Marginal Returns to Health Insurance Subsidies: Evidence from Medicare*

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Abstract

Means-tested subsidies for health insurance are ubiquitous and widely debated. This paper estimates the causal effects of health insurance subsidies on marginal recipients by exploiting discontinuities in the schedule of eligibility redeterminations for Medicare's Low-Income Subsidy (LIS) program. LIS subsidizes premiums and cost-sharing in Medicare's Part D prescription drug benefit. Beneficiaries who enroll in LIS upon first becoming eligible for Medicare and whose birthdays fall before May 1 are subject to earlier redetermination of their eligibility, while Medicare enrollment rules prevent those born after May 1 from enrolling earlier in the year. We find that beneficiaries born in the weeks before May 1 are 6 percentage points (44 percent) more likely to lose their subsidy within the first three years of enrollment. The loss of subsidies leads some beneficiaries to drop prescription drug insurance altogether, while beneficiaries who retain coverage pay a higher share of costs out of pocket. Yet we detect no changes in the overall spending on prescription drugs, or in the use of specific therapeutic classes, with the notable exception of declines in fills for expensive mental health medications. We also find no increases in hospitalizations, emergency care, or physician visits that would signal deteriorating health, nor any changes in overall healthcare spending over a three-year follow-up window.

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1 Introduction

Subsidies for health insurance represent one of the largest categories of social spending in the United States (KFF, 2025). Despite commanding hundreds of billions of dollars in public spending, the topic has rarely been accused of captivating broad audiences, with the remarkable exception of the U.S. government shutdown in October 2025, which put Affordable Care Act health insurance subsidies onto newspaper front pages for weeks (NYT, 2025; WSJ, 2025a,b). The intense public discussion highlighted a set of core policy questions. Namely, who (if anyone) should receive means-tested health insurance subsidies, how much the subsidies should be, and how we expect them to impact healthcare utilization and health of the recipients.

While the public debate tends to focus on the average effects of subsidies, from the standpoint of optimal policy design, what matters the most are the responses at the margin (Akerlof, 1978; Currie and Gahvari, 2008; Chetty, 2009; Finkelstein and Hendren, 2020; Kleven, 2021). Whether to expand or contract eligibility, or to raise or lower subsidy amounts depends on the causal effect of subsidies on those individuals who are just barely included or excluded by current rules.

In this paper, we estimate the returns to health insurance subsidies for marginal recipients in the context of Medicare's prescription drug program, Medicare Part D. Part D accounted for over $128 billion in government spending and covered 51.5 million of the 66.3 million Medicare beneficiaries in 2023 (The Medicare Payment Advisory Commission, 2025). In this part of Medicare, the federal government provides subsidies for plan premiums, deductibles, and cost-sharing for enrollees with income under 150% of the federal poverty level (FPL) and limited assets. Subsidies, known as the "Extra Help" or "Low Income Subsidy" (LIS) program, amounted to $44 billion in government payments to 14 million low-income Part D enrollees in 2023. LIS is administered by the Social Security Administration (SSA). SSA estimates that the average value of the subsidy package is $5,700 per year, or nearly a quarter of annual income at the individual income eligibility cutoff (SSA, 2026).

We use a regression discontinuity design (RDD), together with administrative Medicare claims data for years 2010 to 2022, to estimate the return to extra months of LIS benefits for individuals who are on the margin of LIS eligibility. Our empirical approach takes advantage of quasi-experimental variation created by the intersection of Medicare's enrollment and LIS redetermination rules. For people enrolling in LIS right when they become eligible for Medicare,

i.e. during the Initial Enrollment Period, the LIS enrollment month will be highly correlated with the month of birth. The earliest time beneficiaries become eligible for Medicare (and LIS) due to old age is the month they turn 65.[1] At the same time, SSA selects beneficiaries for eligibility redeterminations based on annual cycles that use May 1 as a cutoff. Beneficiaries enrolled in LIS on or before April 30 of the current year can be selected to verify their LIS eligibility in September of the current year, while those who enrolled on or after May 1 will be included in the next cycle. These initial eligibility and LIS redetermination rules create a discontinuity in the length of LIS enrollment around May 1 birth dates. Beneficiaries with birth dates before May 1 and enrolling in LIS during the Initial Enrollment Period can be selected for LIS redetermination in their first year of enrollment, while those born after May 1 cannot, and are thus effectively as good as randomly assigned to get extra months of LIS.[2]

Within an RDD framework that uses birth dates as the running variable, we zoom in onto the universe of Medicare beneficiaries who were born in the 90-day window around May 1 and enrolled in Medicare and LIS during their Initial Enrollment Period in years 2010 to 2021. This sample selection implies that we are analyzing the "Baby Boomer" cohorts born between 1945 and 1956. We follow these individuals for the first three years they are in the Medicare program.[3]

We start by evaluating different notions of the first stage in the data. We first test whether individuals born earlier in the year are indeed less likely to have subsidies in years two and three after they first enroll in Medicare and LIS. The probability of losing the subsidy sharply changes around May 1, and is both statistically and economically significant. In the second and third year after LIS enrollment, being born before May 1 increases the probability of subsidy loss by 4 and 6 percentage points, respectively. This corresponds to, respectively, 182% and 44% increase relative to the mean probability of subsidy loss among beneficiaries born after May 1. The subsidy loss immediately translates to monetary changes: in the year following the year of LIS enrollment, being born just before May 1 leads to a 2.6 percentage points (or 6%) decline in the share of total drug costs covered by LIS, out of the 41% base level. At the same time, the

[1] We exclude individuals born on the 1st of the month, as they face different Initial Enrollment Period rules.

[2] Beneficiaries can still lose LIS throughout the year due to subsidy changing events rather than redetermination cycles, but those instances are rare in our sample. Subsidy changing events include marriage, death of a cohabiting spouse, divorce, annulment, or separations. These events can be reported by third parties or beneficiaries can self-report them to SSA, though it is not mandatory.

[3] We condition on survival until age 68. We also exclude individuals who are ever dual eligible during these three years, as they are considered automatically eligible for LIS, and hence, are not subject to LIS redetermination. Our empirical checks suggest that none of these sample restrictions generate differential selection around May 1 cutoff.

share of total costs covered by beneficiaries increases by 1 percentage point (or 7%) relative to the 14.4% baseline. These gaps widen in the subsequent year and amount to large changes for the complier population, with a 17 percentage point increase in the share of drug costs paid by beneficiaries when the effect is scaled by the first stage.

We then proceed to analyze the changes in demand for prescription drug insurance plans as well as utilization of prescription drugs, as the most immediate outcomes that we would expect to respond to the loss of LIS. We find that beneficiaries born before May 1 are 0.5 percentage points (9 percentage points when scaled by the first stage) more likely to drop prescription drug coverage in the third year since LIS enrollment. We find small and statistically insignificant behavioral responses in aggregate drug utilization measured by the total number of standardized (30-day) fills and total drug costs, in both the second and third years since LIS enrollment. Analyzing changes in drug utilization by therapeutic class yields similar results, with the exceptions of reductions in fills for expensive mental health drugs, beta blockers, and psycholeptics in the second year since LIS enrollment. Most notably, we find a 1.8 p.p. reduction in the probability of filling an expensive mental health medication in the second year, relative to a control mean of 10.2%. This effect is confined to the second year since LIS enrollment and does not persist into the third year.

These results on drug utilization are somewhat surprising. A rich literature has examined health insurance and prescription drug demand, including in the Medicare population, and has typically found pronounced behavioral responses (Einav et al., 2015a, 2018a; Gross et al., 2022; Chandra et al., 2024, among others). Our results contrast with Chandra et al. (2024) and especially Hollrah (forthcoming), although they are broadly consistent with the notion that prescription drugs tend to generally have inelastic demand Einav et al. (2018a). Our findings suggest the existence of substitution between drugs, but do not show clear discontinuations of classes of medications with the exception of beta blockers and psycholeptics. One key aspect of our analysis is that we are considering beneficiaries who are affected by the subsidy redetermination process and are hence by definition marginal to being eligible for subsidies and may exhibit more limited behavioral responses than an average infra-marginal beneficiary. Indeed, our findings of relatively limited responses in overall drug utilization would be consistent with subsidies targeting beneficiaries right to the point where there is no behavioral response to subsidies (Akerlof, 1978).

Using the richness of Medicare data, we move on to consider non-drug measures of health-

care utilization and, implicitly, health. Despite the pronounced changes in subsidies in the first stage, we find limited changes in many other measures of healthcare utilization we consider. This includes general hospitalizations, more severe hospitalizations with ICU stays, hospitalizations specifically for cardiovascular conditions, and emergency room visits. We similarly see no shifts in office visits, whether in general or specifically for PCPs and specialists. When considering aggregate spending in Medicare, we are able to detect some declines in testing and lower utilization of nursing homes and SNFs. Our null results for a variety of healthcare use outcomes are not sensitive to the specific choices about sample construction. These results are consistent with the findings of limited clinical effects of Medicaid expansion to marginally eligible (albeit younger) adults in the Oregon Health Insurance Experiment (Baicker et al., 2013), as well as with the lack of offsets given the limited response on the prescription drug margin as in Chandra et al. (2024, 2010a).

Our analysis contributes to multiple strands of the literature. First, most directly, we contribute to a rich literature on cost-sharing and moral hazard in health insurance (Chandra et al., 2010a,b; Baicker et al., 2015; Aron-Dine et al., 2015; Einav et al., 2018a; Shigeoka, 2014; Brot-Goldberg et al., 2017; Einav and Finkelstein, 2018; Baicker et al., 2015; Hollrah, forthcoming; Einav et al., 2015b; Chandra et al., 2024, among others). The closest in this space is Hollrah (forthcoming) and Roberts et al. (2025) that both consider the effect of prescription drug subsidy losses in the dual eligible Medicare-Medicaid population and find substantial reductions in drug purchases as well as increases in mortality in response. Our results are consistent with Fung et al. (2024) who document an association between LIS losses and an increase in out-of-pocket costs in the non-dual-eligible population.

Second, our work has implications for the broader literature on subsidies in a variety of healthcare contexts, including but not limited to subsidies to health insurance plans (Carey, 2021; Cabral et al., 2018; Duggan et al., 2016; Decarolis et al., 2020; Decarolis, 2015; Tebaldi, 2017), hospitals and physicians (Einav et al., 2018b; Dafny, 2005), and to consumers (Finkelstein et al., 2019b; Gross et al., 2022; Aron-Dine et al., 2013; Manning et al., 1987; Newhouse, 1993; Finkelstein et al., 2019a). Our findings underscore that subsidy effects may be highly heterogeneous across different types of consumers, which makes understanding the returns for marginal beneficiaries central for policy-making (Hendren and Sprung-Keyser, 2020; Finkelstein and Hendren, 2020).

Finally, outside of the healthcare context, our work contributes to the expansive literature

on the design of means-tested public benefits. Motivated by the logic of targeting benefits to observables that may correlate with the highest marginal benefit from subsidies (Akerlof, 1978), many programs means-test their benefits; and extensive academic work has evaluated the effects of such programs. An important strand of this literature examines how administrative burden may contribute to low take-up of social benefit programs (e.g., Finkelstein and Notowidigdo, 2019; Deshpande and Li, 2019; Ericson et al., 2025). Redetermination processes of the kind we exploit in our empirical design are likely to contribute to low take-up and are also extremely costly to run. A relevant policy question is whether such redetermination efforts are worthwhile. While our results are consistent with marginal beneficiaries being nearly indifferent and hence subsidy discontinuation may have muted effects on healthcare utilization, we also find that removing these subsidies generates limited savings.

