending are -0.12 and -0.23[12]. This is comparable to -0.2, the price elasticity for general medical services estimated by Newhouse and the Insurance Experiment Group (1993) and Aron-Dine et al. (2013) for the US.

The coefficients on age and $post70 \times age^2$ are also statistically significant: prescription spending increases with age, and there is a quadratic trend after the age threshold. The statistically insignificant coefficient on $post70 \times age$ indicates that the rate of increase in spending after the age threshold does not change. More expensive drugs contribute more to total spending, as indicated by the positive significant coefficient on *price*, but past the age threshold, that is less likely to be the case. Similarly, brand-name medications have a significant positive effect on total spending compared to generics, and this effect does not change after age 70. This contrasts the findings by Fukushima et al. (2016), who show that brand-name drugs have a permanent effect on prescription drug spending. This could potentially be explained by the differences in specifications between the studies: the authors limit their window to individuals aged 65 to 75 years old. It is possible that while spending on brand-name drugs is higher for individuals up to age 75, subsequently patients may switch back to generic alternatives.

The estimated coefficients on *price* and *brand* suggest that total spending likely increases due to a higher quantity of drugs being prescribed rather than patients being switched to

[12] The price elasticity of an outcome variable can be calculated using the following formula:

$$Elasticity = \frac{\%\Delta Y}{\%\Delta P} = \frac{\Delta Y/Y}{\Delta P/P} \tag{6}$$

The numerator of the elasticity is given by the coefficient on $post70$ in the regression of interest. The denominator is given by the percent change in price, which is calculated as the average of 1/3 (first decrease from 30% to 20%) and 1/2 (from 20% to 10%).

more expensive medications. This is discussed in further detail in Section 6.1. Finally, in the sample for all drugs, I do not find any statistically significant effects by patient sex.

Estimation results for eq. 5 by therapeutic class are presented in Tables 5 (all cardiovascular drugs, cardiovascular drugs that treat high blood pressure [HBP], and antibiotics) and 6 (vitamins, antihistamines, and psychotropic drugs). Although I classify psychotropic drugs as essential medicine, they are grouped with discretionary drugs because of the trial-and-error nature of determining an appropriate treatment regimen for patients (see Section 3).

Analyzing the data by therapeutic class, I find no statistically significant response to the change in cost sharing for an average man using a generic medication for any of the classes except psychotropic drugs. For this group, spending increases by 74.5 percent. Overall, women spend less on cardiovascular drugs (16.4% less for the whole class and 31.8% less for the HBP drugs), which could be attributed to differences in the prevalence of heart conditions between the two sexes. However, women's spending on all cardiovascular drugs and HBP cardiovascular drugs catches up to men's expenditure at the age threshold, as spending increases by 13.7% and 25.2 percent, respectively. This suggests that either women are being under-treated or men are overtreated[13] for heart conditions prior to age 70. It is also possible that women are being over-treated once their coinsurance rate decreases. Looking at other drug classes, women may be over-treated before age 70 or under-treated after age 70 when it comes to using antibiotics: spending on antibiotics for women and men does not differ before age 70 but decreases abruptly for women over 70 by 11.1 percent.

Women spend more than men on vitamins and antihistamines (12.3% more and 16.3% more, respectively). At the age threshold, men's spending on vitamins not only does not catch up to women's spending but falls further behind: women's spending on vitamins increases by 10.1 percent. There are no statistically significant differences between women and men at the age threshold.

[13] "Under-treatment" can include being prescribed fewer medications and cheaper medications than is recommended/necessary. "Over-treatment", conversely, can include being prescribed more medications and more expensive medications than is recommended/necessary.

As in the sample of all drugs, brand-name medications contribute significantly to higher total spending across all classes. For cardiovascular drugs (all and HBP) and antihistamines, the effect of brand-name drugs on spending becomes even greater after the age threshold. The opposite is the case for psychotropic drugs. The relationship between drug prices and total spending is inverse for cardiovascular drugs, antihistamines, and psychotropic drugs. One possible interpretation is that while patients spend more on brand-name medications, conditional on whether the drug is brand-name or generic, patients spend more on drugs on the cheaper end of the price spectrum.

6 Additional analyses

6.1 Changes in prescription volume

In this section, I discuss the exploratory analysis on the impact of the coinsurance rate change on the volume of prescriptions. In this analysis, I do not standardize the prescription volume either across separate formulations (e.g., 5 mg pill, 10 mg pill) of the same drug or across drugs of the same group that may have similar components but different strength.

Figure B.1 shows the RD plot for the volume of prescriptions for the sample of all drugs by sex. There is a clear discontinuity in the trend line at the age threshold for both women and men. Looking at the regression estimates, the volume of any prescriptions for the average person increases by 13.9%, the volume of generic drugs for an average person increases by 22.5%, and the volume of generics for an average man increases by 28.8%. The respective price elasticities of demand are -0.33, -0.54, and -0.69. Previous studies estimate the demand elasticity for general medical services in Japan to be from -0.16 (Fukushima et al., 2016) to -0.2 (Shigeoka, 2014). The estimates in this study suggest that demand for *prescription drugs* responds more strongly to changes in price than that for *general medical services*.

Patients are prescribed more brand-name medications than generic drugs. This does not change after the patient reaches the age threshold. The negative coefficient on *price* means that patients are prescribed cheaper drugs in greater quantity, and the coefficient on $price \times post70$ means that this effect becomes even more pronounced after age 70. As before, this suggests that patients are sensitive to drug prices within brand-name and generic drugs.

The analysis by therapeutic class explores RD plots by sex (Panels A and B of Figures B.2 through B.7) as well as the distribution of coefficients for drugs in the class. Panel C of Figures B.2 through B.7 presents the histogram of statistically significant coefficients on $post70$ (p-value < 0.05) out of the set of coefficients calculated for each drug-formulation in that class using the model in eq. 5. The histogram excludes outlier coefficients with values greater than 50 for ease of visualization. The histograms shows that there is considerable heterogeneity in the response by drug, while the average effect (as given by the coefficients on $post70$ in Tables B.2 and B.3) is not statistically significant for any groups except vitamins.

As with the regressions on total spending, differences in prescription volume by sex become significant when I break down the analysis by drug class. Women's utilization of all and HBP cardiovascular drugs is lower compared to that of men, but the gap closes or almost closes at the age threshold. In contrast, women's utilization of vitamins and antihistamines is higher compared to that of men, and this gap does not narrow at the age threshold. There are no statistically significant differences between women and men's volume of antibiotics or psychotropic drugs.

I find that individuals (both women and men) use more brand-name medications within essential classes and more generics within discretionary classes (specifically, vitamins and psychotropic drugs). At the age threshold, the average man uses even fewer brand-name medications for vitamins and psychotropic drugs, and the effect is even more pronounced for the average woman using vitamins. This and the negative statistically significant coefficient on $price \times post70$ together point at higher price sensitivity among patients using generic medications. This result makes intuitive sense: patients who are sensitive to the price of drugs would be more likely to use cheaper generic alternatives. When patient cost sharing decreases, those patients are the ones who are likely to respond more to the change in price.

The results in this section are suggestive about changes along the extensive and intensive margins in response to a decrease in patient cost sharing. On the extensive margin, when the price of a drug decreases, physicians may choose to start prescribing drugs to a marginal patient who was not previously receiving treatment. Two changes can happen on the intensive margin. First, physicians may choose to prescribe a higher volume of medication(s) to a patient who is already receiving treatment. This may happen if a patient was previously under-treated and/or there is some physician discretion regarding the appropriate treatment regimen, such as in the case of psychotropic drugs. Second, physicians may choose to switch their patients to more expensive medications. In that case, because of the lower coinsurance rate, the patient's total out-of-pocket cost may still be lower than that when they were prescribed the cheaper drug, so physicians would be able to increase their profits without increasing the financial burden for their patients.

Due to the aggregate structure of the data, I cannot draw a firm conclusion regarding changes on the extensive and intensive margins. It is likewise not possible to determine whether the changes in prescription spending and volume are due to changes in prescribing behavior by the physician (as suggested by Iizuka (2007)) or due to changes in patient preferences. However, some takeaways can be made based on the relative magnitudes of elasticities. The price elasticity of demand (ranging from -0.33 to -0.69) is greater than the price elasticity of spending (ranging from -0.12 to -0.23). This suggests that patients are getting prescribed a greater quantity of medications (either on the intensive or the extensive margin) after the coinsurance rate decreases.

Additionally, I do not find evidence of changes on the intensive margin whereby patients are switched to more expensive drugs. Looking at the coefficients on *price* in Tables 4 and B.1, total spending *increases* and total volume *decreases* with age. At the age threshold, the additional impact of drug prices becomes more negative for both outcomes. Less expensive drugs contribute more to prescription spending and volume relative to more expensive drugs, suggesting that physicians are substituting toward less expensive drugs after their patients' coinsurance rate decreases. This does not necessarily contradict previous findings by Iizuka (2007). The author's study looks specifically at anti-hypertension drugs, and, as this paper has demonstrated, there exists heterogeneity in the response of outcome measures between different therapeutic classes and between drugs in the same class. While physicians may substitute toward more expensive medications for some treatments, I find that physicians substitute toward cheaper prescriptions in the case of cardiovascular drugs (all and HBP), vitamins, and antihistamines, and there is no statistically significant effect for antibiotics, psychotropic drugs, or on aggregate.

6.2 Discontinuity at age 75

As a robustness check, I test a model where the policy threshold is set at age 75 rather than at 70 years of age. The estimation strategy and the corresponding RD plots and regression tables are included in Appendix C. The RD plots (Figure C.1) suggest that there is either a slight *decrease* or no discontinuity in the outcome variable at the age threshold. Visually, the regression model does not seem to be as close of a fit for the pre-threshold data with the discontinuity at age 75, compared to the model fit of the pre-threshold data with the discontinuity at age 70 (Figures 1 and B.1).

Looking at the regression results (Tables C.1 and C.2), I do not find a statistically significant change in the level of spending (coefficient on $post75$). I do find a statistically significant increase in volume for an average man using generics. This is likely explained by this model's assumption that the observations at age 70 fit the same regression line as the observations from age 40 to 65. The regression results presented in Section 5 show evidence of a discrete *increase* in both prescription volume and spending at age 70. Fitting observations at age 70 to the same trend as those for individuals age 40 to 65 likely leads to upward bias in the slope for the pre-threshold data. So although the decrease in patient cost sharing from 20% to 10% may have an impact on either drug prescription volume or spending, the change in the level of the outcome variables is masked by the biased estimation over the pre-threshold part of the sample.

The effect of age and price and the fit of the quadratic polynomial is similar to the results in Tables 4 and B.1. Conversely, brand-name status of a drug is no longer significant for predicting prescription volume, although there is a difference between brand-name and generic drugs that becomes statistically significant at the age threshold. As before, there is no evident heterogeneity by sex in the overall drug sample.

