Prioritizing Value? How Low-Income Patients Respond to Prescription Cost-Sharing

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Abstract

Cost-sharing is widely used in health insurance plans to encourage patients to prioritize cost-effective care. This paper studies whether older low-income patients exhibit this prioritizing behavior when cost-sharing for their prescriptions sharply increases. Variation in cost-sharing comes from a redetermination discontinuity wherein Medicare-Medicaid patients are differentially guaranteed an additional year of a full prescription drug subsidy (the Low-Income Subsidy) based on the month they lose Medicaid. Patients who lose Medicaid after July are highly likely to be guaranteed, whereas patients who lose Medicaid before are not. Absent the subsidy, the fraction of total prescription costs patients pay increases from 2pp to 27pp on average. Regression discontinuity estimates comparing patients across the cutoff show patients that lose Medicaid before the cutoff are 49pp more likely to lose the subsidy in the next year compared to patients that lose Medicaid after. The higher prices resulting from patients losing the subsidy leads to a 38% reduction in total prescription expenditures driven by a 15% reduction in the quantity of prescriptions filled. Higher-priced prescriptions have larger reductions in quantity, irrespective of the drugs' health benefits. For example, patients reduce their quantity of insulin filled by 26%. Elevated cost-sharing, additionally, does not increase switching from brands to equally effective generics. This behavior suggests higher prescription drug cost-sharing greatly reduces prescription accessibility without inducing more cost-effective behavior for low-income groups.

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1 Introduction

Sharing a fraction of the total cost with patients, also known as cost-sharing, is a common feature of health insurance plans. Cost-sharing is widely believed to induce patients to prioritize their most cost-effective care. However, patients' ability to prioritize care may be limited because it takes a high level of expertise to evaluate the benefit of care. This paper evaluates how patients respond to cost sharing in the context of prescription drug insurance for older Americans near the federal poverty line. These patients are unique within the US population because they have both a low ability to pay but are also eligible for federal subsidies that eliminate most costs associated with purchasing prescription drugs. The subsidies generate a tradeoff between improving accessibility of prescriptions and incentivizing cost-effectiveness.

This paper uses a sharp increase in prescription drugs costs caused by a discontinuity to assess the prescription purchase decisions of low-income Medicare beneficiaries. Specifically, the variation comes from losing the Low-Income Subsidy ("the subsidy"), a means-tested federal program that limits its costs for prescription drugs to a few dollars per fill. Those who qualified for the subsidy through enrollment in Medicaid, a public insurance program for low-income individuals, face different exposure to the subsidy based on the month they lose Medicaid benefits. Individuals who lose Medicaid prior to the end of July can lose subsidy benefits as soon as the coming January, but those who lose Medicaid after July are guaranteed benefits through the next calendar year. Importantly, subsidy loss occurs at least several months after the loss of Medicaid. As such, the setting lends itself to a regression discontinuity design comparing otherwise similar patients across the cutoff who vary only in their difference in exposure to the subsidy in the year following Medicaid loss.

In the first January after Medicaid loss, 49 percent of individuals who lose Medicaid before the cutoff will lose the subsidy, with 80 percent of them losing it for the entire calendar year.[1] For those who lose the subsidy, the average increase in cost-sharing is 25 percent of the drug price, or $20 per prescription filled on average. Patients who lose the subsidy on average respond to the cost increases by reducing their quantity, as measured by days' supply, by 15 percent and total prescription expenditures by 38 percent. The average percent reduction in expenditures is more than twice the percent reduction of quantity, indicative that higher priced prescriptions are more apt to be reduced.

For all prescriptions, irrespective of their health value, price appears to be the most significant

[1] Not all individuals will lose subsidy eligibility because about half will regain Medicaid before the end of the year and as soon as they regain Medicaid, they automatically receive the subsidy.

predictor of quantity reductions. The paper reports the percentage reduction in quantity for the 200 most common prescriptions caused by the subsidy loss and the out-of-pocket cost strongly predicts the reduction in quantity. The predicted quantity reduction is nearly identical for prescriptions classified as likely to prevent an adverse health event soon ("high value"), or quality of life improving, but unlikely to impact the rate of adverse events ("low value"),[2] with the value tags adding no predictive power.

Of course, there are many patient-specific factors that determine a drug's value, but there are several prescriptions that are unambiguously valuable and necessary. An example of a higher cost unambiguously valuable class of prescriptions is insulin, which is used for managing severe forms of diabetes. Insulins cost an average of $41 out-of-pocket to fill, which is substantially larger than the $22 out-of-pocket cost of the average prescription. Individuals who lost the subsidy reduced their quantity filled of insulin by 26 percent. Even though insulin is certainly more important than the average prescription, the percentage reduction in insulin prescriptions is 75 percent larger than the average prescription. Accessibility of highly important prescriptions is clearly hindered with higher costs.

The focus on cost has important policy implications because it helps identify where the reduction in aggregate prescription spending would come from if cost-sharing were increased. In the aggregate, 60% of the reduction in spending caused by the loss of subsidy is concentrated in "high value" prescriptions compared to 15% in "low value" prescriptions.[3] The differential in effect between the two types of prescriptions is a result of especially high drops in the utilization of high cost prescriptions, the vast majority of which are "high value". Although cost-sharing does successfully reduce spending, the reductions largely reflect lack of accessibility rather than reducing waste.

The paper additionally shows that cost-sharing does not increase the propensity of consumers to switch from branded versions of drugs to the more cost-effective and equally valuable generics, the simplest way to be more cost-effective. Instead, there is a large reduction of these branded prescriptions altogether.

The analysis provided in this paper combines two previously separate features in the economics literature on prescription drug cost-sharing: low-income groups and large, uncapped increases in prices. Prior work has leveraged large increases in prices, but have only been able to focus on higher

[2] The classifications were formed by a panel of physicians and used in Chandra et. al 2010. 15% of prescriptions are not categorized in the data.

[3] The reduction in spending is relative to the 85% of prescription that are classified by value.

income groups. Combining these two settings is especially important because the small and fixed increases in prices used thus far to study low-income groups may not fully demonstrate how these patients are limited by their financial constraints. In this paper, the large reductions of even unambiguously valuable but higher cost prescriptions showcase the role of these constraints.

The analysis also provides the first causal analysis of the effect of the Low-Income Subsidy, a $26 billion-dollar federal program. The analysis shows the program has at most limited crowd-out of private spending as most of spending reduction comes from "high value" and higher cost prescriptions.

2 Background

2.1 The impacts of cost-sharing on utilization

Sharing a fraction of medical expenditures with the patient, cost-sharing, is health insurers' preferred method to set costs for patients (Baicker and Goldman, 2011). A key motivation for this form of partial cost-sharing is to encourage patients to be more cost-effective, either by limiting wasteful spending or by shopping around for cheaper but similarly valuable care. Indeed, there is literature showing cost-sharing can be effective in inducing patients to seek out more cost-effective care. For example, differential levels of cost-sharing successfully increased the number of patients using low-price high-quality facilities for knee replacements (Zhang, Cowling and Facer 2017).

As cost-sharing is the most common way patient prices are set, there has long been an interest in how cost-sharing impacts utilization, with the seminal RAND Health Insurance Experiment (HIE) on cost-sharing dating back to the 1970s (Newhouse, 1993). Cost-sharing for prescription drugs receives special attention both because it constitutes a rapidly growing sector of healthcare spending,[4] and is often insured separately (Baicker and Goldman, 2011). Moreover, there is budding evidence that prescription utilization is tightly tied to health outcomes (Chandra et al., 2010, 2021; Huh and Reif, 2017).

An established literature on prescription drug cost-sharing demonstrates patients are highly responsive to prices. A common form of pricing variation in this literature comes from broad changes to insurance plans, recovering the effect on prescription utilization from higher overall healthcare costs in addition to higher prescription costs. For example, Brot-Goldberg et al. (2017) leverage a natural experiment that switched patients from no cost-sharing to high-deductible plans with significant cost-sharing and find large reductions in all forms of healthcare utilization including prescription drugs.

[4]The federal government spent $100 billion dollars on prescriptions in 2019

Chandra et al. (2010) are able to partially circumvent the bundled insurance problem by leveraging changes to two separate insurance plan for patients in the California Public Employees Retirement System. The first only changed the cost of prescriptions, and the second was a bundled increase in the cost of office visits and prescriptions. While both plan changes increased the costs of filling prescriptions by around $7 on average, the plan with increased office costs produced a much larger effect size. Papers have also shown that patients respond not only to current prices, but also future prices. In expectation of significant pricing changes in the future, patients respond by shifting more prescription purchases to the cheaper periods (Alpert, 2016; Aron-Dine et al., 2015; Brot-Goldberg et al., 2017; Einav, Finkelstein, and Schrimpf, Einav et al.).

A recent advancement in the literature isolates the effects prescription cost-sharing among non-Medicaid Medicare beneficiaries (Chandra et al., 2021). They leverage a patient's initial enrollment month in Medicare to generate substantially different prescription cost-sharing at the end of the year based on expected utilization and the probability of facing the donut hole, effectively a lapse in prescription coverage. Here only prescription drug costs are affected and the prices reflect a fraction of prescription costs rather than a fixed amount. The reduction in prescription expenditures are substantial and point to a larger consequence of lower prescription utilization, higher mortality rates.

A limitation of the studies listed above is that they largely apply to higher income patients, and might not generalize to low-income patients where financial constraints should make them even more responsive to costs. A potential consequence of larger prescription response could be higher utilization of more costly healthcare like hospitalizations as in Chandra et al. (2010), or in the most serious case mortality (Chandra et al., 2021). However, understanding how low-income groups respond to cost-sharing is difficult because the federal government shields this population from costs. Some advances in understanding how low-income groups respond to prices have leveraged natural experiments in state Medicaid programs where costs increase by small fixed dollar amounts, or copayments (Hartung et al., 2008; Reeder and Nelson, 1985). Even in cases of larger copayment increases as in Chandra et al. (2014), they measure a bundled change to office and prescription costs, making it difficult to identify the sole effect of prescription prices. Still, even in the case of larger copayment increase, the change in costs are relatively small in absolute terms. As such, these papers cannot conclude whether low-income patients respond much differently than their higher income peers. If the small absolute changes in cost-sharing do not push patients against their financial constraints, then there might not be a reason this group would respond differently to prices.

In this paper the increases in costs are considerable and proportional to the prescription cost, likely pushing many low-income patients to the point that financial constraints bind.

This paper provides the first causal evidence on how low-income groups respond to a large, nearly 25pp, increase in prescription cost-sharing [5] caused by quasi-random loss of the Low-Income Subsidy. One of the closest papers in terms of magnitude of variation in low-income groups is Tamblyn et al. (2001). They leverage a 25% increase in cost-sharing in Quebec and reports large reductions in utilization. However, some limitations of this setting include an out-of-pocket maximum $200 for welfare recipients, likely limiting the impact of financial constraints, and the lack of a control population. There is also cross-sectional work that reports patients with the Low-Income Subsidy are much more likely to access extremely high cost and high benefit prescriptions like anti-cancer medications versus those without the subsidy (Chou et al., 2020; Dusetzina et al., 2022). These papers likely understate the impact of the program because the cross-sectional includes differences between low and high resources in addition to subsidy receipt. [6]

2.2 Low-Income Subsidy

The Low-Income Subsidy (the subsidy) is a federal means-tested program that was enacted in the Medicare Modernization Act of 2003, taking effect in 2006. The subsidy is administered by the Social Security Administration (SSA) and provides benefits to nearly 15% of all aged 65 and older Medicare beneficiaries with a total budgetary cost of nearly $26 billion dollars as of 2019. There have traditionally been two levels of the subsidy, full and partial. The partial has slightly more lenient eligibility requirements, but is much less generous.[7] This paper focuses on only the full subsidy.

The subsidy nearly eliminates all costs related to prescription drug insurance. It guarantees prescription drug insurance by covering the premiums and auto-enrolling beneficiaries in a prescription insurance plan if they are not already enrolled, as well as severely limiting the out-of-pocket costs of filling a prescription drug. The costs to the beneficiary are limited through eliminating the deductible, under which beneficiaries are responsible for the full cost of prescriptions, and capping the portion of the total cost patient will pay for any drug to a few dollars. The total value of benefits is estimated to be worth $5,300 per person in 2023 (**?**).

Beneficiaries are eligible and can apply for full benefits if they are on Medicare, have income

[5] Costs are not greatly limited until nearly total prescription expenditures near $5000

[6] There are some very recent papers that use the effectively random assignment into plans via the Low-Income Subsidy to study the effects of prior authorization e.g. (Brot-Goldberg et al., 2023)

[7] All patients who would qualify for the partial subsidy will receive the full subsidy beginning in 2024 as part of the Inflation Reduction Act

beneath 135% of the Federal Poverty Line (FPL), and limited liquid assets.[8] Patients are automatically enrolled in the subsidy if they additionally enrolled in either Medicaid[9] or Supplemental Security Income. Automatic enrollment is the primary method of obtaining the subsidy. Outside of automatic enrollment, take-up is estimated to be 40% of the eligible population (Summer et al., 2010). Once enrolled, benefits generally extend through the end of the year regardless of eligibility, resetting in January in the event of eligibility loss.

In the case of patients who are auto-enrolled via Medicaid, the timing of losing Medicaid has large implications on subsidy status in the coming year. Medicaid is administered at the state level and patients can be checked for Medicaid eligibility and lose access to Medicaid during any month of the year. However, the subsidy is administered federally with the federal office obtaining information on the current stock of Medicaid eligible patients once a year in July (Summer et al., 2010). Patients who no longer qualify through Medicaid will be notified in early September that their benefits will lapse at the end of the year along with instructions of how to apply for benefits if they are eligible. Any patient who is still eligible under the income and asset limits and applies under the eligibility rules will not lose the subsidy in the coming year. A patient who regains Medicaid coverage will also immediately regain the subsidy.

When a patient loses the subsidy, their prescription insurance premiums jump from $0 to around $30 per month. They pay the prescription cost-sharing set by the insurer, on average 25% of total cost, and if their plan has a deductible, are responsible for 100% of the costs prior to clearing it.[10]

If a patient loses Medicaid eligibility in August or later, the federal agency will not be informed of this eligibility change until the following year. As a result, patients who lose Medicaid eligibility after the July will not be included in the stock of patients that can lose the subsidy in the coming year. The first time they could lose the subsidy would instead be the next January. As a result, patients who lose Medicaid after July are guaranteed an additional year of the subsidy.

The most common reason patients lose Medicaid is administrative, not for cause. For example, COVID froze Medicaid rolls for several years with states only recently in the beginning 2023 allowed to update and enforce eligibility requirements. Nearly 72% of the patients that lost Medicaid eligibility after the freeze was lifted was attributed to purely administrative reasons like not having the

[8] In 2020, someone who was single would qualify for full benefits if their income was under $17,225 and assets were under $7,860

[9] Here Medicaid refers to both full Medicaid and partial Medicaid obtained through a Medicare Savings Plan

[10] Patients are now affected by the Part D donut hole without the subsidy

correct paperwork [11]. Even specifically in the Medicare-Medicaid population, administrative issues are believed to be the common reason patients lose access (??, noa). Statistics from the Health and Retirement Study, confirm that large changes in resources are not driving the loss of Medicaid. Table 1 reports the average and median change in both income and assets of patients between the year before patients lost Medicaid and the year they lost Medicaid and neither change in income or assets is substantial.

3 Data

The analysis uses a 20% random sample of Medicare beneficiary claims data from 2008 through 2019. The claims data has several main components in this analysis. First, the data is a panel of Medicaid and Low-Income Subsidy enrollment. Second, the data provides the universe of prescription drug fills for the vast majority of drug plans including the fill date, the total cost, the quantity, the out-of-pocket cost, and specific drug information including the name and NDC code which allow for linkages to several prescription information sources. Some limitations of the prescription data are not capturing prescriptions that are filled outside of insurance, and out-of-pocket costs are not observed if the prescription is not filled.