The rest of the paper proceeds as follows. In section 2, we discuss the empirical context of Medicare prescription drug insurance, our data, and sample selection. Section 3 summarizes our regression discontinuity approach. Section 4 reports the results and Section 5 briefly concludes.

2 Setting and Data

2.1 Institutional Primer

Medicare is a federal health insurance program in the United States, primarily covering adults age 65 and older who have made mandatory payroll contributions to the program during their working lives. Contributions typically make beneficiaries eligible to enroll in Medicare Part A (for inpatient care) without premiums, while Medicare Part B (for outpatient services) and Part D (for prescription drugs) require paying premiums. In addition to premiums, all parts of the program have cost-sharing that beneficiaries have to pay when utilizing healthcare.

Medicare eligibility starts in the month an individual turns 65. To avoid penalties for late enrollment, beneficiaries must enroll during the Initial Enrollment Period (IEP)—a 7-month enrollment window that includes the birthday month as well as three months before and after.[4] Individuals can choose to receive their Medicare benefits either through traditional fee-for-service Medicare, in which the federal government directly reimburses providers of healthcare, or through a managed care Medicare Advantage plan, in which a private insurance plan administers the

[4]For individuals born on the first of the month, eligibility starts in the month before the month they turn 65. To make sure that the timing of eligibility is continuous with respect to the day of birth, we exclude these beneficiaries from the sample.

benefit. Medicare Part D program has no fee-for-service analogue and is always administered by a private insurer. Part D plans can be purchased as stand-alone prescription drug plans to supplement Traditional Medicare (TM), or as part of a Medicare Advantage (MA) plan.

Means-testing of benefits has become increasingly common in these different parts of Medicare. Starting in 2007, income-related Medicare premiums (also known as the Income Related Monthly Adjustment Amount) were enacted in Part B as part of the Medicare Modernization Act (MMA) of 2003. Further, several state-run Medicare Savings Program (MSP) initiatives that reduce premiums and cost-sharing have seen enrollment steadily increase over the past decade (MACPAC, 2024). The focus of our study are means-tested subsidies in Medicare Part D, which the federal government has provided since the program's inception in 2006.

Medicare Part D means-tested subsidies are known as Extra Help or Low Income Subsidy (LIS). SSA administers the LIS program. SSA deems many beneficiaries automatically eligible for LIS through participation in other programs, primarily Medicaid and Supplemental Security Income. Individuals can also apply for LIS and be approved or denied by SSA after review. LIS eligibility is based on modified income and asset tests. In 2026, single beneficiaries with less than $18,090 in resources and less than $23,475 in annual income (circa 150% FPL) were eligible. If approved, beneficiaries get a subsidy to defray the cost of plan premiums and cost-sharing. For example, in 2026, co-pays of beneficiaries with LIS for a one-month supply of generic and branded drugs cannot exceed $5.1 and $12.7, respectively, up until $2,100 after which the copay becomes $0 (CMS, 2026). Further, LIS covers 100% of premiums for a selection of Part D plans. SSA estimates that the average value of the subsidy package is $5,700 per year, which is equal to nearly a quarter of annual income at the income eligibility cutoff (SSA, 2026). SSA regularly reviews continued eligibility for LIS.

As we discuss in Section 3, the combination of administrative rules that guide the timing of Medicare enrollment and SSA's redetermination of LIS benefits creates quasi-experimental variation in the length of LIS benefits for marginally eligible beneficiaries.

2.2 Data

The primary data source for this study are administrative Medicare data files provided by the Centers for Medicare and Medicaid Services (CMS). The files cover enrollment, prescription drug, inpatient, and outpatient records for years 2010-2022.

Beneficiary Characteristics For each beneficiary, 100% Master Beneficiary Summary Files (MBSF) provides information on the basic demographics and enrollment status for the universe of Medicare beneficiaries: age, sex, race, the SSA standard two-digit state code of residence, the reason for original and current Medicare entitlement, whether a beneficiary is receiving benefits through the TM or MA program, and enrollment in Medicare Part D if any. For beneficiaries with prescription drug coverage, we also observe monthly data on each beneficiary's plan type and cost-sharing group. The latter allows us to determine if a beneficiary has any type of LIS in a given month.[5]

Aggregate Healthcare Utilization We use the Cost and Use segment of 100% MBSF files to measure aggregate spending and utilization of all services covered by Medicare, including inpatient, outpatient, home health, durable medical equipment, and hospice care. These files cover the universe of healthcare utilization by beneficiaries in Traditional Medicare. We supplement these aggregate statistics with more detailed data for each type of service.

Prescription Drug Purchases When a Medicare beneficiary with Part D coverage fills a prescription, the prescription drug plan submits a record to CMS. Part D Event (PDE) files include all transactions by the random 20% sample of Medicare beneficiaries. Drug fills are observed for beneficiaries enrolled in stand-alone Prescription Drug Plans (PDPs) as well as those enrolled in Medicare Advantage Prescription Drug Plans (MA-PDs). The detailed administrative records contain key elements necessary to track drug fills and spending, such as drug name, dosage form, quantity purchased, date of service, and payments made by the beneficiary, plan, and third parties, including the LIS program. We assign drugs to therapeutic classes by mapping National Drug Codes (NDCs) observed at the claim level to Anatomical Therapeutic Chemical (ATC) classifications (up to ATC-4) using the RxNorm API provided by the National Library of Medicine.[6]

Physician Services For a 20% random sample of beneficiaries in Traditional Medicare, we observe professional charges by physicians and other clinical providers in Fee-for-Service Carrier files. These files cover outpatient office visits and procedures, as well as physician fees for inpatient services.

[5] In addition to the distinction between "deemed eligible" and "not deemed eligible" beneficiaries, individuals can receive partial LIS that provides a 15% coinsurance and a more limited premium subsidy.

[6] We are grateful to Fabrício Kury for developing and publicly sharing programs that query RxNorm API.

Hospitals and SNFs To trace the broader health consequences of prescription drug subsidies, we include the utilization of inpatient care in our analysis. The 100% Medicare Provider Analysis and Review (MedPAR) files contain full records of short- and long-term acute hospital and skilled nursing facility (SNF) stays for TM beneficiaries, as well as informational records (without payments) for MA beneficiaries.[7] We observe dates of admission and discharge, the type of admission (emergency or elective), the use of ICU, and a diagnosis-related group (DRG) code classifying stays by diagnosis and complexity for billing purposes.

Long-Term Care To track the use of long-term care nursing facilities, we leverage 100% Long Term Care Minimum Data Set (MDS) files, which contain records for regular health status screenings of all residents of nursing facilities certified by CMS, including beneficiaries in Traditional Medicare and Medicare Advantage.

2.3 Sample Construction

Our baseline sample starts with the universe of beneficiaries who first enrolled in Medicare Parts A and B at age 65 due to old age eligibility between 2010 and 2021. For each beneficiary, we find their first LIS spell if any. We consider this first spell to be the month of LIS enrollment. We exclude beneficiaries who are "deemed eligible" for LIS at any point within the first three calendar years following their LIS enrollment as they are automatically enrolled by SSA and are not subject to the same redetermination process(SSA, 2017).[8]

We restrict the resulting sample to beneficiaries who applied and enrolled in LIS during their Initial Enrollment Period and who were born in the 90-day window around May 1.[9] All these individuals enrolled in Medicare and LIS around the time when they turned 65 and first became eligible. We follow these individuals for the first three years they are in the Medicare program.[10] The first — enrollment — year is not a full year, as it only captures the months between enrollment month and December of enrollment year. The subsequent two years are full calendar years. We restrict our baseline sample to a balanced panel of individuals who survive

[7] MedPAR is estimated to capture nearly 90% of MA-covered hospitalizations (Cotterill, 2023).

[8] This primarily excludes beneficiaries who were dual eligible at any point during the year of LIS enrollment or the following two years. The probability of being dual-eligible exhibits no discontinuities at May 1 birth date.

[9] We exclude beneficiaries born on the first day of any calendar month, as their Initial Enrollment Period is shifted by one month and they can enroll in Medicare one month before they turn 65. We do this to ensure a continuous relationship between date of birth and Medicare eligibility start date. We further exclude very few beneficiaries who drop Part D coverage before the end of the first calendar year of enrollment, i.e., by December of the enrollment year. This excludes beneficiaries who churn out of LIS immediately after initial enrollment.

[10] To facilitate a clean three-year follow-up window, we only keep beneficiaries who continuously reside in one of the 50 U.S. states or Washington D.C. during the first three years following LIS enrollment.

until 68 years of age.[11]

In addition to our baseline sample that we use for the main intent-to-treat analysis, we also construct a direct sample of beneficiaries at risk of losing LIS. We use ex post enrollment outcomes to define this "marginal LIS beneficiaries" sample, namely by restricting our baseline sample to beneficiaries who lost LIS over the course of the first three redetermination cycles. Since the first redetermination occurs in the second year after enrollment for beneficiaries born before May 1 and in the third year for beneficiaries born after May 1, we include beneficiaries who lose LIS over the first 4 and 5 years since enrollment among those born before and after May 1, respectively. While everyone in this subsample eventually loses LIS (and hence is likely a marginal LIS beneficiary), we verify that early-birthday beneficiaries are more likely to have lost their subsidy faster than late-birthday beneficiaries, as we would expect from the institutional context.

2.4 Summary Statistics

Table 1 reports the basic facts for our baseline sample. We observe a total of 128,600 individuals, roughly equally split between those born 90 days before versus 90 days after May 1. As expected given our focus on the Initial Enrollment Period, the average age in the sample is 65. 60% of beneficiaries are women. 54% are non-Hispanic White, 20% are Hispanic, 18% are non-Hispanic Black, and 6% are Asian or Pacific Islander. 43% of beneficiaries choose Medicare Advantage when first enrolling in Medicare. As we would expect, we see nearly no differences in these characteristics among individuals born in the 90 days before versus the 90 days after May 1.

In the first year of enrollment, beneficiaries are spending around $1,500 in total on prescription drugs, with around 30 fills per year (Table 2, control means). LIS benefit covers about 40% of this total cost, with beneficiaries paying closer to 15%. More than half of the beneficiaries in our sample fill cardiovascular medications, while roughly a fifth purchase diabetes and mental health drugs, each. About 5% of beneficiaries have a hospitalization and about 1% have an ICU stay. About a third visit a PCP. And less than 1% have a SNF or a long-term care stay.

[11] Survival rates to age 68 are very high and we did not uncover any evidence of selection that this restriction introduces. See Appendix for details as well as robustness checks that probe the sensitivity of our results to all key sample restrictions. For the 2021 enrollment cohort, the post-enrollment observation window is truncated by data availability until 2022. We require survival through the end of 2022 rather than to age 68.

3 Empirical Approach

3.1 Regression Discontinuity Design

There are two institutional facts that we leverage in our empirical approach. First, beneficiaries who enroll in LIS right when they become eligible for Medicare — i.e., during the Initial Enrollment Period — most commonly enroll in LIS in their month of birth or (less commonly) in the three months right after their birth month.

