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ABSTRACT

There is substantial evidence that cost-sharing in medical care constrains total health spending. However, there is relatively little (and unclear) evidence on its health effects, particularly in low- and middle-income countries. This paper re-evaluates the link between outpatient cost-sharing and health, studying Colombia's entire formal sector workforce observed monthly between 2011 and 2018 with individual-level health care utilization records linked to payroll data and vital statistics. Because Colombia's national health system imposes discrete breaks in outpatient cost-sharing requirements across the earnings distribution, we estimate a dynamic regression discontinuity model, finding that greater outpatient cost-sharing initially reduces use of outpatient care (including consultations and drugs), resulting in fewer diagnoses of common chronic diseases – and over time, increases the prevalence and severity of chronic diseases as well as use of inpatient care. Ultimately, greater outpatient cost-sharing measurably increases mortality, raising 8-year mortality by 4 deaths per 10,000 individuals. To the best of our knowledge, this study is the first to show a relationship between cost-sharing and adult mortality risk in a low- or middle-income country, a relationship important to incorporate into social welfare analyses of cost-sharing policies.

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1 INTRODUCTION

Patient cost-sharing in medical care (through co-payments, co-insurance, and deductibles) is strongly related to the use of health care services and health spending (Brot-Goldberg et al., 2017; Finkelstein et al., 2012; Lagarde & Palmer, 2011; Manning et al., 1987; Newhouse, 1996; Powell-Jackson et al., 2014; Saksena et al., 2010). Traditionally, the role of cost-sharing under health insurance is to balance protection against financial risk with overuse of medical care (i.e., "moral hazard") (Arrow, 1963; Pauly, 1968; Zeckhauser, 1970), constraining total health care spending (Chandra et al., 2010; Chernew & Newhouse, 2008; Ezzati & Riboli, 2012). However, cost-sharing can also be associated with reductions in preventive care, disease detection, and the use of clinically important services, potentially leading to costly increases in subsequent hospital care (Gaziano & Pagidipati, 2013; NCD Countdown 2030 collaborators, 2018). This concern may be particularly true for common chronic conditions such as hypertension and diabetes, which often develop and progress undiagnosed in their early stages without routine clinical monitoring – and which are growing rapidly in prevalence worldwide (Chernew et al., 2007; Goldman et al., 2006; Rosen et al., 2005).[i] Nonetheless, there is relatively little (and unclear) evidence on the effect of patient cost-sharing on health (Abaluck et al., 2021; Chandra et al., 2021; Newhouse, 1996; Shigeoka, 2014; W. Dow et al., n.d.).

This study presents new population-level evidence of a causal relationship between outpatient cost-sharing and adult mortality risk in Colombia. Previous studies have shown that health insurance can lead to reductions in adult mortality. However, health insurance can also

[i] The price elasticities of services related to the detection and long-term management of major chronic diseases may also be larger (i.e., service use may be more sensitive to prices) than for services addressing acute illnesses. Recent developments in value-based insurance design could, in principle, help to structure patient cost-sharing to differentially encourage use of higher vs. lower value health services, but the data requirements for doing so are onerous, and potentially infeasible in many countries (Chernew et al., 2007; Goldman et al., 2006; Rosen et al., 2005).

influence the availability and quality of medical care as well as supply-side incentives (incentives of health care providers, for example). Studying the consequences of health insurance is therefore conceptually distinct from our specific focus on demand-side cost-sharing (Bauernschuster et al., 2020; Sood et al., 2014; Anderson et al., 2014; S. Miller et al., 2021; Sommers et al., 2012; Goldin et al., 2021; Card et al., 2009; Sommers et al., 2014).[ii]

Specifically, we study Colombia's entire formal sector workforce over the span of nearly a decade using monthly health service claims data linked, at the individual-level, to administrative payroll records and vital statistics. With this data, we use a dynamic regression discontinuity (RD) study design to take advantage of a discrete change in the Colombian health system's outpatient co-payment requirement (from 46% of the daily minimum wage to 122% of the daily minimum wage) at a sharp earnings threshold. Static RD models are quasi-experimental methods increasingly common in health policy research capable of providing internally valid estimates of causal relationships (Bor et al., 2014; Cattaneo & Titiunik, 2022; Hahn et al., 2001a; Lee & Lemieux, 2010; Maas et al., 2017; Thistlethwaite & Campbell, 1960; Venkataramani et al., 2016). Relative to the static model, the dynamic RD model accounts for varying treatment assignment over time, allowing assignment to change period-to-period (monthly in our case) in temporally-dependent ways (Cellini et al., 2010a) – and enabling us to study how the consequences of outpatient cost-sharing evolve over a long period of time.

Decisions about cost-sharing in health care are central in many countries around the world (Evans & Etienne, 2010; Lancet, 2010; Titelman et al., 2015). Low (or no) cost-sharing

[ii] One recent working paper finds evidence of a link between patient cost-sharing and mortality at age 65 in the US (Chandra et al., 2021). Focusing on Indonesia, a working paper reporting results from a health care price experiment finds that higher co-payments reduce self-reported basic activities of daily living (W. Dow et al., 1997). For a systematic review of the effect of user fees and health insurance on health outcomes in lower-income countries, see Qin et al. (2018) (Qin et al., 2018a).

requirements impose larger financing burdens on governments (Reeves et al., 2015), at least in the short-run, but government financing constraints must be balanced with health benefits and other social welfare implications (Gertler et al., 1987).[iii] This paper provides an important new input into policy decisions about cost-sharing in national health programs – and elevates the need to include consequences for health outcomes into such decisions.

2 MATERIALS AND METHODS

2.1 Setting and Population

Our study population is the universe of all Colombian employees working in the formal sector – and hence enrolled in Colombia's national health insurance program for formal sector workers (the Régimen Contributivo, or Contributory Regime) for at least one month between January 2011 and December 2018. We exclude individuals who reached the legal retirement age (57 for women and 62 for men) by 2011 because of differences in health care benefits for pensioners. We also exclude self-employed individuals from the sample. For each person in our sample, we then match individual-level records across four Colombian government administrative databases: (1) Contributory Regime enrollment records (Base de Datos Única de Afiliación, or BDUA)); (2) monthly payroll data submitted by employers to the Colombian social security agency (Planilla Integrada de Liquidación de Aportes, or PILA); (3) individual health service utilization records (contained in the Base del Estudio de Suficiencia de la Unidad Por Capitación, or UPC); and (4) death certificates (Registro Único de Afiliación). These data sources were provided by the Colombian Ministry of Health to the Clinical Research Institute of the National

[iii] Gertler et al. (1987) find that the welfare loss due to cost-sharing falls disproportionately on the poor because health care use among the poor is more sensitive to cost-sharing (Gertler et al., 1987).

University of Colombia for use in our research. Our final sample includes approximately 13 million Colombians and 433 million individual-month observations. SI Appendix 1 Section 1.2.1 provides more detail about each data source. SI Appendix 1 Figure S1 shows a flow diagram detailing the construction of our sample.

This study was granted IRB ethical approval by the Research and Institutional Ethics Committee of the School of Medicine at the National University of Colombia (February 14, 2020) and the University College London Research Ethics Committee (September 29, 2020).

2.2 Exposure and Outcomes Variables

The primary exposure or treatment that we study is the copayment level (higher or lower) that each individual working in the formal sector faced during each month of the study period. We assign this exposure/treatment using exact earnings during the previous month (in units of monthly minimum wages (MMWs)) recorded in the PILA database (according to the policy rules of Acuerdo 260 issued in 2004 by the Consejo Nacional de Seguridad Social en Salud). Copayment levels can change from month to month.[iv] As SI Appendix 1 Figure S1 shows, there is a sharp break in outpatient cost-sharing at 5 MMWs; individuals earning between 2 and 5 MMWs (inclusive) pay 46.1% of the daily minimum wage for each outpatient service, and individuals earning above 5 MMWs pay 121.5% of the daily minimum wage.[v] Importantly, note that there are no differences in inpatient cost-sharing requirements for individuals on either side of the threshold (so any

[iv] On December 31, 2020, one Colombian monthly minimum wage was COP 877.803 Colombian Pesos (or USD $255.73)

[v] The corresponding copayment amount these copayment tiers (CT) are: CT2: 46.1% of a daily minimum wage, or COP 13 500 (roughly USD $ 3.93); and CT3: 121.5% of a daily minimum wage, or COP 35 600 (roughly USD $10.37). Copayments are charged for specific components (rather than episodes) of care. For example, when an individual has a consultation with a doctor, buy a medication, and has a laboratory test performed, they are required to make a copayment for each of these three separate components.

inpatient care effects observed at the 5 MMW threshold cannot be attributed to differences in inpatient cost-sharing).[vi]

Our primary outcome is probability of death. Additionally, we also study other outcomes that can contribute to survival: outpatient service use (total and by type: number of clinical consultations, number of drugs purchased, number of laboratory procedures, and number of diagnostic imaging procedures); a Charlson comorbidity index (Sundararajan et al., 2004); and inpatient or hospital care use (number of hospital stays and probability of using an intensive care unit (ICU)).

2.3 Statistical Analysis

Our statistical analyses take advantage of a discrete change in outpatient cost-sharing at a sharp threshold (at 5 MMWs) in the underlying continuous distribution of monthly earnings (as shown in SI Appendix 1 Figure S1). We first use a static regression discontinuity (RD) design to estimate the contemporaneous relationship between higher (vs. lower) outpatient cost-sharing and outpatient service use. This framework is a quasi-experimental study design capable of yielding an unbiased estimate of a local average treatment effect (LATE) in the absence of treatment randomization. RD estimation was first developed in the field of psychology (Thistlethwaite & Campbell, 1960), has since been adopted in other fields including epidemiology and public health, and was recently incorporated into the UK Medical Research Council guidelines for evaluating population health interventions (Bor et al., 2014; Craig et al., 2012; Hahn et al., 2001a; Hilton

[vi] Formal sector workers do not face any cost-sharing for inpatient care on either side of the 5 MMW threshold. Dependents of formal sector workers (including those who do not work in the formal sector for short spells) are also in the Contributory Regime and face an additional copayment for inpatient care ("*Copagos*"), depending on which side of the 5 MMW threshold their partner lies. However, we only use an individual's own income (rather than their partner's income).