Drugs are linked to external data sources by NDC code to assign a metric of value and therapeutic class. The primary quality metric is the classification of prescriptions into three different groups by likelihood of adverse event occurring in the absence of taking the prescription (Chandra et al., 2010). [12] Prescriptions whose absence increases that chances of an adverse event within two months are considered "high value," prescriptions whose absence increase the changes of an adverse event within a year are considered "medium value", and those that largely improve quality life, but may not impact the likelihood of an adverse event are considered "low value". Of course, value to a patient depends on many patient-specific factors, but this classification is useful for making broad comparisons between types of prescriptions [13]. Prescriptions are also classified into therapeutic class using the 4-digit Anatomical Therapeutic Chemical (ATC) codes that are maintained by the World Health Organization [14] Exact details of the linkages can be found in the appendix.

[11] https://www.kff.org/report-section/medicaid-enrollment-and-unwinding-tracker-overview/

[12] Classifications are taken from the Lavetti and Simon (2018) replication package. The switcher surplus measure, which captures how insurers value prescriptions, created in Lavetti and Simon (2018) is used to validate the main results

[13] The broad classifications are certainly relevant for insurers, as the average fraction of cost-sharing for high-, medium- and low-value prescriptions in this paper is 25%, 30% and 44% respectively. Pricing on value and elasticity is common in the prescription insurance market (Einav et al., 2018; Lavetti and Simon, 2018; Starc and Town, 2020)

[14] An example of the specificity of a 4-digit code is C10A, statins, the most common treatment of high cholesterol.

3.1 Out-of-Pocket Prices

The prescription plan formularies in 2019 are used to construct a representative out-of-pocket price the average patient would pay for each prescription. The measure is constructed by calculating the price of each drug in every prescription insurance plan open to all patients.[15] The final measure is the average of all the prescription prices weighted by the proportion of patients from the main sample that are enrolled in the plans. A constructed measure of out-of-pocket is useful because the claims data only contains the price the patient paid if the prescription were filled. Given that there is considerable variation in prescription prices across plans, using observed prices would likely be more representative of patients who faced the lowest prices. The constructed measure is used to supplement the prescription expenditure information described above.

3.2 Sample Construction

The primary sample is comprised of all Medicare beneficiaries that lose Medicaid for at least two months[16]. The sample is restricted to beneficiaries that gained Medicare eligibility at age 65 under Old Age and Survivors Insurance, that is to exclude those with severe disability and End Stage Renal Disease. The data is then restricted to patients who fill at least one prescription while covered by the subsidy. The fill restriction both eliminates beneficiaries who are enrolled in plans that do not have reporting and those least likely to be impacted by a change in pricing[17]. Additionally, only patients who enter the year with Medicaid are kept. Many new Medicaid enrollees also gain access to prescription insurance for the the first time and have very different spending patterns. Finally, the sample is restricted to patients who lose Medicaid from June through September, or two months on either side of the cutoff. These restrictions leaves 88,000 beneficiaries, which are the analysis sample[18].

The panel is constructed in event time for years around the first time a patient loses Medicaid [19]. The panel spans the three years beginning in the year a beneficiary loses Medicaid. The three years each cover distinct periods in time for when treatment applies. In the year of Medicaid loss, all patients receive the subsidy. In the first post year, only patients who lost Medicaid before July will have the potential to lose the subsidy. In the final post year, all patients will have been redetermined and can lose the subsidy.

[15] Special needs plans are excluded here.
[16] A loss of one-month or less is plausibly a state administration error that might not require a patient to directly address.
[17] Requiring 1 fill drops 15% of the sample
[18] The additional restrictions are largely to improve precision and can be relaxed. Sample includes patients until their month of death. 84,000 patients survive until treatment
[19] 90 percent of beneficiaries will only have one observed loss event

The top panel of Table 2 shows summary statistics for patients calculated from the Medicare claims data. The first row reports the statistics for the analysis sample of patients who lose Medicaid in the year they lost Medicaid. Patients are on average 75.7 when they lose Medicaid. Given the older ages, it is increasingly unlikely that large changes in income would drive the loss of Medicaid since most of these beneficiaries are no longer in the labor market. Also, 45 percent of patients are non-white, an underrepresented demographic of non-Medicaid enrollees, and a demographic shown to have larger benefits from prescription drug insurance (Huh and Reif, 2017). The average total prescription expenditures, the total paid by the patient and insurer, are \$3,091 for prescriptions. To produce statistics for income and assets in the bottom panel of Table 2, this paper uses data from the 1992-2018 biennial waves of the Health and Retirement Study (HRS). The HRS is not matched to the analysis sample, but the sample can be split into patients over 65 that have Medicare and that lost Medicaid, always had Medicaid and never had Medicaid.

The sample differs from other papers using Medicare to study the effect of cost-sharing on prescription drug utilization. Typically, the Medicaid population is dropped from the analysis because they do not have any major cost-sharing, but as can be seen from the other columns of Table 2, doing so focuses on a healthier and higher income portion of the population.[20] The population studied in this paper is fairly close to patients who are always Medicaid eligible in both health spending and measures of income and assets that are produced externally from the Health and Retirement Study. The low-income Medicare population is also highly policy relevant they have the lowest ability to pay, but also are the target of a high amount of federal spending aimed at reducing or eliminating their healthcare costs.

4 Empirical Approach

The analysis leverages a cutoff in subsidy guarantee based on Medicaid loss month in a discrete regression discontinuity (RD) framework. Patients who lose Medicaid after July are guaranteed an additional year of the subsidy, whereas patients who lose Medicaid before the cutoff are likely to lose the subsidy at the beginning of the next year. In practice, this is a "fuzzy" RD design since losing Medicaid before the cutoff does not ensure subsidy loss. There are other ways to qualify for the subsidy and some individuals may regain Medicaid before the end of the year. Additionally, Medicaid and subsidy status are only observed at the monthly level lending this setting to a a RD with discrete mass

[20] For example, Aron-Dine et al. (2015); Chandra et al. (2021); Einav, Finkelstein, and Schrimpf (Einav et al.); Lavetti and Simon (2018); Starc and Town (2020)

points [21]. The assumption required to identify a discrete RD model is within a small bandwidth of the cutoff patients are as good as randomly assigned to treatment via the running variable. To track how utilization changes over time relative to subsidy loss, this paper primarily reports estimates of the following RD for each relative calendar month.

Under the assumption of local randomization, the primary estimating equation is:

$$Y_{ig}^{k} = \pi_1^k \mathbb{1}(LM_i \leq July) + \gamma_g^k + \varepsilon_{ig}^k \tag{1}$$

Here Y_{ig}^{k} refers to an enrollment or usage outcome for each individual in cohort g at relative month k = 1, 2,..., 36. A cohort is a combination of state by Medicaid loss year, taking into account that states have and use discretion on how strongly to enforce Medicaid requirements.[22] The k=1 month is the January of the year a patient loses Medicaid and the k=36 month is the December two years after losing Medicaid. γ_g^k is a cohort fixed effect, which absorbs and time-invariant differences between cohorts. The identifying assumption is that within each cohort, Medicaid loss month between June and September is as good as random. Finally, LM_i stands for month of Medicaid loss. Treatment status is indicated by whether a patient lost Medicaid before or after the end of July. The coefficient attached to the indicator, π_1, captures the effect of potentially losing the Low-Income Subsidy, or the intent-to-treat (ITT). The paper reports standard errors clustered at the cohort level. P-values are calculated using randomization inference.

The discrete RD approach relies on the assumption that within the narrow bandwidth around the cutoff, assignment to the treatment is as good as random. This paper estimates if observables are different for patients based on their relation to the cutoff to test this assumption. The demographic covariates tested are age, race, ethnicity, drug expenditures and drug supply.[23] Table 3 reports estimates of equation (1) for each covariate listed and none are significantly different for those before versus after the cutoff. Moreover, as a fraction of the mean, the differences are effectively zero. The paper also checks if running variable appears to be manipulated around the cutoff. In the setting of this paper with just four mass points, Figure 1 shows the counts of patients by the month they lost Medicaid. It would be worrisome if there were a large spike counts in August, the first month a patient has access

[21] With only a few mass points, the assumptions needed to estimate an RD with a local polynomial function are not met. (Cattaneo et al., 2023)

[22] Appendix table X shows states are highly variable in the amount of Medicaid patients who are removed from the rolls each year

[23] Here drug utilization measures are from the first quarter the year a patient loses Medicaid so there are no program differences between patients across the cutoff.

to the subsidy guarantee. However, the counts in July and August are similar, with August having slightly fewer patients who lose Medicaid as compared to July. [24] These results suggest neither the patients nor the states are manipulating Medicaid loss month in consideration of access to the subsidy.

A feature of this paper's setting as compared to a traditional RD design is the panel structure of the data. In addition to the standard RD tests, the panel structure can be used to validate that the outcomes of patients who lost Medicaid before versus after the cutoff were similar before any change in subsidy receipt[25]. Figure 2 shows the sample averages at each relative month of subsidy loss and prescription expenditures grouped by whether the patients lost Medicaid before or after the cutoff. Both subsidy receipt and prescription expenditures track each other closely throughout the year of Medicaid loss, before diverging in the first post year, and then converging in the second post year when the after cutoff group will have faced the same redetermination procedure. There is a break between the two groups average prescription expenditures from June through August in the year of Medicaid loss even though subsidy status is constant. The break can be explained by the effects of just Medicaid receipt on prescription utilization. As patients are grouped by the month they lose Medicaid, this difference in Medicaid receipt in mechanical, and the break in prescription expenditures disappears in September, the first month all patients in the sample have lost Medicaid.

It is additionally important to report the effects of subsidy loss on the patients who actually lost the subsidy, i.e. the local average treatment effect (LATE) of this group. To recover the LATE the paper estimates a two-stage least squares model that instruments for ever losing the subsidy with the Medicaid loss month discontinuity [26] Intuitively, the RD is "fuzzy," where only a fraction of patients subsidy status is affected by relation to the cutoff, so the instrument will scale the ITT by the fraction of patients who do lose the subsidy as a result of losing Medicaid before the cutoff. In this empirical setting, the LATE is nearly identical to the treatment on the treated (TOT) because the subsidy guarantee if a patient loses Medicaid after the cutoff is effectively 100% (i.e. there are effectively no never takers). Formally, below are the estimating equations, with π_3 representing the LATE.

$$LostSubsidy_{ig} = \pi_2^k(LM_i \leq July) + \gamma_g^k + \epsilon_{ig}^k \tag{2}$$

[24]The higher count in June reflects that states tend to bunch when they redetermine patients. Similar increases occur in the beginning and end of the year

[25]In comparison to the assumptions to estimate a difference-in-difference model where the patients need to be on parallel trends, but not necessarily at the same level, in the RD setting they should be equivalent.

[26]The paper estimates ever lost the subsidy as compared to the average or current loss of subsidy to account for higher costs in even a single period potentially reducing prescription utilization through the rest of the year. To the extent this prolonged effect is not present, the LATE will understate the contemporaneous effect of the subsidy.

$$Y_{ig}^{k} = \pi_3^k Lost\hat{Subsidy}_{ig} + \gamma_g^k + v_{ig}^k \tag{3}$$

To understand the magnitude of the effects, it is important to characterize the compliers since patients who lose Medicaid before the cutoff and lose the subsidy may be different that those who maintain the subsidy. The patients should differ because the primary way patients regain subsidy eligibility is through regaining Medicaid. Patients who have higher health and prescription for example should be more likely to push through the common administrative issues to regain Medicaid coverage. Formally, compliers are patients whose subsidy status changes based on their relation to the cutoff, and always takers in this context are patients who always maintain the subsidy. Under the assumption of local randomization, this paper follows the methodology presented in Heller et al. (2017) to calculate the complier means used to properly benchmark the LATE as percent of the compliers' baseline. [27] The demographic characteristics of the compliers are compared to the always takers in Table 4. Indeed, patients who lose the subsidy on average have a lower level of prescriptions expenditures, \$3000 vs \$3200. However, the prescription utilization differences between always takers and compliers are small meaning the results should be generalizeable to the full sample.

5 Results

The results of this section show a sharp increase in prescription costs causes large reductions in prescription utilization for low-income individuals. The loss of subsidy increases prices to standard Medicare levels, which are uncapped and tied to the price of the prescription. The out-of-pocket cost strongly predicts the quantity reduction regardless of the type of prescription.

5.1 Medicaid Loss Month Highly Predictive of Subsidy Loss in the Following Year

Losing Medicaid after July functions as a subsidy guarantee in the following calendar year. Figure 3 shows the difference in subsidy loss over time between patients who lost Medicaid before the cutoff (treated patients) versus those that lose Medicaid after (control patients) estimated via equation (1). In the figure, the red lines denotes the breaks between calendar years. In the year of Medicaid loss, there is no difference in subsidy loss based on which side of the July individuals lose Medicaid, with neither group having lost the subsidy. In the January following Medicaid loss, as soon as the subsidy can lapse, the estimated increase in subsidy loss between treated an control patients is 49pp

[27] Details of how to construct the complier means including alternate viable assumptions from Kim and Lee (2017) are available in the appendix.

and highly significant. Subsidy loss does not increase to one because there are other options to retain the subsidy and some beneficiaries regain Medicaid within the year they lose it. Consistent with patients regaining Medicaid over the period, by the end of year following Medicaid loss the estimated difference shrinks to 39pp but remains large and significant. In the final year when the guarantee no longer applies, the difference in subsidy loss immediately converges with small differences accounted for by treated patients mechanically having more time to regain into Medicaid. Note that while the estimated difference had disappeared in the final year, nearly 35 percent of patients that lost Medicaid are now without the subsidy by the end of the period. These patterns indicate that the month of Medicaid loss has a substantial impact on access to the subsidy, with patients that lose Medicaid prior to July experiencing higher rates of subsidy loss.

5.2 Loss of Low-Income Subsidy Greatly Reduces Prescription Utilization

The loss of subsidy caused large reductions in both quantity of prescriptions filled and total expenditures on prescriptions. Figure 4 plots the reduced form estimates of the difference between treated and control patients in both quantity, as measured by days' supply, and total prescription expenditures starting from the year of Medicaid loss to two years after. The differences in prescription utilization measures across time mirror the reduction in the subsidy with no difference prior to the change in subsidy, a sharp break when there is differential exposure to the subsidy, followed by a rapid convergence once all groups have been redetermined. The one major deviation that occurs in the year of Medicaid loss year be explained by differential levels of Medicaid.[28] To benchmark the estimates, the complier means are estimated in the first post year and reported in the bottom right of the figure.

To summarize the monthly differences, the main equations are estimated for the entire first post year and are presented in Table 5. Column (1) shows the first stage, columns (2) and (4) show the reduced form estimates and columns (3) and (5) show the LATE, which in this setting is effectively the TOT as effectively no control patients lose the subsidy. The average reduction in quantity over the year for those that lost the subsidy shown in column (3) is 227 days supply, which is comparable to 8 fewer prescriptions filled per year assuming 30 days supply per fill. Compared to the complier mean of 1488 days, this is a reduction of 15%. The effect of losing the subsidy on prescription expenditures shown in column (5) is $1,157, or 38% of the complier mean of $3,088. The percentage reduction in expenditures is more than double the percentage reduction in quantity. The difference in magnitudes

[28] Mechanically, everyone in the pre cutoff group has lost Medicaid in July, whereas no one in the post cutoff group has. The effect of just Medicaid on prescription drug utilization is further explored in Hollrah 2023

indicates that higher priced prescriptions are more likely to be reduced.

5.3 Out-of-Pocket Costs Strongly Predict Amount of Reduction

In order to understand the predictors of which drugs patients reduce, the reduced form yearly quantity responses are separately estimated by each of the 200 most common prescriptions using the same estimation approach. In order to make the estimated reduction of each prescription comparable to each other, the quantity reduction is divided by the baseline mean. The resulting outcomes can then all be interpreted as the percent change in quantity for each individual drug [29]. The constructed measure of out-of-pocket prices described in section 3.1 is used to test how well price faced by patients predicts reductions.

Figure 5 shows a binscatter of the percentage reduction in quantity on the y-axis plotted against the constructed out-of-pocket price on the x-axis from the 200 most common prescriptions. The weights used to form the binscatter are the inverse variance of the estimates, giving more precisely estimated coefficients higher weights. The drugs' out-of-pocket price strongly predicts the percent reduction in quantity. The OLS estimate of percent reduction in prescription quantity against the out-of-pocket price is highly significant with a slope of 0.127, and an R^2 of 0.23. While this pattern could be consistent with patients making cost-effective decisions, results splitting drugs into value classes described in 3 suggest this is not the case.