Second, SSA conducts annual LIS redeterminations to verify continued eligibility for non-deemed LIS beneficiaries. Initial redeterminations happen right away in the first year of LIS eligibility and cyclical redeterminations happen in subsequent years.[12] Crucially, SSA anchors its redetermination cycles around May 1 eligibility cutoff. Initial redeterminations in a given calendar year are done only among beneficiaries who became eligible for LIS from May of the previous year to April of the redetermination year. Those who became eligible on or after May 1 fall into the next year's redetermination cycle. Since beneficiaries who enroll in LIS during the Initial Enrollment Period cannot enroll before their 65th birthday, those born after May 1, will not be included in SSA's initial redetermination cycle until the second calendar year of their enrollment. Those born before May 1, in contrast, can be subject to initial redeterminations in the first calendar year and thus can lose LIS at the start of their second year of enrollment.

This combination of Medicare enrollment and LIS eligibility verification rules creates as good as random assignment of the probability of losing LIS around May 1 birthday, in the second and third calendar year after enrollment. This setup lends itself well to using a regression discontinuity design (RDD) to analyze the effect of losing subsidies on a variety of outcomes.

To operationalize the RDD idea empirically, we estimate a parametric regression discontinuity specification with the week of birth as a running variable, allowing both the slope and

[12] In both cases, SSA does not run the redetermination process for all beneficiaries; instead it randomly selects subsets of beneficiaries among those who satisfy the relevant criteria. Beneficiaries selected for redeterminations are sent a letter in early September with SSA form 1026 (SSA-1026-OCR-SM-REDE) that asks beneficiaries to provide information to verify their LIS eligibility. Beneficiaries have 30 days to respond to this letter with the possibility of a one-time 30-day extension that must be requested during the original response period. If the form is returned before November 30, then any changes are effective January 1. If the form is returned after November 30, then any changes are effective the first day of the second month following the month the form is returned. For those who do not respond to the eligibility verification request, a local SSA office follows up in January-February of the following year (usually by calling them) and if there is still no response, then the subsidy is terminated effective April 1. Beneficiaries are entitled to appeal the SSA's decision and their LIS coverage may be extended until SSA responds to the appeal.

intercept to vary on each side of the May 1 birthday cutoff:

$$Y_{i(t)} = \beta_0 + \beta_1 \mathbf{1}[w_i < 0] + \beta_2 w_i + \beta_3 w_i \mathbf{1}[w_i < 0] + \delta_t + \varepsilon_i \tag{1}$$

where $Y_{i(t)}$ is the outcome of beneficiary i who enrolled in LIS in calendar year t. w_i is the week of birth, centered at zero for the week of May 1–May 7, which is the earliest week of birth unaffected by LIS redetermination in the year after LIS enrollment. Our coefficient of interest is β_1, which captures the discontinuity at the May 1 cutoff. Since beneficiaries born *before* May 1 are more likely to be affected by redeterminations, β_1 is the coefficient on an indicator for having an *earlier* birthday relative to the May 1 cutoff. Coefficients β_2 and β_3 allow for linear trends in the outcome, with different slopes on the two sides of the cutoff. δ_t are year fixed effects for the year of LIS enrollment that capture a general time trend in outcomes. Standard errors are clustered at the week of birth by year of LIS enrollment level.

There are several identifying assumptions needed to support this RD approach. First, individuals with birthdays close to May 1 need to not vary systematically in their eligibility for health insurance subsidies, health, and healthcare utilization except for their treatment by the SSA's LIS redetermination rules. Second, individuals born before versus after May 1 cannot manipulate their birthdays. And finally, individuals born before versus after May 1 need to not manipulate the timing of outcomes.

All of these assumptions are highly likely to hold in our setting. As we observe in Table 1 and Table 2, there are no differences in basic demographics and health between beneficiaries born before May 1 versus after May 1. The inability to manipulate the date of birth is mechanical. Further, for non-prescription drug outcomes, the coverage does not change and hence there is no incentive to change the timing of healthcare utilization. For prescription drug outcomes, there is an incentive for individuals born before May 1 to reallocate their drug consumption towards the first year of their program enrollment. In practice, this kind of reallocation is unlikely for two reasons. First, while the May 1 cutoff increases the probability of being asked to verify eligibility, individuals cannot know with certainty whether they will be selected. Moreover, beneficiaries likely have limited or no knowledge of the details of the SSA's administrative process. Second, even if beneficiaries had perfect information and foresight, their ability to reschedule prescription fills is constrained by limits on days of supply dispensed at pharmacies. Nevertheless, to assess the plausibility of such re-timing of fills, we check that prescription drug consumption in the first

year of enrollment is not higher among those born before May 1. We observe no such differences.

We estimate specification 1 separately for outcomes in the first and second full calendar years following the year of LIS enrollment. In the year following LIS enrollment, beneficiaries born before May 1 and selected for initial LIS redetermination may lose LIS, while beneficiaries born after May 1 are unaffected by the LIS redetermination process. In the third year since LIS enrollment, beneficiaries born before May 1 may experience cyclical LIS redetermination, whereas those born after May 1 may be selected for initial LIS redetermination. As a placebo exercise, we also estimate our regressions for outcomes in the calendar year of LIS enrollment, when all beneficiaries are not yet affected by LIS redetermination. We track beneficiaries from the month of their enrollment through December and annuitize utilization and spending measures to account for differences in the length of their enrollment in that year.

We consider several outcomes of interest, moving from the first stage that measures the presence of subsidies, to decisions about maintaining prescription drug coverage that we expect to be directly affected by subsidies, to utilization of prescription drugs. We then expand our set of analyses to non-drug utilization of healthcare that provides us with claims-based measures of health outcomes.

3.2 Outcomes

Using the RDD methodology outlined in Section 3.1, we examine outcomes across three time periods: the LIS enrollment year (from enrollment month through December), the subsequent year, and the year thereafter. We analyze each period separately. The specific outcome measures are described below.

First Stage We examine how LIS redetermination rules — which subject beneficiaries enrolled before May 1 to earlier redetermination — affect LIS enrollment duration. Our first-stage outcomes capture the extensive margin of subsidy loss, identified using the monthly Part D cost-sharing group variable from the Medicare Master Beneficiary Summary Files (MBSF). The subsidy loss indicator equals one if a beneficiary experiences at least one month in a given year with either Medicare Part D coverage without LIS or no Part D coverage. We also calculate the share of months per calendar year during which beneficiaries lacked LIS coverage.

Insurance Take-Up and Cost-Sharing Our indicator for lacking LIS includes both beneficiaries with Part D coverage but no subsidy and those who disenroll from Part D entirely. To

separate these effects, we examine the probability of complete Part D disenrollment, defined as having no months of Part D coverage in a given year, and the share of months per year without Part D coverage. We further quantify the immediate effects on who pays for prescription fill using Medicare Part D Event files, specifically the share of drug expenditures covered by LIS and the share paid out-of-pocket by beneficiaries. Changes in these measures reflect both the mechanical loss of LIS coverage, as well as behavioral responses in drug consumption, which we examine next.

Prescription Drug Utilization The most immediate consequence of losing LIS is increased premiums and cost-sharing in Part D. We examine whether subsidy loss affects drug consumption behavior by analyzing total standardized fills and total prescription drug costs per year.

Beyond aggregate measures, we analyze the effects of subsidy loss on prescription drug fills within the most common therapeutic classes: cardiovascular drugs, diabetes treatments, and mental health medications (excluding dementia-related diagnoses). We define these three classes using ATC-3 therapeutic classes (see the notes for Figure 3).

We then examine substitution patterns between expensive and inexpensive medications within these classes by zooming in on consumption of expensive drugs in these three therapeutic classes. A nonproprietary (generic) name is classified as "expensive" if its average cost per day of supply falls in the top tercile among nonproprietary names within its therapeutic class, weighted by the number of users in our sample.

Finally, we estimate RD coefficients for drug consumption by therapeutic class in the year following the year of LIS enrollment at the ATC-2 level.[13] We define the outcome variable as the share of Part D beneficiaries with at least one claim in each therapeutic class.

Inpatient and Outpatient Care We explore spillover effects of increased premiums and cost-sharing in Part D on broader healthcare utilization. For inpatient healthcare utilization, we examine hospital, SNF, and long-term care facility stays using Medicare Provider Analysis and Review (MedPAR) files and Long Term Care Minimum Data Set (MDS) files. In addition to looking at any hospital admissions, we focus separately on emergency admissions and ICU stays, as these typically involve urgent medical needs rather than elective care, and on hospital stays

[13] We exclude ATC-2 classes with fewer than 500 beneficiaries in our baseline sample having at least one claim in that therapeutic class in the year following the year of LIS enrollment. We also exclude A11 (Vitamins) and A12 (Mineral Supplements), as these are frequently purchased over-the-counter, and V03 (All Other Therapeutic Products).

for circulatory conditions, which are common among elderly patients and potentially preventable through medication adherence.

For outpatient healthcare utilization, we examine the probability of having any outpatient physician visit and, separately, primary care physician and cardiology visits using Carrier Fee-For-Service files.

Overall Healthcare Utilization and Spending We complement this analysis using aggregate measures of healthcare events and spending in different categories in the year following the year of LIS enrollment using Medicare MBSF Cost and Use files. Due to data restrictions, this analysis includes only beneficiaries enrolled in traditional Medicare during the year following the year of LIS enrollment.

4 Results

4.1 First Stage

We begin by examining whether the administrative rules governing LIS redetermination generate meaningful differences in subsidy receipt between beneficiaries born just before and just after May 1. Figure 1 plots the raw relationship between week of birth and LIS loss, separately for each of the three years following initial enrollment. Panel A of Tables 2, 3, and 4 report the corresponding regression discontinuity estimates from Equation 1, estimated for outcomes in year 1, 2, and 3 since LIS enrollment, respectively.

The empirical patterns are consistent with our understanding of SSA's redetermination rules. In the year of initial LIS enrollment, subsidy loss is rare regardless of birth date: only 0.6% of beneficiaries in the control group (born after May 1) lose the subsidy, and there is no discontinuity at the cutoff (RD coefficient: 0.13 p.p., 95% CI: [–0.07, 0.33]). This is expected, as no beneficiaries in our sample are subject to redetermination cycles in their enrollment year.

A sharp discontinuity emerges in the second year since enrollment. Among beneficiaries born after May 1, only 2.2% lose their subsidy. Being born before May 1 raises this probability by 4.0 percentage points (CI: [3.6, 4.4]), a 182% increase over the control mean. On the intensive margin, early-birthday beneficiaries spend an additional 3.4 percentage points of the year (12 days) without the subsidy, relative to a base of just 0.76% (3 days) among control beneficiaries.[14].

[14]The 2.2% loss rate among beneficiaries born after May 1 likely reflects SSA reassessment processes that

These differences persist and widen in the third year. As beneficiaries born after May 1 face their first initial redetermination, subsidy loss in the control group rises to 14.2%. However, early-birthday beneficiaries undergo their first cyclical redetermination, producing an even larger discontinuity of 6.2 percentage points in the probability of losing LIS and 5.1 percentage points in the share of the year spent without a subsidy.

4.2 Insurance Take-Up and Cost-Sharing

Losing the low-income subsidy raises both beneficiaries' premium and out-of-pocket payments. A combination of these financial pressures may affect the extensive margin of prescription drug insurance, leading some beneficiaries to drop Part D coverage altogether. We observe some changes along this margin: as Panels (a)–(b) of Figure 2 demonstrate, beneficiaries in the treatment group are 0.54 p.p. more likely to have no Part D coverage in any month of the third year since enrollment and spend, on average, 0.33 p.p. and 0.78 p.p. less time with Part D coverage in the second and third years, respectively. While these reduced-form estimates of the extensive margin are very small, they become more economically meaningful when scaled by the first stage, which implies that compliers are 9 percentage points more likely to drop Part D coverage.