Boon et al., 2021; Lee & Lemieux, 2010; Maas et al., 2017; Moscoe et al., 2015; Thistlethwaite & Campbell, 1960; Venkataramani et al., 2016).

In our specific case, outpatient copayment tier (and corresponding copayment amount) is the treatment of interest, and treatment assignment shifts discontinuously at the 5 MMW threshold in the underlying continuous distribution of earnings. Because this deterministic treatment assignment rule generates differences in the probability of treatment (higher vs. lower copayment) among individuals with essentially identical earnings on either side of the threshold (identical in the limit as one approaches the threshold from either side), treatment assignment is 'as-good-as-random' for individuals close to the threshold, enabling causal inference (Calonico et al., 2014; Lee & Lemieux, 2010; Moscoe et al., 2015; Thistlethwaite & Campbell, 1960).

For static RD estimation, we use local linear regression with outpatient service use by an individual in a given month as the outcome variable, and the 'running variable' is an individual's earnings in the previous month in units of monthly minimum wages (MMWs). We use robust bias-corrected 'optimal' sample bandwidths, and we adjust our standard errors for heteroskedasticity and clustering at the individual-level (Calonico et al., 2014, 2020). SI Appendix 1 Section 1.5.1 provides more detail about this estimation procedure.

An important assumption of our statistical analyses is that individuals do not manipulate or 'game' their earnings to obtain eligibility for lower copayments (McCrary, 2008). We evaluate this assumption in Section 2.2 of SI Appendix 2. As it shows, there are expected mass points at round focal earning values (CO$ 3,000,000; CO$ 3,500,000; CO$ 4,000,000 …) dispersed across the earnings distribution (both close to and far from the 5MW threshold), but the observed pattern is inconsistent with manipulation related to outpatient care copayments (see SI Appendix 2 Figure S7).

We also test for balance in individual characteristics within our RD framework, using individual characteristics that could not plausibly respond to differences in outpatient cost-sharing as dependent variables. SI Appendix 2 Figure S6 shows p-values for each of these balance variables. In general, we find evidence of balance, with the exception of the probability that an individual resides in Bogota. However, with a sufficient number of balance tests, this would probabilistically be expected, and SI Appendix 2 Figure S8 shows that focal-point round earning values are simply relatively more common in Bogotá.

We then extend our statistical framework to study how the effects of higher (vs. lower) outpatient cost-sharing accumulate over time to influence (i.) subsequent outpatient service use, (ii.) detection and diagnosis of chronic diseases, (iii.) use of potentially avoidable inpatient and other hospital care, and (iv.), ultimately, mortality risk. Our approach allows varying treatment assignments over time, and it also allows for treatment assignment to change in each period (month-to-month in our case) in temporally interdependent ways (Cattaneo & Titiunik, 2022).

In doing so, we estimate two different treatment effect parameters of interest. One is an intention-to-treat (θ_{τ}^{ITT}) parameter, which includes both the direct effect of falling above the cost-sharing threshold in a lagged month $(t - \tau)$ on an outcome in month *t*, as well as the indirect effects of falling above the cost-sharing threshold in that lagged month $(t - \tau)$ on the probability, and effect of, falling above the cost-sharing threshold in all subsequent months until month *t*. The other is a treatment-on-treated (θ_{τ}^{TOT}) parameter, which isolates the effect facing a higher (vs. lower) outpatient copayment in a given lagged month $(t - \tau)$ on an outcome in month *t*, holding constant copayment requirements in all subsequent lagged months. We solve for these treatment-on-treated parameters recursively (see SI Appendix 1 Equation 7) using both the intention-to-treat parameters and month-to-month transition probabilities (i.e., the effect of falling above the cost-sharing threshold in a lagged month ($t - \tau$) on the probability of falling above the cost-sharing threshold in all subsequent lagged months until month t, as SI Appendix 2 Figure S4 shows). Note that for mortality risk, we are only able to estimate ITT parameters because mortality is an absorbing state, so the recursive relationship used to obtain treatment-on-treated parameters is not applicable. In all cases, we obtain standard errors using 500 bootstrap replications (Efron, 1979).

For comparison with our ITT mortality estimates, we also use a duration model to estimate survival differences between those facing higher vs. lower outpatient cost-sharing requirements. Specifically, we use a parametric model (instead of the semi-parametric Cox model) because we find that the proportional hazards assumption does not hold in our case, and we select a Weibull distribution among other possible parametric distributions using Akaike and Bayesian information criteria (Bor et al., 2014). Conditioning on a quadratic polynomial of earnings, this model estimates the probability of surviving to each month, conditional on surviving to the preceding month (SI Appendix 1 Section 1.5.3 describes this model in detail) (Lim, 2021; Zhang, 2016).

Finally, we investigate the robustness of our dynamic RD ITT mortality estimates in several ways. Specifically, we assess sensitivity to (i.) controlling for individual characteristics (age, sex, region – including a dichotomous indicator for Bogota, and public insurer) that could not plausibly respond to differences in outpatient cost-sharing; (ii.) using a constant bandwidth (1 MMW) for all lags; and (iii.) restricting our sample to those below the official retirement age (ages 18-62 for men and ages 18-57 for women) in every month of our study period. We also repeat our estimation using subsamples of individuals continuously working in the formal sector for varying durations of time (24, 48, and 72 months). In general, our mortality estimates are robust across these varying approaches and sample restrictions.

3 RESULTS

Among 4,649,188 individuals meeting our inclusion criteria (i.e., all employees enrolled in the Contributory Regime for at least one month between January 2011 and December 2018, excluding those past the legal retirement ages of 57 for women and 62 for men as of January 2011), there were 4,115,581 individuals with mean monthly earnings between 2 and 5 monthly minimum wages (MMWs)[vii] (in the lower outpatient copayment tier) and 533,607 individuals with mean monthly earnings above 5 MMWs (in the higher outpatient copayment tier). Table 1 shows summary statistics for our sample, both overall and by copayment tier.

First, using a static RD study design to examine the direct effect of outpatient cost-sharing on monthly use of outpatient services, Figure 1 shows a discrete reduction in total outpatient service use at the 5 MMW threshold of 0.046 [95% CI -0.058 to -0.035] services per month, a relative decline of 7.71% and implying a price elasticity of -0.09 (for more details, see SI Appendix 2 Table S2).[viii] Breaking this cost-sharing effect on total outpatient services into its components, outpatient care reductions are largely due to decreases in outpatient drug purchases and outpatient clinical consultations – the components most under patient control, and components central in the detection and management of chronic diseases (drug purchases: -0.024 [95% CI -0.029 to -0.018]; clinical consultations: -0.016 [95% CI -0.020 to -0.012]) (SI Appendix 2, Figure S9).

[vii] Monthly minimum wages (MMWs) are workers' monthly earnings divided by Colombia's official minimum wage (a worker earning the minimum wage therefore earns 1 MMW). For formal sector workers, the Colombian health care system requires different copayments for workers earning less than 2 MMWs, 2-5 (exclusive) MMWs, and 5+ MMWs. Because there are other public subsidy programs in Colombia (a transportation program, an employee attire program, and a housing program) that use the 2 MMW threshold for benefit assignment, we focus on the 5 MMW threshold. See the SI Appendix 1 for more details.

[viii] An elasticity is the ratio of the percent change in quantity of services to the percent change in cost-sharing (or price). The larger the absolute value of the elasticity, the more sensitive the service is to cost-sharing. Health services consumption elasticities in this paper are smaller in absolute value than those reported in other papers using USA data such the RAND health insurance experiment (-0.2) (Aron-Dine et al., 2013) and Chandra et al. (-0.16) (Chandra et al., 2014). However, it is similar to the elasticity on Colombian data reported by Serna (-0.05) (Serna, 2021).

Figure 2 Panel A then presents dynamic RD intention-to-treat (ITT) estimates for total outpatient care over a period of 8 years – estimates which incorporate both the effect that higher cost-sharing today has on future cost-sharing as well as the implications that higher cost-sharing today has for future health care use. Notably, over an 8-year period of time, initially higher outpatient cost-sharing eventually leads to an *increase* in outpatient service use. Specifically, a higher initial copayment reduces outpatient service use for about 32 months, but this effect then becomes zero and eventually turns positive. Figure 2 Panels B and C show a similar pattern for outpatient clinical consultations and outpatient prescription drug use (and SI Appendix 2 Figure S10 and Tables S10 and S12 show a similar relationship for the other components of outpatient service use).

Figure 2 Panel A also shows cumulative dynamic RD treatment-on-treated (TOT) estimates, capturing the effect of systematically being above the cost-sharing threshold and facing a higher outpatient copayment in every period over time. Cumulative outpatient service use steadily decreases over the same period that the ITT estimates are negative, plateaus when the ITT estimates reach zero, and finally, rises when the ITT estimates are positive, but always remains in the negative range. Figure 2 Panels B and C show analogous TOT estimates for outpatient clinical consultations and outpatient drug use (SI Appendix 2 Tables S7 and S9 and Figures S10, Tables S11, and S13 report TOT estimates for outpatient laboratory procedures and diagnostic imaging).

A potential explanation consistent with past research (Brot-Goldberg et al., 2017; Chernew & Newhouse, 2008) that could explain the eventual *increase* in outpatient service use due to higher outpatient cost-sharing is lower rates of early detection and management of chronic diseases. To investigate this possibility directly, Figure 3 Panel A (and SI Appendix 2 Tables S14 and S15) shows the effect of higher outpatient cost-sharing on a Charlson Comorbidity Index constructed using ICD-10 codes in our health care utilization data (combining prevalence and severity for major chronic diseases, including vascular and cerebrovascular disease, chronic pulmonary disease, diabetes, kidney or liver disease, and some cancers) (Charlson et al., 2022). Mirroring the pattern of outpatient service use over time shown in Figure 2, the dynamic RD ITT estimates for the Charlson Index are initially negative, presumably reflecting lower chronic disease detection rates due to less use of outpatient care. Then, at the same lags at which the outpatient care ITT estimates reach zero, the Charlson Index ITT estimates also plateau. Finally, when the outpatient care estimates become consistently positive, the Charlson Index ITT estimates also turn positive. Panel B shows cumulative dynamic RD TOT estimates for the Charlson Index. Notably, although the TOT estimates for outpatient care do not fully reach zero at the longest lags, the Charlson Index TOT estimates do (implying that chronic disease prevalence and severity exceed changes in detection opportunities over time).