6.3 Internal validity of the results

As stated above, a necessary assumption for identification is that there are no other changes that coincide with the decrease in the coinsurance rate that may affect prescription drug spending and volume. I examine potential threats to internal validity following the approach in Chay and Greenstone (2003), by investigating the effect on an outcome that should not be affected by changes in the coinsurance rate. A statistically significant change in this outcome at the age threshold would suggest that there is an omitted factor that coincides with the change in the coinsurance rate that may be a source of bias in the estimates for the outcomes of interest.

Similar to Chay and Greenstone (2003), I consider death rates from homicides as the placebo outcome. For a more detailed discussion on the choice of outcome, see Appendix D. Plots for homicide death rates by sex are presented in Figure D.1. While visually there may be a significant association between age and homicide death rates in 2014, there does appear to be a similar relationship for other years. Table D.1 presents the regression results to test for statistical significance. The only statistically significant relationship in the regression is the difference by sex. While this exercise does not provide evidence for the causal relationship between the coinsurance rate and prescription drug outcomes, it lends validity to the assumption that there are no unobserved changes that coincide with the change in patient cost sharing.

7 Conclusion

In this paper, I study how a change in patient cost sharing, determined by a policy discontinuity in the coinsurance rate, affects total expenditure on prescription drugs. I contribute to the existing literature by examining heterogeneous responses by patient sex and therapeutic class of drugs, which can provide insights to design better targeted policy and create incentives for physicians and patients that align with cost-effective, health-improving care.

I find that total spending increases in response to a decrease in the coinsurance rate. The price elasticity of spending for prescription drugs is comparable to the estimates of price elasticity of spending for general medical services estimated by previous studies. I also find that significant differences in spending between women and men become apparent when I break down analysis by therapeutic class.

I also conduct exploratory analysis on the impact of the change in patient cost sharing on the total volume of prescription drugs. I find suggestive evidence that the price elasticity of demand for prescription drugs is greater than that for general medical services, meaning that drug spending responds more strongly to changes in patient out-of-pocket costs. I also find evidence that physicians respond by prescribing a greater volume of drugs, although it is not possible to conclude with the available data whether the change happens on the extensive or the intensive margin or both. The analysis also suggests that physicians do not respond on the intensive margin by prescribing more expensive medications to their patients, although this response varies based on the drug therapeutic class. Finally, although patients are more likely to be prescribed brand-name medications, prescriptions of generics are more responsive to changes in the coinsurance rate.

This study highlights that prescription drug spending and demand do respond differently to changes in the coinsurance rate depending on the patient sex and the class of drugs that is being prescribed. These differences are present for essential drugs, including antibiotics which typically treat acute health episodes, and non-essential drugs where physicians have discretion regarding treatment. In future work on this topic, I will leverage detailed patient-level data on individuals' prescription history to examine the margin (extensive vs. intensive) on which physicians and patients respond to changes in patient cost sharing. I will also determine whether the changes in the coinsurance rate and prescribing have a significant effect on health outcomes and whether differences by patient sex persist here as well. Additionally, the more granular data will make it possible to disentangle the effect of the consecutive changes in the coinsurance rate that occur at 70 and 75 years of age, and to determine, similar to the work by Fukushima et al. (2016), whether there are any transitive effects that are being masked by the aggregate data. Finally, using individual-level data on expenditure, I will be able to estimate the true out-of-pocket spending for patients, which classes of drugs constitute the greatest share of expenditure, and whether the financial burden on the patients disproportionately affects one of the sexes.

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Tables

Table 1: Cost sharing under the Japanese health insurance, from April 2014

Age	Regular residents	High-income earners
75 years +	10%	30%
70-74 years	20%	
6-69 years	30%	
0-5 years	20%	

Source: *About the National Health Insurance System*, Ministry of Health, Labor and Welfare (MHLW). From April 2008 to March 2014 the coinsurance rate for individuals aged 70-74 was 10%. Starting in April 2014, the coinsurance rate for this group was increased to 20 percent.

Table 2: Number of brand-name and generic drugs

Therapeutic Class	Brand-name	Generic	Total
All drugs	2,837	1,529	4,366
Cardiovascular (all)	237	162	399
Cardiovascular (high blood pressure)	96	58	154
Antibiotics	110	96	206
Vitamins	157	111	268
Antihistamines	68	41	109
Psychotropic	61	9	70

Data source: *National Database of Health Insurance Claims and Specific Health Checkups of Japan*, 2014-2016, MHLW. Drug groups are identified directly in the data. Therapeutic classes are defined based on classifications in World Health Organization (2018). Each separate formulation of a drug (e.g., 5 mg pills, 10 mg pills, etc.) is counted as a distinct drug. The sample is restricted to individuals 40 years and older.

Table 3: Data summary statistics

Prescription spending							
		All		Women		Men	
	N	Mean	SD	Mean	SD	Mean	SD
All drugs	96,052	17.38	85.90	16.14	83.17	19.39	113.89
Cardiovascular (all)	8,778	38.21	119.15	36.28	120.26	40.17	120.53
Cardiovascular (hbp)	3,388	56.97	143.21	51.58	134.72	62.76	155.48
Antibiotics	4,532	4.02	12.51	3.91	12.10	4.30	14.50
Vitamins	5,896	7.20	68.98	9.27	100.22	4.11	28.93
Antihistamines	2,398	19.41	58.80	179.09	536.2	154.76	490.5
Psychotropic	1,540	23.48	45.04	26.33	50.26	19.48	39.23

Prescription volume							
		All		Women		Men	
	N	Mean	SD	Mean	SD	Mean	SD
All drugs	96,052	490.54	10562.79	485.05	11001.3	491.17	9167.2
Cardiovascular (all)	8,778	644.05	1488.39	608.92	1525.7	681.22	1492.4
Cardiovascular (hbp)	3,388	981.85	1711.20	897.88	1647.52	1075.00	1841.94
Antibiotics	4,532	53.88	158.90	55.80	169.0	53.73	157.2
Vitamins	5,896	261.84	1631.73	321.60	1912.8	178.65	1317.4
Antihistamines	2,398	272.48	591.62	293.47	626.8	259.26	600.9
Psychotropic	1,540	443.43	1198.49	514.76	1469.79	343.98	819.28

Data source: *National Database of Health Insurance Claims and Specific Health Checkups of Japan*, 2014-2016, MHLW. Prescription cost is measured in 1,000s of yen per 1,000 individuals (of total population or by sex), indexed to the 2014-15 Japanese fiscal year as the baseline year. Prescription volume is measured as the number of prescriptions per 1,000 individuals (of total population or by sex). Each separate formulation of a drug (e.g., 5 mg pills, 10 mg pills, etc.) is counted as a distinct drug. The sample is restricted to individuals 40 years and older. *N*: number of observations for each sex, at drug-age group-year level. hbp: high blood pressure.

Table 4: Regression estimates (discontinuity at age 70): Rx spending, all drug groups

	(1)	(2)	(3)
Age	0.0172***	0.0172***	0.0172***
	(0.0019)	(0.0019)	(0.0019)
Post70	0.0760***	0.0503	0.0955*
	(0.0114)	(0.0329)	(0.0411)
Post70 × Age	0.0081	0.0081	0.0081
	(0.0053)	(0.0053)	(0.0053)
Age^2	-0.0001	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0001)
Post70 × Age^2	-0.0015***	-0.0015***	-0.0015***
	(0.0001)	(0.0001)	(0.0001)
Price	0.0097**	0.0083**	0.0083**
	(0.0026)	(0.0025)	(0.0025)
Price × Post70	-0.0054**	-0.0055**	-0.0055**
	(0.0015)	(0.0015)	(0.0015)
Brand-name		0.5909***	0.6002***
		(0.0683)	(0.0695)
Brand-name × Post70		0.0399	0.0399
		(0.0514)	(0.0514)
Female			0.0260
			(0.0432)
Female × Post70			-0.0904
			(0.0559)
Female × Brand-name			-0.0187
			(0.0243)
Observations	192104	192104	192104

Outcome: log prescription spending (in 1000s of yen) on drug j in therapeutic class k by 1000 individuals of sex s in age group a in year t. Standard errors are in parentheses and are clustered at the therapeutic class level. All estimations include year fixed effects, which is determined by the Japanese fiscal year (from April 1 to March 31 of the following year). Regression model is estimated with patient coinsurance rate discontinuity at age 70. Significance levels $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 5: Regression estimates (discontinuity at age 70): Rx spending, by therapeutic class

	(1) Cardiovascular (all)	(2) Cardiovascular (HBP)	(3) Antibiotics
Age	0.0230*	0.0270	0.0154*
	(0.0089)	(0.0152)	(0.0073)
Post70	-0.1226	-0.2339	0.0126
	(0.0898)	(0.1516)	(0.0697)
Post70 × Age	0.0258	0.0252	-0.0020
	(0.0135)	(0.0225)	(0.0107)
Age^2	-0.0005*	-0.0007	0.0002
	(0.0002)	(0.0004)	(0.0002)
Post70 × Age^2	-0.0015**	-0.0008	-0.0007
	(0.0005)	(0.0009)	(0.0004)
Price	-0.1064***	-0.4446***	0.0214
	(0.0176)	(0.0835)	(0.0265)
Price × Post70	-0.0493	-0.3770*	0.1217*
	(0.0329)	(0.1647)	(0.0496)
Brand-name	0.9674***	1.2121***	0.3267***
	(0.0378)	(0.0649)	(0.0307)
Brand-name × Post70	0.2791***	0.4277***	0.0758
	(0.0479)	(0.0801)	(0.0402)
Female	-0.1636***	-0.3180***	0.0405
	(0.0343)	(0.0600)	(0.0279)
Female × Post70	0.1370**	0.2516**	-0.1109**
	(0.0505)	(0.0839)	(0.0404)
Female × Brand-name	-0.0449	0.0055	-0.0115
	(0.0465)	(0.0772)	(0.0389)
Observations	17556	6776	9064

Outcome: log prescription spending (in 1000s of yen) on drug j in therapeutic class k by 1000 individuals of sex s in age group a in year t. Standard errors are in parentheses and are clustered at the therapeutic class level. All estimations include year fixed effects, which is determined by the Japanese fiscal year (from April 1 to March 31 of the following year). Regression model is estimated with patient coinsurance rate discontinuity at age 70. Significance levels $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 6: Regression estimates (discontinuity at age 70): Rx spending, by therapeutic class

	(1) Vitamins	(2) Antihistamines	(3) Psychotropic
Age	0.0143**	-0.0014	-0.0443*
	(0.0051)	(0.0172)	(0.0210)
Post70	0.0747	0.1006	0.7451***
	(0.0549)	(0.1620)	(0.1985)
Post70 × Age	0.0179*	0.0173	0.0440
	(0.0088)	(0.0247)	(0.0293)
Age^2	0.0001	-0.0002	-0.0009
	(0.0001)	(0.0005)	(0.0006)
Post70 × Age^2	-0.0013***	-0.0005	0.0001
	(0.0004)	(0.0010)	(0.0011)
Price	1.6251***	-0.1371***	-0.0065*
	(0.0653)	(0.0308)	(0.0033)
Price × Post70	-0.1599	-0.0596	-0.0332***
	(0.1066)	(0.0497)	(0.0038)
Brand-name	0.0998***	0.2910***	1.1202***
	(0.0212)	(0.0700)	(0.0801)
Brand-name × Post70	-0.0634	0.1769*	-0.6668***
	(0.0335)	(0.0895)	(0.1108)
Female	0.1829***	0.1634*	0.1087
	(0.0235)	(0.0720)	(0.0954)
Female × Post70	0.1012**	-0.1653	0.1850
	(0.0340)	(0.0935)	(0.1112)
Female × Brand-name	-0.0979**	0.0228	-0.0339
	(0.0317)	(0.0877)	(0.1053)
Observations	11792	4796	3080