The loss of the low-income subsidy immediately affects the structure of prescription drug cost sharing. After losing LIS, beneficiaries no longer receive cost-sharing subsidies and are expected to cover a larger share of their drug costs out of pocket. Panels (c)–(d) of Figure 2 and Panel B of Tables 2–4 quantify these shifts.

In the second year since enrollment, the share of total drug costs covered by LIS declines by 2.6 percentage points (CI: [–4.0, –1.2]), or about 6% of the 40.8% base level, accompanied by a 1.0 p.p. (CI: [0.1, 1.9], 7% of the 14.4% baseline) increase in the share covered out of pocket by beneficiaries[15]. In the third year, these effects grow to a 3.3 percentage point decline in the LIS payment share and a 1.7 percentage point increase in the beneficiary payment share, consistent with the widening first-stage discontinuity documented above.

operate outside the schedule of initial and cyclical redeterminations. In particular, beneficiaries may lose LIS outside the annual redetermination cycle if they report subsidy-changing events (e.g., marriage, divorce, or the death of a spouse) or experience changes in income, assets, or household composition that affect eligibility (Social Security Administration, 2017).

[15]The remainder of total drug costs is covered primarily by Part D plans, with some costs also paid by third-party payers, including former employers, VA and TRICARE programs, state pharmacy assistance programs, and charities.

4.3 Prescription Drug Utilization

An increase in out-of-pocket drug costs could reduce total drug consumption. Panels (e)–(f) of Figure 2 and Panel B of Tables 2–4 present evidence on this margin. We find no such behavioral response in our sample. In the second year since enrollment, the reduced-form effect of an early birthday on the number of standardized fills is +0.06 (95% CI: $[-1.7, +1.8]$) over a baseline of 34.8 fills. The effect on total annual drug cost is −\$45 (95% CI: $[-\$250, +\$159]$) over a baseline of \$1,982. The third-year estimates are similarly small. In other words, a beneficiary who is marginally eligible for LIS does not meaningfully decrease their overall drug consumption in response to losing the subsidy.

We next explore whether the aggregate null effects on utilization mask changes in the composition of drugs consumed. Figure 3 and Panel C of Tables 2–4 explore the behavioral response in the use of drugs in three major therapeutic classes: cardiovascular, diabetes, and mental health medications. We find no evidence that subsidy loss leads beneficiaries to discontinue entire drug classes. In the second year, the probability of filling at least one cardiovascular prescription is 61.8% in the control group, with a statistically insignificant RD coefficient of 0.73 p.p. The corresponding estimates for diabetes drugs (−0.21 p.p.) and mental health drugs (−0.84 p.p.) are also indistinguishable from zero. These patterns hold in the third year as well.

Within each drug class, we examine whether beneficiaries substitute away from expensive medications toward cheaper alternatives. For cardiovascular and diabetes drugs, we find null effects on the use of expensive molecules in both years 2 and 3, suggesting no meaningful within-class substitution. We do estimate a statistically significant 1.8 p.p. reduction in the probability of filling an expensive mental health medication in year 2 (CI: [–3.2, –0.4]) relative to a control mean of 10.2%; however, this effect does not persist into year 3.

Figure 4 extends the analysis to a broader set of therapeutic classes at the ATC-2 level, estimating separate RD coefficients for the probability of filling drugs in each class. The figure reports estimates for both the full baseline sample and the subsample of marginal LIS beneficiaries, defined as beneficiaries who lose the subsidy in one of the first three annual eligibility redetermination cycles.

Across most classes, the discontinuity at the May 1 cutoff is estimated to be zero. However, there is suggestive evidence of a decline in the use of psycholeptics — medications with calming effects, including antipsychotics, sedatives, and hypnotics. We also observe tentative substitution across cardiovascular drug classes: a decrease in the use of beta blockers and cardiac therapy

drugs (stimulants, vasodilators, and antiarrhythmics), alongside an increase in the use of ACE inhibitors and angiotensin II receptor blockers. Restricting the sample to marginal beneficiaries, we confirm that these shifts are likely driven by beneficiaries who are most likely to lose the subsidy.

4.4 Inpatient and Outpatient Care

We next ask whether changes in prescription drug subsidies have spillover effects on other dimensions of healthcare utilization and, implicitly, health. If subsidy loss causes beneficiaries to reduce adherence to medically necessary medications, we might expect to see increases in acute care — a pattern documented in related settings (e.g. Chandra et al., 2010a, 2024). Moreover, changes in drug affordability may affect beneficiaries' propensity to seek care that involves prescription drugs.

Figure 5 and Panel D of Tables 2–4 report the results for inpatient care utilization. The loss of LIS does not lead to a change in inpatient hospitalization rates in years 2 (RD coefficient: –0.17 p.p., CI: [–0.74, 0.40], control mean: 7.8%) and 3 (RD coefficient: –0.17 p.p., CI: [–0.82, 0.48], control mean: 8.2%). Exploring particular types of hospitalizations — stays involving the use of ICU, emergency admissions, and stays for circulatory system conditions — we find a similar absence of discontinuity at the May 1 cutoff.

Despite no detectable changes in inpatient hospital stays, we find suggestive evidence of reduced utilization of post-acute and long-term care facilities following subsidy loss. The probability of a skilled nursing facility (SNF) stay falls by 0.08 p.p. relative to a control mean of 0.50% in the second year and by 0.15 p.p. relative to a mean of 0.62% in the third year. For long-term care nursing facilities, the reductions are 0.15 p.p. (control mean: 0.73%) and 0.23 p.p. (control mean: 0.89%), respectively.

Figure 6 and Panel D of Tables 2–4 present the results for outpatient physician visits. We find no significant discontinuities in the probability of an office visit with a primary care provider (year 2 RD coefficient: +0.35 p.p., control mean: 27.1%) or a cardiologist (year 2 RD coefficient: −0.61 p.p., control mean: 5.5%).[16] These null effects persist in the third year.

[16] Our measures of office visits are based on Fee-for-Service Carrier files and exclude stays by beneficiaries in Medicare Advantage (MA). Notably, we observe no changes in MA enrollment rates around May 1 discontinuity.

4.5 Overall Healthcare Utilization and Spending

Figures 7 and 8 provide a comprehensive view of the effects of subsidy loss across all categories of healthcare utilization, reporting standardized RD coefficients (in units of the outcome's standard deviation) for event counts and spending, respectively, in the second year since LIS enrollment. Both figures present estimates for the full baseline sample as well as the subsample of marginal LIS beneficiaries.

In the baseline sample, we document no effect on the number of Part D fills, events, or payments, consistent with the evidence in Section 4.3. In the subsample of marginal beneficiaries, however, we observe borderline significant shifts: a –0.06 (CI: [–0.11, –0.01]) standard deviation effect on the number of Part D fills and a –0.06 (CI: [–0.10, –0.02]) standard deviation effect on total Part D spending. This decline is entirely driven by a reduction in Medicare payments and is not offset by an increase in beneficiary out-of-pocket spending. These shifts contribute to a –0.04 (CI: [–0.10, 0.01]) standard deviation discontinuity in total Medicare payments, again reflecting differences in Medicare rather than beneficiary spending.

Zooming in on specific non-drug healthcare utilization categories — including inpatient stays, hospice, SNF, various types of physician services, durable medical equipment (DME), and emergency room visits — we find that point estimates are generally small and centered near zero. The number of inpatient stays does not exhibit a discontinuity at the May 1 cutoff (CI: [–0.03, +0.02]), consistent with the evidence in Section 4.4, while the number of SNF stays shows a small, statistically insignificant decline of 0.02 standard deviations (CI: [–0.05, +0.01]). Likewise, the number of hospital outpatient stays exhibits an insignificant decrease of 0.03 standard deviations (CI: [–0.06, +0.003]). At the same time, the total number of events for physician services (Carrier Part B) and DME, as well as the corresponding payments, do not change. Finally, there is no increase in the total number of emergency room visits, including both inpatient and hospital outpatient ERs (CI: [–0.03, 0.03]).

4.6 Summary

Taken together, our results suggest limited behavioral responses to the loss of subsidy by marginal beneficiaries. The LIS redetermination rules generate large and precisely estimated differences in subsidy receipt between beneficiaries born just before and just after May 1. These differences translate into meaningful increases in the share of drug costs borne by LIS and beneficiaries. Yet the behavioral response to this increase in cost sharing is strikingly limited. We

find no evidence of reductions in aggregate drug consumption or in the use of drugs in major therapeutic classes, with the exception of a transitory decline in expensive mental health medications. The null effects extend to most measures of non-drug healthcare utilization, including hospitalizations, outpatient visits, physician services, and emergency room visits. The possible exception is a reduction in SNF and long-term care stays.

5 Discussion and Conclusion

In this paper, we estimate the returns to health insurance subsidies for marginal low-income recipients in the Medicare Part D prescription drug program. Exploiting quasi-experimental variation generated by the intersection of Medicare initial enrollment rules and SSA's LIS redetermination schedule, we find that beneficiaries born just before May 1 are disproportionately more likely to lose their low-income subsidy shortly following enrollment. This loss translates into a pronounced shift in the burden of drug costs — both premiums and cost-sharing — from the LIS program to the patient.

Despite these changes in cost-sharing, we find limited behavioral responses among marginal LIS beneficiaries. Aggregate drug consumption — measured in standardized fills and total spending — is unaffected by subsidy loss. Beneficiaries do not discontinue major therapeutic drug classes, with the exception of a transitory reduction in expensive mental health medications, beta blockers, and psycholeptics. Outside of prescription drugs, we find no changes in hospitalizations, emergency admissions, ICU use, or physician office visits. The one exception is a reduction in skilled nursing facility and long-term care stays in the third year after enrollment.

These findings are somewhat surprising in light of a large literature documenting substantial demand responses to cost-sharing in health insurance. Several features of our setting may help explain the limited responses we observe.

First, our estimates are identified from individuals who are marginal to LIS eligibility. These are beneficiaries whose income and assets place them near the eligibility threshold and who are subject to the administrative process of eligibility redetermination. The fact that we observe limited demand responses at this margin is consistent with the subsidy program being designed — whether by intention or not — so that the marginal recipient is one for whom the subsidy has limited effects on utilization. This interpretation would be consistent with the optimal policy framework of Akerlof (1978), in which means-tested benefits should be targeted

to the point where the marginal return is equalized across programs.

Second, even after losing LIS, beneficiaries in our sample retain their eligibility for Medicare Part D that is partially funded by the federal government for all beneficiaries. Only a limited fraction of beneficiaries choose to drop Part D altogether when faced with higher premiums. For the vast majority who remain enrolled, cost sharing increases but does not become prohibitive — particularly for generic drugs, which constitute a large share of fills in our population. The limited response we document is then consistent with the view that the most common (often generic) prescription drugs tend to have relatively inelastic demand, particularly for chronic medications in the elderly population (Einav et al., 2018a).