Figure 6 shows the same estimates as in figure 5, but with prescriptions split into three broad value classes formed by a physician panel (Chandra et al., 2010): Acute care prescriptions likely to prevent an adverse health event in a couple months ("high value"); Chronic care prescriptions likely to prevent an adverse health event in within the year ("medium value"); and Quality of life improving medications that are important, but unlikely to result in an adverse health event ("low value"). The figure shows the OLS line for each value type of prescription. If patients are prioritizing prescriptions with based on health value, then the slopes the the OLS lines should be flattest for the "high value" prescriptions and steepest for the "low value" ones. One the other hand, the more similar the slopes, the more weight patients are putting solely on their out-of-pocket price. However as can be seen in table 6 the lines for each class of prescription are relatively similar - and can certainly reject that "high value" prescriptions are reduced at lower rates than similarly prices "medium value" or "low value" drugs. In fact, a test comparing the slope coefficients of "low value" drugs and "high value" drugs

[29]The paper avoids the log transformations because they do not do well with the numerous zeros as observed in the data (Mullahy and Norton 2022).

shows a marginally significant flatter slope for "low value" drugs, perhaps capturing patients prioritizing the more immediate relief quality of life improving drugs may have for a patient. Reflecting the relatively similar slopes and intercepts, the additional predictive power of fully interacting the value classifications with the out-of-pocket price is essentially 0.[30] The takeaway from the lack of additional predictive power is in the aggregate patients treat prescriptions like they are of similar value and maximize the number of prescriptions rather than the ones most likely to prevent adverse health outcomes. These results are also unlikely to be driven by cross-drug substitution as the takeaway is similar when estimated using common therapeutic classes instead of individual prescriptions. The results are also validated using an alternative measure of value taken from Lavetti and Simon (2018), "switcher surplus," which is constructed to measure how important insurers believe a prescription is for patients with the insurer objective to lower costs. The results are presented in appendix table X, with zero coefficient on "switch surplus" in the regression including out-of-pocket price.

Naturally broad classifications will not necessarily capture the many patient-specific factors that determine a drugs' value, but there are several that unambiguously important. For example, insulin and inhaler medications are clearly vital for any patient who is taking them, but are both relatively expensive prescriptions with expected out-of-pocket costs of $41 and $35 respectively per fill. Insulin is a classic inelastic good in economics textbooks, and should show not large reductions if this is the case. Table 7 reports the reduced form of the average quantity reductions of these two classes of prescriptions along with other clinically important ones. The average quantity reductions for a patient who loses the subsidy are 28 percentage for insulin and 34 percentage for inhaler medications. Even in the highest value prescriptions patient cost greatly influences the decision.

Patient focus on price over value has notable policy implications regarding the significant declines in prescription expenditures due to increased cost-sharing. Ideally, the primary source of cost reductions would stem from prescriptions with lower health value. As evident from the data presented in table 8, prescriptions of higher value are a disproportionate share of expensive prescriptions and total expenditures. As a result of being the majority of high-cost prescriptions, 60% of the spending reduction is driven by decreased utilization of "high value" prescriptions. Increased cost-sharing is a blunt instrument that will disproportionately curtail spending on medications most likely to prevent adverse health outcomes.

[30]The F-statistic comparing the two models is 1.18 (p-value of .32), so unable to reject that the models are same

5.4 Cost-sharing leads to discontinuations of prescriptions, not substitutions

Even if the primary impact of increased cost-sharing is a reduction in overall utilization, is possible patients also use simple cost-saving strategies like switching from branded versions of prescriptions to their equally effective and cheaper generic versions. Figure 7 reports the difference across the cutoff in quantity of prescriptions that have been switched from brands to generics. For any patient, a prescription is considered switchable if in the prior year the patient only took the branded version of a prescription that has a generic equivalent. Then in the current year, a prescription is considered switched if the patient continues to take the prescription but now takes its generic form. The quantity of prescriptions switched to generics does not increase, and if anything decreases slightly over the year, reflecting patients are less likely to fill prescriptions in general.

There is no evidence that patients choose the alternative of switching to generics, remaining on these branded prescriptions. Rather, figure 8 shows treated patients have large quantity reductions in switchable branded drugs. The average difference for patients who lose the subsidy is 2 days' supply, or 20% of the complier mean of 10. The pattern and baseline shown in Figures 7 and 8 is effectively identical in states with and without mandates to switch branded prescriptions to generics absent instructions from the prescriber to dispense as written (i.e. there is no difference in either baseline or switching rate between the two types of states). The lack of difference between mandate and no mandate state implies the lack of switching to generics is largely physician driven, not patient driven, since the only drugs not already generics in mandate states are ones specified by the physician. As the baselines between the states are the same, it is reasonable to assume the same physician behavior in non-mandate states. It is worth noting that generics are far more common than their branded counterparts, so there is already not a large margin for patients to be more cost-effective in this dimension.

5.5 Higher Costs lead to less Prescription Insurance

The most extreme response to higher prescription costs is to no longer maintain prescription insurance. Without the subsidy, patients are responsible for the prescription insurance premium of around $30 per month over this sample period. Combined with higher prescription prices, prescription insurance has become considerably less valuable to patients. For example, if higher prices mean a patient would only fill minimal prescriptions, they may find it optimal not to purchase prescription insurance at all. This paper reports the combined effect of the premium and higher prescriptions costs on prescription insurance enrollment in Figure 9. Panel (a) of the figure shows there is a lagged reduction of prescription insurance, with nearly 5pp of patients who lose Medicaid before the cutoff dropping off of prescription insurance by the end of the year. By the end of the year, the share of patients who have not regained the subsidy is 35pp. Therefore, of the population that can lose prescription insurance, 1 in every 7 do. [31]

There is clear evidence of adverse selection in who maintains prescription insurance. Panel (b) of the figure reports estimates of the effect of subsidy loss on prescription insurance enrollment at the end of the year for patients with higher expected expenditures, split by the median of prescription expenditures in the pre-period. Patients are more likely to maintain prescription insurance the higher their expenditures were in the pre-period. However, even patients above the meidan wherein the value of prescription insurance should greatly exceed its cost, 7 percent of patients without the subsidy at the end of the year have allowed their prescription insurance coverage to lapse.[32] The reduction in insurance even among those that should value it highly reflects how even a relatively modest $30 per month meaningfully impacts access the prescriptions for low-income groups.

5.6 Health Impacts

Large reductions of prescription may lead to observable direct impacts on patient health, potentially with higher costs in other parts of the medical system. A testable instance of lower prescription utilization leading to higher medical costs would be if patients are now more likely to receive treatment in emergency departments (ED). Despite the large reductions in valuable care, there no significant increases in ED visits, with figure 10 showing noisy and insignificant monthly estimates of the effect of subsidy loss on emergency department visits. However, the lack of change can likely be explained by how treatment occurs. In order to remain treated, that is without the subsidy, a patient must not be reenrolled in Medicaid. Moreover, once reenrolled in Medicaid a patient has additional benefits other than just the subsidy. These two factors combined bias any measurable adverse health outcomes toward zero.

There are several observable mechanisms as to why there is selection into who is reenrolled in Medicaid. First, mechanically the patients in the pre-cutoff group have had more time to regain Medicaid. Second, those most likely to benefit from prescriptions, proxied by pre-period prescription expenditures, are more likely to regain Medicaid first as seen in table 4. This type of selection likely

[31] The loss of prescription insurance does lead to measurement issues since only prescriptions purchased through insurance can be observed. However, the fraction purchases off of insurance is likely small, and the results are robust to assuming patients fully maintain their prescriptions after losing their insurance.

[32] This is highly consistent with the findings in Finkelstein et al. (2019) that low-income patients appear considerably less willing to pay for insurance that its value to them

captures that patients may exert more effort to regain the subsidy via regaining Medicaid the larger the subsidy benefit is to them. Finally, adverse events interact with subsidy receipt. Figure 11 shows the fraction of patients who regain Medicaid sharply increases after an adverse event, proxied for by the first emergency department visit after losing Medicaid.[33] Hospitals have both the incentives and resources in the form of case workers to help patients regain Medicaid. As adverse events increase the likelihood of leaving treatment, future adverse events should be less likely to occur. As a result, patients who lose the subsidy (compliers) that are prone to adverse events occurring in a relatively short window will resemble always takers.

In terms of the prescription utilization results, the selection induced by adverse events would attenuate the estimates toward zero.

5.7 Robustness to alternative specifications

The paper reports several analyses to asses if the results are robust to alternate specifications. The first is to conduct all analyses using only a single month of bandwidth around the cutoff instead of two. The main results from this specification are shown in figure A1. Estimating the model on this sample does not change the results, but does reduce the precision due to the more limited sample size.

The second approach instead estimates the following difference-in-difference (DiD) model that assigns treatment and control groups based on relation to the cutoff with cohort by time and individual fixed effects. The main difference in assumptions between DiD and discrete RD is the parallel trends assumption versus the local randomization assumption. Parallel trends requires the average change in patient outcomes to be the same across the cutoff absent losing Medicaid, whereas local randomization requires the average patient potential outcome to be the same across the cutoff. Under the DiD assumptions, the treatment effect is valid for only the treated patients. Under the discrete RD assumption, the treatment is valid for both treatment and control patients, a more general interpretation. To estimate the most comparable DiD model to the RDs presented, the estimates are normalized to January in the year of Medicaid loss, so that patients are normalized to have the same utilization before any changes in Medicaid or subsidy status. Below is the estimating equation:

$$y_{igt} = \alpha_i + \gamma_{gt} + \sum_{l=-11}^{23} \mu_l D_{i,t}^l + \varepsilon_{igt} \tag{4}$$

As can be seen in figure A2, the near zero coefficients absent the mechanical difference caused

[33] For patients who are never hospitalized, the average relative month is used

by Medicaid between June and August suggest the parallel trends assumption is true in the pre-period. The magnitude of the results are also comparable. The total yearly reduction on expenditures estimated from the RD is 565 and 543 from the DiD. Similarly, the yearly reduction in day's supply estimated from the RD is 111 and 109 from the DiD. The main takeaway is either set of assumptions yield similar results, with the findings not sensitive to the model specification.

The third approach is to relax some of the sample restrictions made, namely to require a patient enter the year with Medicaid or have filled at least one prescription and is shown in figure A3. Here the estimates scaled by the complier means are still quite similar. The levels of both the complier means and reductions in utilization shrinks, reflecting a change in the composition of the sample.

A potential other factor of concern is utilization is not observed for patients who do not have prescription drug insurance. In the main analysis, patients without drug insurance are assumed to fill no prescriptions. If these patients are still able to purchase some prescriptions without insurance, this would overstate their decrease in utilization. Figure A4 provides an upper bound on the effect these patients could have by replacing these zeros with the usage in the month prior to losing prescription insurance. The main results are quite similar to the original results.

Overall, these analyses show that the results are not sensitive to choice of model or sample.

5.8 Comparison to previous estimates

Other research has estimated how patients respond to prescription cost-sharing in a various other settings. The settings differ both in population, starting price and type of price change. Recent work by Chandra et al. (2021) use timing in Medicare enrollment month to generate as-if-random increase in solely prescription prices in the Medicare only population. They find that an 11 pp increase in coinsurance, \$10.40 increase in price per prescription, leads to a 22.6% reduction from a baseline of \$270 in one month of prescription expenditures. The magnitude of their effect is inline with the magnitude of effect in this paper that finds a 25pp increase in coinsurance, \$20.6 increase in price per prescription, leads to an average monthly reduction of 39.6% from a baseline of \$257.67 of prescription expenditures. It is worth noting that the populations studied have different financial constraints, and the initial price points in the settings differ greatly, \$31 vs \$1.8, so while the magnitudes are similar and reasonable, they are not estimating the same effect.

Chandra et al. (2010) study the effects of a bundled increase in both office and prescription drug costs in low-income patients aged 19-65 in Massachusetts. In the setting, the patients face an average increase in prescriptions and office costs of \$4 from a baseline of \$9. The elasticity of total expenditures, which should largely be driven by prescriptions, to increased copayments is -0.315[34]. While not directly comparable, the semi-arc price elasticity,[35] here the percent change in quantity relative to the baseline mean over the level change in coinsurance fraction, reported in this paper is -1.86.

A paper with highly similar initial price and uncapped pricing increase is Brot-Goldberg et al. (2017) who study the effects of switching patients from full insurance to high-deductible plans. The pricing change is again a change to both office and prescription costs, but a large difference between the setting in this paper is the population is high income (92% have incomes greater than \$100,000 a year). The semi-arc elasticities on total medical spending range through -0.69, or about 1/3 of the semi-arc elasticity in this papers setting. The papers are measuring different outcomes, but it is not unreasonable that the more constrained population is more responsive to increases in cost-sharing. Brot-Goldberg et al. (2017) also compare their estimates to semi-arc elasticities computed using the RAND health insurance experiment, which may be the most comparable to the setting population and initial price wise, they report an overall elasticity of -2.11. The overall elasticities are not directly comparable, but the results in this paper are certainly inline with prior work.

In summary, the elasticities that are more comparable are from the RAND HIE and Brot-Goldberg et al. (2017) since the prices begin at 0, then increase by a fraction of the costs. The estimates are roughly inline with the RAND HIE, which covers a similar resourced population compared to the one in this paper, but roughly 3 times as large as the elasticity reported in the higher-income population. It is worth noting that the while estimates in this paper are large and meaningfully, they should also be interpreted as a lower bound of the effect of prescription cost-sharing on low-income groups both because they are unable to estimate the effect on the very poorest since they are much less likely to lose Medicaid in this setting and that the effects of higher cost-sharing may grow over the years if paying for prescriptions now makes patients less able to afford them in the future.

[34] Chandra et al. (2014) improve on this analysis, but do not report estimates by income group

[35] The use of a semi-arc-elasticity instead of arc-elasticity is discussed in Brot-Goldberg et al. (2017). If the initial price is 0, the arc-elasticity will be equivalent to the percent change. In this setting, the out-of-pocket prices before subsidy loss are very close to \$0 on average. The semi-arc-elasticity reported is $\frac{2(q2-q1)}{(q2+q1)(p2-p1)}$. The reduction in prescription expenditures is \$1157 (q2-q1), relative to the complier mean of \$3088 (q2+q1). The prices are computed using proportion of expenditures consumers would have paid with and without the subsidy during the pre-period, the year a patient loses Medicaid. The proportions with and without the subsidy are 0.02 and 0.27 respectively. In terms of out-of-pocket price, the subsidy price is \$1.8 and non-subsidy price is \$20.6.