Investigating further the possibility that higher outpatient cost-sharing leads to more severe disease over time, we also find that although individuals on either side of the discontinuity face no inpatient cost-sharing requirement, higher outpatient cost-sharing leads to *increases* in the number of inpatient hospital stays over time (Figure 4 and SI Appendix 2 Tables S18 y S19). This is also true for the probability of using an intensive care unit (SI Appendix 2, Figure S11 and Tables S16 and S17).

Finally, Figure 5 reports dynamic RD ITT estimates showing an increase in mortality risk over time among individuals with higher outpatient cost-sharing.[ix] This increase is statistically significant at the longest lags (starting at about 80 months, rising to an increase of 11.5 percentage

[ix] Death is an absorbing state, so the ITT estimates for mortality capture the effect of a higher copayment on the probability of dying between the exposure month and the evaluated lag, and the recursive formula (equation 7 in SI Appendix 1) for TOT effects is not applicable.

points by 95 months) and corresponds to an increase of about 4 deaths per 10,000 population over 8 years. Figure 6 also shows survival curves among those with higher and lower outpatient cost-sharing over time generated using a parametric Weibull survival model.[x] Similar to the results in Figure 5, it shows that those facing higher (vs. lower) outpatient cost-sharing requirements experience an increase in mortality risk of about 5 deaths per 10,000 population over a period of 8 years (SI Appendix 2 Table S20 reports estimates in tabular form).

We consider the robustness of our dynamic RD ITT mortality estimates in Figure 7. Panel A shows that the results in Figure 5 are robust to: controlling for covariates (age, sex, region – including a dichotomous indicator for Bogota, and public insurer) (shown with red dots); using a fixed bandwidth of 1 MMW for all lags (shown with blue dots); and using a subsample of individuals below the official retirement age throughout the entire study period (shown with orange dots). Panel B also shows that these results are robust to using restricted subsamples of workers continuously in the workforce for 24, 48, and 72 consecutive months (shown with purple, yellow, and gray dots, respectively).

4 DISCUSSION

This paper provides new evidence that greater outpatient cost-sharing reduces the use of outpatient services in the short-term – but in doing so, can also unintentionally reduce the detection of new chronic diseases and increase the use of more expensive, potentially avoidable hospital services – ultimately increasing adult mortality risk. To the best of our knowledge, our study is the first to demonstrate an effect of cost-sharing alone (holding insurance enrollment constant) on the

[x] This Weibull survival model conditions on a quadratic polynomial of earnings in the previous month.

long-term survival of adults in a low-/middle-income country, and to explicitly analyze potential causal pathways.

Our analyses have several important methodological strengths, including their use of unusually large linked administrative databases provided by the Colombian Ministry of Health (covering the universe of formal sector workers over a period of 8 years) and their application of a dynamic RD framework to address potential endogeneity in health care cost-sharing (which is determined by income and therefore also potentially by health). Static RD models are increasingly common research tools in public health and medicine (Bor et al., 2014; Craig et al., 2012; Hilton Boon et al., 2021; Maas et al., 2017; Moscoe et al., 2015; Venkataramani et al., 2016), and they offer advantages over other observational study designs when randomized controlled trials are not possible or ethical. Given our setting, we extend this approach using a dynamic RD model that allows treatment assignment to change over time (in our case, each month) in temporally-dependent ways (Cellini et al., 2010a).

Our paper also makes several substantive contributions to existing research. First, many past studies of cost-sharing focus on settings in which variation in cost-sharing is accompanied by variation in health insurance enrollment (Bauernschuster et al., 2020; Card et al., 2009; Goldin et al., 2021; S. Miller et al., 2021; Sommers et al., 2012, 2014). Although cost-sharing is a tool used almost ubiquitously by health insurance programs, comparisons of those with and without health insurance also reflect differences in access to health providers and differences in the incentives that providers serving the insured vs. the uninsured face (Shigeoka, 2014). Analyses isolating the effects of cost-sharing are particularly important for policy decisions about cost-sharing in the presence of insurance – as is the case in many countries with some form of insurance, but nonetheless aiming to make further progress towards universal health coverage (UHC).

Additionally, research to date isolating the role of cost-sharing (holding insurance enrollment constant) focuses on specific demographic groups (such as infants or the elderly) (Chandra et al., 2010, 2021; Lamichhane et al., 2017; McKinnon et al., 2015; Rice & Matsuoka, 2004; Shigeoka, 2014), focuses only on high-income countries (such as the U.S. and Japan,) (Chandra et al., 2021; Rice & Matsuoka, 2004; Shigeoka, 2014), does not generally include mortality as an outcome (Chandra et al., 2010; Newhouse, 1996), or suffers from important methodological weaknesses (Lagarde & Palmer, 2011; Qin et al., 2018b; Rice & Matsuoka, 2004).

Our study also has several limitations. First, we assume that individuals do not manipulate or 'game' their earnings recorded in the Colombian government's public finance records to obtain eligibility for lower outpatient cost-sharing. However, we consider this possibility directly by implementing tests for manipulation, finding evidence consistent with continuity across the earnings threshold in individuals' characteristics and providing support for this assumption (McCrary, 2008).[xi] Second, although our RD estimates are internally valid, they do not generalize to individuals with earnings not close to the cost-sharing threshold (Gertler et al., 1987; Lee & Lemieux, 2010).

As countries around the world continue to make progress toward providing UHC, difficult health policy decisions remain. Government financing requirements for UHC can, in part, be met through patient cost-sharing (Evans & Etienne, 2010; Lancet, 2010; Titelman et al., 2015) – a rationale consistent with a low tax base, as is common in many low- and middle-income countries, and concerns about inappropriate overuse of some health services. However, higher patient cost sharing also increases the financial risk that households face when they become ill (Finkelstein &

[xi] Although a test of continuity in density of the running variable formally rejects the null hypothesis because of the presence of round focal earnings values (CO$ 3,000,000; CO$ 3,500,000; CO$ 4,000,000 …), with one falling close to the 5MW threshold, as we explain in paragraph four of the Statistical Analysis section, the pattern that we observe is nonetheless inconsistent with manipulation.

McKnight, 2008; G. Miller et al., 2013; Wagstaff et al., 2020), and our paper shows that it could have a detrimental effect on health and mortality as well.