Our results have several implications for policy. The finding that marginal LIS beneficiaries exhibit limited utilization responses to subsidy loss suggests that, at the current eligibility margin, contracting the program would have modest effects on drug consumption and health. At the same time, we find no clear evidence of meaningful fiscal savings, while the subsidy clearly provides financial protection: beneficiaries who lose LIS pay a larger share of their drug costs out of pocket.

Several caveats are worth noting. Our estimates are local to a specific margin — beneficiaries who enroll in LIS during the Initial Enrollment Period and whose income and assets are near the eligibility threshold. Responses may differ for beneficiaries who are infra-marginal to eligibility, enter LIS through automatic enrollment pathways, or for populations with different health profiles. Our analysis is also limited to the first three years following LIS enrollment; longer-run effects on medication adherence, health, and mortality remain an important open question. Finally, while we observe detailed prescription drug claims, our measures of non-drug utilization are based on claims data that capture healthcare encounters but not health status directly. Changes in health that do not manifest in claims-based utilization within our follow-up window would not be detected by our analysis.

In summary, this paper estimates that marginal returns to prescription drug subsidies in Medicare are limited along the dimensions of drug consumption and healthcare utilization that we can measure. These findings contribute to a growing body of evidence on the design of means-tested health insurance subsidies, and suggest that the returns to such subsidies may vary substantially across beneficiaries— a consideration that is central to the optimal design of social insurance programs.

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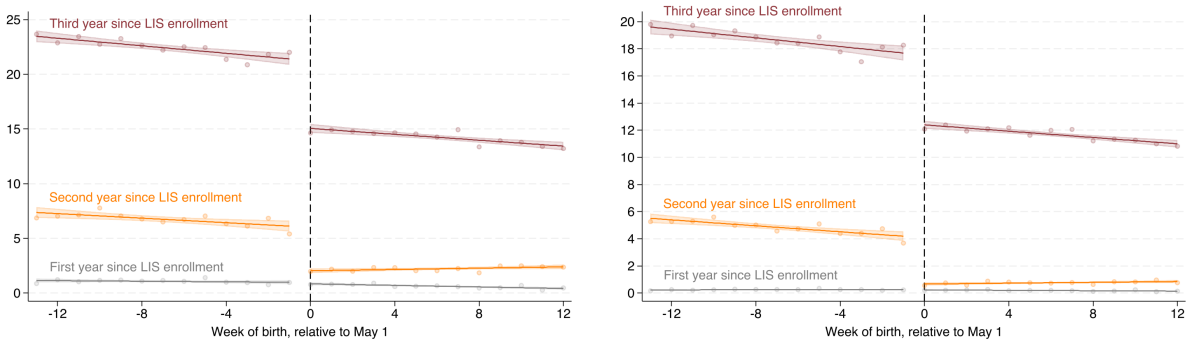
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Figures and Tables

Figure 1: Week of Birth and Low-Income Subsidy Loss

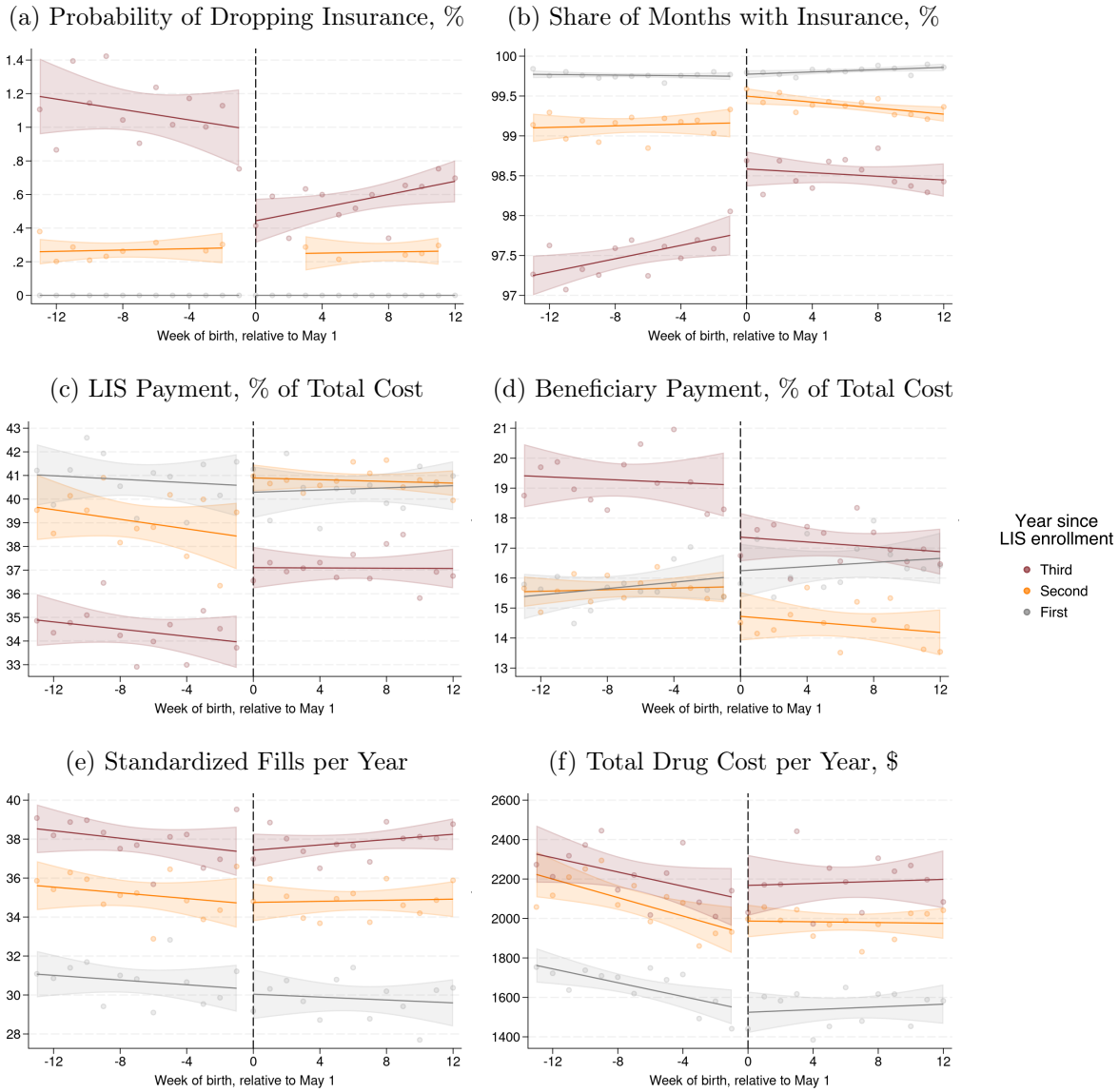
(a) Beneficiaries Losing Subsidy, %

(b) Beneficiary-Months with No Subsidy, %



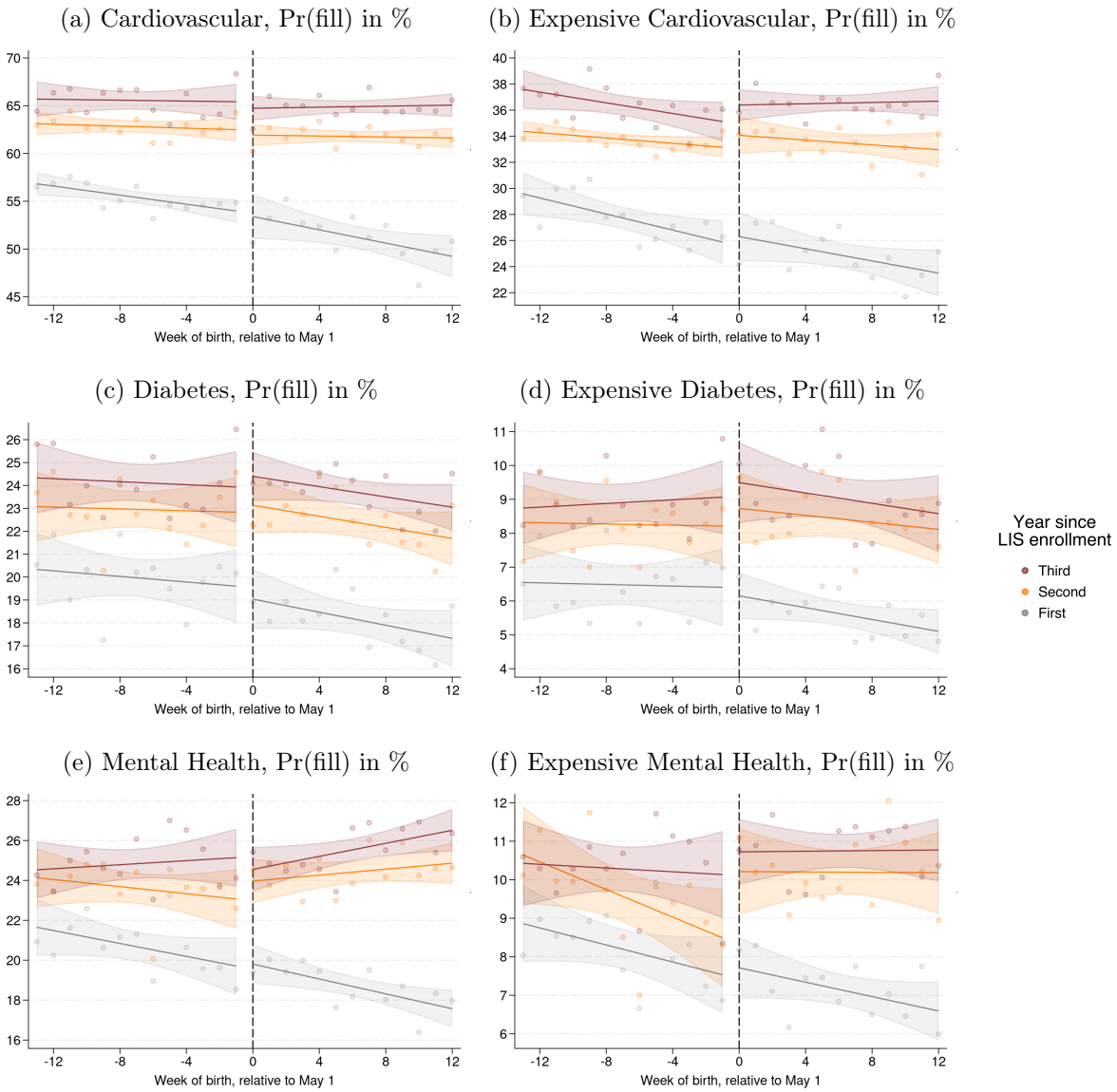
Notes. The figure illustrates the relationship between a beneficiary's week of birth (on the x-axis) and the probability of losing LIS prescription drug subsidy (Panel a) as well as the share of months in a calendar year without a subsidy (Panel b). Beneficiaries are aggregated into 7-day bins based on their day of birth within the year. We index the May 1–7 week-of-birth bin as zero. The outcomes are reported separately for the first (partial) year of LIS enrollment, second and third full years since LIS enrollment. The sample includes the universe of Medicare beneficiaries who enrolled in the low-income subsidy (LIS) during the Initial Enrollment Period upon turning 65 in 2010–2021, born within a 90-day window around May 1. See Section 2.3 for sample construction and 3.2 for outcome variable definitions. N = 128,600 beneficiaries are observed in the year of enrollment and in the second year since enrollment. Of these, N = 120,436 beneficiaries are also observed in the third year since enrollment after cohorts enrolling in 2020 are excluded. In years 2–3, outcomes are tracked for the full year for all beneficiaries. In year 1, outcomes are tracked only from the month of LIS enrollment onward; for Panel (b), we first compute the share of months between LIS enrollment and December at the beneficiary level and then aggregate these shares with equal weights. Lines of linear best fit and 95% confidence intervals are included, weighted by the population in each week of birth without controls. Tables 2, 3, and 4 presents the corresponding regression discontinuity estimates from Equation 1.