6 Conclusion

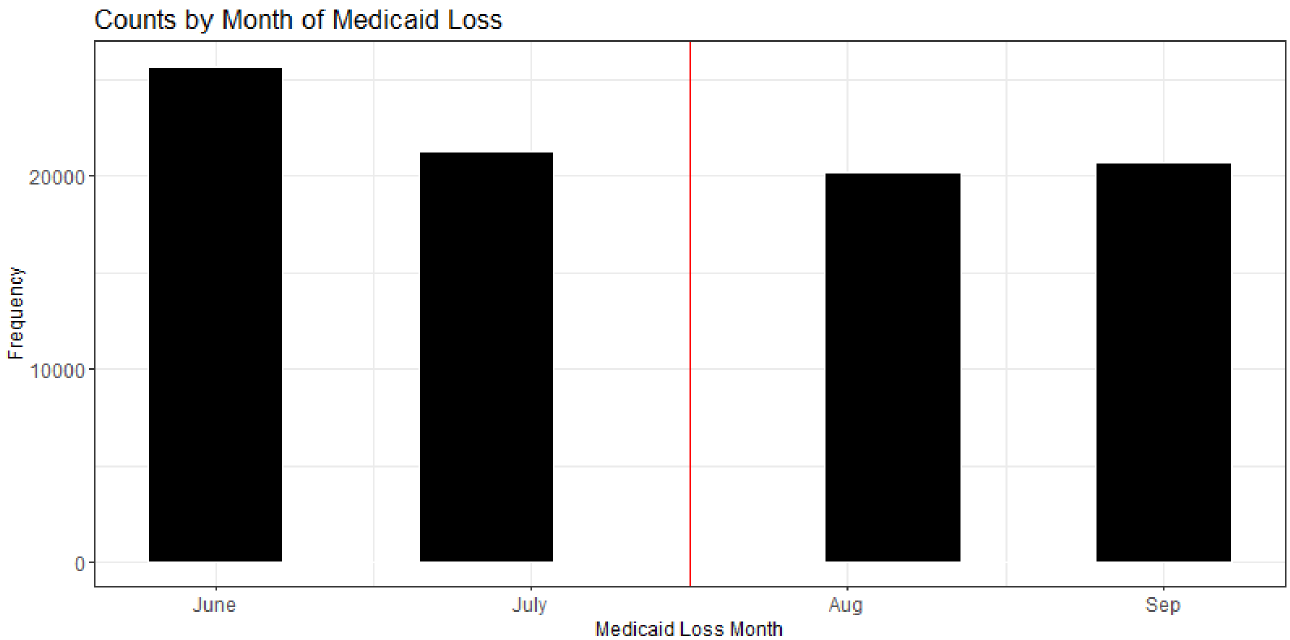
This paper estimates how a large increase in prescription cost-sharing for low-income Medicare patients affects their prescription utilization. The paper leverages plausibly random variation in a guarantee of a full subsidy for prescription drugs, the Low-Income Subsidy, generated by the month a Medicare-Medicaid patient loses Medicaid. patients who lose Medicaid after July are guaranteed the subsidy throughout the following calendar year, whereas patients who lose Medicaid before can lose the subsidy as soon as the coming January. Nearly 50 percent of patients who lose Medicaid before July will lose the subsidy in the following calendar year, leading to an average increase of 25% in cost-sharing in addition to insurance premiums. patients who lose the subsidy respond to higher prescription costs by reducing their quantity of prescriptions filled by 16% and prescription expenditures by 40%. Switching to generics does not contribute to reduced expenditures as there is no increase in the quantity of prescriptions switched from branded prescriptions to their more cost-effective generic versions. Additionally, by the end of the calendar year 15% of patients who remain without the subsidy will no longer have prescription insurance, the most extreme form of response.

The paper leverages the large and uncapped increase in costs to separately estimate the quantity response of 200 of the most common prescriptions. Prescriptions with higher out-of-pocket costs show the greatest reductions in utilization, irrespective of the value of the prescription as determined by physicians. The lack of value consideration reflects that patients act as if all prescriptions are of similar value, or rather that they are maximizing the total number of prescriptions filled. The pattern of focusing on price could reflect the complexity of comparing the value of one more expensive prescription to several less expensive ones. An additional explanation could be financial constraints greatly limit low-income patients ability to afford more expensive prescriptions. For example, insulin is clearly an extremely high value but costly prescription, and without the subsidy patients reduce their quantity filled by 28%.

This paper has several implications for low-income program design. First, it is clear that while there is a potential tradeoff between accessibility and incentivizing cost-effective decisions when fully subsidizing prescriptions, imposing cost-sharing only affects accessibility in this context. One potential reason patients do not appear more cost-effective is that the structures in place including prices, state laws and physicians prescribing behavior already do most of the work (i.e. there's not much left for patients to do). Further, to the extent patients could shop around for similarly effective, but different prescriptions, it likely requires too much expertise to do so effectively. As patients certainly use their out-of-pocket cost more so that other factors, program design should lean heavily into value-based pricing when possible under restrictive budgets.

In terms of policy, a key finding of this paper is the Low-Income Subsidy is a highly successful program in improving patient access to prescriptions. As most of the expenditure reduction when patients lose the subsidy comes from high cost and "high value" prescriptions, it is also unlikely that the program is crowding out patient spending. The efficiency of the program may be improved by targeting providers or institutions who have the expertise needed to be more cost-effective since the paper concludes patients do not appear to do so on their own. For example, Medicare could adopt a bundled payment structure to physicians to treat certain kinds of patients, which has had success knee replacements in reducing cost without sacrificing quality, strongly incentivizing those with the most expertise to design a more cost-effective plan.

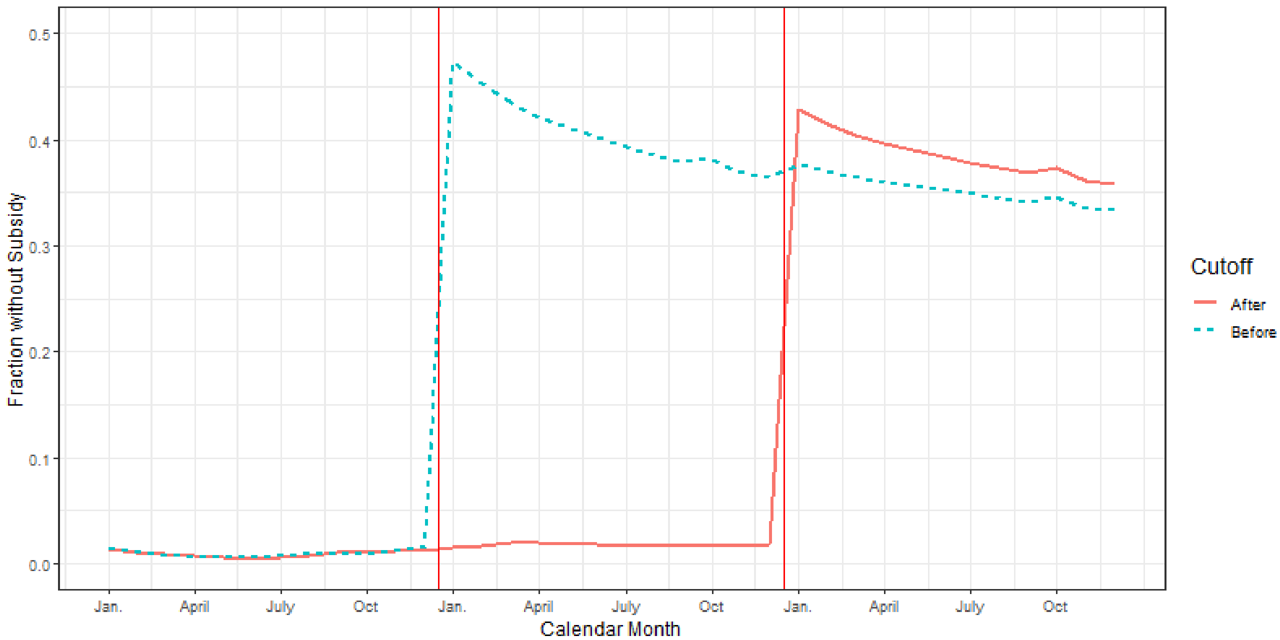
Figure 1: Frequency by Medicaid Loss Month



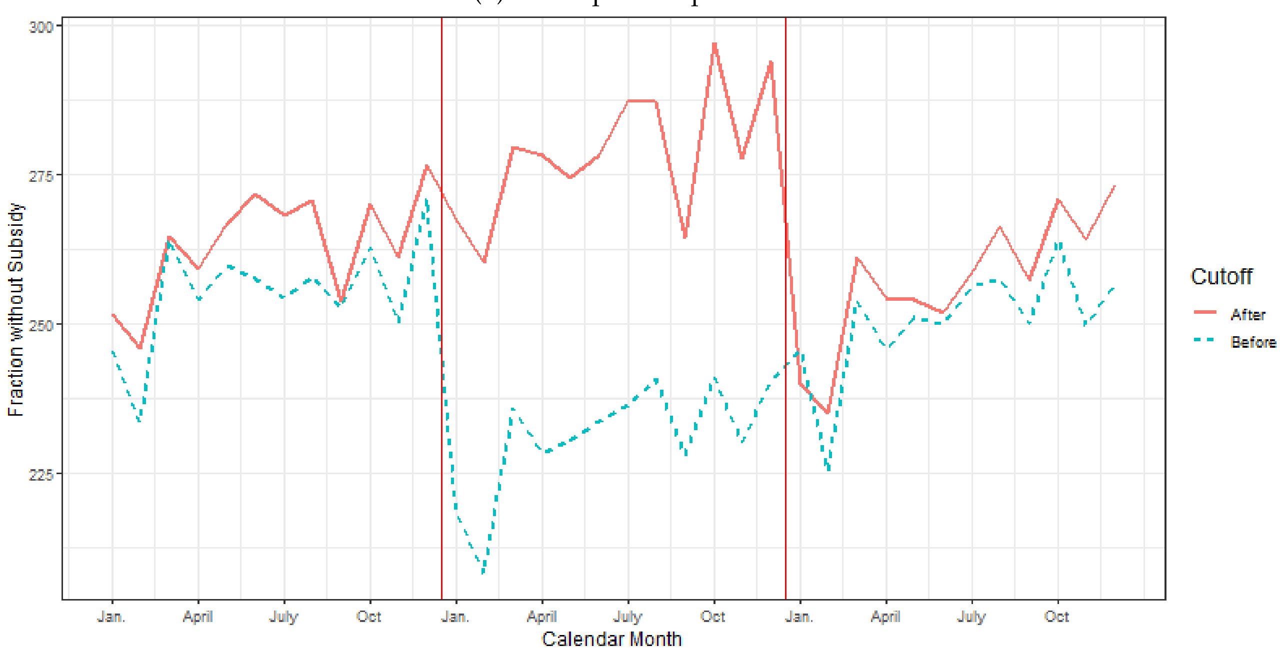
Note: Figure shows the counts of patients of that lost Medicaid by the month of Medicaid loss.

Figure 2: Subsidy and Expenditures over Time by Relation to the Cutoff

(a) Low-Income Subsidy Loss

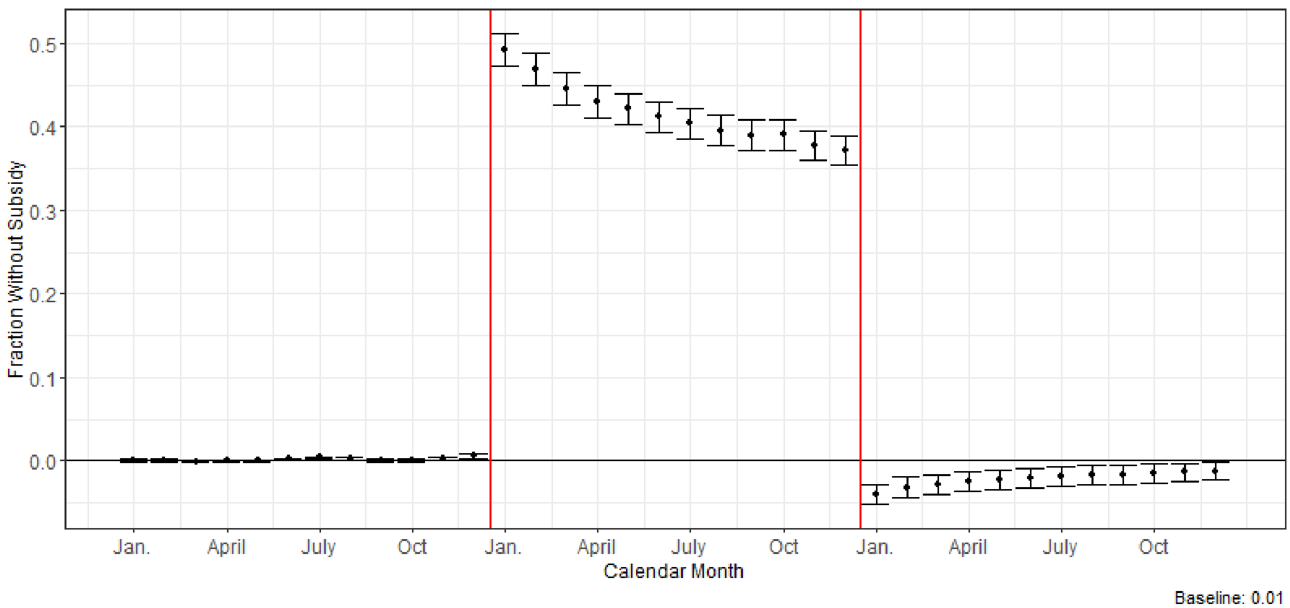


(b) Prescription Expenditures



Note: Figure shows the raw fraction over the three year panel beginning the year a patient loses Medicaid. The fractions calculated by grouping patients by their relation to the July cutoff. The blue dashed line correspond to all patients who lose Medicaid prior to July and the solid red line to all patients who lose Medicaid after July.

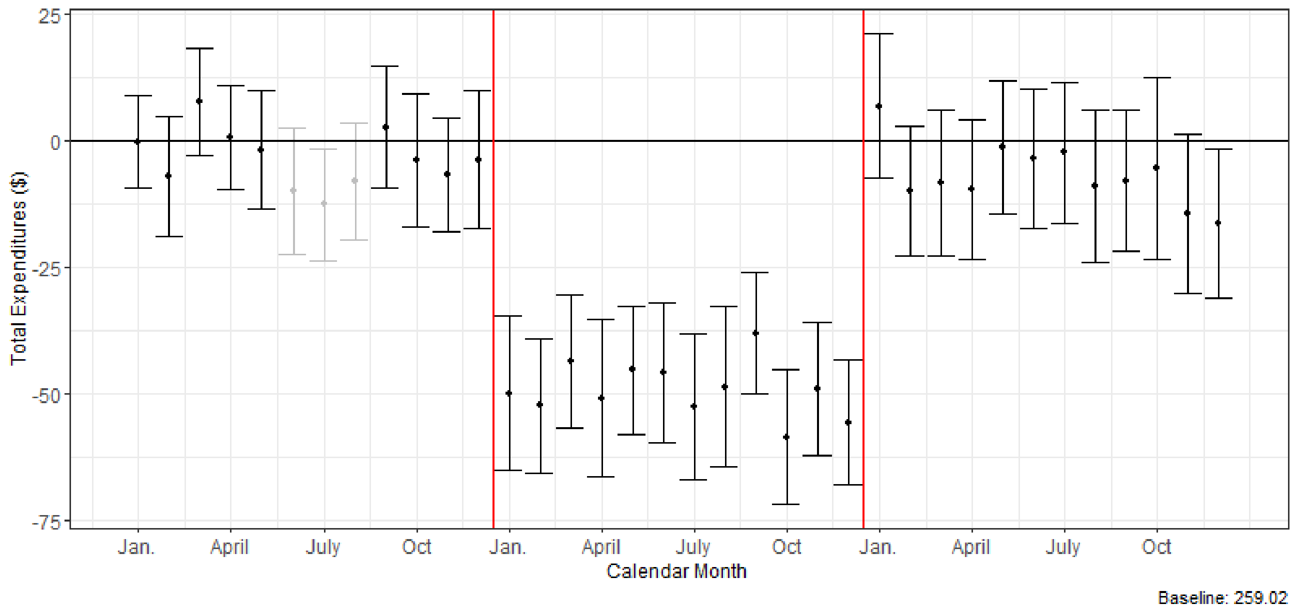
Figure 3: Monthly RD Coefficients of Low-Income Subsidy Loss



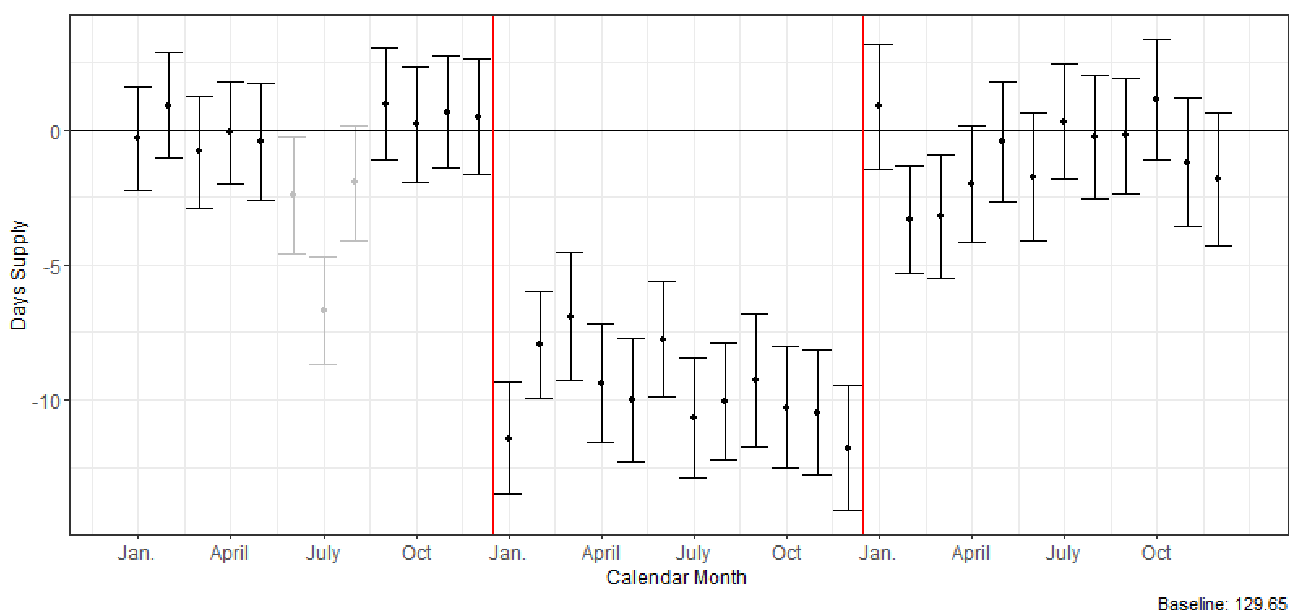
Note: Figure shows the separate discrete regression discontinuity estimates for each relative calendar month of the difference between patients that lose Medicaid before the cutoff versus patients that lose Medicaid after. The reported baseline is yearly average of patients that lose Medicaid before the cutoff and lose the subsidy in the following year (complier mean). Robust standard errors clustered at the cohort (state by year of Medicaid loss) level.