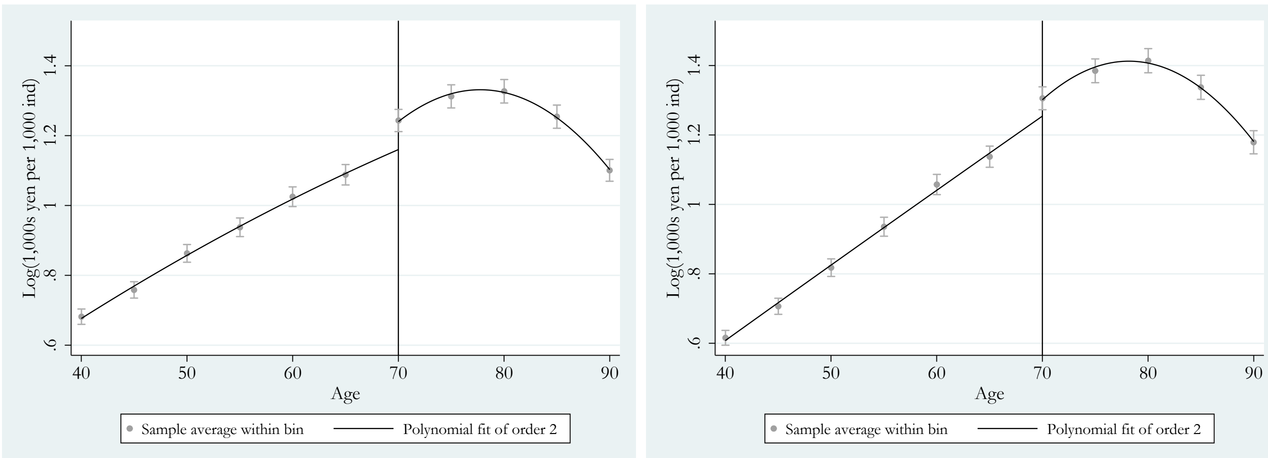
Outcome: log prescription spending (in 1000s of yen) on drug j in therapeutic class k by 1000 individuals of sex s in age group a in year t. Standard errors are in parentheses and are clustered at the therapeutic class level. All estimations include year fixed effects, which is determined by the Japanese fiscal year (from April 1 to March 31 of the following year). Regression model is estimated with patient coinsurance rate discontinuity at age 70. Significance levels $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$
HBP: high blood pressure.

Figures

Figure 1: RD plots by sex, all drug groups

Panel A:
Rx spending, women

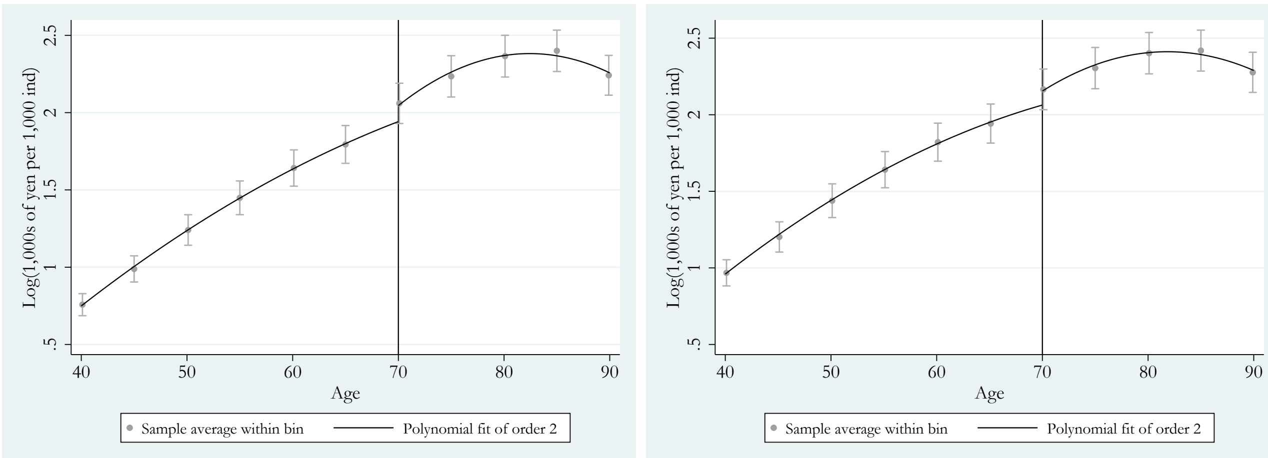
Panel B:
Rx spending, men



Each point is a sample mean for an age group bin. Each age bin corresponds to 5 years. Discontinuity at age 70 only. Brackets around each point estimate are the 95% CI.

Figure 2: RD plot by therapeutic class: Cardiovascular drugs (all groups)

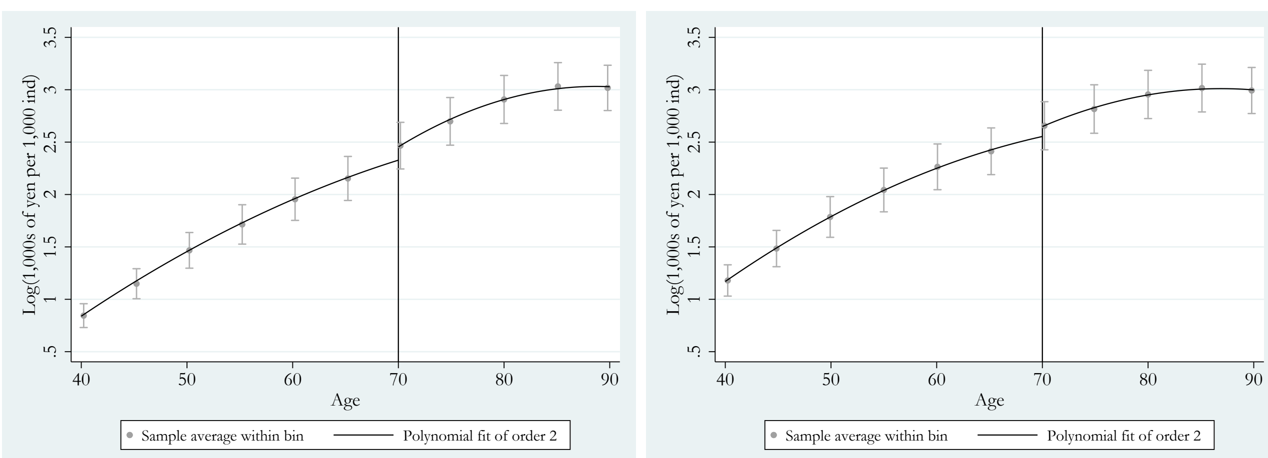
Panel A: Rx spending, women | **Panel B: Rx spending, men**



Each point is a sample mean for an age group bin. Each age bin corresponds to 5 years. Brackets around each point estimate are the 95% CI.

Figure 3: RD plot by therapeutic class: Cardiovascular drugs (high blood pressure groups)

Panel A: Rx spending, women | **Panel B: Rx spending, men**

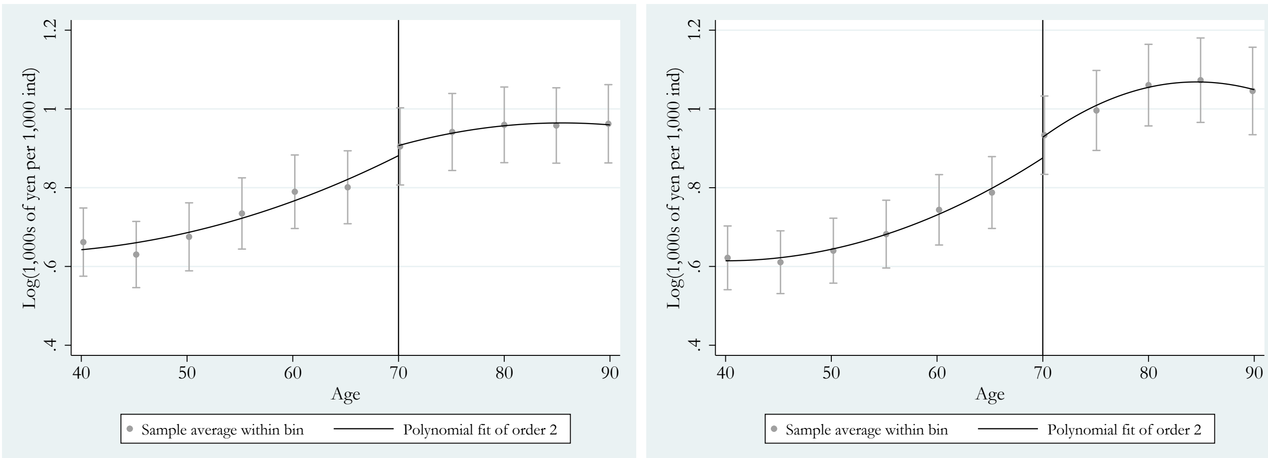


Each point is a sample mean for an age group bin. Each age bin corresponds to 5 years. Brackets around each point estimate are the 95% CI.

Figure 4: RD plot by therapeutic class: Antibiotics

Panel A:
Rx spending, women

Panel B:
Rx spending, men

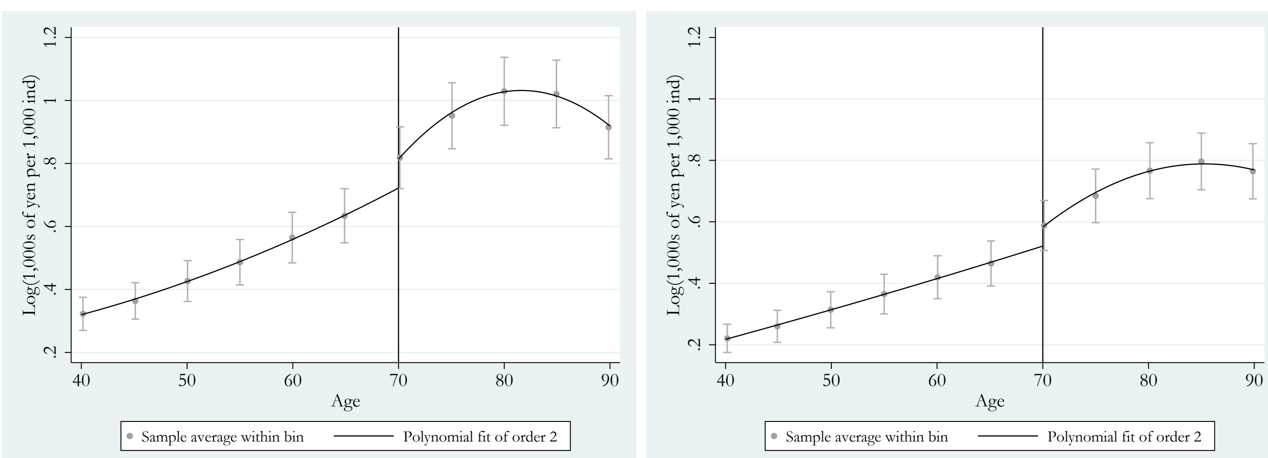


Each point is a sample mean for an age group bin. Each age bin corresponds to 5 years. Brackets around each point estimate are the 95% CI.