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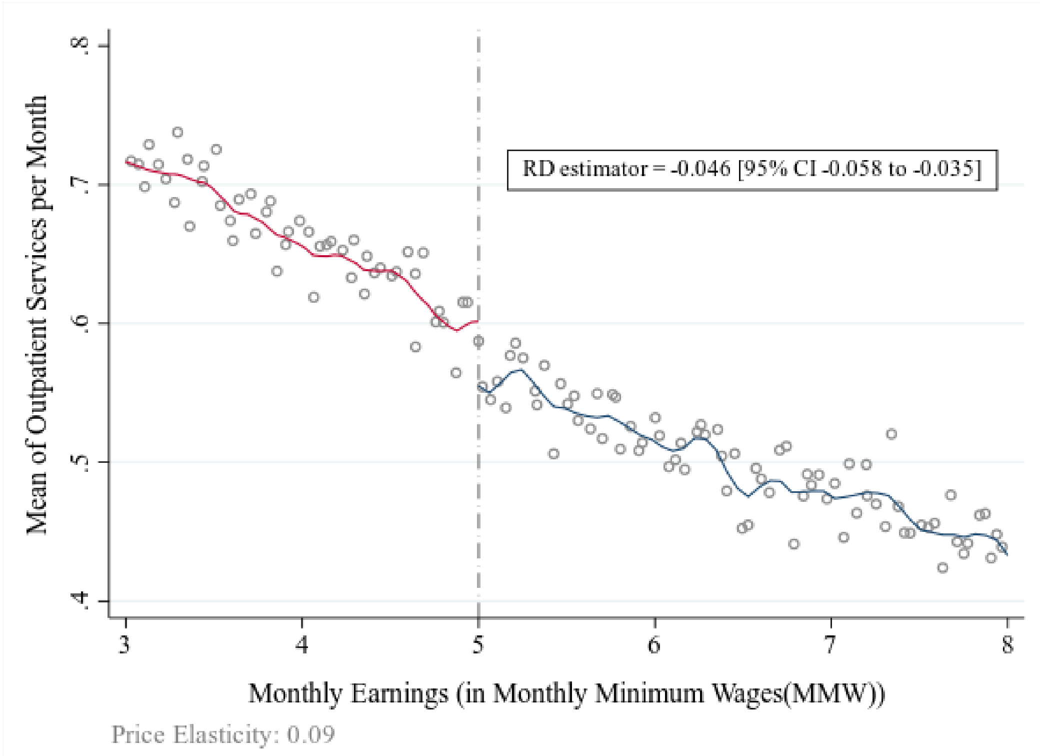
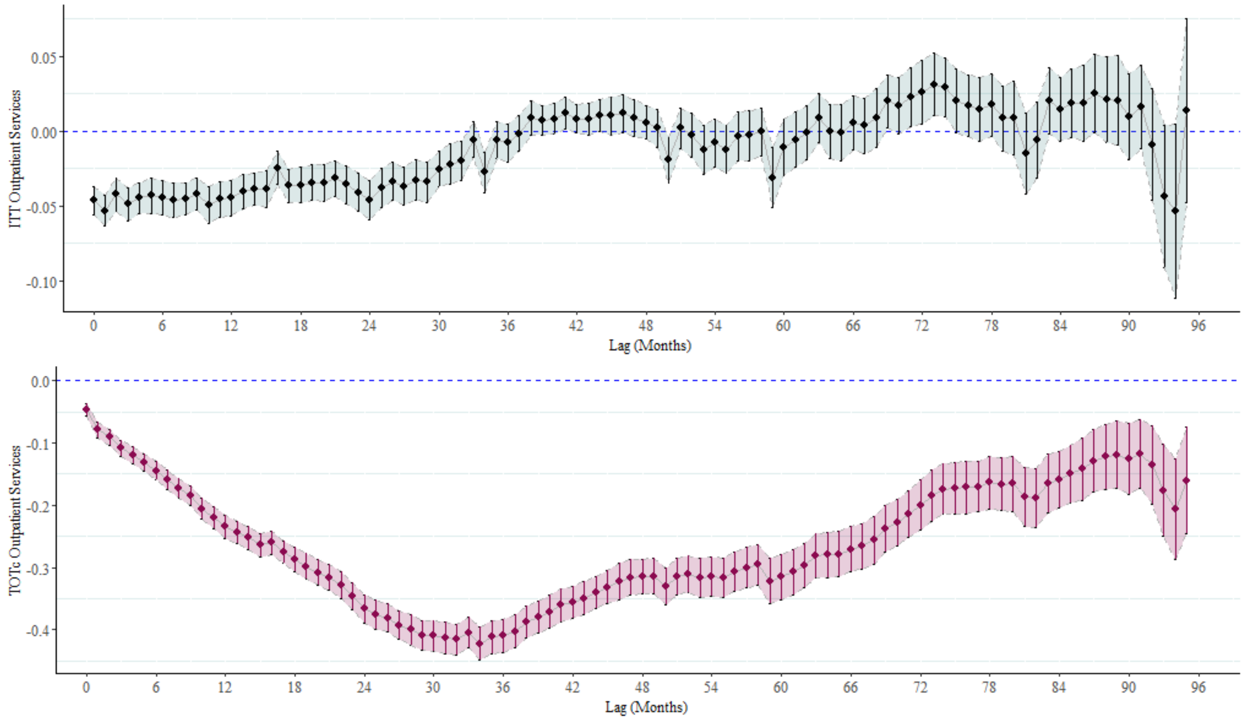
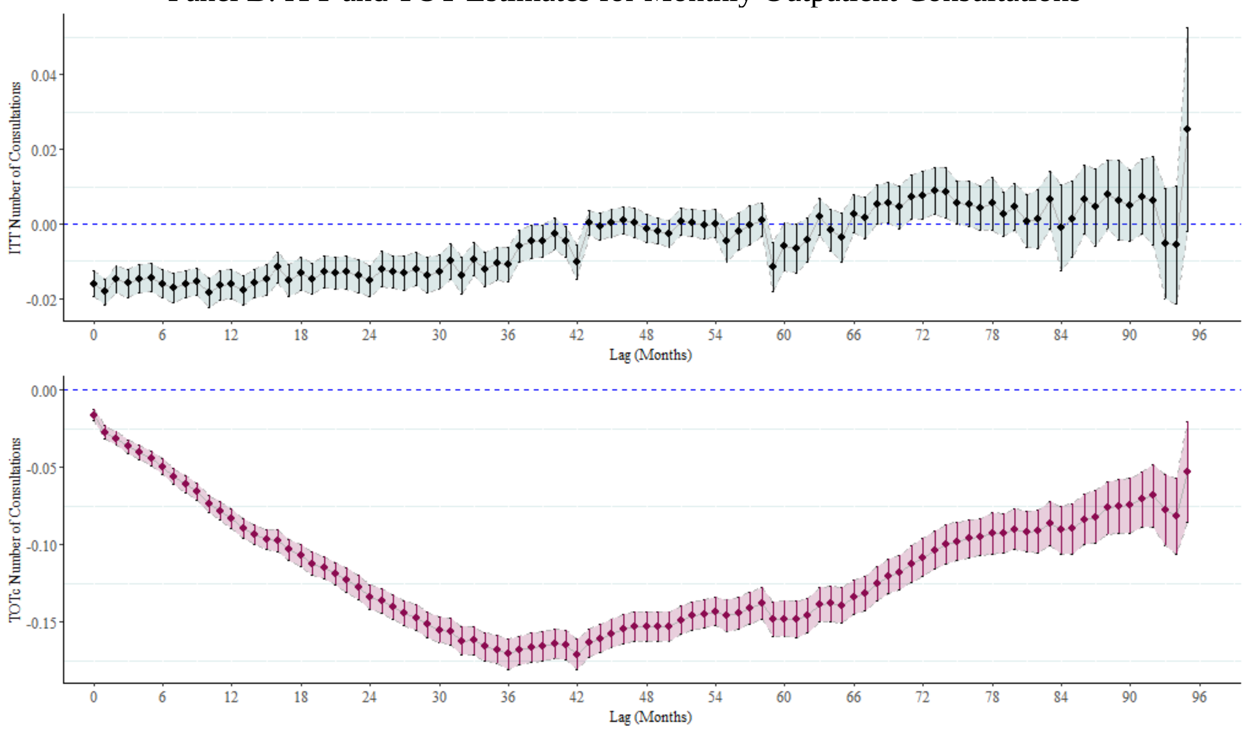


Figure 1. The Static Effect of Higher Outpatient Cost-Sharing on Total Outpatient Service Use. Mean total outpatient service use per month by earnings (in units of monthly minimum wages (MMWs)) among formal sector workers in Colombia between 2011 and 2018, with local linear smoothing on each side of the 5 MMW threshold**.** Static regression discontinuity (RD) estimates obtained by local linear regression using SI Appendix 1 Equation (2) with robust bias-corrected 'optimal' sample bandwidths; standard errors adjusted for heteroskedasticity and clustered at the individual level (Calonico et al., 2020; Fan & Gijbels, 1996a; Hahn et al., 2001a).

Panel A. ITT and TOT Estimates for Total Monthly Outpatient Service Use



Panel B. ITT and TOT Estimates for Monthly Outpatient Consultations



Panel C. ITT and TOT Estimates for Monthly Outpatient Drug Purchases

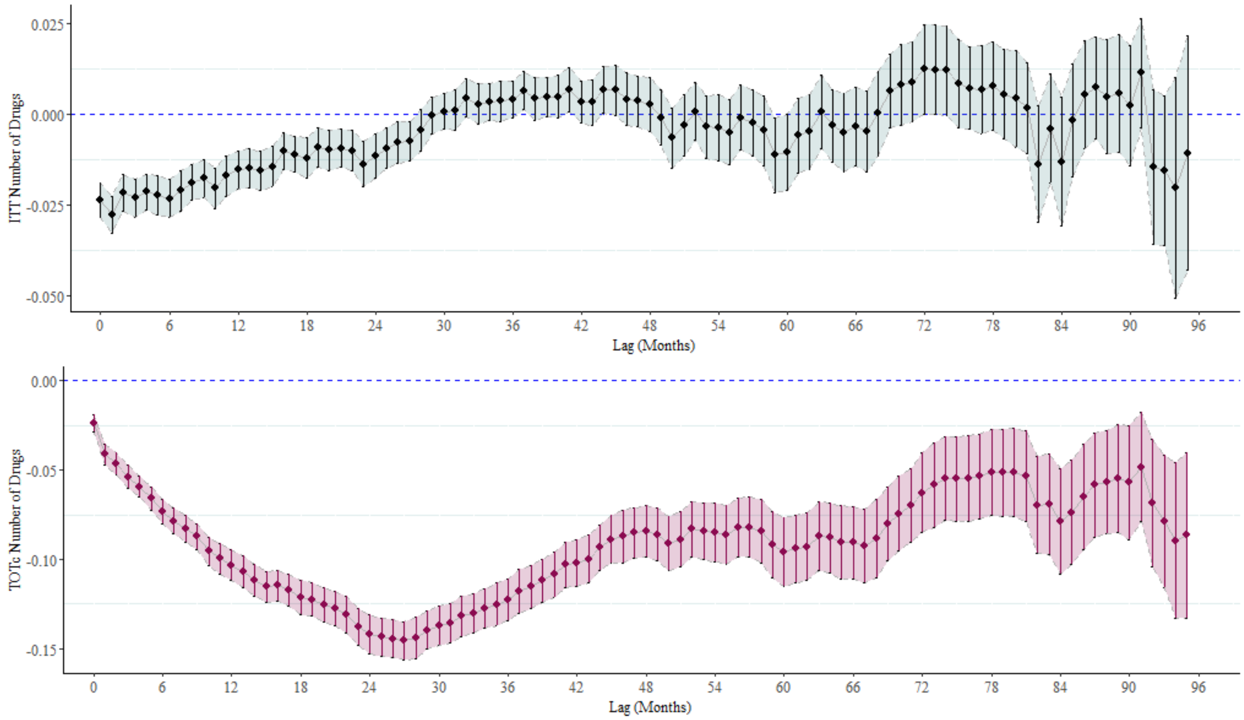


Figure 2. The Dynamic Effect of Higher Outpatient Cost-Sharing on Total Outpatient Service Use, Outpatient Consultations, and Drug Purchases. Intention-to-Treat (ITT) (shown in red) and cumulative Treatment-on-Treated (TOT) (shown in grey) dynamic regression discontinuity (RD) estimates obtained by local linear regression using SI Appendix 1 Equation (6) with robust bias-corrected 'optimal' sample bandwidths; standard errors adjusted for heteroskedasticity and clustered at the individual-level (Cellini et al., 2010a; Enami et al., 2023; Fan & Gijbels, 1996a; Hahn et al., 2001a; Hsu & Shen, 2022a).