Figure 2: Week of Birth and Prescription Drug Insurance and Utilization



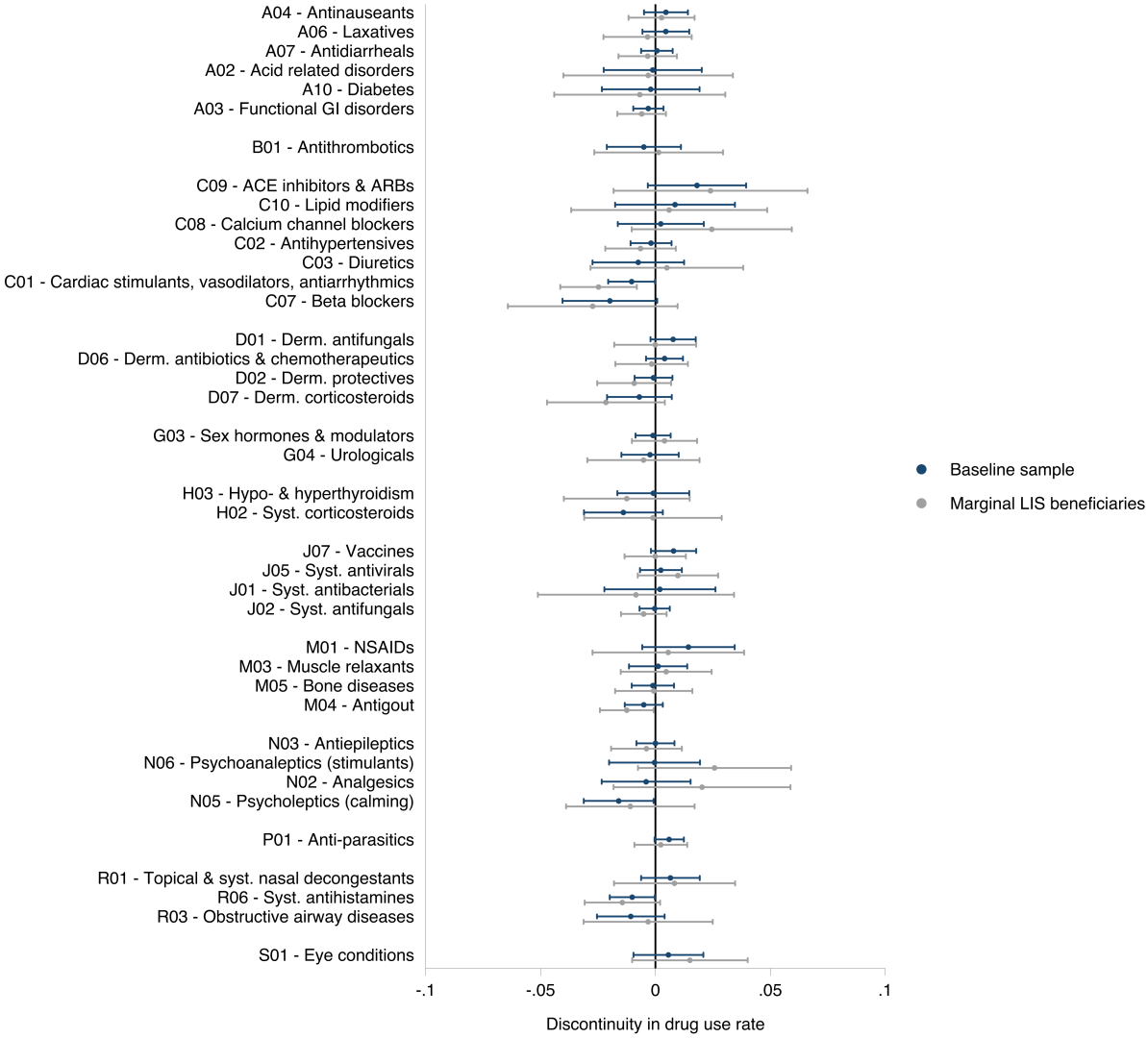
Notes. The figure illustrates the relationship between a beneficiary's week of birth (x-axis) and measures of Medicare Part D insurance discontinuation (Panels a–b), cost allocation by payer (Panels c–d), and drug utilization (Panels e–f). Beneficiaries are aggregated into 7-day bins based on their day of birth within the year. We index the May 1–7 week-of-birth bin as zero. The outcomes are reported separately for the first (partial) year of LIS enrollment, second and third full years since LIS enrollment. Panels (c)–(f) use Part D Event data, available for the random 20% subsample of the baseline sample of LIS enrollees. See Section 2.3 for sample construction and 3.2 for outcome variable definitions. Panels (a)–(b) include all N = 128,600 beneficiaries in the baseline sample (N = 120,438 in year 3 that excludes beneficiaries enrolled in 2020). Panels (c)–(d) include N = 19,372, 21,221, and 20,139 beneficiaries in the 20% subsample with positive total drug costs in years 1, 2, and 3, respectively. Panels (e)–(f) include N = 26,560, 26,495, and 24,638 beneficiaries in the 20% subsample who spend at least one month in Part D in each year. Lines of linear best fit and 95% confidence intervals are included, weighted by the population in each week of birth without controls. Tables 2, 3, and 4 presents the corresponding regression discontinuity estimates from Equation 1.

Figure 3: Drug Utilization by Therapeutic Class and Price



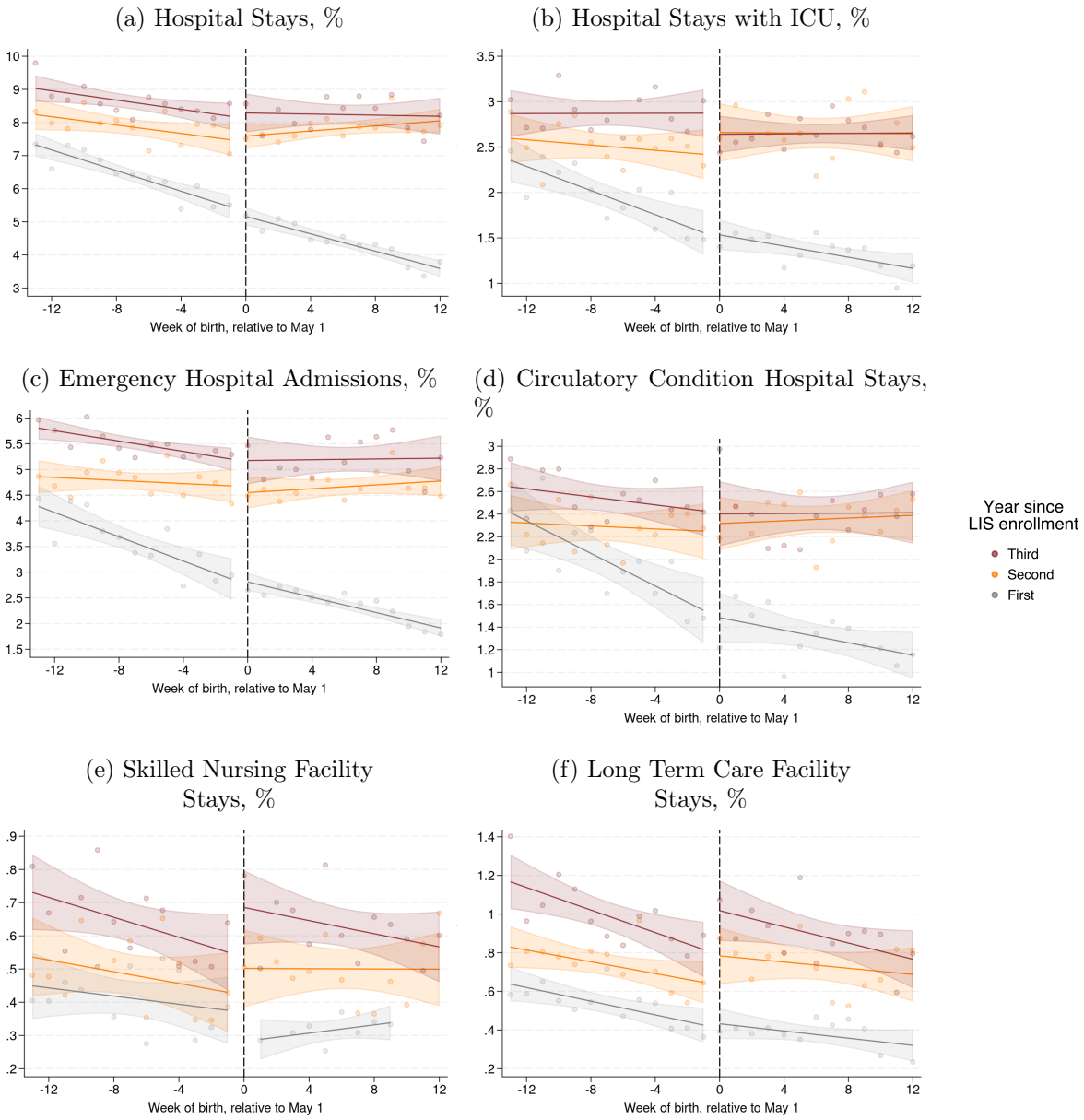
Notes. The figure illustrates the relationship between a beneficiary's week of birth (x-axis) and the probability of filling prescription drugs in three common therapeutic classes, overall (Panels a, c, e) and for the most expensive medications within a class (Panels b, d, f). Drug classes are defined as follows: cardiovascular drugs are all medications in ATC-1 class C (heart and circulatory conditions); diabetes drugs are in ATC-3 categories A10A (insulins and analogues) and A10B (glucose-lowering drugs); mental health drugs are in ATC-2 classes N05 (psycholeptics) and N06 (psychoanaleptics), excluding anti-dementia drugs (ATC-3 category N06D). Beneficiaries are aggregated into 7-day bins based on their day of birth within the year. We index the May 1–7 week-of-birth bin as zero. The outcomes are reported separately for the first (partial) year of LIS enrollment, second and third full years since LIS enrollment. All panels use Part D Event data, available for the random 20% subsample of the baseline sample of LIS enrollees. See Section 2.3 for sample construction and 3.2 for outcome variable definitions. All Panels include N = 26,560, 26,495, and 24,638 beneficiaries in the 20% subsample who spend at least one month in Part D in each year. Lines of linear best fit and 95% confidence intervals are included, weighted by the population in each week of birth without controls. Tables 2, 3, and 4 presents the corresponding regression discontinuity estimates from Equation 1.

Figure 4: Drug Utilization by Therapeutic Class



Notes. The figure illustrates regression discontinuity estimates from Equation 1 for year 2 since LIS enrollment. Separate regressions are estimated for each outcome. Outcomes are indexed on the y-axis and measure the probability of filling prescription drugs in most common therapeutic classes at the ATC-2 code level. All specifications use Part D Event data, available for the random 20% subsample of the baseline sample of LIS enrollees. Navy lines report point estimates on this baseline subsample. Light gray point estimates are from specifications that restrict the sample to those beneficiaries who are at a higher risk of losing LIS as they are observed to lose the subsidy at some point during the first three annual redetermination cycles. See Section 2.3 for sample construction and 3.2 for outcome variable definitions. $N = 26{,}495$ beneficiaries in the baseline sample and 7,608 in the subsample of marginal LIS beneficiaries. Tables 2, 3, and 4 present the tabular version of the same specifications for the baseline sample.