Figure 5: RD plot by therapeutic class: Vitamins

Panel A:
Rx spending, women

Panel B:
Rx spending, men

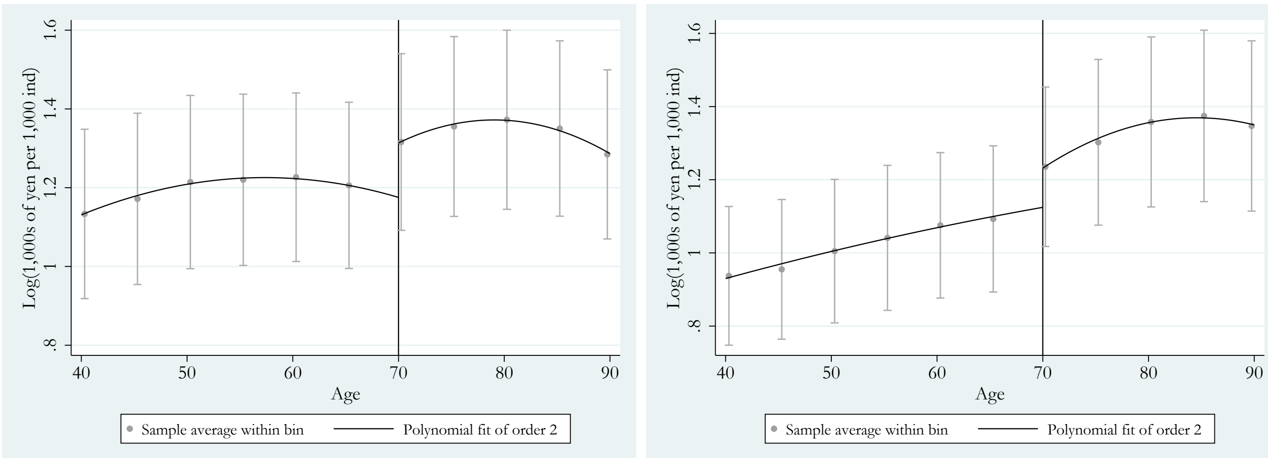


Each point is a sample mean for an age group bin. Each age bin corresponds to 5 years. Brackets around each point estimate are the 95% CI.

Figure 6: RD plot by therapeutic class: Antihistamines

Panel A:
Rx spending, women

Panel B:
Rx spending, men

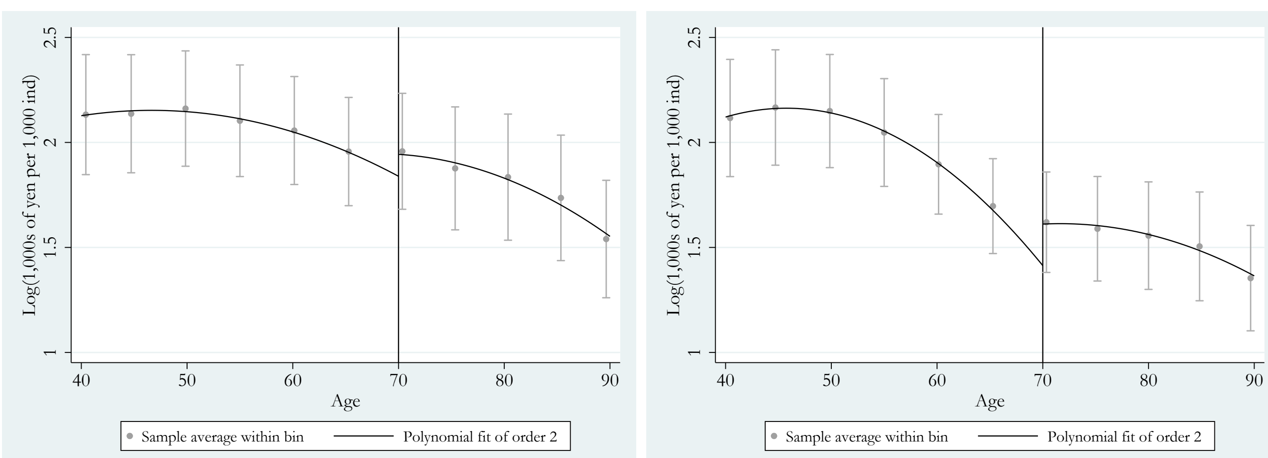


Each point is a sample mean for an age group bin. Each age bin corresponds to 5 years. Brackets around each point estimate are the 95% CI.

Figure 7: RD plot by therapeutic class: Psychotropic drugs

Panel A:
Rx spending, women

Panel B:
Rx spending, men



Each point is a sample mean for an age group bin. Each age bin corresponds to 5 years. Brackets around each point estimate are the 95% CI.

Appendix A Therapeutic classes and drug groups

Table A.1: Therapeutic classes and corresponding drug groups

Therapeutic Class	Drug Groups
Cardiovascular	Cardiotonics Arrhythmia agents Diuretics[a] Anti-hypertensive agents[a] Capillary stabilizing agents Vasoconstrictors Vasodilators[a] Agents for hyperlipedemia Other cardiovascular drugs
Antibiotics	Drugs targeting gram-positive bacteria Drugs targeting gram-negative bacteria Drugs targeting gram-positive and negative bacteria Drugs targeting gram-positive bacteria and mycoplasma Drugs targeting gram-positive/negative bacteria, rickettsia, and chlamydia Drugs targeting acid fast bacteria Drugs targeting mold Other antibiotics
Vitamins	Vitamin A and D combinations Vitamin B1 combinations Vitamin B combinations (excluding vitamin B1) Vitamin C combinations Vitamin E combinations Vitamin K combinations Mixed vitamin doses (excluding Vitamin A and D)
Antihistamines	Antihistamines Stimulation therapy agents Non-specific immunogenic agents Other allergy drugs
Psychotropic	Psychotropic drugs (one group)

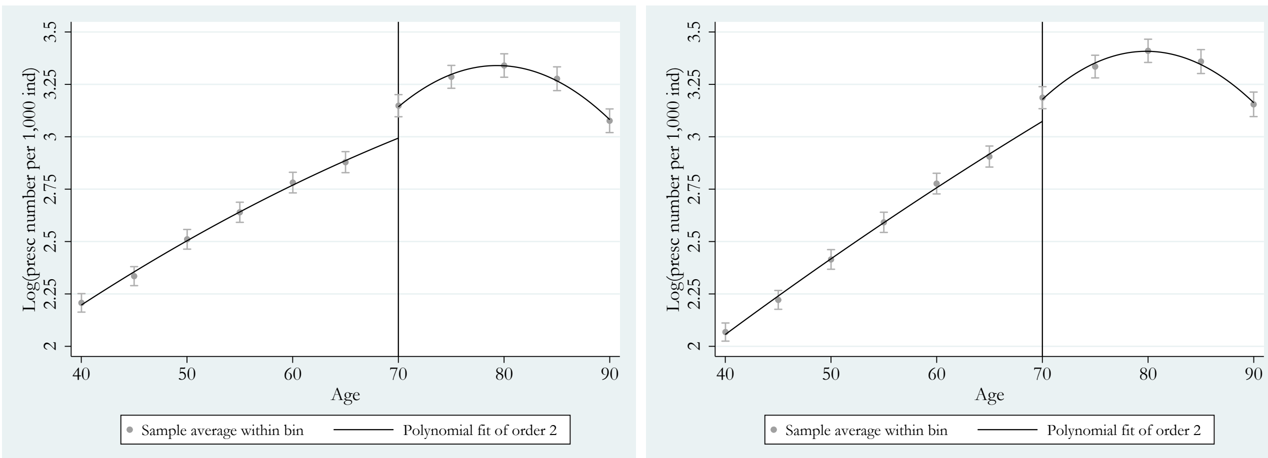
[a] Drug groups that treat high blood pressure.

Appendix B Effect of changes in patient cost sharing on prescription volume

Figure B.1: RD plots by sex, all drug groups

Panel A: Rx volume, women

Panel B: Rx volume, men



Each point is a sample mean for an age group bin. Each age bin corresponds to 5 years. Discontinuity at age 70 only. Brackets around each point estimate are the 95% CI.

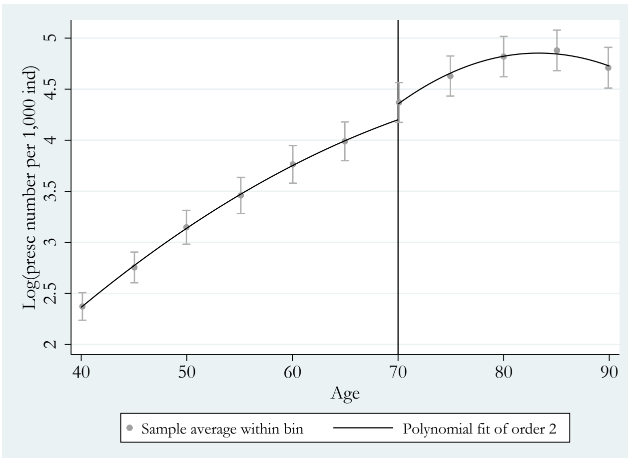
Table B.1: Regression estimates (discontinuity at age 70): Rx volume, all drug groups

	(1)	(2)	(3)
Age	0.0255***	0.0255***	0.0255***
	(0.0025)	(0.0025)	(0.0025)
Post70	0.1387***	0.2253***	0.2883***
	(0.0169)	(0.0531)	(0.0641)
Post70 × Age	0.0190**	0.0190**	0.0190**
	(0.0052)	(0.0052)	(0.0052)
Age^2	-0.0002	-0.0002	-0.0002
	(0.0001)	(0.0001)	(0.0001)
Post70 × Age^2	-0.0022***	-0.0022***	-0.0022***
	(0.0002)	(0.0002)	(0.0002)
Price	-0.0099**	-0.0105**	-0.0105**
	(0.0029)	(0.0029)	(0.0029)
Price × Post70	-0.0051***	-0.0048***	-0.0048***
	(0.0011)	(0.0011)	(0.0011)
Brand-name		0.2531*	0.2503*
		(0.1155)	(0.1171)
Brand-name × Post70		-0.1345	-0.1345
		(0.0664)	(0.0664)
Female			0.0587
			(0.0827)
Female × Post70			-0.1260
			(0.0691)
Female × Brand-name			0.0058
			(0.0609)
Observations	192104	192104	192104