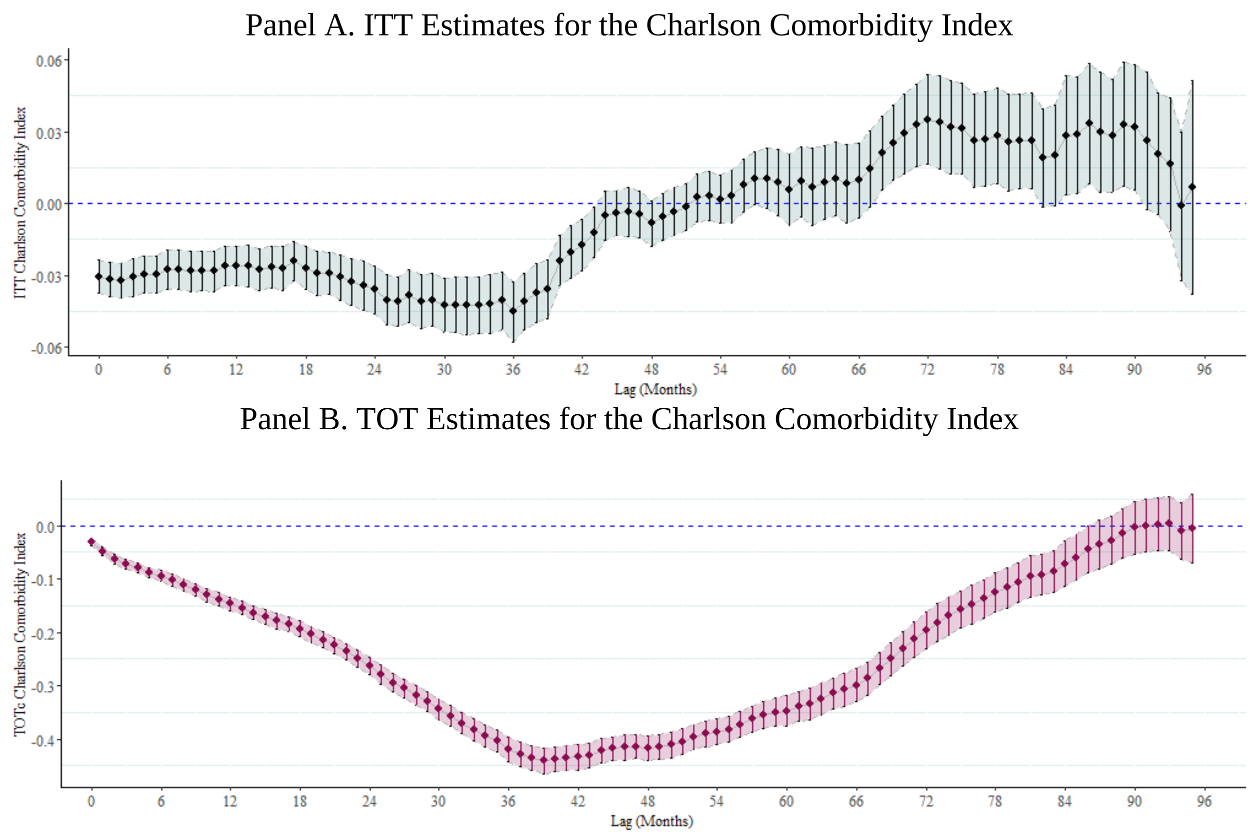
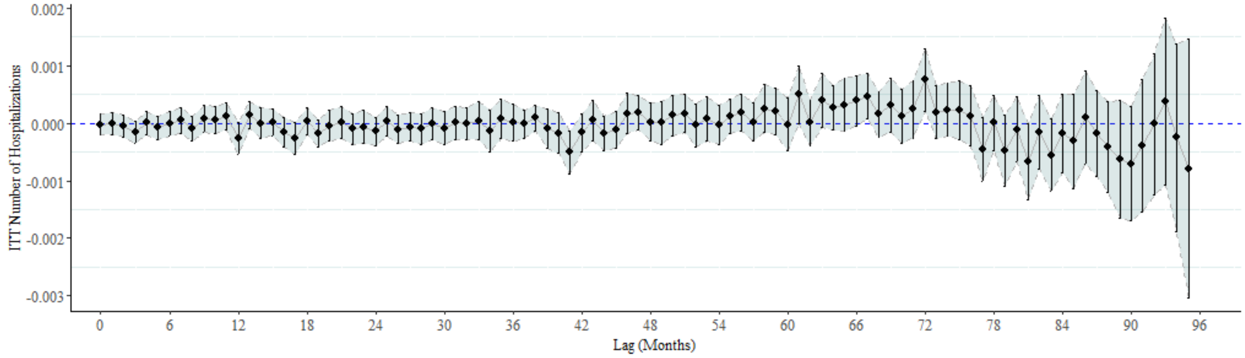


Figure 3. The Dynamic Effect of Higher Outpatient Cost-Sharing on the Charlson Comorbidity Index. Intention-to-Treat (ITT) (Panel A) and cumulative Treatment-on-Treated (TOT) (Panel B) dynamic regression discontinuity (RD) estimates obtained by local linear regression using SI Appendix 1 Equation (6) with robust bias-corrected ‘optimal’ sample bandwidths; standard errors adjusted for heteroskedasticity and clustered at the individual-level (Cellini et al., 2010a; Enami et al., 2023; Fan & Gijbels, 1996a; Hahn et al., 2001a; Hsu & Shen, 2022a).

Panel A. ITT Estimates for Average Number of General Hospitalizations



Panel B. TOT Estimates for Average Number of General Hospitalizations

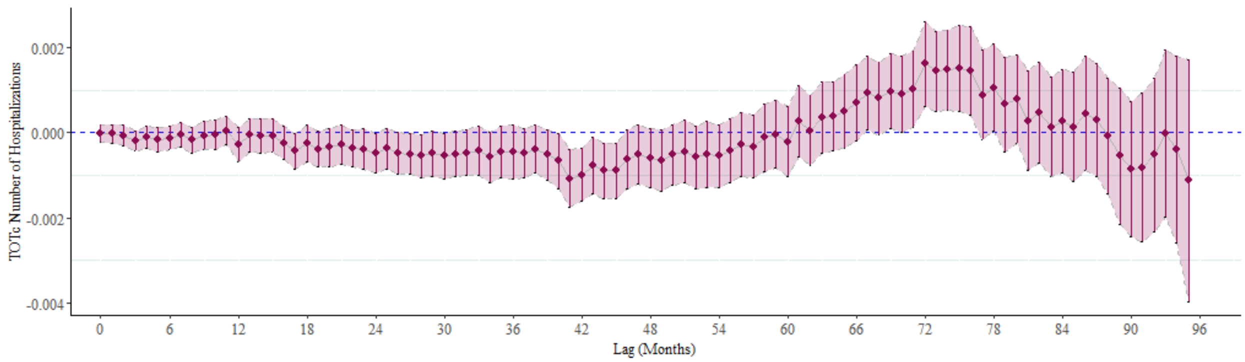


Figure 4. The Dynamic Effect of Higher Outpatient Cost-Sharing on Number of General Hospitalizations. Intention-to-Treat (ITT) (Panel A) and cumulative Treatment-on-Treated (TOT) (Panel B) dynamic regression discontinuity (RD) estimates obtained by local linear regression using SI Appendix 1 Equation (6) with robust bias-corrected 'optimal' sample bandwidths; standard errors adjusted for heteroskedasticity and clustered at the individual-level (Cellini et al., 2010a; Enami et al., 2023; Fan & Gijbels, 1996a; Hahn et al., 2001a; Hsu & Shen, 2022a).

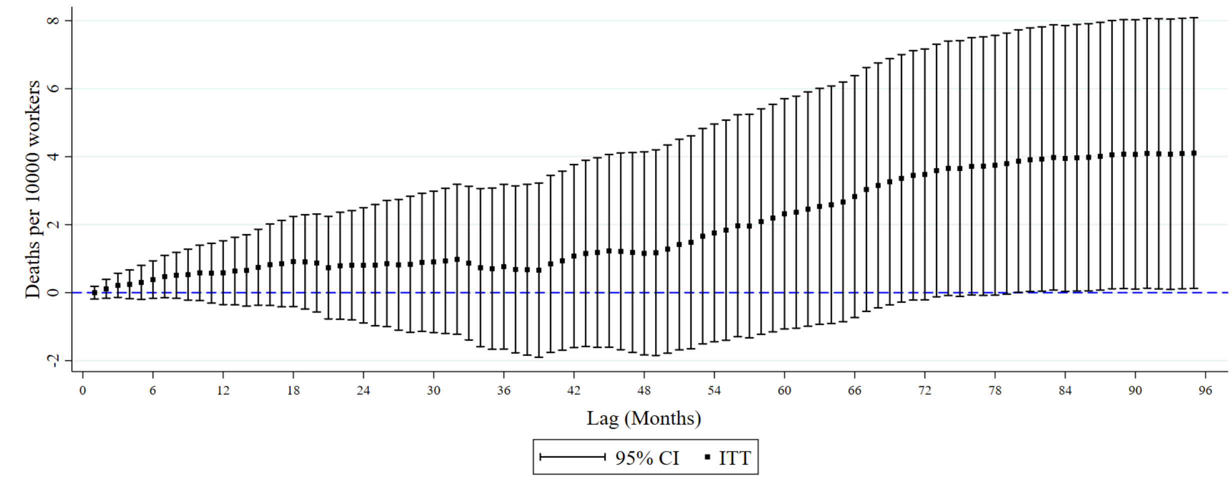


Figure 5. The Dynamic Effect of Higher Outpatient Cost-Sharing on Mortality Risk. Intention-to-Treat (ITT) dynamic regression discontinuity (RD) estimates obtained by local linear regression using SI Appendix 1 Equation (6) with robust bias-corrected 'optimal' sample bandwidths; standard errors adjusted for heteroskedasticity and clustered at the individual-level (Cellini et al., 2010a; Enami et al., 2023; Fan & Gijbels, 1996a; Hahn et al., 2001a; Hsu & Shen, 2022a).