Figure 4: Monthly RD Coefficients of Prescription Utilization

(a) Prescription Expenditures

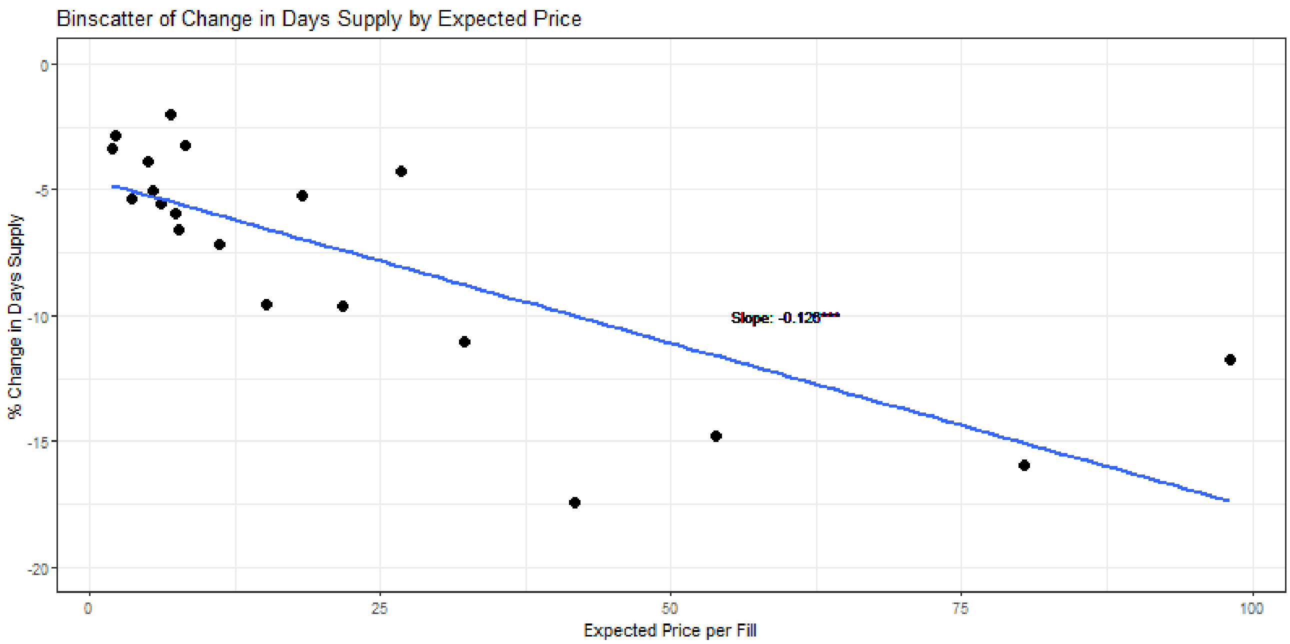


(b) Prescription Days' Supply



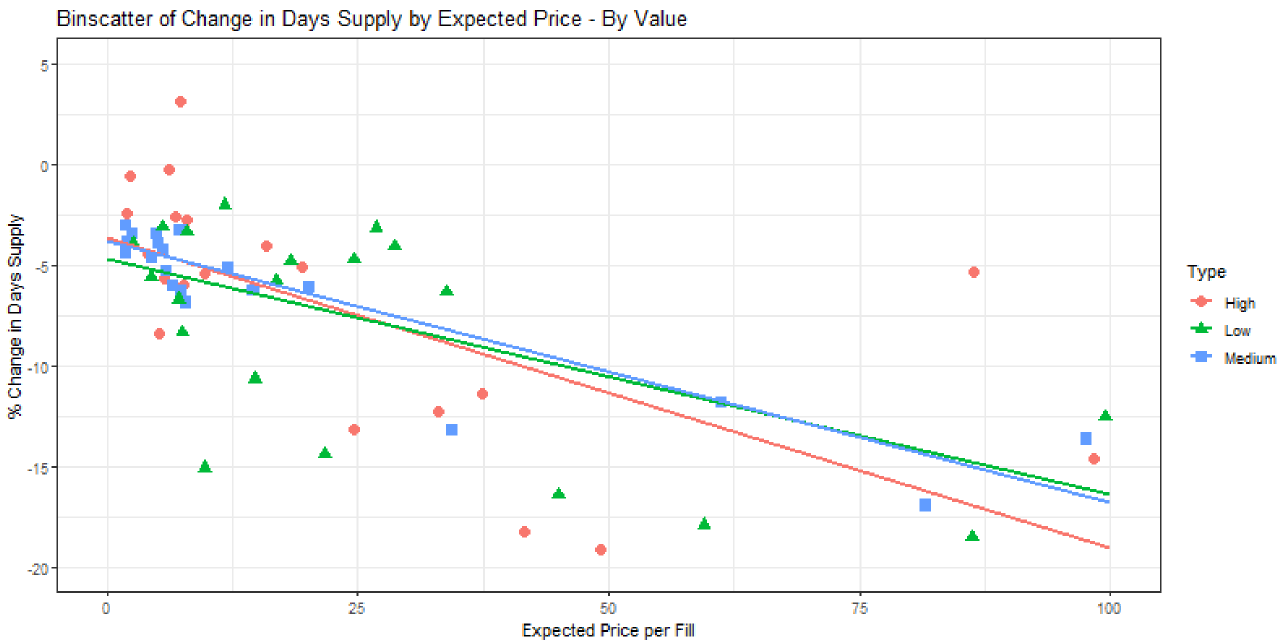
Note: Figure shows the separate discrete regression discontinuity estimates for each relative calendar month of the difference between patients that lose Medicaid before the cutoff versus patients that lose Medicaid after. The reported baseline is yearly average of patients that lose Medicaid before the cutoff and lose the subsidy in the following year (complier mean). The coefficients of June through August are greyed out since they capture a mechanical difference in Medicaid receipt. Robust standard errors clustered at the cohort (state by year of Medicaid loss) level.

Figure 5: Binscatter of Individual Drug RD Estimates of % Change in Days' Supply Against Out-of-Pocket Price



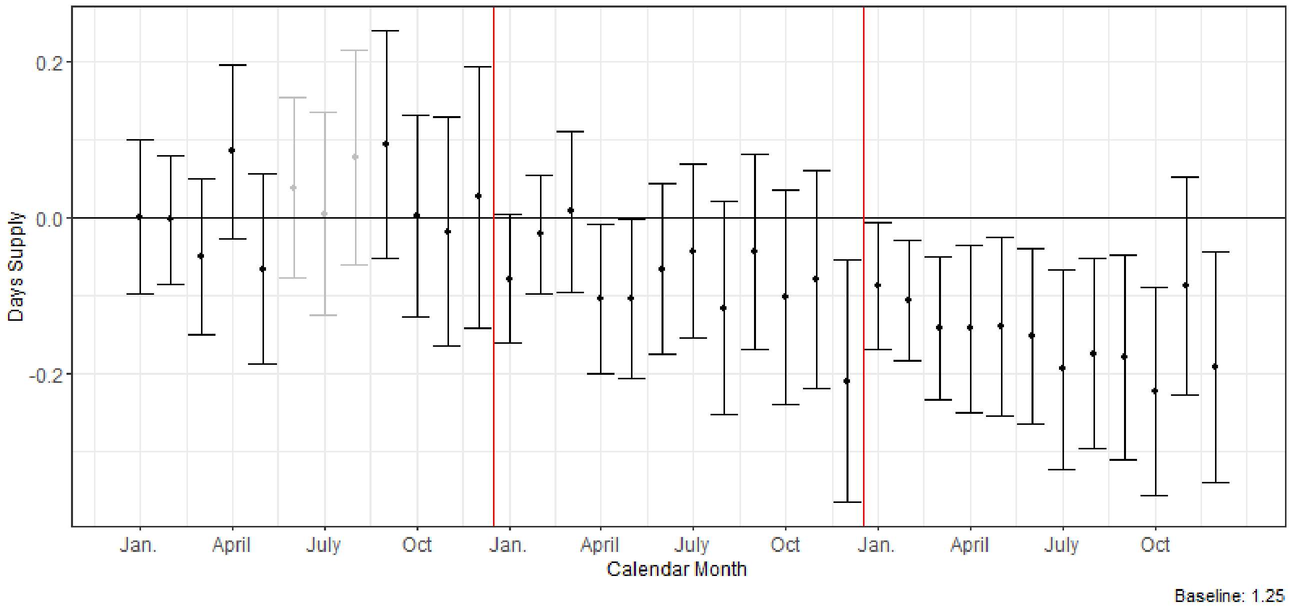
Note: Figure shows the binscatter of separate discrete regression discontinuity coefficients of yearly days' supply for each of the most common of prescriptions. The regression discontinuity estimates the difference between patients that lose Medicaid before the cutoff versus patients that lose Medicaid after. The coefficients are plotted against the average out-of-pocket price to fill the prescription. The line is the OLS estimate of % change in days' supply against out-of-pocket price.

Figure 6: Binscatter of Individual Drug RD Estimates of % Change in Days' Supply Against Out-of-Pocket Price: Split by Drug Value



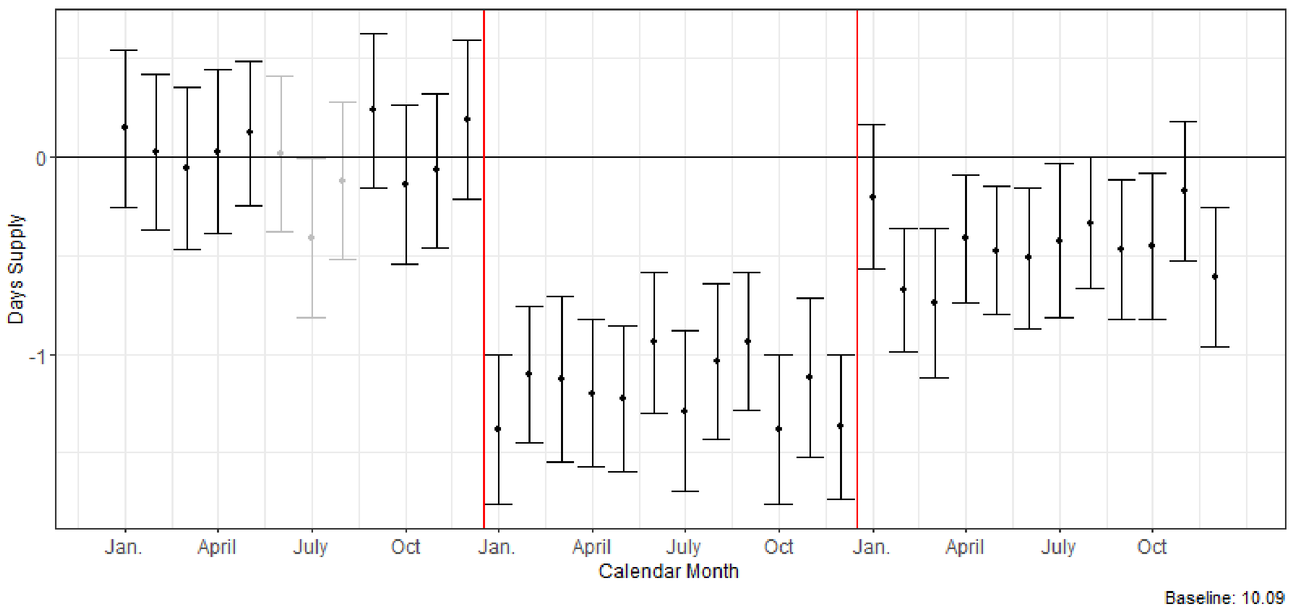
Note: Figure shows the binscatter of separate discrete regression discontinuity coefficients of yearly days' supply for each of the most common of prescriptions grouping prescriptions into either "high value" (red circles), "medium value" (blue squares) and "low value" (green triangles) based on likelihood of preventing an adverse event. "High" The regression discontinuity estimates the difference between patients that lose Medicaid before the cutoff versus patients that lose Medicaid after. The coefficients are plotted against the average out-of-pocket price to fill the prescription. The lines are the OLS estimate of % change in days' supply against out-of-pocket price for each value type.

Figure 7: Monthly RD Coefficients of Days' Supply of Prescriptions Switched to Generics



Note: Figure shows the separate discrete regression discontinuity estimates for each relative calendar month of the difference between patients that lose Medicaid before the cutoff versus patients that lose Medicaid after. A prescription is counted as switched if a patient fills the generic version of a prescription after only taking the branded version in the prior year before. The reported baseline is yearly average of patients that lose Medicaid before the cutoff and lose the subsidy in the following year (complier mean). The coefficients of June through August are greyed out since they capture a mechanical difference in Medicaid receipt. Robust standard errors clustered at the cohort (state by year of Medicaid loss) level.