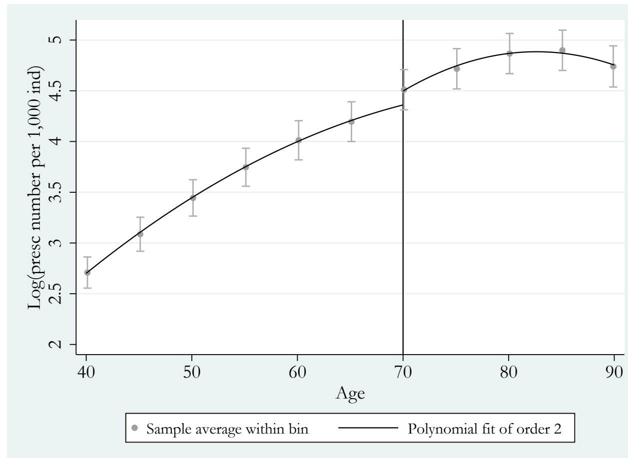
Outcome: log number of prescriptions for drug j in therapeutic class k per 1000 individuals of sex s in age group a in year t. Standard errors are in parentheses and are clustered at the therapeutic class level. All estimations include year fixed effects, which is determined by the Japanese fiscal year (from April 1 to March 31 of the following year). Regression model is estimated with patient coinsurance rate discontinuity at age 70. Significance levels $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Figure B.2: RD plot by therapeutic class: Cardiovascular drugs (all groups)

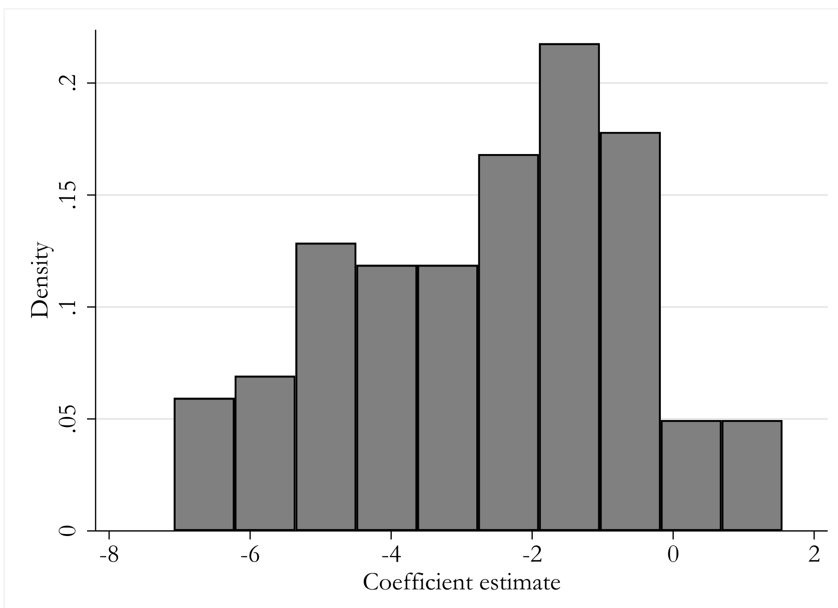
Panel A:
Rx volume, women



Panel B:
Rx volume, men



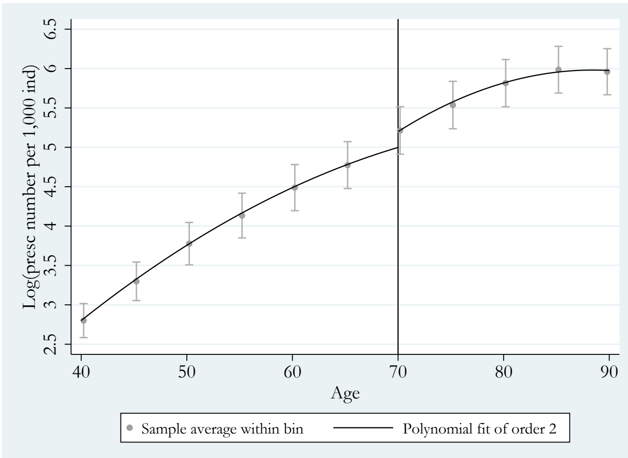
Panel C: Distribution of coefficients



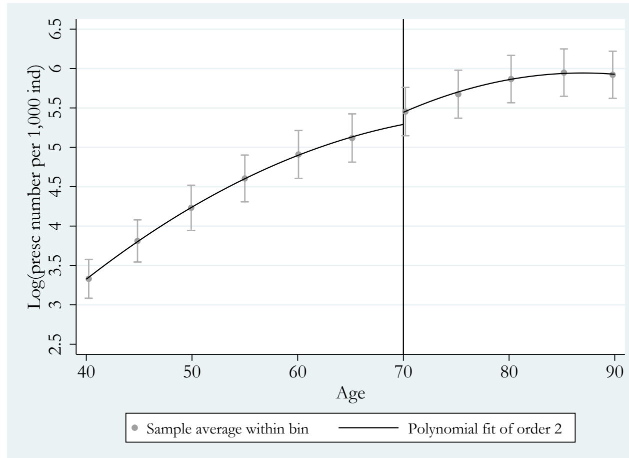
Panels A and B: Each point is a sample mean for an age group bin. Each age bin corresponds to 5 years. Brackets around each point estimate are the 95% CI.
Panel C: Histogram shows distribution of statistically significant (p-value< 0.05) coefficients for individual drug-formulations in this class of drugs. Coefficients with values greater than 50 omitted for ease of visualization.

Figure B.3: RD plot by therapeutic class: Cardiovascular drugs (high blood pressure groups)

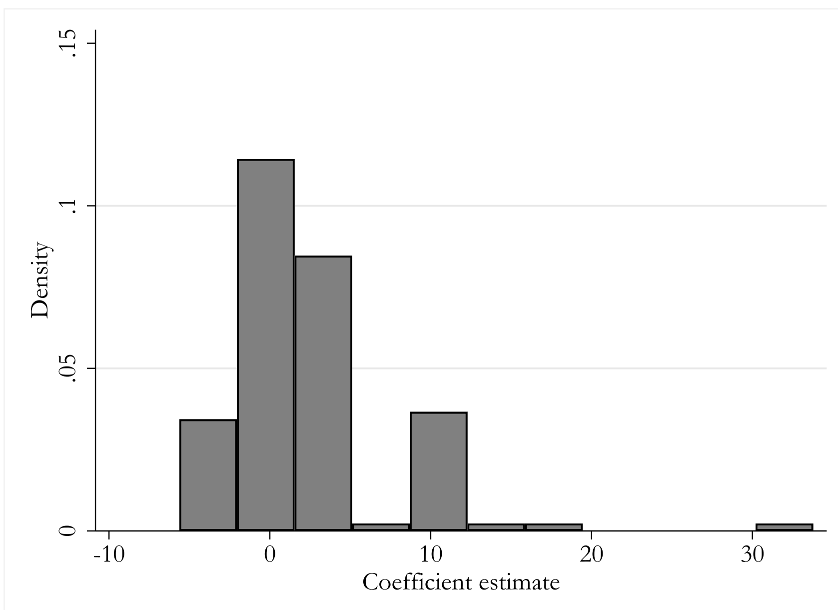
Panel A:
Rx volume, women



Panel B:
Rx volume, men



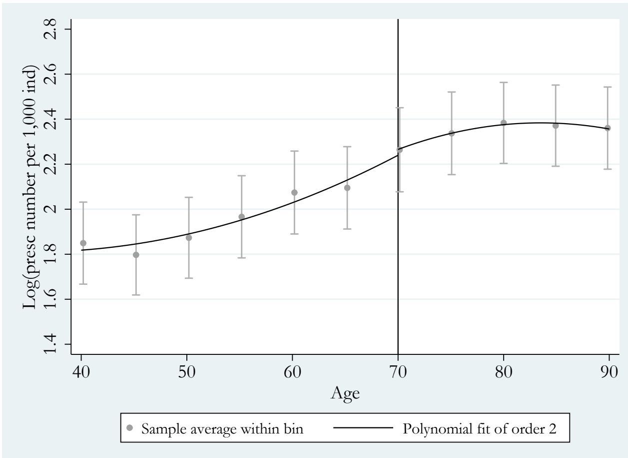
Panel C: Distribution of coefficients



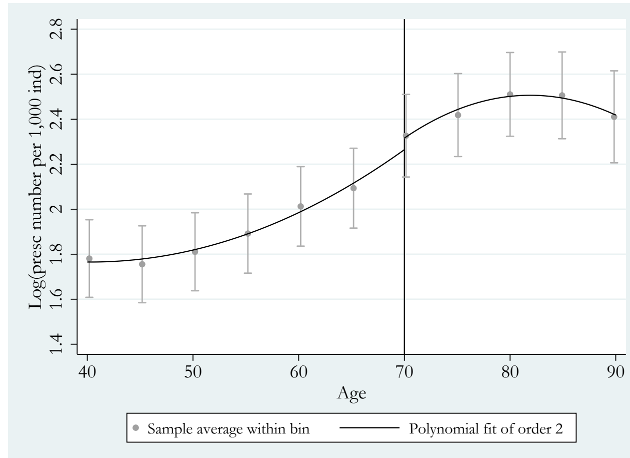
Panels A and B: Each point is a sample mean for an age group bin. Each age bin corresponds to 5 years. Brackets around each point estimate are the 95% CI.
Panel C: Histogram shows distribution of statistically significant (p-value< 0.05) coefficients for individual drug-formulations in this class of drugs. Coefficients with values greater than 50 omitted for ease of visualization.

Figure B.4: RD plot by therapeutic class: Antibiotics

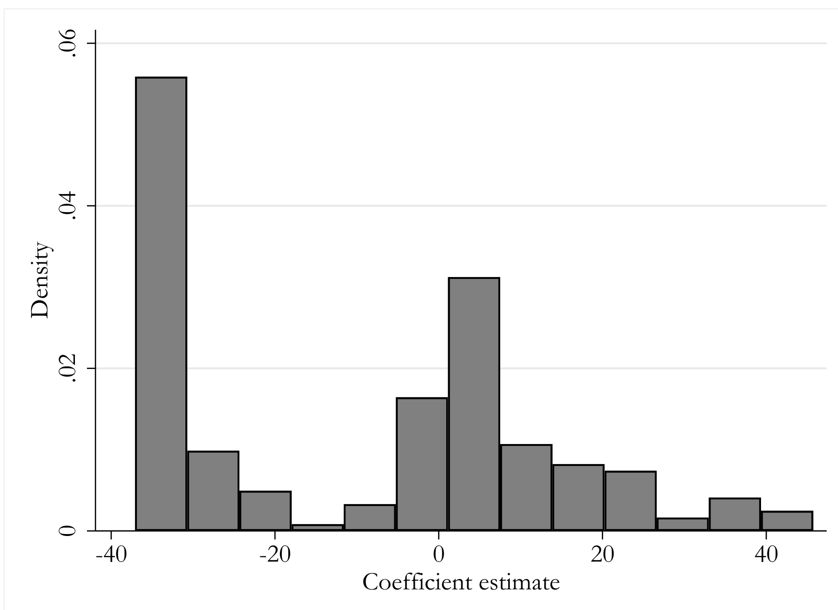
Panel A:
Rx volume, women



Panel B:
Rx volume, men



Panel C: Distribution of coefficients



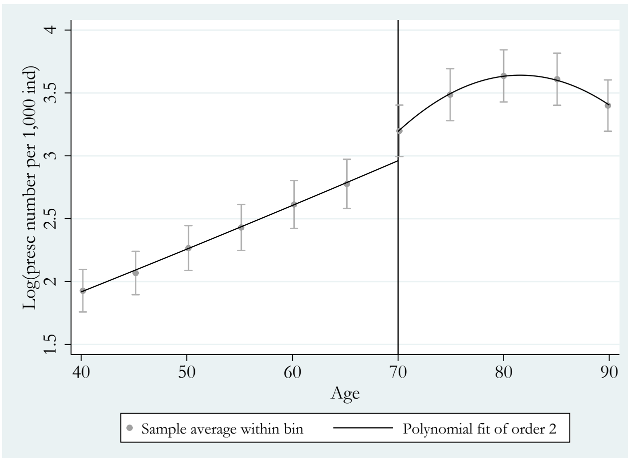
Panels A and B: Each point is a sample mean for an age group bin. Each age bin corresponds to 5 years. Brackets around each point estimate are the 95% CI.
Panel C: Histogram shows distribution of statistically significant (p-value< 0.05) coefficients for individual drug-formulations in this class of drugs. Coefficients with values greater than 50 omitted for ease of visualization.