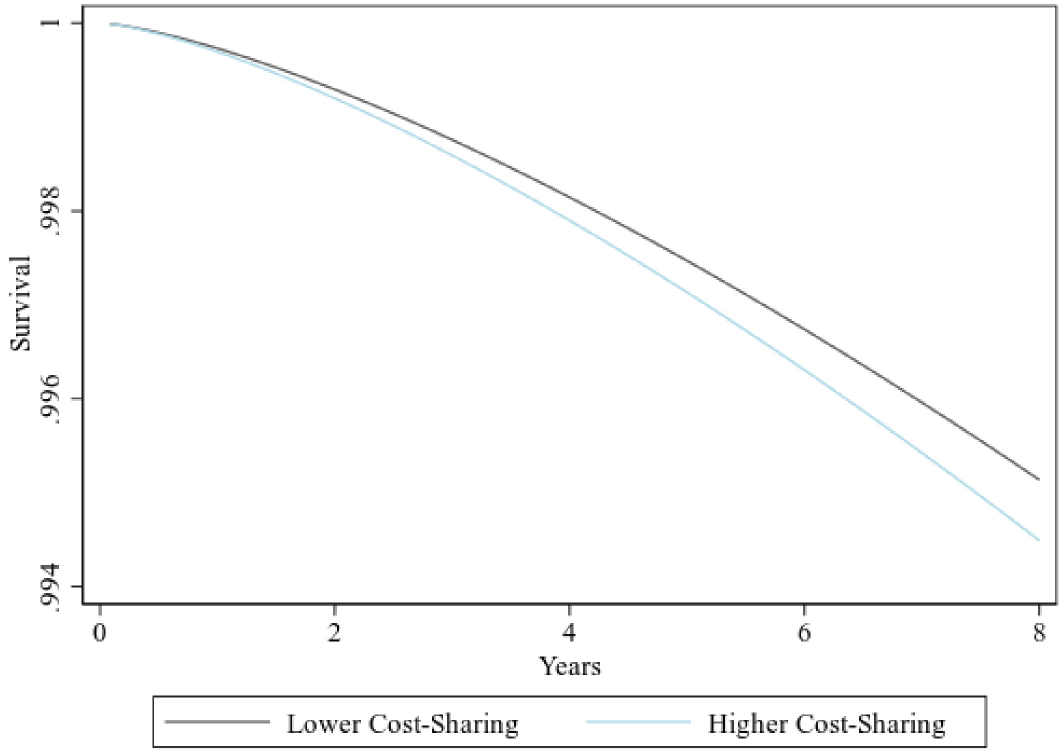
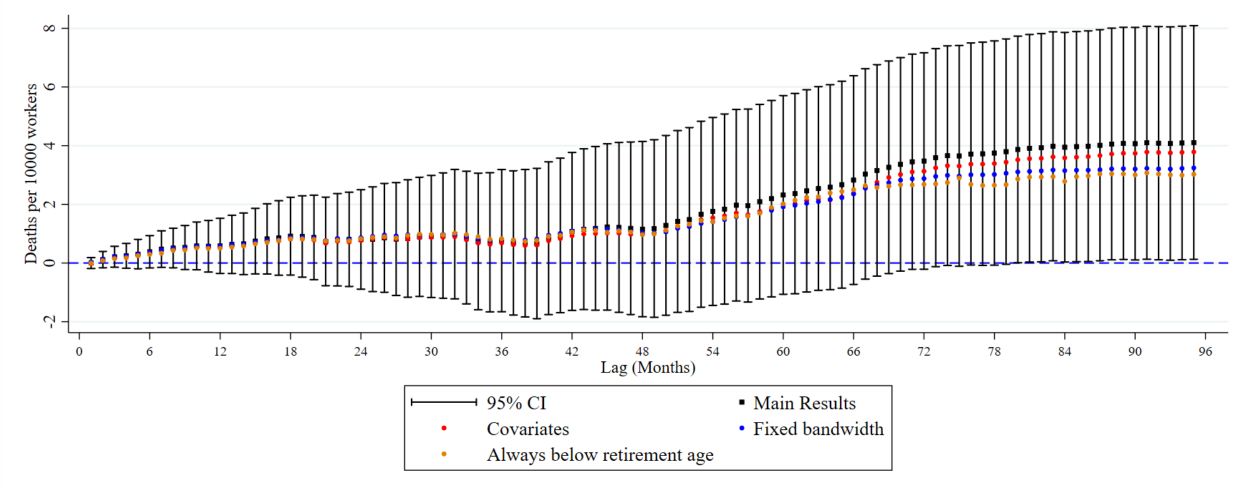


Figure 6. Cumulative Effect of Higher Outpatient Cost-Sharing on 8-Year Survival.
Survival curves for the cumulative effect of higher outpatient cost-sharing on mortality risk at the 5 MMW threshold using a parametric Weibull model adjusted by covariates (age, sex, region, and public insurer) and a bandwidth of 0.5 monthly minimum wages (MMWs).

Panel A.



Panel B.

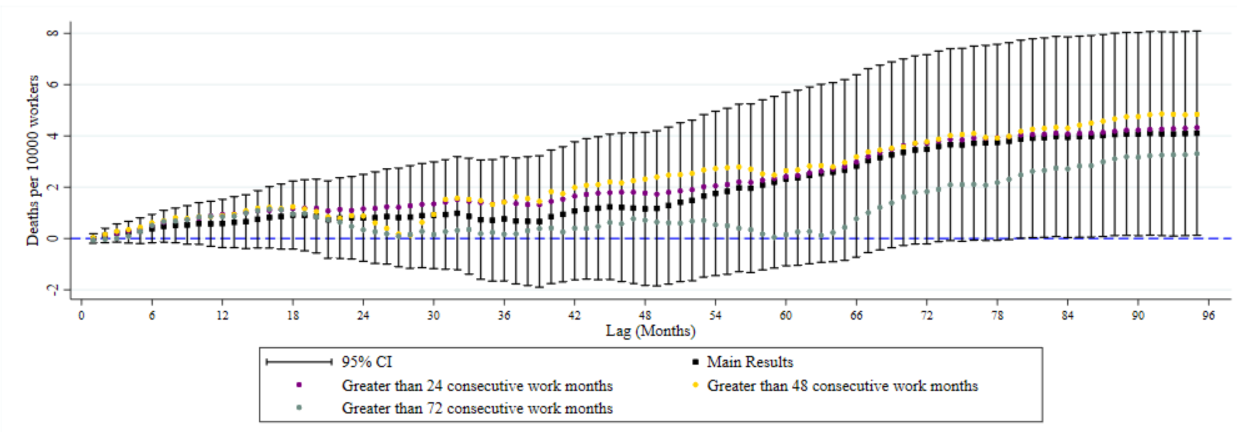


Figure 7. Robustness of the Dynamic Effect of Higher Outpatient Cost-Sharing on Mortality Risk. Panel A shows Intention-to-Treat (ITT) dynamic regression discontinuity (RD) estimates obtained by local linear regression using SI Appendix 1 Equation (6) with robust bias-corrected 'optimal' sample bandwidths shown in black; standard errors adjusted for heteroskedasticity and clustered at the individual-level (Cellini et al., 2010b; Fan & Gijbels, 1996b; Hahn et al., 2001b; Hsu & Shen, 2022b; Rohlin et al., 2022). Estimates produced the same way but controlling for covariates (age, sex, region – including a dichotomous indicator for Bogota, and public insurer) shown in red, using a fixed bandwidth of 1 MMW shown in blue, and using a subsample of individuals eligible for inclusion at every age (below retirement age, 57 for women and 62 for men) shown in orange. Panel B shows Intention-to-Treat (ITT) dynamic regression discontinuity (RD) estimates restricted to subsamples of workers with salary data for at least 24 consecutive months shown in purple, 48 consecutive months shown in yellow, and 72 consecutive months shown in gray.

Table 1. Descriptive Statistics.

VARIABLES	(1) Full sample	(2) $2 < w_{imt} \leq 5$	(3) $w_{imt} > 5$
Age (in Years)	34.70	34.16	38.83
	(0.00464)	(0.00488)	(0.0135)
Share Women (%)	38.54	38.23	40.95
	(0.0226)	(0.0240)	(0.0673)
Share Enrolled in the Public Plan (%)	8.190	8.447	6.204
	(0.0127)	(0.0137)	(0.0330)
Share by Geographical Region (%)			
Atlántica	13.70	13.83	12.67
	(0.0159)	(0.0170)	(0.0455)
Bogotá	31.87	30.40	43.23
	(0.0216)	(0.0227)	(0.0678)
Central	24.02	24.37	21.33
	(0.0198)	(0.0212)	(0.0561)
Oriental	15.86	16.49	10.99
	(0.0169)	(0.0183)	(0.0428)
Pacífica	11.74	12.01	9.717
	(0.0149)	(0.0160)	(0.0405)
Others	2.810	2.907	2.062
	(0.00766)	(0.00828)	(0.0195)
8-year Cumulative Mortality Risk (%)	0.512	0.513	0.503
	(0.00331)	(0.00352)	(0.00968)
Charlson Comorbidity Index	0.371	0.369	0.391
	(0.000461)	(0.000487)	(0.00142)
Earnings (in Monthly Minimum Wages (MMWs))	3.188	2.812	6.089
	(0.000598)	(0.000370)	(0.00108)
Annual Outpatient Services Use			
Average of all Outpatient Services Used	4.179	4.202	3.997
	(0.00350)	(0.00370)	(0.0106)
Average of Drugs Purchased	1.741	1.768	1.538
	(0.00185)	(0.00195)	(0.00566)
Average of Medical Consultations Used	1.449	1.463	1.345
	(0.00112)	(0.00119)	(0.00326)
Average of Laboratory Procedures Used	0.762	0.749	0.863
	(0.000863)	(0.000907)	(0.00275)
Average of Diagnostic Imaging Procedures Used	0.226	0.223	0.251

	(0.000290)	(0.000308)	(0.000867)
Annual Inpatient Care Use			
Probability of visiting Emergency Room (%)	35.34	35.18	36.59
	(0.0222)	(0.0235)	(0.0659)
Average of visits to Emergency Room	0.247	0.252	0.212
	(0.000271)	(0.000291)	(0.000718)
Probability of Hospitalization (%)	9.003	8.895	9.831
	(0.0133)	(0.0140)	(0.0408)
Average Number of Hospitalizations	0.0343	0.0345	0.0334
	0.000083	0.000089	(0.000234)
Average of Days of Hospital Stay	0.0813	0.0817	0.0783
	(0.000340)	(0.000363)	(0.000974)
Probability of Hospitalization in the ICU (%)	0.670	0.667	0.697
	(0.00378)	(0.00401)	(0.0114)
Average of Hospitalizations in the ICU	0.00234	0.00236	0.00216
	0.000025	0.000028	0.00006
Average of Days of Hospital Stay in the ICU	0.0129	0.0131	0.0115
	(0.000138)	(0.000149)	(0.000366)
Observations	4,649,188	4,115,581	533,607

Note: Descriptive statistics for all individuals enrolled in Contributory Regime for at least one month between January 2011 and December 2018, excluding individuals who reached the legal retirement age (57 for women and 62 for men) by 2011. Standard errors in parentheses. w_{imt} is individual's i earnings (in units of monthly minimum wages (MMWs)) in month m and year t; ICU: Intensive Care Unit.