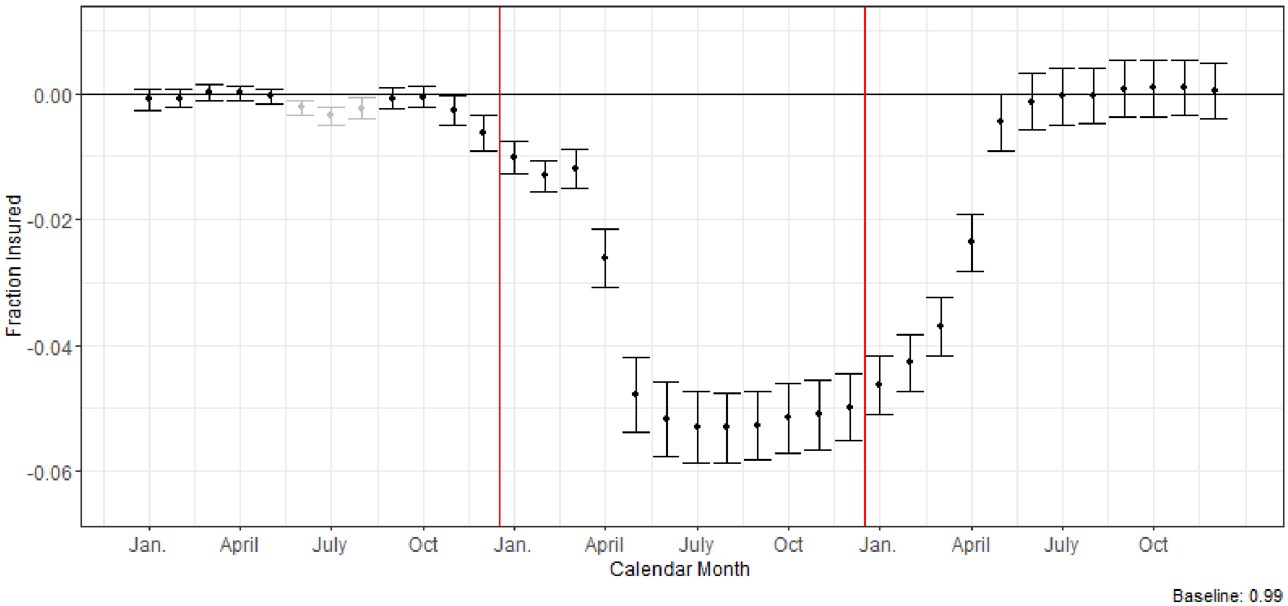
Figure 8: Monthly RD Coefficients of Days' Supply of Switchable Branded Prescriptions



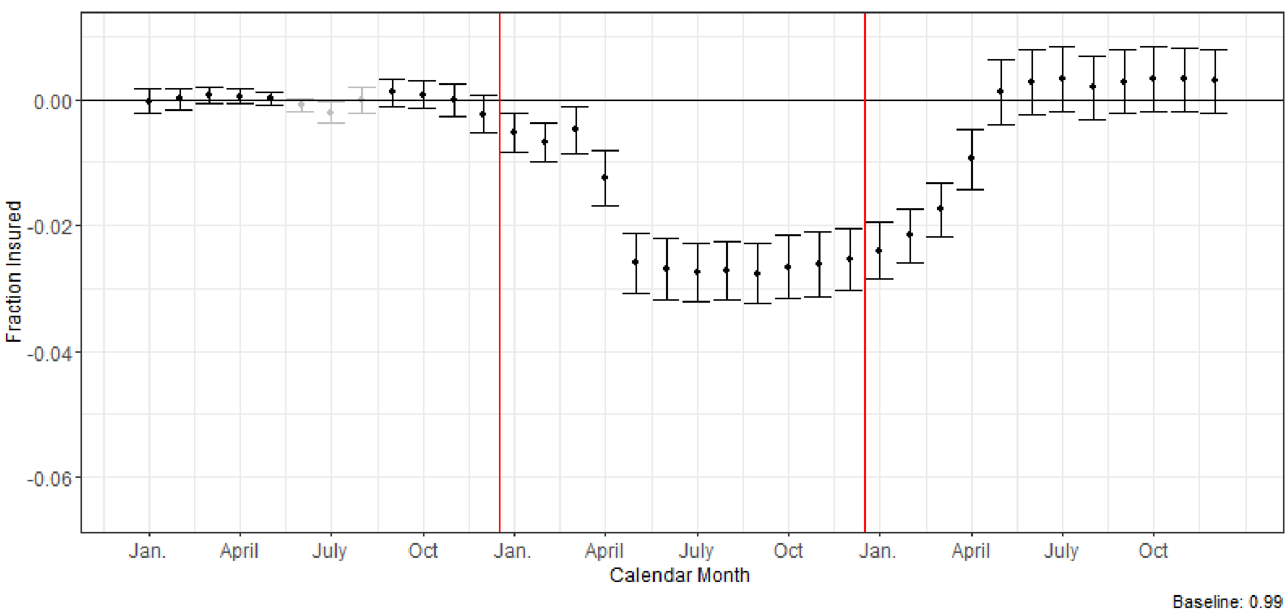
Note: Figure shows the separate discrete regression discontinuity estimates for each relative calendar month of the difference between patients that lose Medicaid before the cutoff versus patients that lose Medicaid after. A prescription is counted as switchable if a patient fills the branded version of a prescription after only taking the branded version in the prior year before. The reported baseline is yearly average of patients that lose Medicaid before the cutoff and lose the subsidy in the following year (complier mean). The coefficients of June through August are greyed out since they capture a mechanical difference in Medicaid receipt. Robust standard errors clustered at the cohort (state by year of Medicaid loss) level.

Figure 9: Monthly RD Coefficients of Insurance Loss

(a) Full Sample

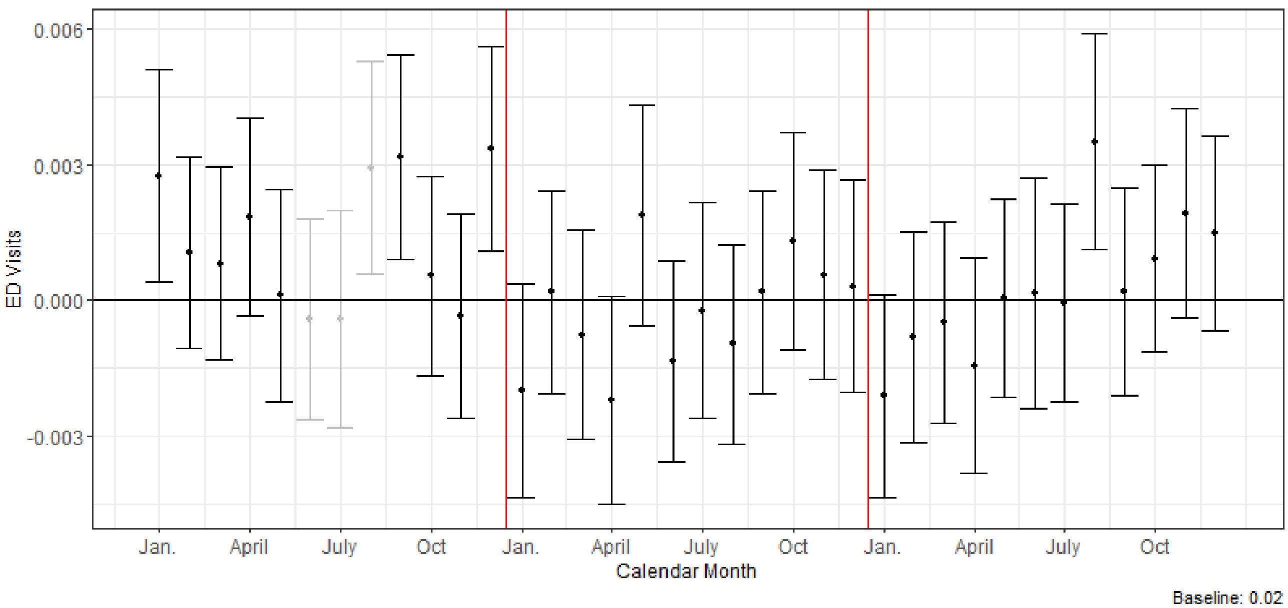


(b) Above Median Expenditures in Baseline Period



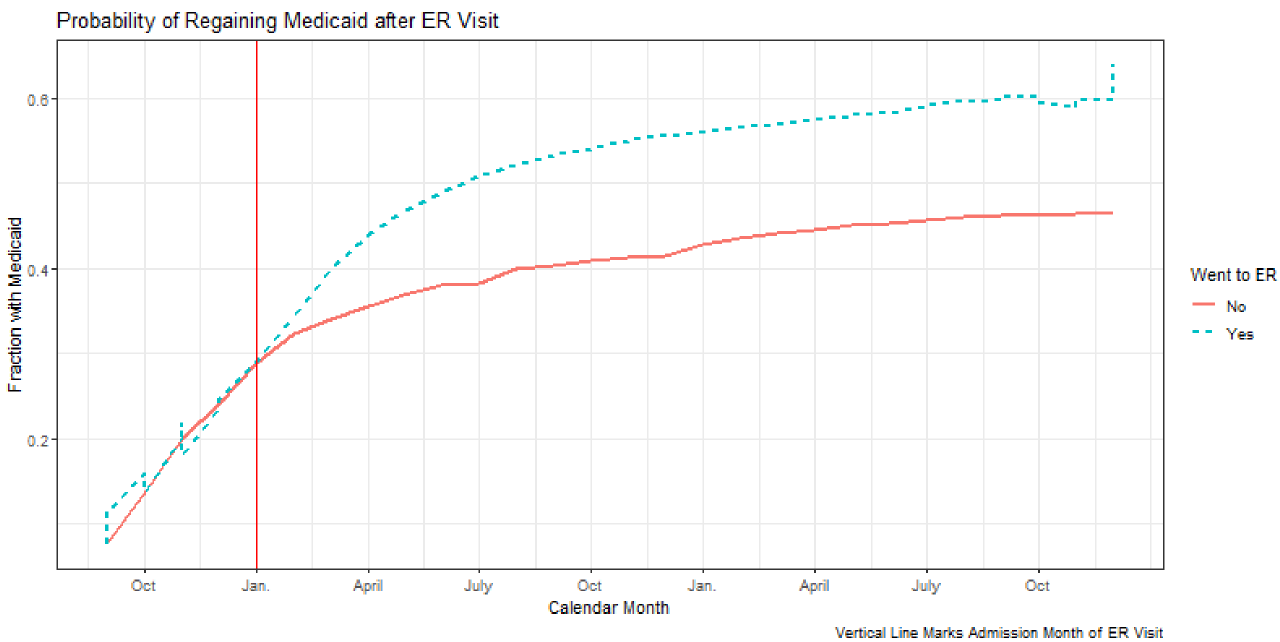
Note: Figure shows the separate discrete regression discontinuity estimates for each relative calendar month of the difference between patients that lose Medicaid before the cutoff versus patients that lose Medicaid after. The reported baseline is yearly average of patients that lose Medicaid before the cutoff and lose the subsidy in the following year (complier mean). The coefficients of June through August are greyed out since they capture a mechanical difference in Medicaid receipt. The median prescription expenditures in the baseline is $1500. Robust standard errors clustered at the cohort (state by year of Medicaid loss) level.

Figure 10: Monthly RD Coefficients of Emergency Department Visits



Note: Figure shows the separate discrete regression discontinuity estimates for each relative calendar month of the difference between patients that lose Medicaid before the cutoff versus patients that lose Medicaid after. The reported baseline is yearly average of patients that lose Medicaid before the cutoff and lose the subsidy in the following year (complier mean). The coefficients of June through August are greyed out since they capture a mechanical difference in Medicaid receipt. Robust standard errors clustered at the cohort (state by year of Medicaid loss) level.

Figure 11: Fraction with Medicaid after Emergency Department Visit



Note: Figure shows the fraction of patients with Medicaid split by whether then went to the emergency department (ED). The vertical red line marks the patient first ED encounter, which is then matched to the average calendar month an ED visit occurs. The average calendar month the first ED occurs is the January immediately following Medicaid loss. The average over the relative calendar months is plotted for patients without an ED encounter for comparison.

Table 1: Resource Changes Around Losing Medicaid

Income	
Avg. Change	-441
Median Change	388
Assets	
Avg. Change	2614
Median Change	0

Notes: The descriptive statistics are calculated using data from the 1992-2018 waves of the Health and Retirement Study from patients 65 and older who reported enrollment in Medicaid in one wave and reported no enrollment in Medicaid in next. The reported numbers are the change from the year with Medicaid to the year without Medicaid. All statistics are weighted using person weights.

Table 2: Patient Demographics Split by Patient Type

	Analysis Sample	Always Medicaid	Never Medicaid
Age	75.7	77.9	74.9
Female	0.68	0.70	0.56
White	0.56	0.55	0.84
Drug Expenditures	3091	3796	1291
Drug Days' Supply	1548	1645	759
Rel. % of Medicare	4.3	8.4	87.3
Median Income	14624	7236	35244
Median Assets	1900	70	91100

Notes: The first column shows descriptive statistics for all patients from their Medicaid loss year that lost Medicaid between June and September, filled at least one prescription, and entered the year with Medicaid. The second column are all patients that are continuously enrolled in Medicaid. The third column are all patients that are never enrolled in Medicaid. The relative fraction of Medicare corresponds to the overall fraction of patients that lose Medicaid, are continuously enrolled in Medicaid, and never enrolled in Medicaid. The descriptive statistics presented on income are calculated using data from the 1992-2018 waves of the Health and Retirement Study from patients 65 and older who reported enrollment in Medicaid in one wave and reported no enrollment in Medicaid in next. The reported numbers are the from the year without Medicaid. All statistics are weighted using person weights.

Table 3: Balance Table around Cutoff

	Before Cutoff	After Cutoff	Cond. RD	Frac. Mean
Age	75.6	75.8	0.0216	0
Female	0.677	0.686	0.00523	0.01
White	0.553	0.564	0.00122	0
Q1 Days Supply	377.	387.	0.221	0
Q1 Prescription Expenditures	743.	762.	-0.506	0
N	46953	40842		

Notes: The table shows descriptive statistics for all patients from their Medicaid loss year that lost Medicaid between June and September, filled at least one prescription, and entered the year with Medicaid. The first column presents the descriptives for patients that lose Medicaid before the cutoff and the second column patients who lose Medicaid after the cutoff. The third column reports the discrete regression discontinuity estimates of the difference between the before and after cutoff groups with cohort fixed effects. P-values calculated using randomization inference. Significance levels: *=10%, **=5%, ***=1%.

Table 4: Complier and Always Taker Demographics

	Compliers	Always Takers
Age	75.5	77.6
Female	0.68	0.68
White	0.63	0.50
Drug Expenditures	3020	3239
Drug Days' Supply	1555	1595

Notes: The table shows descriptive statistics for all patients from their Medicaid loss year that lost Medicaid between June and September, filled at least one prescription, and entered the year with Medicaid. The first column presents the descriptives for the compliers and the second column the always takers. Utilization outcomes are from the year a patient loses Medicaid.

Table 5: RD Estimates of Subsidy Receipt and Prescription Utilization

	Subsidy	Quantity		Expenditures	
	FS	RF	IV	RF	IV
RD Estimate	-0.49***	-110.80***	-226.81***	-564.77***	-1156.72***
	(0.01)	(10.01)	(14.70)	(64.27)	(124.45)
Frac. Mean	**0.49**	**0.07**	**0.15**	**0.18**	**0.38**
Cohort FE	X	X	X	X	X
N	84143	84143	84143	84143	84143
Complier Mean	0.99	1488	1488	3088	3088

Notes: Coefficients are estimated using discrete regression discontinuity; robust standard errors clustered at the cohort (state by year of Medicaid loss) level; p-values calculated using randomization inference. Significance levels: *=10%, **=5%, ***=1%.

Table 6: OLS Estimates of Factors Predicting Percent Reductions of Individual Drugs

	OOP Only	Value Only	Combined
Intercept	-4.718***	-7.963***	-5.221***
	(0.459)	(0.794)	(0.886)
OOP	-0.127***		-0.142***
	(0.017)		(0.028)
Low Type		1.210	0.128
		(1.306)	(1.497)
Medium Type		2.248*	0.822
		(1.003)	(1.068)
OOP × Low Type			0.067
			(0.045)
OOP × Medium Type			0.004
			(0.039)
Num.Obs.	200	200	200
R2 Adj.	0.227	0.015	0.229

Notes: This table shows the OLS estimates of how much variation in the percentage reduction of individual prescriptions are explained with the out-of-pocket cost and broad value classifications Significance levels: *=10%, **=5%, ***=1%.

Table 7: RD Estimates of Days' Supply of Select Prescription Classes

	Insulin	Inhalers	Statins
RD Estimate	-3.62***	-4.58***	-10.16***
	(0.37)	(0.59)	(1.38)
Frac Mean	0.14	0.17	0.07
Cohort FE	X	X	X
N	84143	84143	84143
Complier Mean	27.42	26.64	145.29
Avg. OOP	41.7	35.17	18.35

Notes: Coefficients presented are reduced form and are estimated using discrete regression discontinuity; Days' supply of a prescription can be interpreted like number of prescription pills; robust standard errors clustered at the cohort (state by year of Medicaid loss) level; p-values calculated using randomization inference. Significance levels: *=10%, **=5%, ***=1%.

Table 8: RD Estimates of Prescription Expenditures by Value Type

	High Value	Medium Value	Low Value
Cutoff	-251.75***	-104.46***	-59.63***
	(34.54)	(19.85)	(5.93)
Cohort FE	X	X	X
N	84143	84143	84143
Complier Mean	1390	743	405
Avg. OOP	24.28	13.9	22.6

Notes: Coefficients presented are reduced form and are estimated using discrete regression discontinuity; Prescription expenditures are the total price paid by the insurer and the patient. Value classifications are based on likelihood of preventing adverse health event. 15% of prescription expenditures are not categorized. Coefficients are estimated using discrete regression discontinuity; robust standard errors clustered at the cohort (state by year of Medicaid loss) level; p-values calculated using randomization inference. Significance levels: *=10%, **=5%, ***=1%.