Table B.2: Regression Estimates: Rx volume, by therapeutic class

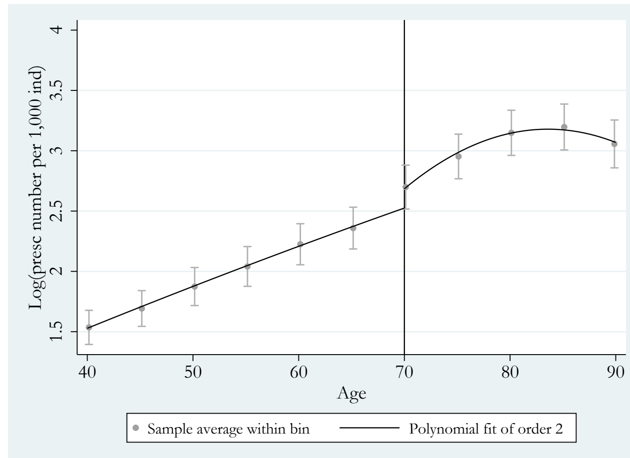
	(1) Cardiovascular (all)	(2) Cardiovascular (HBP)	(3) Antibiotics
Age	0.0317*	0.0332	0.0291*
	(0.0139)	(0.0221)	(0.0144)
Post70	0.0558	0.0654	0.0498
	(0.1392)	(0.2205)	(0.1381)
Post70 × Age	0.0364	0.0386	-0.0044
	(0.0201)	(0.0312)	(0.0202)
Age^2	-0.0009*	-0.0012*	0.0005
	(0.0004)	(0.0006)	(0.0004)
Post70 × Age^2	-0.0017*	-0.0008	-0.0015
	(0.0008)	(0.0012)	(0.0008)
Price	-1.1589***	-2.2832***	-0.8237***
	(0.0275)	(0.1091)	(0.0543)
Price × Post70	-0.3209***	-0.6248**	-0.0247
	(0.0506)	(0.2052)	(0.0783)
Brand-name	0.9037***	1.1011***	0.3196***
	(0.0619)	(0.1020)	(0.0626)
Brand-name × Post70	0.1222	-0.0027	0.1286
	(0.0753)	(0.1209)	(0.0778)
Female	-0.2624***	-0.5189***	0.0568
	(0.0626)	(0.1061)	(0.0639)
Female × Post70	0.2193**	0.3851***	-0.1427
	(0.0751)	(0.1162)	(0.0760)
Female × Brand-name	-0.0374	0.1015	-0.0096
	(0.0742)	(0.1182)	(0.0755)
Observations	17556	6776	9064

Figure B.5: RD plot by therapeutic class: Vitamins

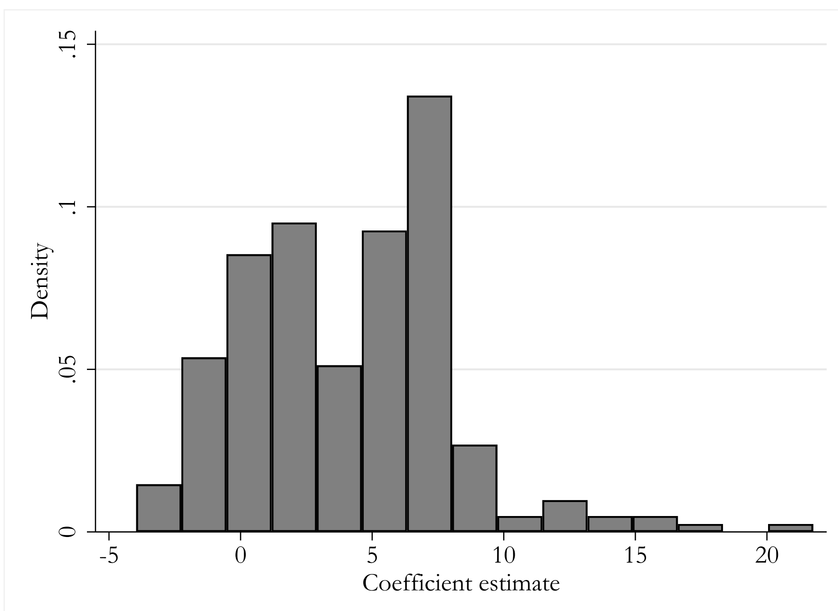
Panel A: Rx volume, women



Panel B: Rx volume, men



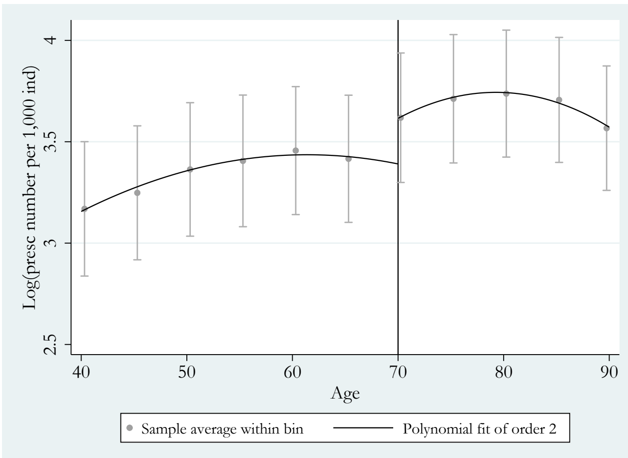
Panel C: Distribution of coefficients



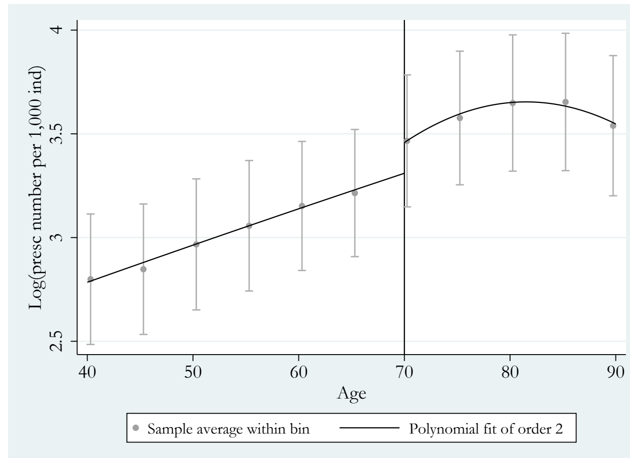
Panels A and B: Each point is a sample mean for an age group bin. Each age bin corresponds to 5 years. Brackets around each point estimate are the 95% CI.
Panel C: Histogram shows distribution of statistically significant (p-value< 0.05) coefficients for individual drug-formulations in this class of drugs. Coefficients with values greater than 50 omitted for ease of visualization.

Figure B.6: RD plot by therapeutic class: Antihistamines

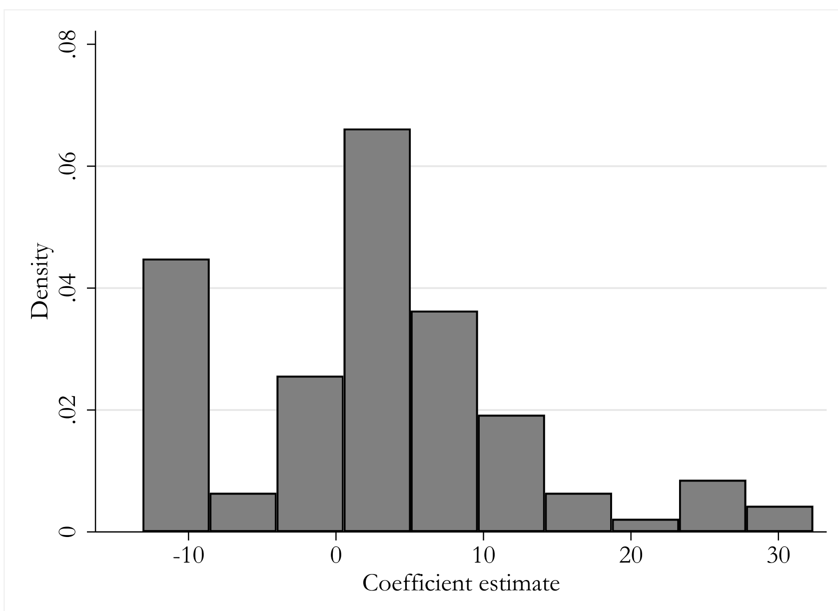
Panel A:
Rx volume, women



Panel B:
Rx volume, men



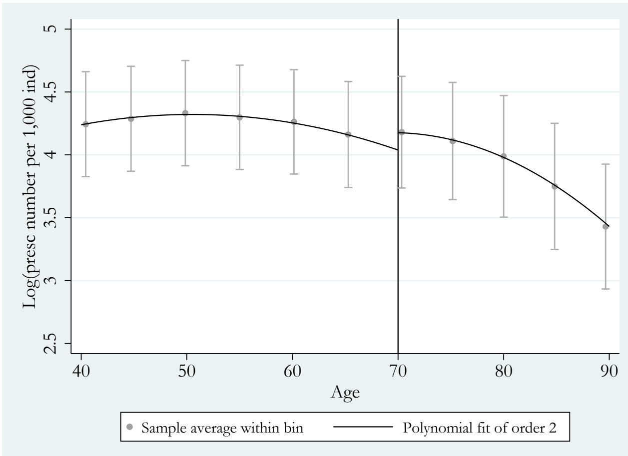
Panel C: Distribution of coefficients



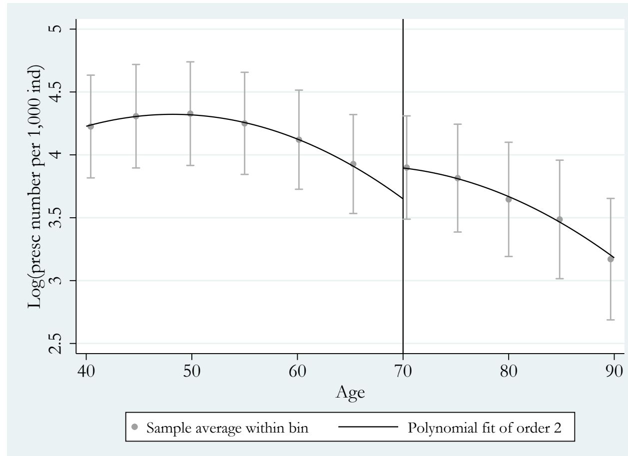
Panels A and B: Each point is a sample mean for an age group bin. Each age bin corresponds to 5 years. Brackets around each point estimate are the 95% CI.
Panel C: Histogram shows distribution of statistically significant (p-value< 0.05) coefficients for individual drug-formulations in this class of drugs. Coefficients with values greater than 50 omitted for ease of visualization.