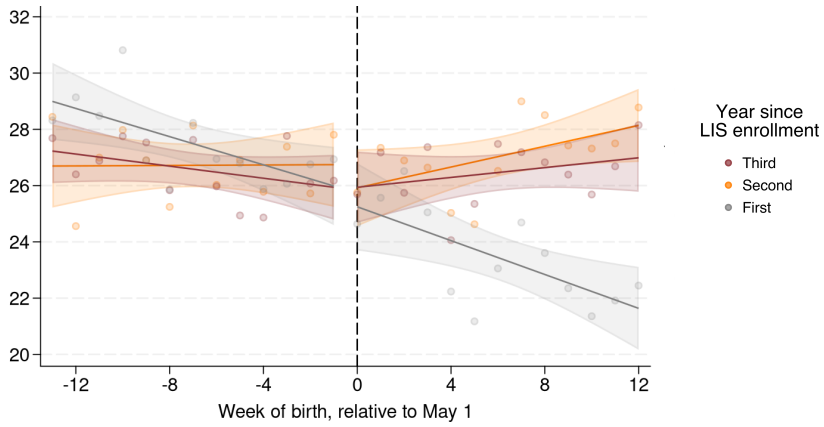
Figure 5: Inpatient Healthcare Utilization



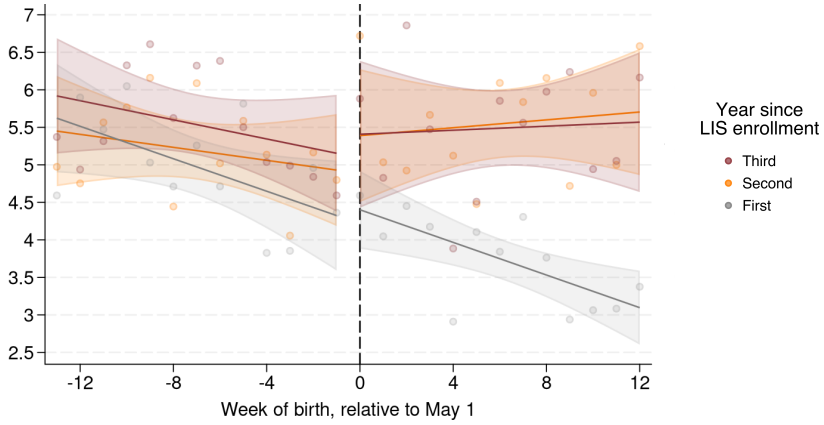
Notes. The figure illustrates the relationship between a beneficiary's week of birth (x-axis) and several measures of inpatient healthcare utilization. Beneficiaries are aggregated into 7-day bins based on their day of birth within the year. We index the May 1–7 week-of-birth bin as zero. The outcomes are reported separately for the first (partial) year of LIS enrollment, second and third full years since LIS enrollment. Data on inpatient hospital stays in Panels (a)–(d) and SNF stays in Panel (e) are based on Medicare Provider Analysis and Review (MedPAR) files, available for the full baseline sample. Data on long-term care facility utilization in Panel (f) come from the Long Term Care Minimum Data Set 3.0. In year 1, we only observe utilization after LIS enrollment, which induces mechanical negative trends by week of birth. See Section 2.3 for sample construction and 3.2 for outcome variable definitions. Lines of linear best fit and 95% confidence intervals are included, weighted by the population in each week of birth without controls. Tables 2, 3, and 4 presents the corresponding regression discontinuity estimates from Equation 1.

Figure 6: Outpatient Healthcare Utilization

(a) PCP Office Visits, %

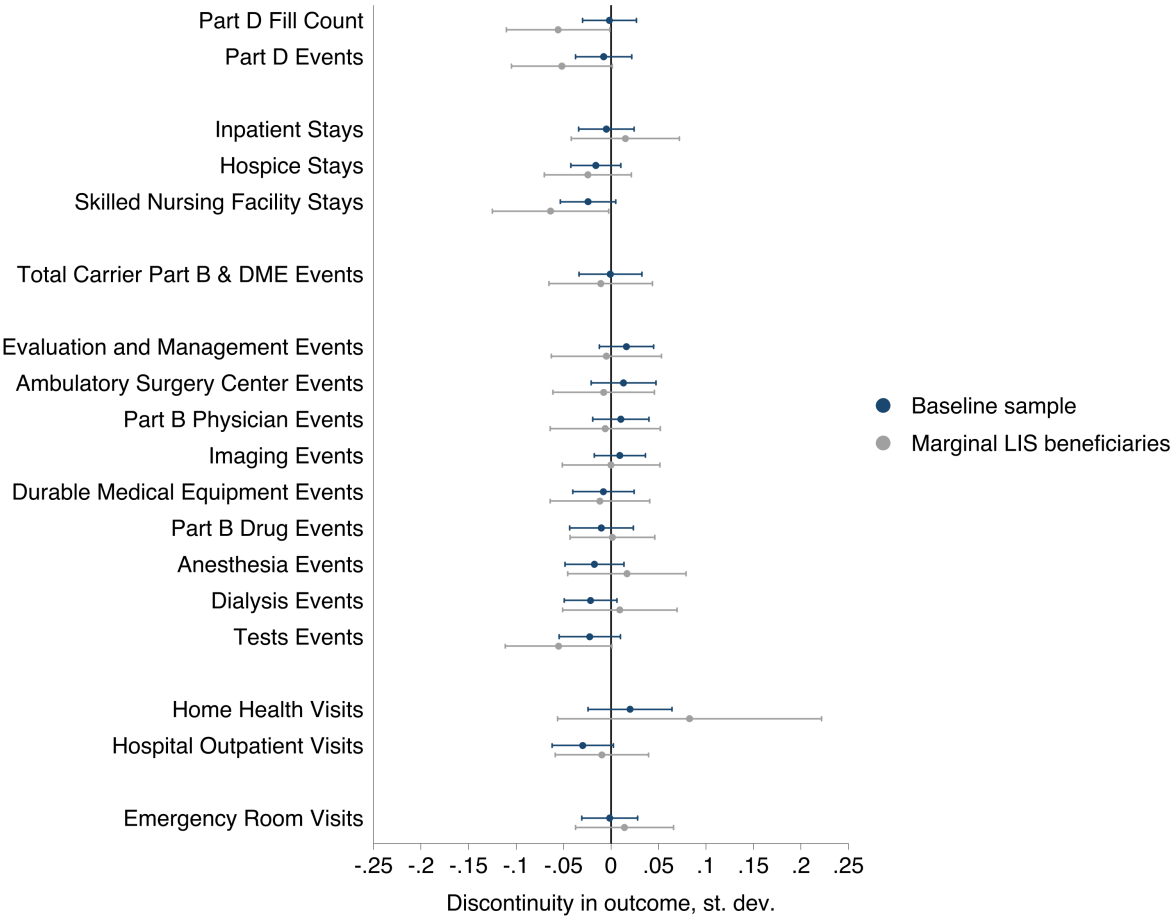


(b) Cardiologist Office Visits, %



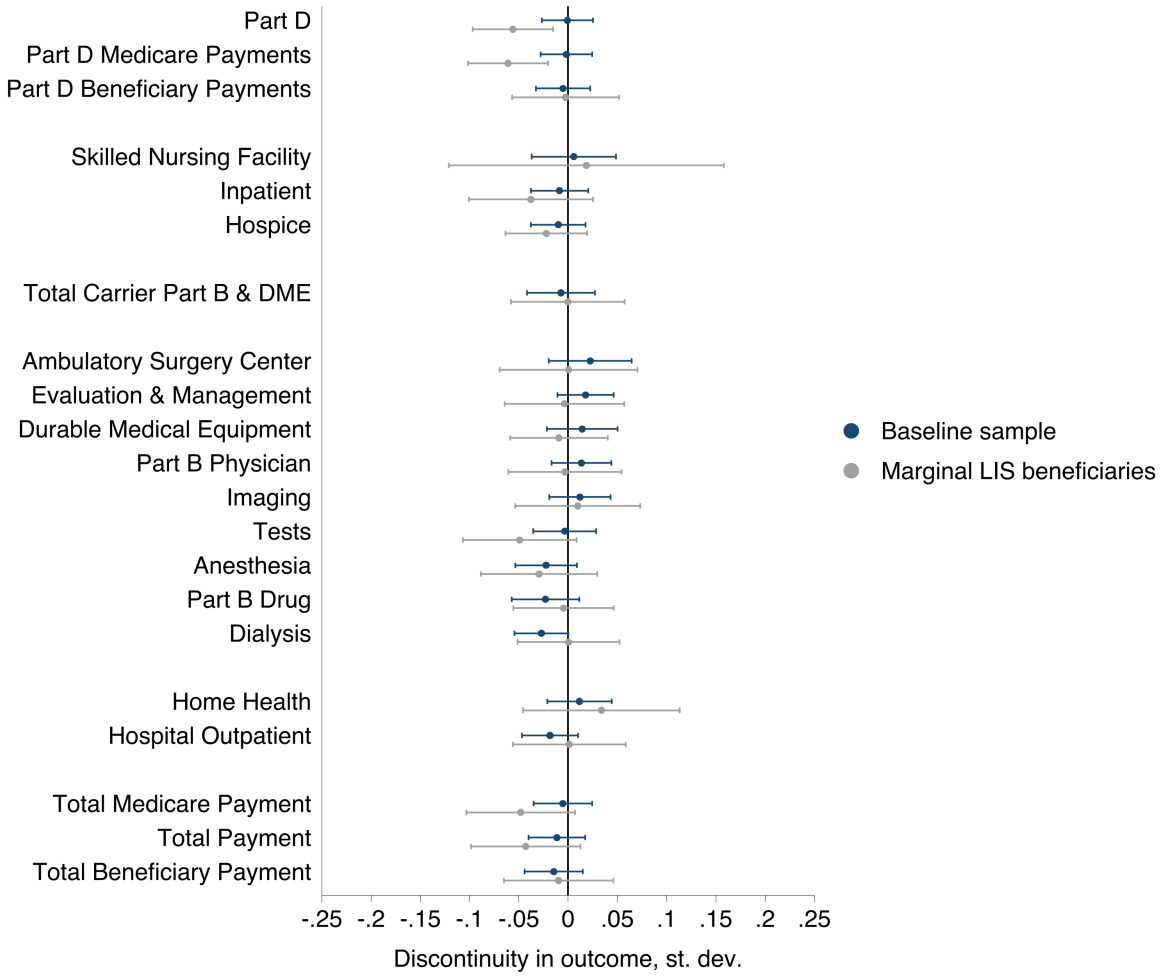
Notes. The figure illustrates the relationship between a beneficiary's week of birth (x-axis) and measures of outpatient healthcare utilization. Beneficiaries are aggregated into 7-day bins based on their day of birth within the year. We index the May 1–7 week-of-birth bin as zero. The outcomes are reported separately for the first (partial) year of LIS enrollment, second and third full years since LIS enrollment. Data are based on 20% Fee-for-Service Carrier files. In year 1, we only observe utilization after LIS enrollment, which induces mechanical negative trends by week of birth. See Section 2.3 for sample construction and 3.2 for outcome variable definitions. Lines of linear best fit and 95% confidence intervals are included, weighted by the population in each week of birth without controls. Tables 2, 3, and 4 presents the corresponding regression discontinuity estimates from Equation 1.