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Prioritizing Value? How Low-Income Patients Respond to Prescription Cost-Sharing

Appendix

Christopher Hollrah

A Prescription Linkages

The level a prescription is identified by is its generic compound and whether it is a generic or branded version. Identifying prescriptions this way means all branded versions of a prescription are treated as if they are the same brand, and all delivery methods (e.g. tablet or capsule) are combined into a single prescription type. The linking variable used to link the value classifications from Chandra et al. (2010); Lavetti and Simon (2018) and therapeutic class information are the NDC9 codes. NDC codes are available at the NDC11 level, but as the last two digits are the delivery method, only the first nine are needed. Classifications are matched based on NDC9 codes, and a prescription is matched to a value as long as a single match occurs. In terms of match quality, the prescriptions that make up the vast majority of prescription expenditures are matched as shown in the table below.

B Complier Means

Under the assumption of local randomization within each state year, the average outcomes of always takers (A), compliers (C) can be calculated directly. Here instrument (Z) refers to losing Medicaid before versus after the July cutoff. Patients who lose Medicaid after the cutoff are guaranteed access to the subsidy, and patients that lose Medicaid before the cutoff are not. Always takers are patients that maintain access to the subsidy without the guarantee. Compliers are patients that only maintain the subsidy with the guarantee. In this setting, never takers a patients for which the guarantee did not bind, and are less than 2 percent of the population. Note this population did not choose to lose the subsidy.

Of the patients that are not guaranteed access to the subsidy, 51 out of every 100 will maintain the subsidy, are treated (D). These patients are the always takers and since they are the only before cutoff patients with the subsidy, their outcomes can be directly observed. The observed outcomes of patients with the guarantee on the other hand are a weighted average of the compliers and the always takers. The weighted average is equal to the treated outcome of the always takers weighted by the proportion of always takers among patients guaranteed with the subsidy plus the treated outcome of the compliers, the object to recover, weighted by the the proportion of compliers among patient guaranteed the subsidy. A graphical example using prescription expenditures analagous to Kowalski (2023) is shown in appendix figure A5. Explicitly, the complier mean is:

$$E(Y|Z=1,D=1) = E(Y|Z=1,A=1)\left(\frac{E(A|Z=1}{E(P|Z=1)}\right) + E(Y|Z=1,C=1)\left(1-\frac{E(A|Z=1}{E(P|Z=1)}\right)$$

Under the assumption of local randomization, the mean is easy to calculate:

- The outcome of all patients with the guarantee $E(Y|Z=1,D=1)$ is directly observed.
- The outcome of the always takers $E(Y|Z=1,A=1) = E(Y|Z=0,A=1)$ is directly observed.
- The proportion of always takers $\left(\frac{E(A|Z=1}{E(P|Z=1)}\right) = \left(\frac{E(A|Z=0}{E(P|Z=1)}\right)$ is directly observed.
- The proportion of compliers $\left(1-\frac{E(C|Z=1}{E(P|Z=1)}\right)$ is 1 less the proportion of always takers.

$$\begin{aligned}E(Y|Z=1,C=1) = E(Y|Z=1,D=1)&\left(\frac{E(P|Z=1)}{E(P|Z=1)-E(A|Z=1)}\right) - \\ E(Y|Z=1,A=1)&\left(\frac{E(A|Z=1)}{E(P|Z=1)-E(A|Z=1)}\right)\end{aligned}$$

A baseline complier mean can also be calculated using the pre-period of the panel directly since who is a complier is a realized event. Then under the randomization assumptions, it should generalize to be the same across the cutoff. In this case, the complier mean in the baseline period would be the mean of the outcome for patients who lost the subsidy. Reassuringly, the complier mean calculated from the baseline are very similar to the complier means using the post-period.

Valid estimates of the complier means can also be calculated under looser assumptionsi. The assumptions for an RD are the existence of a first stage, monotonicity, and independence (Almond and Doyle 2010, (Kim and Lee, 2017)). The first stage assumption is empirically tested - patients without the guarantee are much more likely to lose the subsidy. Monotonicity would mean that patients that maintain the subsidy without the guarantee would also do so with the guarantee. Since the treatment is a guarantee, this must be true. Finally, independence will follow if assignment to treatment is as good as random. This cannot be observed, but the lack of manipulation around the cutoff and similarity of covariates across the cutoff suggests this is unlikely to be violated.

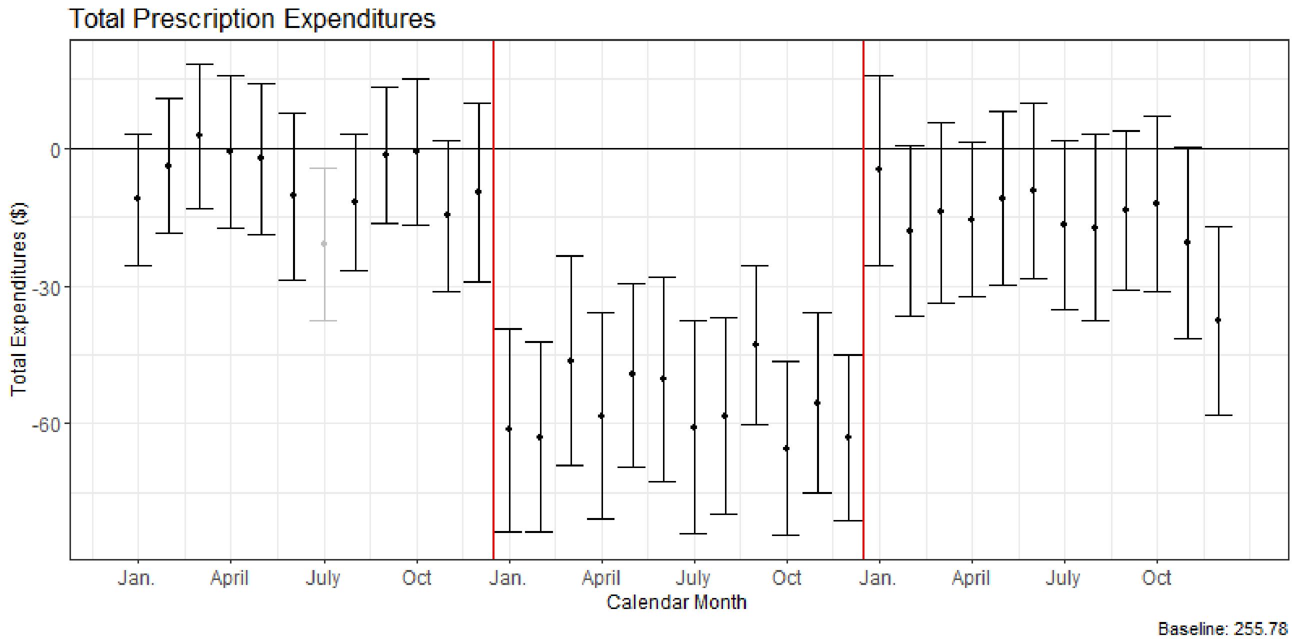
Table A1: OLS Estimates of Factors Predicting Percent Reductions of Individual Drugs

	OOP Only	Surplus Only	Combined
Intercept	-4.718***	-6.049***	-4.415***
	(0.459)	(0.491)	(0.506)
OOP	-0.127***		-0.129***
	(0.017)		(0.019)
SS		-0.009*	-0.007
		(0.004)	(0.005)
OOP × SS			0.000
			(0.000)
Num.Obs.	200	190	190
R2 Adj.	0.227	0.027	0.229

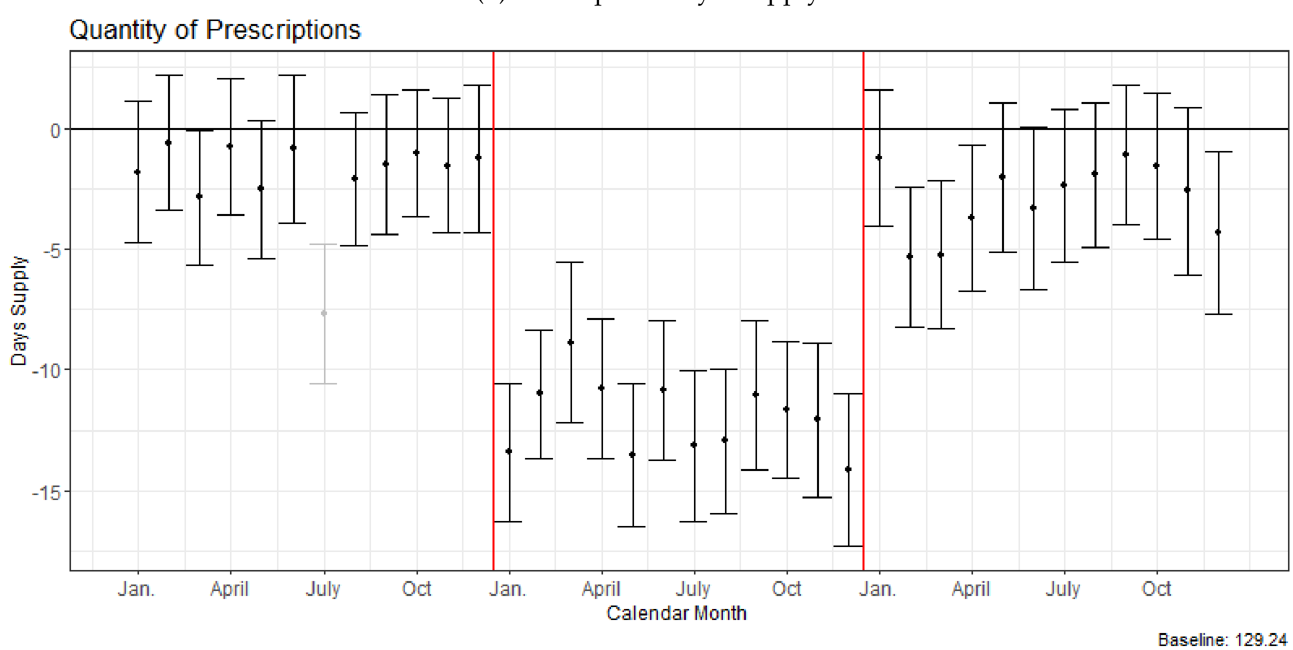
Notes: This table shows the OLS estimates of how much variation in the percentage reduction of individual prescriptions are explained with the out-of-pocket cost and switcher surplus (SS) measure defined in Lavetti and Simon (2018) classifications Significance levels: *=10%, **=5%, ***=1%.

Figure A1: Monthly RD Coefficients of Prescription Utilization: 1-Month Bandwidth

(a) Prescription Expenditures



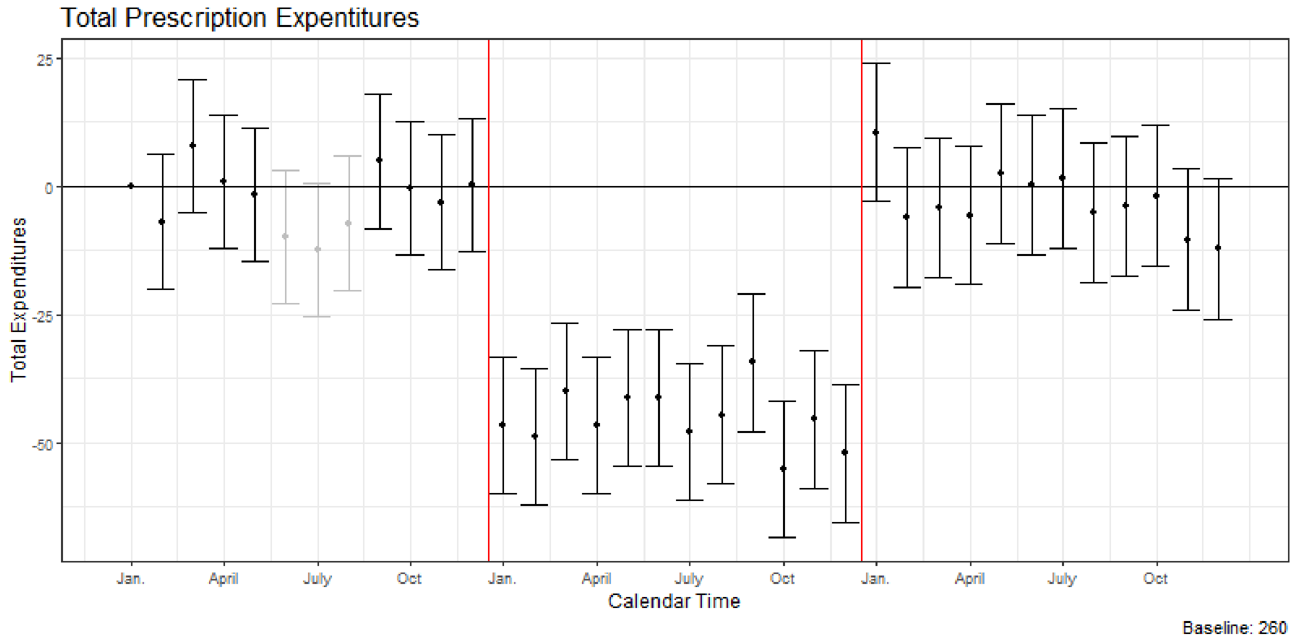
(b) Prescription Days' Supply



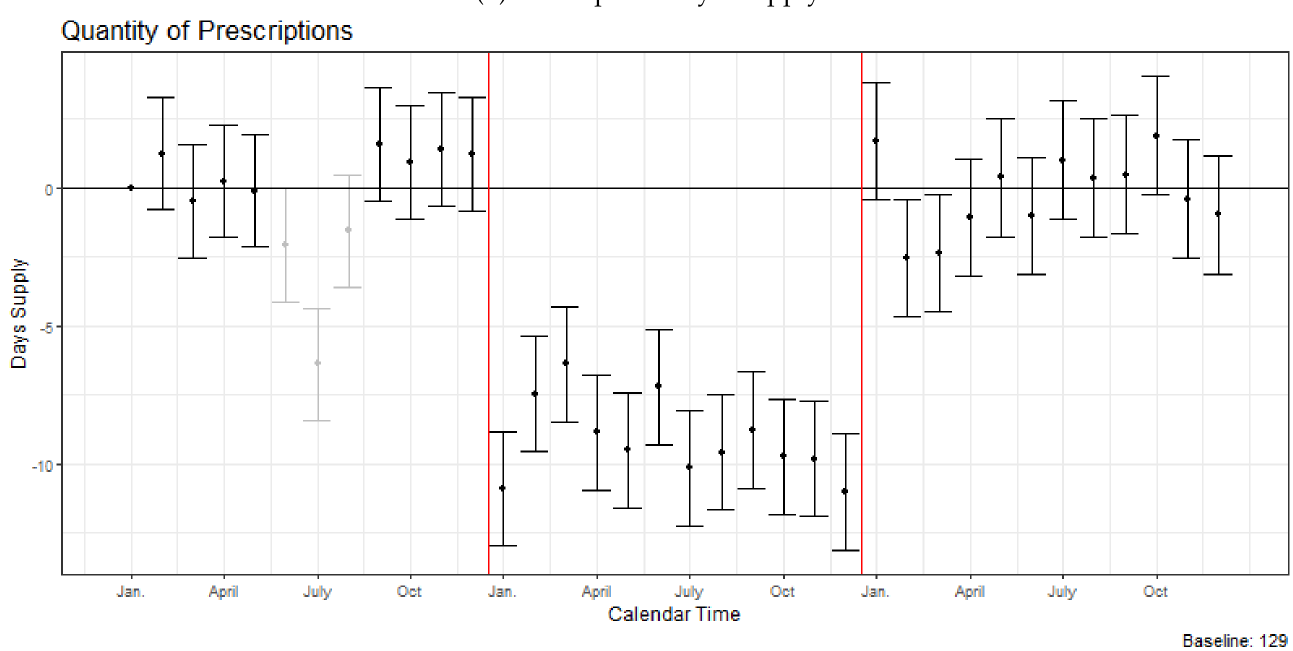
Note: Figure shows the separate discrete regression discontinuity estimates for each relative calendar month of the difference between patients that lose Medicaid before the cutoff versus patients that lose Medicaid after. The reported baseline is yearly average of patients that lose Medicaid before the cutoff and lose the subsidy in the following year (complier mean). The coefficients of June through August are greyed out since they capture a mechanical difference in Medicaid receipt. Robust standard errors clustered at the cohort (state by year of Medicaid loss) level.