Figure B.7: RD plot by therapeutic class: Psychotropic drugs

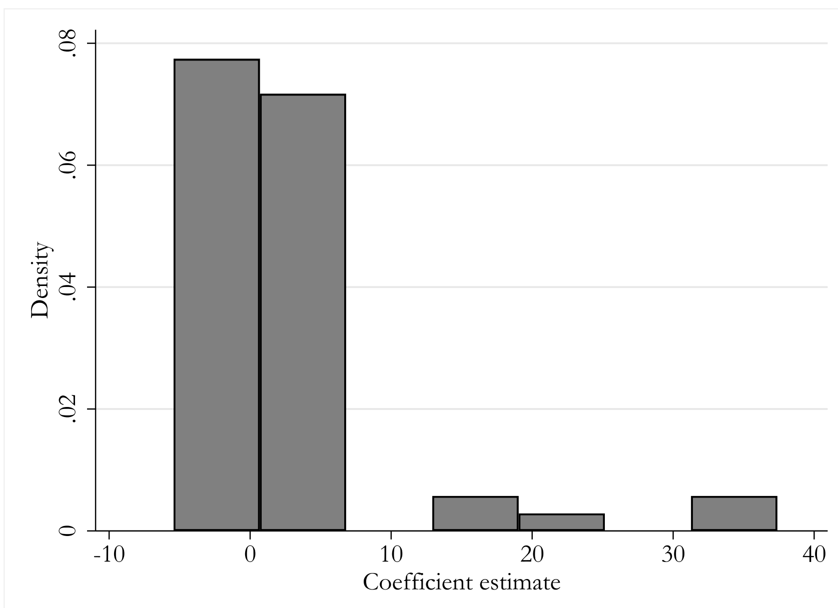
Panel A:
Rx volume, women



Panel B:
Rx volume, men



Panel C: Distribution of coefficients



Panels A and B: Each point is a sample mean for an age group bin. Each age bin corresponds to 5 years. Brackets around each point estimate are the 95% CI.
Panel C: Histogram shows distribution of statistically significant (p-value< 0.05) coefficients for individual drug-formulations in this class of drugs. Coefficients with values greater than 50 omitted for ease of visualization.

Table B.3: Regression Estimates: Rx volume, by therapeutic class

	(1) Vitamins	(2) Antihistamines	(3) Psychotropic
Age	0.0335*	0.0032	-0.0453
	(0.0145)	(0.0262)	(0.0305)
Post70	0.4283**	0.2114	0.6315
	(0.1415)	(0.2475)	(0.3600)
Post70 × Age	0.0416*	0.0277	0.0394
	(0.0211)	(0.0363)	(0.0447)
Age^2	-0.0000	-0.0003	-0.0011
	(0.0004)	(0.0007)	(0.0009)
Post70 × Age^2	-0.0030***	-0.0012	-0.0004
	(0.0008)	(0.0014)	(0.0018)
Price	-0.1400	-0.8226***	-0.0938***
	(0.0787)	(0.0284)	(0.0029)
Price × Post70	-0.4561***	-0.0886*	0.0062
	(0.1223)	(0.0390)	(0.0046)
Brand-name	-0.4541***	0.1082	-0.5382**
	(0.0613)	(0.1146)	(0.1916)
Brand-name × Post70	-0.3943***	0.1698	-0.6523*
	(0.0810)	(0.1384)	(0.2652)
Female	0.5963***	0.3659**	0.1571
	(0.0653)	(0.1214)	(0.2415)
Female × Post70	0.0627	-0.2453	0.2170
	(0.0792)	(0.1367)	(0.1722)
Female × Brand-name	-0.3474***	-0.0468	-0.0987
	(0.0778)	(0.1367)	(0.2547)
Observations	11792	4796	3080

Appendix C Regression discontinuity at age 75

In this section I test a model with a regression discontinuity at age 75 for the full sample of drugs. I test heterogeneity by patient sex but not by drug therapeutic class. Figure C.1 presents the corresponding RD plots. Outcomes are prescription spending (Panels A and B) and prescription volume (Panels C and D) for drug j in therapeutic class k per 1000 individuals of sex s in 5-year age group a in year t.

Columns (1), (2), and (3) in Tables C.1 and C.2 present the results for the following regressions, respectively:

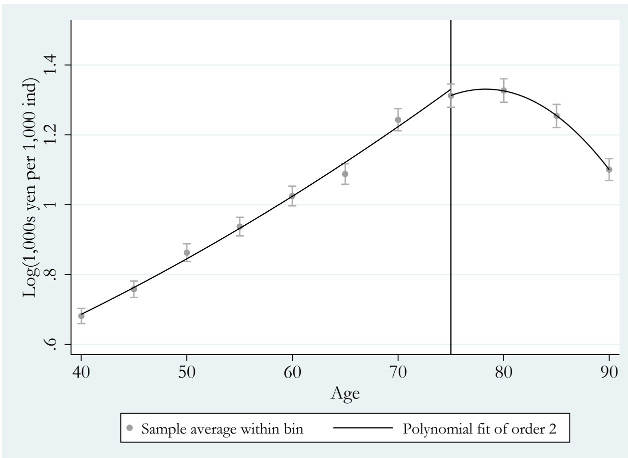
$$Y_{ajkst} = \beta_0 + \beta_1' f(a) + \beta_2 \times post75_{ajkst} + \beta_3' g(Price_{jkt}) + \delta_t + \tau_k + \epsilon_{ajkst} \tag{7}$$

$$\begin{aligned} Y_{ajkst} = \alpha_0 + \alpha_1' f(a) + \alpha_2 \times post75_{ajkst} + \alpha_3' g(Price_{jkt}) + \\ + \alpha_4' h(brand_{jkt}) + \alpha_5 + \delta_t + \tau_k + \omega_{ajkst} \end{aligned} \tag{8}$$

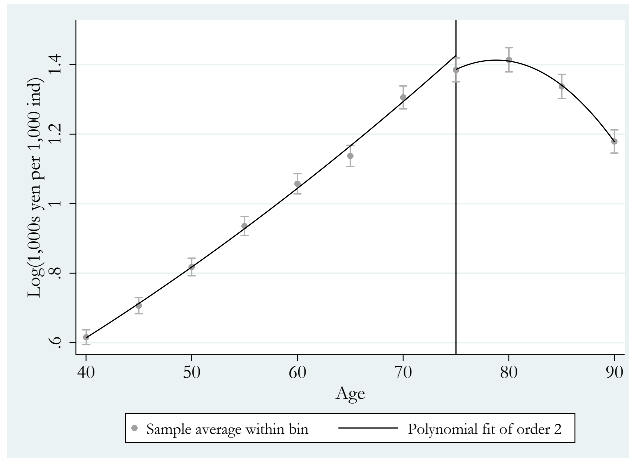
$$\begin{aligned} Y_{ajkst} = \gamma_0 + \gamma_1' f(a) + \gamma_2 post75_{ajkst} + \gamma_3' g(Price_{jkt}) + \gamma_4' h(brand_{jkt}) \\ + \gamma_5' m(female_{ast}) + \gamma_6 brand_{jkt} \times female_{ast} + \delta_t + \tau_k + \varepsilon_{ajkst} \end{aligned} \tag{9}$$

Figure C.1: RD plot (discontinuity at age 75): Rx spending and volume, by sex

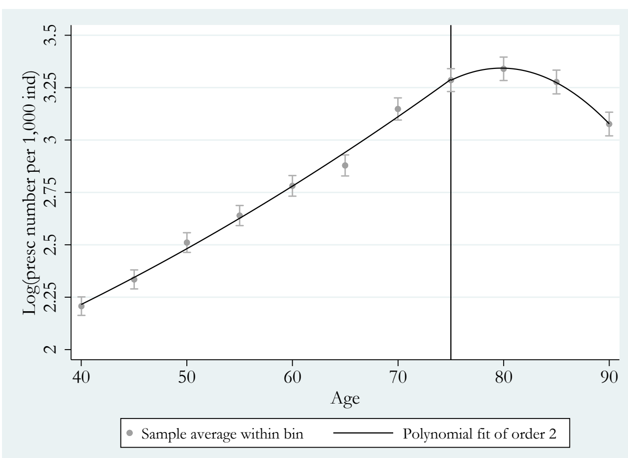
Panel A:
Rx spending, women



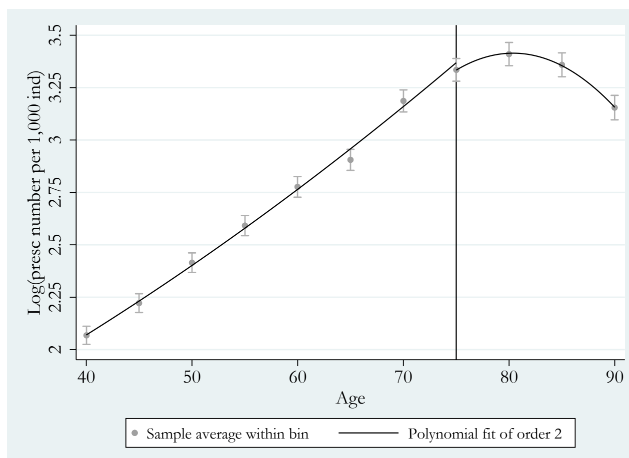
Panel B:
Rx spending, men



Panel C:
Rx volume, women



Panel D:
Rx volume, men



Each point is a sample mean for an age group bin. Each age bin corresponds to 5 years. Discontinuity at age 75 only. Brackets around each point estimate are the 95% CI.