Appendix 1
Supporting Information for

"Cost-Sharing in Medical Care Can Increase Adult Mortality: Evidence from Colombia"

Giancarlo Buitrago, Javier Amaya, Grant Miller,* and Marcos Vera-Hernández

Details of Materials and Methods

1.1. Institutional Background

The current Colombian health care system (called *Sistema General de Seguridad Social en Salud*) was created in 1993 under Law 100. This social health insurance system offers a benefits package defined by the Ministry of Health and administered by both public and private insurers. There are two major 'regimes' within this system: the 'Contributory Regime' and the 'Subsidized Regime.' The Contributory Regime includes all formal-sector workers (and their dependents) earning one or more legally-established monthly minimum wages (MMW). Alternatively, the Subsidized Regime covers all individuals (and their dependents) earning less than one MMW and also meeting a proxy means test through the *Sistema de Identificación de Beneficiarios* (SISBEN). The benefits package is the same for both regimes and is generally comprehensive, covering all outpatient and inpatient care for almost all diseases, only some health technologies are excluded due to the absence of a sanitary register or non-clinical purposes (cosmetic plastic surgery, for example). Nearly the entire Colombian population is enrolled in one of these two regimes – in 2016, for example, the overall population coverage rate was 95.6%, with 45.54% in the Contributory Regime and 45.48% in the Subsidized Regime (Ministerio de Salud y Protección Social, 2017).

Nodal Contributory Regime enrollees (called *Cotizantes*) face a step-function copayment for outpatient services (including consultations with general practitioners and specialists, drugs, and diagnostic tests) that varies with monthly earnings (measured in MMWs) and is officially recorded by Ministry of Health and Social Protection using payroll data from employers.[i] There are three copayment tiers:

$$CT_{it} = \begin{cases} CT1 & if \quad 1 \leq w_{it-1} < 2 \\ CT2 & if \quad 2 \leq w_{it-1} \leq 5 \\ CT3 & if \quad w_{it-1} > 5 \end{cases}$$

[i] Dependents (*beneficiarios*) are also enrolled in the Contributory regime and face the same cost-sharing requirement as the nodal formal sector worker (*Cotizante*) through whom they are enrolled. However, these dependent beneficiaries are also required to pay an additional cost-sharing amount (*cuota moderadora*) that is calculated as a proportion of the service consumed. This additional cost-sharing also varies across tiers and has an annual limit.

where CT_{it} is the individual's i copayment amount (in Colombian Pesos) in the previous month $t-1$; w_{it-1} is individual's i earnings (in monthly minimum wages units) in the previous month $t-1$.[ii] However, because there are two other public subsidy programs (a transportation allowance and a housing support program) that also use the 2 MMW threshold for eligibility, we focus our analysis on the 5 MMW threshold distinguishing the second and third copayment tiers (Figure S1). The copayment amounts in these tiers are:

CT2: 46.1% of a daily minimum wage, which was roughly COP $ 13,500 (USD $ 3.65) in 2020.
CT3: 121.5% of a daily minimum wage, which was roughly COP $ 35,600 (USD $ 9.62) in 2020.

The copayment is paid by the nodal enrollee (i.e., the *Cotizante*) for all outpatient care, which includes consultations with general practitioners and specialists, drugs, and diagnostic tests. There is no limit on the annual copayment that a worker can pay in a year.

Additionally, some outpatient services have no copayment requirement – most relevant to our study are those related to chronic disease management (for hypertension and diabetes, for example) after an individual has been diagnosed and enrolled in an appropriate disease management program. Also note that there are no differences in cost-sharing requirements for inpatient care in either side of the threshold for nodal enrollees (so inpatient care effects observed at the 5 MMW threshold cannot be attributed to differences in inpatient cost-sharing).[iii] Whenever an individual ceases to be a nodal enrollee, but continues to be enrolled as a dependent of a nodal enrollee, the dependent beneficiary then has a cost-sharing requirement for inpatient care, but these vary according to the nodal enrollee's earnings; importantly, we instead use each individual's own earnings for treatment assignment.

1.2. Data and Study Population

Our study includes all individuals enrolled in the Contributory Regime for at least one month between January 2011 and December 2018. We excluded individuals who reached the legal minimum retirement age (57 for women, 62 for men) by 2011 because benefits are different for public pension beneficiaries – but we are unable to identify pensioners in our data.

1.2.1. Data Sources

To build our database of all Contributory Regime enrollees, we used the following data sources:

1. 'Unique Affiliation Database' (*Base de Datos Única de Afiliación*, or BDUA). The BDUA is the official government registrar tool for tracking and designating individual

[ii] $w_{it-1} = W_{it-1}/MMW_{t-1}$ where the numerator is individual's I earnings (in Colombian Pesos) in the previous month t , and MMW_t is the legal monthly minimum wage for the previous month t.
[iii] It is important to clarify that policyholders (formal sector workers) do not face any cost-sharing for inpatient care on either side of the 5 MMW threshold. However, formal sector workers who stop working in the formal sector, but are dependent on a partner who works in the formal sector, remain enrolled in the *Contributivo* system. In the case, the beneficiary will face an additional copayment for inpatient care ("*copagos*") depending on which side of the 5 MMW threshold their partner lies. However, we only use the individual's own (rather than their partner's) income.

enrollee status in the Colombian health system. This database also includes basic socio-demographic characteristics of enrollees.

2. 'Integrated Contribution Settlement Worksheet' (*Planilla Integrada de Liquidación de Aportes,* or PILA). The PILA contains monthly payroll data on the economic contributions of citizens and their employers to Colombian social security systems, as reported by employers.

3. 'Study Basis for Calculation of the Capitation Unit' (*Base del Estudio de Suficiencia de la Unidad Por Capitación,* or UPC). The UPC database contains detailed records of each health service use by each Colombian enrolled in the country's health care system (including identity of the enrollee, location of service, date of service, specific type of service, any diagnostic information, identity (and type) of health professional providing the service, and payments/reimbursements for the service). The UPC is the database used by the Ministry of Health and Social Protection for computation of risk-adjustment payments added to the insurance premiums paid to insurers.

4. 'Single Registry of Enrollees, Module ND' (*Registro Único de Afliación,* or RUAF), which is administered by the Ministry of Health and Social Protection. This is the main source that the National Administrative Department of Statistics (*Departamento Administrativo Nacional de Estadística,* or DANE) uses to generate the country's vital statistics. RUAF was created in 2007 through the *Circular Externa Conjunta* No. 0081 of November 13rd, 2007. RUAF contents and its operation have been assessed by international institutions, which have concluded that the system has made great progress since its establishment in terms of coverage, completeness, and timeliness.[iv] 91% of the deaths reported in Colombia between 2011 and 2018 were reported in the ND module. The main reason for the latter gap was that not all deaths verified by the National Institute of Legal Medicine and Forensic Sciences were registered in RUAF's Module ND (these deaths are related to external causes, namely homicides and traffic accidents).[v]

1.2.2. Data Access Permissions

The Clinical Research Institute of the School of Medicine at Universidad Nacional de Colombia made a formal request to the Office of Information Technology and Communication of the Ministry of Health and Social Protection to obtain the sources of information mentioned previously, with the stated reason for this request being to use such data sources in several research projects. The Ministry of Health granted our request and provided the databases in question to the Clinical Research Institute (including an anonymous identifier that allowed the different databases to be linked), through communications from March 5th, March 21st, and May 27th, 2019. In these communications, the Ministry of Health authorizes the Clinical Research

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[iv] Colombia Implementation Working Group. Colombia: A strategy to improve the registration and certification of vital events in rural and ethnic communities. CRVS country perspectives. Melbourne, Australia: Bloomberg Philanthropies Data for Health Initiative, Civil Registration and Vital Statistics Improvement, the University of Melbourne; 2018

[v] Toro Roa, Juan Pablo; Iunes, Roberto F.; Mills, Samuel. 2019. Achieving Health Outcomes in Colombia: Civil Registration and Vital Statistics System, Unique Personal Identification Number, and Unified Beneficiary Registry System for Births and Deaths. Health, Nutrition, and Population Discussion Paper; World Bank, Washington, DC. © World Bank. https://openknowledge.worldbank.org/handle/10986/32538 License: CC BY 3.0 IGO.

Institute to carry out academic research with these databases, under the condition that researchers share the research results with the Ministry.

1.2.3. Construction of the Analytic Databases

Using these data sources, we first used PILA to identify all formal sector employees with incomes greater than or equal to one MMW in any month of the 96-month study period (January 2011-December 2018). Next, at the individual level, we link each person with the individual's information in the BDUA database to merge health insurance enrollment status and socio-demographic characteristics. Then, using UPC data, we link each individual in the database with her health care utilization records for each service in each study month. Finally, we use RUAF data to identify each individual in our database who died during the study period, merging that individual with information about her death (death date, location, and cause(s)). Figure S2 shows the flow diagram for the construction of our database from primary sources (blue boxes) to the final databases with full information (red boxes). We used one final dataset to perform the analyses as described in Figure S2.

1.3. Treatment Assignment

The primary exposure or treatment that we study is the copayment level that each individual Contributory Regime enrollee faced in each study month. We assign this exposure/treatment using the precise earnings (in MMW units) reported by employers to PILA.

1.4. Outcomes

The primary outcome in our study is the probability of death (or mortality risk) over time. For example, if an individual worker dies in month 12 of our 96 month study, that individual is also coded as deceased in ever subsequent month as well. The maximum survival time observed is eight years (96 months).

Additionally, we also study other outcomes related to health service use that contribute to mortality: outpatient service use, chronic disease diagnoses and severity, and inpatient care use.

Outpatient Services:

1. Number of outpatient services per month.[vi]
2. Number of drugs purchased per month.
3. Number of medical consultations per month.
4. Number of laboratory procedures per month.
5. Number of diagnostic imaging procedures per month.

Chronic Disease Diagnosis and Severity:

[vi] Total number of outpatient services represents a sum of the other outpatient type of services (number of drugs purchased, number of medical consultations, number of laboratory procedures and number of diagnostic imaging procedures.