Figure A2: Difference-in-difference Coefficients of Prescription Utilization

(a) Prescription Expenditures



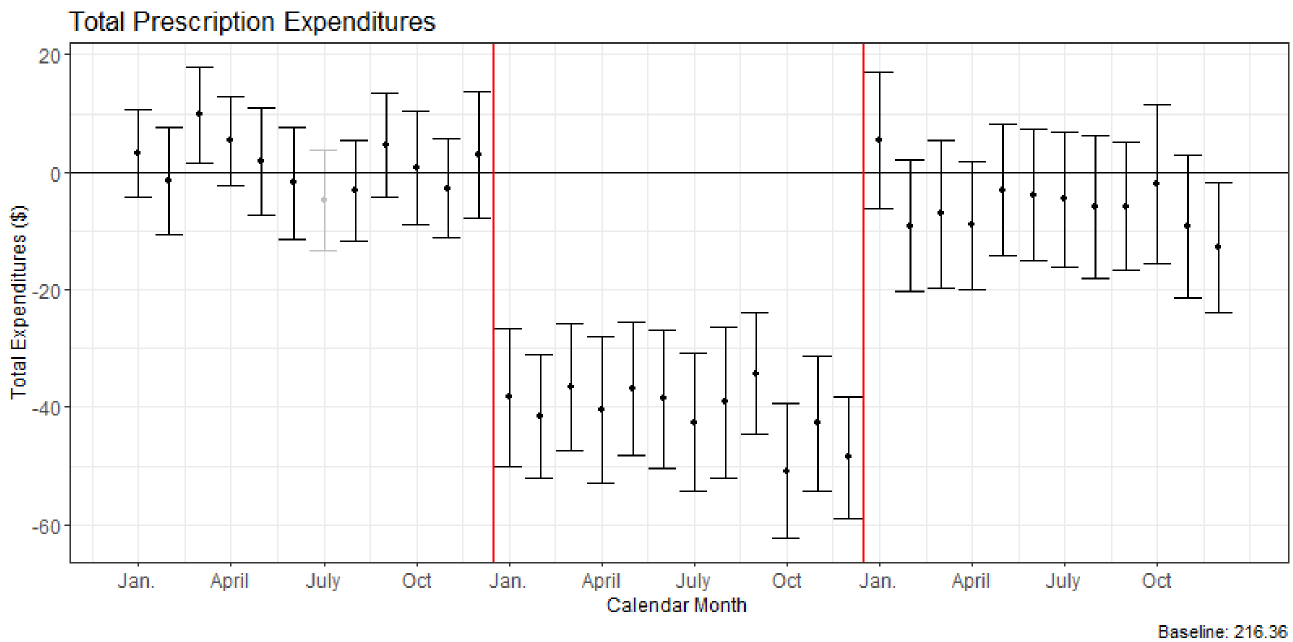
(b) Prescription Days' Supply



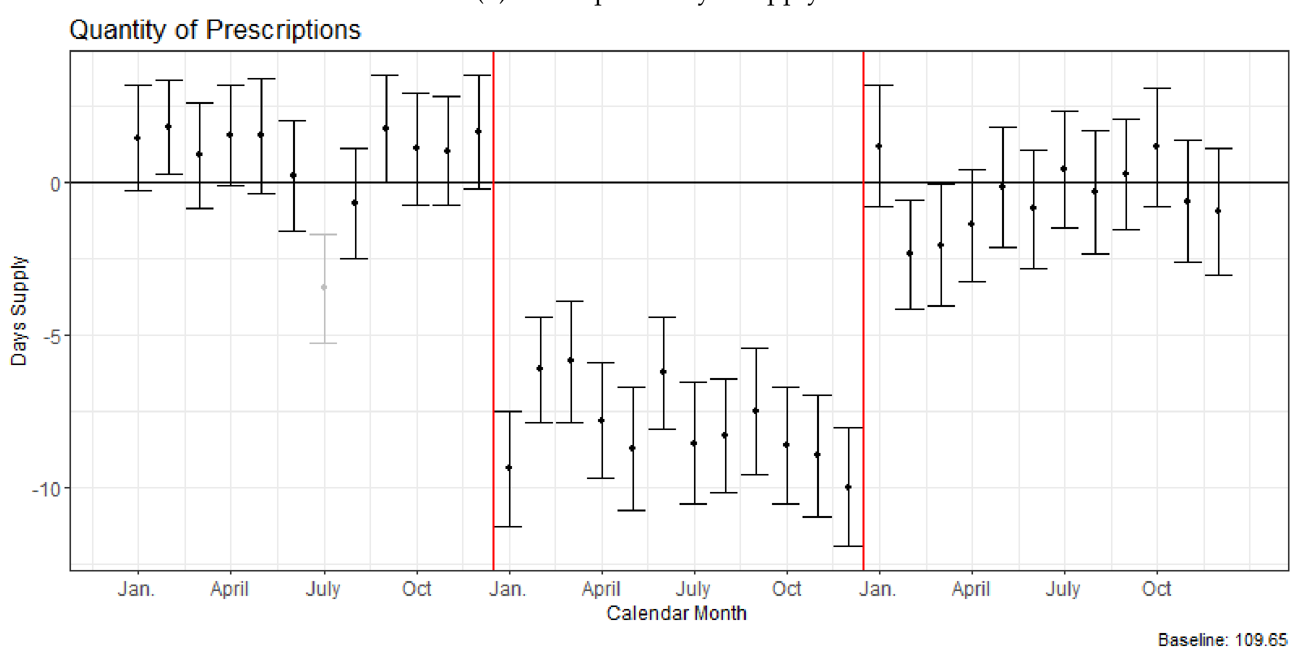
Note: Figure shows the difference-in-difference estimates between patients that lose Medicaid before the cutoff versus patients that lose Medicaid after. The reported baseline is yearly average of patients that lose Medicaid before the cutoff and lose the subsidy in the following year (complier mean). The coefficients of June through August are greyed out since they capture a mechanical difference in Medicaid receipt. Robust standard errors clustered at the cohort (state by year of Medicaid loss) level.

Figure A3: Monthly RD Coefficients of Prescription Utilization: Relaxed Sample

(a) Prescription Expenditures



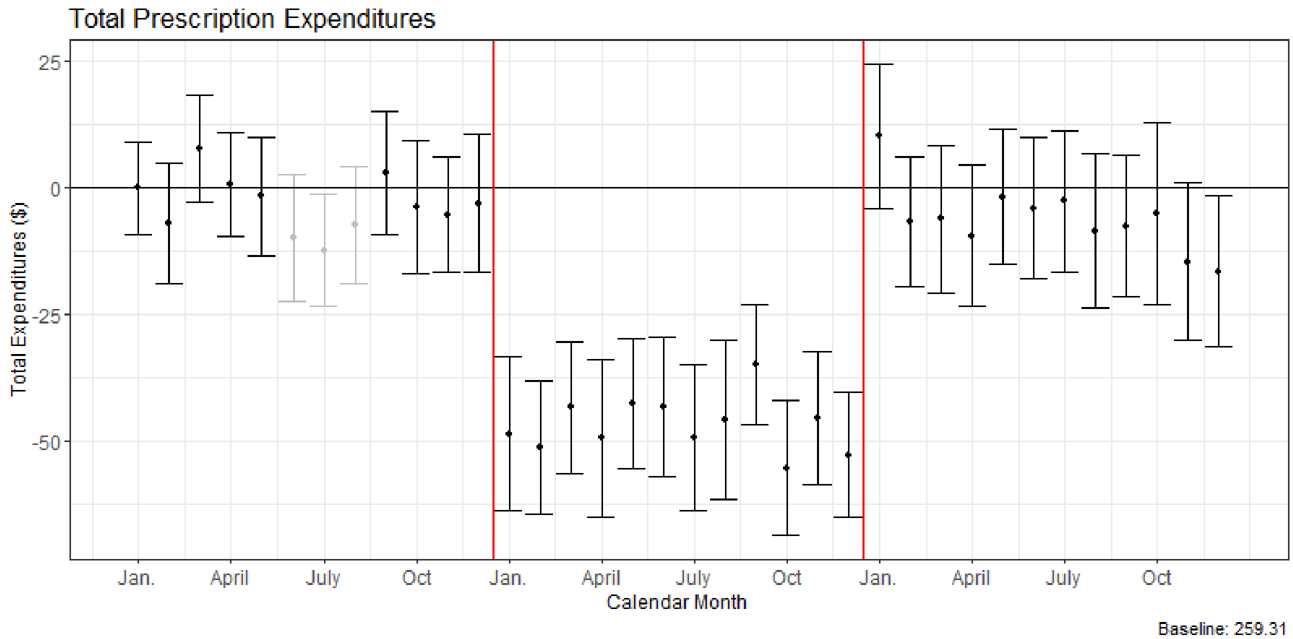
(b) Prescription Days' Supply



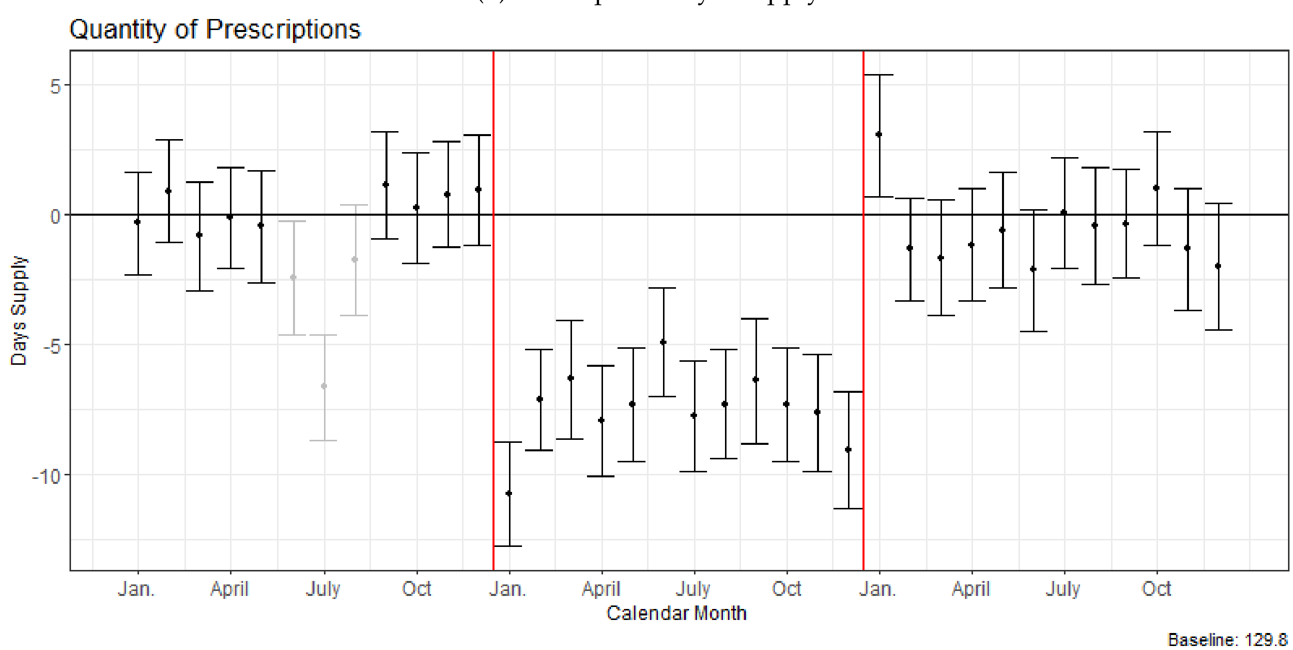
Note: Figure shows the separate discrete regression discontinuity estimates for each relative calendar month of the difference between patients that lose Medicaid before the cutoff versus patients that lose Medicaid after. The sample is relaxed to allow patients regardless of number of fills or Medicaid status entering the year. The reported baseline is yearly average of patients that lose Medicaid before the cutoff and lose the subsidy in the following year (complier mean). The coefficients of June through August are greyed out since they capture a mechanical difference in Medicaid receipt. Robust standard errors clustered at the cohort (state by year of Medicaid loss) level.

Figure A4: Monthly RD Coefficients of Prescription Utilization: Assume Utilization Unchanged Without Insurance

(a) Prescription Expenditures

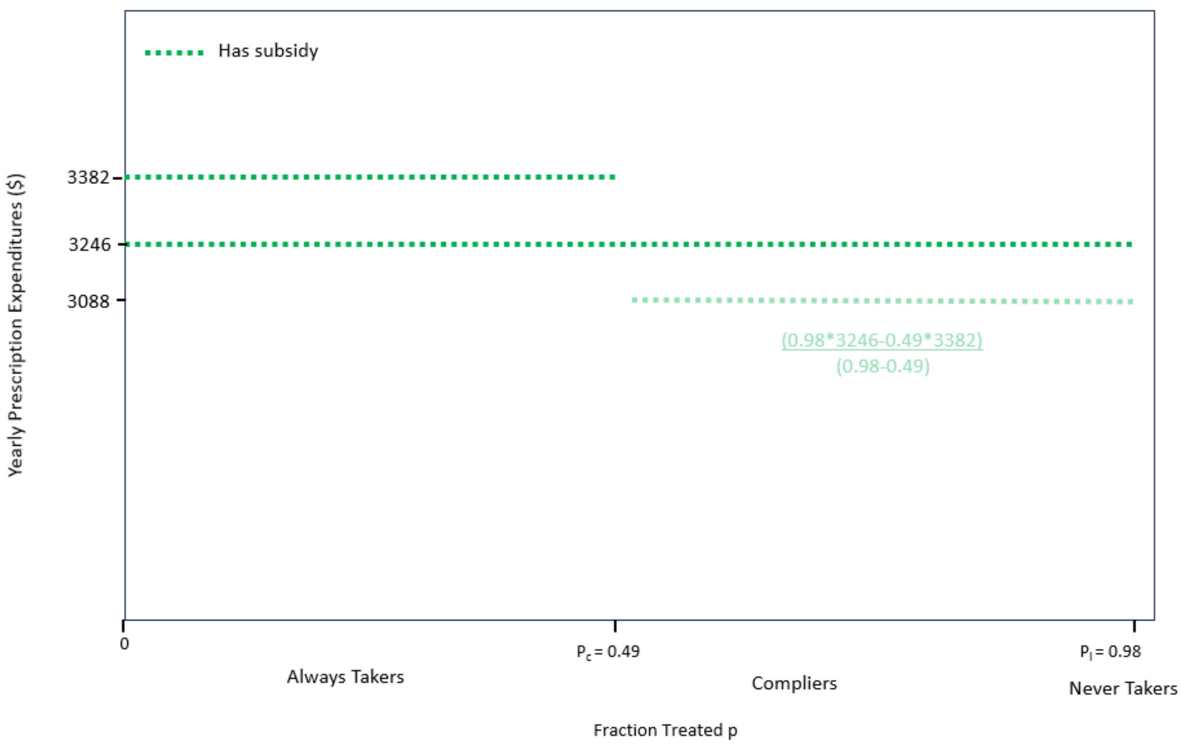


(b) Prescription Days' Supply



Note: Figure shows the separate discrete regression discontinuity estimates for each relative calendar month of the difference between patients that lose Medicaid before the cutoff versus patients that lose Medicaid after. In the event a patient's prescription insurance lapses, they are assumed to fully maintain their utilization from their last month of insurance. The reported baseline is yearly average of patients that lose Medicaid before the cutoff and lose the subsidy in the following year (complier mean). The coefficients of June through August are greyed out since they capture a mechanical difference in Medicaid receipt. Robust standard errors clustered at the cohort (state by year of Medicaid loss) level.

Figure A5: Example Calculation of Complier Mean of Prescription Expenditures



Note: Figure visually shows how to compute the complier means using prescription expenditures in the year after losing Medicaid as the example.