Table C.1: Regression estimates (discontinuity at age 75): Rx spending, all drug groups

	(1)	(2)	(3)
Age	0.0246***	0.0246***	0.0246***
	(0.0019)	(0.0019)	(0.0019)
Post75	-0.0117	-0.0221	0.0194
	(0.0103)	(0.0330)	(0.0395)
Post75 × Age	-0.0119*	-0.0119*	-0.0119*
	(0.0050)	(0.0050)	(0.0050)
Age^2	0.0001	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)
Post75 × Age^2	-0.0019***	-0.0019***	-0.0019***
	(0.0002)	(0.0002)	(0.0002)
Price	0.0100**	0.0086**	0.0086**
	(0.0027)	(0.0027)	(0.0027)
Price × Post75	-0.0076***	-0.0076***	-0.0076***
	(0.0018)	(0.0018)	(0.0018)
Brand-name		0.6031***	0.6125***
		(0.0702)	(0.0714)
Brand-name × Post75		0.0161	0.0161
		(0.0509)	(0.0509)
Female			0.0151
			(0.0405)
Female × Post75			-0.0831
			(0.0522)
Female × Brand-name			-0.0187
			(0.0243)
Observations	192104	192104	192104

Outcome: log prescription spending (in 1000s of yen) on drug j in therapeutic class k by 1000 individuals of sex s in age group a in year t. Standard errors are in parentheses and are clustered at the therapeutic class level. All estimations include year fixed effects, which is determined by the Japanese fiscal year (from April 1 to March 31 of the following year). Regression model is estimated with patient coinsurance rate discontinuity at age 75. Significance levels $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table C.2: Regression estimates (discontinuity at age 75): Rx volume, all drug groups

	(1)	(2)	(3)
Age	0.0395***	0.0395***	0.0395***
	(0.0031)	(0.0031)	(0.0031)
Post75	-0.0078	0.0853	0.1443*
	(0.0132)	(0.0493)	(0.0605)
Post75 × Age	-0.0123**	-0.0123**	-0.0123**
	(0.0037)	(0.0037)	(0.0037)
Age^2	0.0002	0.0002	0.0002
	(0.0001)	(0.0001)	(0.0001)
Post75 × Age^2	-0.0028***	-0.0028***	-0.0028***
	(0.0002)	(0.0002)	(0.0002)
Price	-0.0103**	-0.0109**	-0.0109**
	(0.0029)	(0.0030)	(0.0030)
Price × Post75	-0.0053***	-0.0049***	-0.0049***
	(0.0013)	(0.0012)	(0.0012)
Brand-name		0.2446	0.2417
		(0.1181)	(0.1196)
Brand-name × Post75		-0.1446*	-0.1446*
		(0.0659)	(0.0659)
Female			0.0443
			(0.0807)
Female × Post75			-0.1179
			(0.0663)
Female × Brand-name			0.0058
			(0.0609)
Observations	192104	192104	192104

Outcome: log number of prescriptions for drug j in therapeutic class k per 1000 individuals of sex s in age group a in year t. Standard errors are in parentheses and are clustered at the therapeutic class level. All estimations include year fixed effects, which is determined by the Japanese fiscal year (from April 1 to March 31 of the following year). Regression model is estimated with patient coinsurance rate discontinuity at age 75. Significance levels $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table C.3: Regression estimates (discontinuity at age 75): Rx spending, by therapeutic class

	(1) Cardiovascular (all)	(2) Cardiovascular (HBP)	(3) Antibiotics
Age	0.0308***	0.0341**	0.0225***
	(0.0071)	(0.0120)	(0.0058)
Post75	-0.1849*	-0.2833*	-0.0601
	(0.0864)	(0.1443)	(0.0677)
Post75 × Age	0.0087	0.0116	-0.0124
	(0.0160)	(0.0263)	(0.0125)
Age^2	-0.0002	-0.0004	0.0003*
	(0.0002)	(0.0003)	(0.0001)
Post75 × Age^2	-0.0024**	-0.0015	-0.0009
	(0.0009)	(0.0015)	(0.0007)
Price	-0.1080***	-0.4923***	0.0317
	(0.0172)	(0.0808)	(0.0258)
Price × Post75	-0.0573	-0.3400	0.1236*
	(0.0360)	(0.1836)	(0.0541)
Brand-name	1.0019***	1.2691***	0.3400***
	(0.0369)	(0.0632)	(0.0297)
Brand-name × Post75	0.2542***	0.3779***	0.0582
	(0.0512)	(0.0848)	(0.0427)
Female	-0.1515***	-0.3001***	0.0315
	(0.0330)	(0.0578)	(0.0265)
Female × Post75	0.1381*	0.2655**	-0.1139**
	(0.0538)	(0.0889)	(0.0428)
Female × Brand-name	-0.0449	0.0055	-0.0115
	(0.0466)	(0.0772)	(0.0389)
Observations	17556	6776	9064

Outcome: log number of prescriptions for drug j in therapeutic class k per 1000 individuals of sex s in age group a in year t. Standard errors are in parentheses and are clustered at the therapeutic class level. All estimations include year fixed effects, which is determined by the Japanese fiscal year (from April 1 to March 31 of the following year). Regression model is estimated with patient coinsurance rate discontinuity at age 75. Significance levels $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table C.4: Regression estimates (discontinuity at age 75): Rx spending, by therapeutic class

	(1) Vitamins	(2) Antihistamines	(3) Psychotropic
Age	0.0246***	0.0115	-0.0346*
	(0.0044)	(0.0135)	(0.0163)
Post75	0.0279	0.0008	0.7341***
	(0.0573)	(0.1560)	(0.1936)
Post75 × Age	-0.0008	0.0002	0.0364
	(0.0114)	(0.0287)	(0.0336)
Age^2	0.0003**	0.0001	-0.0005
	(0.0001)	(0.0003)	(0.0004)
Post75 × Age^2	-0.0018**	-0.0009	-0.0008
	(0.0007)	(0.0016)	(0.0019)
Price	1.6444***	-0.1450***	-0.0107***
	(0.0618)	(0.0290)	(0.0029)
Price × Post75	-0.2530*	-0.0528	-0.0299***
	(0.1114)	(0.0532)	(0.0036)
Brand-name	0.0928***	0.3033***	1.0528***
	(0.0209)	(0.0672)	(0.0774)
Brand-name × Post75	-0.0599	0.1874*	-0.6481***
	(0.0372)	(0.0938)	(0.1205)
Female	0.1979***	0.1496*	0.1456
	(0.0231)	(0.0684)	(0.0930)
Female × Post75	0.0855*	-0.1685	0.1297
	(0.0377)	(0.0982)	(0.1161)
Female × Brand-name	-0.0979**	0.0228	-0.0339
	(0.0317)	(0.0877)	(0.1062)
Observations	11792	4796	3080

Outcome: log number of prescriptions for drug j in therapeutic class k per 1000 individuals of sex s in age group a in year t. Standard errors are in parentheses and are clustered at the therapeutic class level. All estimations include year fixed effects, which is determined by the Japanese fiscal year (from April 1 to March 31 of the following year). Regression model is estimated with patient coinsurance rate discontinuity at age 75. Significance levels $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Appendix D Internal validity check

For this check of internal validity, I focus on homicide death rates as the placebo outcome variable. Chay and Greenstone (2003), who study the influence of pollution on infant mortality, use mortality from external causes such as accidents and homicides as the outcome in their validity check. I do not consider deaths from accidents for the placebo outcomes, since a reduction in the coinsurance rate may worsen moral hazard and make individuals behave in a riskier manner, leading to more accident-related deaths. I likewise do not consider other types of spending as placebo outcomes, since a reduction in the price of medical services would have an income effect on the consumption of other goods. Depending on the magnitude of the substitution effect, a change in the coinsurance rate could have a significant effect on spending for other goods and services, making it a poor choice to pick up the effect of other coinciding factors.

Data on homicide death rates from 2014 to 2016 come from General Mortality files of the Vital Statistics of Japan (Ministry of Health, Labor and Welfare, 2021). The death rate is defined as:

$$\text{(Death Rate)}_{ast} = \frac{\text{(Number of deaths)}_{ast}}{\text{Population}_{ast}} \tag{10}$$

for 5-year age group a, sex $s \in Male, Female$, in year t. Population is annual population of Japan for the given sex and age group on October 1 of year t. To match my prescription drug sample, I focus on individuals from 40 (40-44 age group) to 94 (90-94 age group) years of age.

To test for statistical significance, I use the following regression:

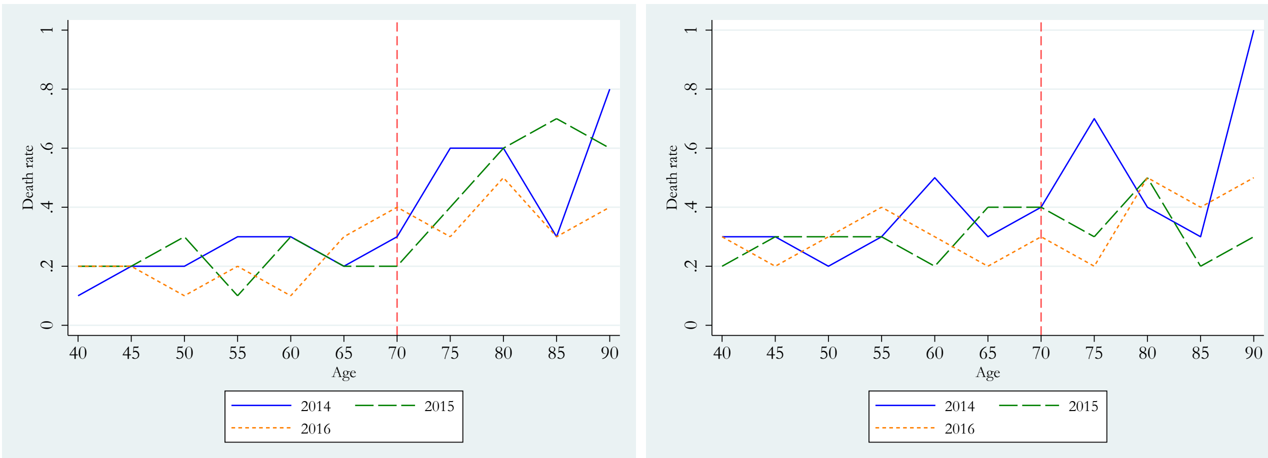
$$Y_{adst} = \kappa_0 + \kappa_1' f(a) + \kappa_2 \times post70_{adst} + \kappa_3 female_{ast} + \xi_{adst} \tag{11}$$

where $f(a)$, $post70$, and $female$ are defined as they were for eq. 5, and ξ_{adst} is the error term.

Figure D.1: Homicide death rates by sex

Panel A: Homicide death rate, women

Panel B: Homicide death rate, men



Data source: *Vital Statistics of Japan*, 2014-2016, Ministry of Health, Labor and Welfare. Homicide death rate for each 5-year age group a for sex s in year t is defined as number of deaths for group a sex s year t divided by the population for group a sex s on October 1 of year t.

Table D.1: Regression results: Homicide death rates

	(1) Homicides
Age	-0.0000
	(0.0081)
Post70	0.0160
	(0.0834)
Post70 × Age	0.0068
	(0.0155)
Age^2	-0.0001
	(0.0002)
Post70 × Age^2	0.0002
	(0.0008)
Female	-0.0889**
	(0.0268)
Female × Post70	0.1289
	(0.0689)
Observations	66

Outcome is homicide death rate for 5-year age group a for sex s. Regression includes year fixed effects. Standard errors are robust.