Figure 7: Overall Healthcare Utilization: Event Counts



Notes. The figure illustrates regression discontinuity estimates from Equation 1 for year 2 since LIS enrollment. Separate regressions are estimated for each outcome. Outcomes are indexed on the y-axis and measure the count of healthcare utilization events as reported in the MBSF Cost and Use segment. All specifications use the baseline sample of beneficiaries, restricted to those enrolled in Traditional Medicare. Navy lines report point estimates on this baseline subsample. Light gray point estimates are from specifications that restrict the sample to those beneficiaries who are at a higher risk of losing LIS as their are observed to lose the subsidy at some point during the first three annual redetermination cycles. See Section 2.3 for sample construction and 3.2 for outcome variable definitions. $N = 63{,}000$ beneficiaries in the baseline sample and 18,224 in the subsample of marginal LIS beneficiaries. Tables 2, 3, and 4 present the tabular version of the same specifications for the baseline sample.

Figure 8: Overall Healthcare Utilization: Spending



Notes. The figure illustrates regression discontinuity estimates from Equation 1 for year 2 since LIS enrollment. Separate regressions are estimated for each outcome. Outcomes are indexed on the y-axis and measure healthcare spending for different utilization categories as reported in the MBSF Cost and Use segment. All specifications use the baseline sample of beneficiaries, restricted to those enrolled in Traditional Medicare. Navy lines report point estimates on this baseline subsample. Light gray point estimates are from specifications that restrict the sample to those beneficiaries who are at a higher risk of losing LIS as their are observed to lose the subsidy at some point during the first three annual redetermination cycles. See Section 2.3 for sample construction and 3.2 for outcome variable definitions. $N = 26{,}495$ beneficiaries in the baseline sample and 7,608 in the subsample of marginal LIS beneficiaries. Tables 2, 3, and 4 present the tabular version of the same specifications for the baseline sample.

Table 1: Summary Statistics: Baseline Sample

	Overall				By birthday (mean only)	
	Mean (1)	SD (2)	Min (3)	Max (4)	Before May 1 (5)	After May 1 (6)
Age at LIS enrollment	65.1	0.1	64.9	65.3	65.1	65.1
Female	0.60	—	0	1	0.60	0.60
Race / Ethnicity						
White non-Hispanic	0.54	—	0	1	0.54	0.54
Black	0.18	—	0	1	0.18	0.17
Asian / Pacific Islander	0.06	—	0	1	0.06	0.06
Hispanic	0.20	—	0	1	0.19	0.21
American Indian / Alaska Native	0.00	—	0	1	0.00	0.00
In MA at enrollment	0.43	—	0	1	0.42	0.43
N	128,600				63,480	65,120

Notes. This table provides summary statistics for the baseline sample of the universe of Medicare beneficiaries who enrolled in the low-income subsidy (LIS) during the Initial Enrollment Period upon turning 65 in 2010–2021. Only beneficiaries born within a 90-day window around May 1 of any year, and not on the first day of a month, are included in the sample. See Section 2.3 for sample construction. Beneficiary characteristics are constructed from Medicare Beneficiary Summary Files (MBSF). All statistics are computed at the beneficiary level at the time of LIS enrollment.

Table 2: Regression Discontinuity Estimates, Year 1 Since LIS Enrollment

	Control mean (1)	RD coefficient (2)	N (3)
Panel A. Loss of drug subsidy			
Beneficiaries losing subsidy, %	0.62	0.13 (0.10)	128,600
Beneficiary-months with no subsidy, %	0.18	0.03 (0.03)	128,600
Panel B. Prescription drug cost sharing and drug insurance			
Probability of dropping insurance, %	0.00	—	128,600
Share of months with no insurance, %	0.20	0.03 (0.03)	128,600
LIS payment, % of total cost	40.4	0.20 (0.74)	19,372
Beneficiary payment, % of total cost	16.4	-0.15 (0.55)	19,372
Standardized fills per year	29.8	0.42 (0.80)	26,560
Total drug cost per year, $	1546.1	31.5 (89.5)	26,560
Panel C. Drug use by therapeutic class and price			
Cardiovascular, Pr(fill) in %	51.2	0.60 (1.3)	26,560
Expensive cardiovascular, Pr(fill) in %	24.8	-0.40 (1.0)	26,560
Diabetes, Pr(fill) in %	18.1	0.63 (0.95)	26,560
Expensive diabetes, Pr(fill) in %	5.6	0.36 (0.56)	26,560
Mental health, Pr(fill) in %	18.6	-0.11 (0.96)	26,560
Expensive mental health, Pr(fill) in %	7.1	-0.17 (0.64)	26,560
Panel D. Non-drug healthcare utilization			
Hospital stays, %	4.3	0.14 (0.26)	128,600
Hospital stays with ICU, %	1.3	-0.04 (0.16)	128,600
Emergency hospital admissions, %	2.3	-0.06 (0.18)	128,600
Circulatory condition hospital stays, %	1.3	-0.01 (0.15)	128,600
Skilled nursing facility stays, %	0.32	0.05 (0.06)	128,600
Long term care facility stays, %	0.38	-0.04 (0.07)	128,600
PCP office visits, %	23.4	0.17 (1.0)	26,560
Cardiologist office visits, %	3.7	-0.26 (0.44)	26,560

Notes. This table reports the estimates of β_1, the regression discontinuity coefficient of interest from Equation 1, for all outcomes. The table is restricted to outcomes measured in the first year of LIS enrollment. Each row of the table is a separate regression with outcomes defined in row titles. Column (1) reports that mean of the outcome among beneficiaries born in the 90 days after May 1 ("control" beneficiaries). Column (2) reports the point estimate and clustered standard error for β_1. Column (3) reports the sample size. Sample size varies across outcomes depending on whether we have access to 100% or 20% versions of the corresponding Medicare data. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Regression Discontinuity Estimates, Year 2 Since LIS Enrollment

	Control mean (1)	RD coefficient (2)	N (3)
Panel A. Loss of drug subsidy			
Beneficiaries losing subsidy, %	2.2	4.0*** (0.22)	128,600
Beneficiary-months with no subsidy, %	0.76	3.4*** (0.18)	128,600
Panel B. Prescription drug cost sharing and drug insurance			
Probability of dropping insurance, %	0.26	0.04 (0.05)	128,600
Share of months with no insurance, %	99.4	-0.33*** (0.07)	128,600
LIS payment, % of total cost	40.8	-2.6*** (0.71)	21,221
Beneficiary payment, % of total cost	14.4	1.0** (0.48)	21,221
Standardized fills per year	34.8	0.06 (0.91)	26,495
Total drug cost per year, $	1982.1	-45.4 (104.4)	26,495
Panel C. Drug use by therapeutic class and price			
Cardiovascular, Pr(fill) in %	61.8	0.73 (1.3)	26,495
Expensive cardiovascular, Pr(fill) in %	33.5	-0.67 (1.1)	26,495
Diabetes, Pr(fill) in %	22.4	-0.21 (1.1)	26,495
Expensive diabetes, Pr(fill) in %	8.4	-0.42 (0.67)	26,495
Mental health, Pr(fill) in %	24.4	-0.84 (1.1)	26,495
Expensive mental health, Pr(fill) in %	10.2	-1.8** (0.73)	26,495
Panel D. Non-drug healthcare utilization			
Hospital stays, %	7.8	-0.17 (0.29)	128,600
Hospital stays with ICU, %	2.7	-0.25 (0.18)	128,600
Emergency hospital admissions, %	4.7	0.11 (0.23)	128,600
Circulatory condition hospital stays, %	2.4	-0.07 (0.18)	128,600
Skilled nursing facility stays, %	0.50	-0.08 (0.07)	128,600
Long term care facility stays, %	0.73	-0.15 (0.09)	128,600
PCP office visits, %	27.1	0.35 (1.1)	26,560
Cardiologist office visits, %	5.5	-0.61 (0.50)	26,560

Notes. This table reports the estimates of β_1, the regression discontinuity coefficient of interest from Equation 1, for all outcomes. The table is restricted to outcomes measured in the second year since LIS enrollment. Each row of the table is a separate regression with outcomes defined in row titles. Column (1) reports that mean of the outcome among beneficiaries born in the 90 days after May 1 ("control" beneficiaries). Column (2) reports the point estimate and clustered standard error for β_1. Column (3) reports the sample size. Sample size varies across outcomes depending on whether we have access to 100% or 20% versions of the corresponding Medicare data. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Regression Discontinuity Estimates, Year 3 Since LIS Enrollment

	Control mean (1)	RD coefficient (2)	N (3)
Panel A. Loss of drug subsidy			
Beneficiaries losing subsidy, %	14.2	6.2*** (0.70)	120,436
Beneficiary-months with no subsidy, %	11.7	5.1*** (0.60)	120,436
Panel B. Prescription drug cost sharing and drug insurance			
Probability of dropping insurance, %	0.57	0.54*** (0.10)	120,436
Share of months with no insurance, %	1.5	0.78*** (0.14)	120,436
LIS payment, % of total cost	37.1	-3.3*** (0.74)	20,139
Beneficiary payment, % of total cost	17.1	1.7*** (0.64)	20,139
Standardized fills per year	37.9	-0.02 (0.99)	24,638
Total drug cost per year, $	2184.6	-59.2 (115.6)	24,638
Panel C. Drug use by therapeutic class and price			
Cardiovascular, Pr(fill) in %	64.9	0.83 (1.2)	24,638
Expensive cardiovascular, Pr(fill) in %	36.5	-1.1 (1.2)	24,638
Diabetes, Pr(fill) in %	23.7	-0.43 (1.1)	24,638
Expensive diabetes, Pr(fill) in %	9.0	-0.34 (0.69)	24,638
Mental health, Pr(fill) in %	25.6	0.80 (1.1)	24,638
Expensive mental health, Pr(fill) in %	10.7	-0.48 (0.82)	24,638
Panel D. Non-drug healthcare utilization			
Hospital stays, %	8.2	-0.17 (0.33)	120,436
Hospital stays with ICU, %	2.6	0.23 (0.19)	120,436
Emergency hospital admissions, %	5.2	-0.03 (0.27)	120,436
Circulatory condition hospital stays, %	2.4	0.00 (0.21)	120,436
Skilled nursing facility stays, %	0.62	-0.15* (0.09)	120,436
Long term care facility stays, %	0.89	-0.23** (0.12)	120,436
PCP office visits, %	26.5	-0.34 (1.2)	24,845
Cardiologist office visits, %	5.5	-0.42 (0.54)	24,845

Notes. This table reports the estimates of β_1, the regression discontinuity coefficient of interest from Equation 1, for all outcomes. The table is restricted to outcomes measured in the third year since LIS enrollment. Each row of the table is a separate regression with outcomes defined in row titles. Column (1) reports that mean of the outcome among beneficiaries born in the 90 days after May 1 ("control" beneficiaries). Column (2) reports the point estimate and clustered standard error for β_1. Column (3) reports the sample size. Sample size varies across outcomes depending on whether we have access to 100% or 20% versions of the corresponding Medicare data. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.