Using ICD-10 disease classification codes in the UPC database, we construct the Charlson comorbidity index that serves as a tool for measuring prevalence of diseases and their severity because it allows to predict long-term and hospital mortality (Charlson et al., 2022; Sundararajan et al., 2004) and to this index we add diagnoses of hypertension to create our measure. In constructing our Charlson index, once an individual is coded as diagnosed with a chronic disease, we assume that individuals have that disease in all subsequent periods. Supplement Table S1 (below) shows the specific ICD-10 codes that we classify as reflecting the presence of a major chronic disease.

Inpatient Care:

1. Number of Hospital Stays per Month
2. An indicator variable taking value 1 if an individual receives care in intensive care unit (ICU) during the month, and 0 otherwise.

1.5. Statistical Analysis

In our analyses, we first use a static regression discontinuity (RD) design. In doing so, we focus on outpatient care because outpatient services should respond contemporaneously to variation in out-of-pocket cost-sharing for outpatient services. Then, to study the accumulation of effects over time generated by variation in outpatient care, we also implement a dynamic RD model to study cost-sharing effects for other outcomes (outpatient care, inpatient care, Charlson comorbidity index, and mortality) over a period of 96 months. We describe both approaches below.

1.5.1. Static RD Estimation for Contemporaneous Outpatient Service Use

In this study we use a static RD framework to estimate the contemporaneous causal relationship between copayment tier and outpatient service use in a given month. Copayment tier (and corresponding copayment amount) is the ‘treatment’ of interest, and treatment assignment shifts discontinuously at the 5 MMW threshold in the underlying continuous monthly earnings distribution. Following Moscoe et al. (Moscoe et al., 2015) and the potential outcome framework, the average causal effect (ACE) in the sharp RD (SRD) design is defined as:

$$ACE_{SRD} = \lim_{w \uparrow c} E[Y_i(1)|w_i = w] - \lim_{w \downarrow c} E[Y_i(0)|w_i = w], \quad (1)$$

Where $Y_i(1)$ is an outcome of interest (outpatient service use and its components) for individual i when “exposed” (i.e., an individual has earnings just above the threshold); $Y_i(0)$ is the outcome for individual i when “unexposed” (i.e., an individual has earnings just below the threshold); and w_i is the continuous running variable (i.e., earnings in the previous month in units of the monthly minimum wages). In our study, the deterministic cost-sharing assignment rule generates a discontinuity in the probability of treatment among individuals with essentially identical earnings on either side of the 5 MMW threshold (identical in the limit as one approaches the threshold), meaning that treatment assignment is ‘as-good-as-random’ for individuals in the neighborhood of the threshold, enabling causal inference (Bor et al., 2014; Lee & Lemieux, 2010).

Specifically, for the threshold c of 5 MMW, we estimate (1) using a standard local linear regression (Fan & Gijbels, 1996; Hahn et al., 2001). In particular, the estimate of ACE_{SRD} is given by:

$$\widehat{ACE}_{SRD} = \widehat{a_r} - \widehat{a}_l, \tag{2}$$

where

$$(\hat{a}_r, \hat{b}_r) = ArgMin\ \sum_{t=1}^{96} \sum_{i=1}^{n} 1[w_{i,t-1} \geq c] \left(y_{it} - a_r - b_r(w_{i,t-1} - c) \right)^2 K\left(\frac{(w_{i,t-1}) - c}{h} \right) \tag{3}$$

$$(\hat{a}_l, \hat{b}_l) = ArgMin\ \sum_{t=1}^{96} \sum_{i=1}^{n} 1[w_{i,t-1} < c] \left(y_{it} - a_l - b_l(w_{i,t-1} - c) \right)^2 K\left(\frac{(w_{i,t-1}) - c}{h} \right) \tag{4}$$

In these expressions, y_{it} is an outcome (outpatient services as well as each component of outpatient care described in Section 1.4) for individual i in month t; w and c are the continuous running variable (previous month earnings in minimum wage units) and the cost-sharing threshold, respectively; h is the robust bias-corrected 'optimal' sample bandwidth; and K(.) is the triangular kernel density function; and $(\hat{a}_r, \hat{b}_r)$ and $(\hat{a}_l, \hat{b}_l)$ represent the weighted least squares coefficients (Calonico et al., 2014, 2020). This estimation procedure restricts the sample to a distance h from either side of a threshold: $c - h \leq w_{i,t-1} \leq \text{c} + h$. Standard errors are adjusted for heteroskedasticity and are clustered at the individual level.

1.5.1.1. Elasticities

To facilitate the interpretation of the magnitude of our estimates, we also compute price as follows:

$$\varepsilon_{Y,c} = \frac{\dfrac{\lim_{w\uparrow c} E[Y] - \lim_{w\downarrow c} E[Y]}{\left(\lim_{w\uparrow c} E[Y] + \lim_{w\downarrow c} E[Y]\right)/2}}{\dfrac{CT_{r,c} - CT_{l,c}}{\left(CT_{r,c} + CT_{l,c}\right)/2}} \tag{5}$$

where $\varepsilon_{Y,c}$ is the arc elasticity of an outcome Y at threshold c (5 MMW); $\lim_{w\uparrow c} E[Y]$ is the limit of the expected value of Y as earnings w approaches the threshold from above (in the earnings distribution); $\lim_{w\downarrow c} E[Y]$ is the limit of the expected value of Y as earnings approaches the threshold from below (in the earnings distribution); $CT_{r,c}$is the copayment value (in daily minimum wages) above the threshold (CT3); and $CT_{l,c}$is the copayment value (in daily minimum wages) below the threshold (CT2).

1.5.2. Dynamic RD Estimation for Outpatient Care, the Charlson Comorbidity Index, Inpatient Care, and Mortality Risk

Assignment to copayment tier can change month to month over our 8-year study period. Given that the assignment of higher or lower outpatient cost-sharing to individuals varies month-to-month in ways that can also potentially be interdependent, we also extend our static RD approach above to the dynamic regression discontinuity framework of Cellini et al. (2010) to estimate dynamic effects of outpatient cost-sharing over time for our study outcomes (Cellini et al., 2010; Enami et al., 2023; Hsu & Shen, 2022). Within this dynamic RD framework, Cellini et al. represent $y_{i,t}$ as:

$$y_{i,t} = \sum_{\tau=0}^{\tau_{max}} b_{i,t-\tau}\, \theta_{\boldsymbol{\tau}}^{\boldsymbol{TOT}} + u_{i,t} \tag{6}$$

where $y_{i,t}$ is an outcome for individual i at time t; $b_{i,t-\tau} = 1\left[w_{i,t-\tau-1} \geq c\right]$ is a dichotomous indicator variable for an individual falling above the cost-sharing threshold, and thus facing the higher co-payment at period $t-\tau$, which is determined by earnings in period $t-\tau-1$; and θ_{τ}^{TOT} is a treatment-on-treated (TOT) parameter for each lag τ, capturing the effect of switching $b_{i,t-\tau}$ from 0 to 1, holding cost-sharing in all subsequent months ($b_{i,t-\tau+1}, \ldots b_{i,t}$) constant. However, it is not generally possible to estimate Equation (6) directly.

Instead, Cellini et al. (2010)'s approach first defines Intention-to-Treat (ITT) parameters for each lag (τ) as the effect of treatment in month ($t-\tau$) on an outcome in month (t) (in our case, the effect of falling above the cost-sharing threshold in each lagged month ($t-\tau$) on outcomes in month (t), for lags 1 through 95). These ITT parameters (θ_{τ}^{ITT}) include both the direct effect of falling above the cost-sharing in month ($t-\tau$) as well as the indirect effects of falling above the cost-sharing threshold in month ($t-\tau$) on the probability, and effect of, falling above the cost-sharing threshold in all subsequent months until month (t).[vii] We use standard regression discontinuity techniques (local linear regression) to estimate ITT parameters separately for each lag (τ), following Equations (2), (3), and (4) but replacing $w_{i,t-1}$ with $w_{i,(t-1)-\tau}$ in separate regressions for each lag τ.

To capture the temporal interdependence among the cost-sharing levels across lags, we also follow Cellini et al. (2010) in estimating the parameters π_{τ} defined as the probability that $b_{i,t} = 1$ if $b_{i,t-\tau}$ is changed from 0 to 1 – or in other words, the effect of being above the threshold at time $t-\tau$ on the probability of being above the threshold τ months later. To estimate these π_{τ} parameters, we use exactly the same approach as we do to estimate the θ_{τ}^{ITT} parameters, but we replace y_{it} with b_{it}.

As Cellini et al. (2010) show, with estimates of all of the $\theta_{\boldsymbol{\tau}}^{\boldsymbol{ITT}}$ and π_{τ} parameters, we can then recover the corresponding $\theta_{\boldsymbol{\tau}}^{\boldsymbol{TOT}}$ parameters by solving the following recursive relationship:

$$\theta_0^{TOT} = \theta_0^{ITT},$$
$$\theta_1^{TOT} = \theta_1^{ITT} - \pi_1\theta_0^{TOT},$$
$$\theta_2^{TOT} = \theta_2^{ITT} - \pi_1\theta_1^{TOT} - \pi_2\theta_0^{TOT},$$

and in general,

$$\theta_{\tau}^{TOT} = \theta_{\tau}^{ITT} - \sum_{h=1}^{\tau} \pi_h \theta_{\tau-h}^{TOT}. \tag{7}$$

[vii] For example, if an individual faces a higher copayment at time $t-\tau$, the individual may also be more likely to face a higher copayment at lags $t-\tau+1, t-\tau+2, \ldots, t$.

To obtain standard errors and 95% confidence intervals for each θ_{τ}^{TOT} parameter, we generate the empirical distributions of the θ_{τ}^{ITT} and π_{τ} parameters for each lag τ by block bootstrap (Efron, 1979) (using 500 iterations) with clustering at the individual level and then recover the corresponding standard errors and confidence intervals for the θ_{τ}^{TOT} parameters.[viii]

Finally, we also compute the sum of the TOT parameters ($\theta_0^{TOT} + \theta_1^{TOT} + \ldots + \theta_{\tau}^{TOT}$), yielding the effect of being above the cost-sharing threshold for (τ) consecutive months, and we generate standard errors using a block bootstrap procedure (Efron, 1979) with 500 iterations and clustering at the individual level.

For mortality risk, we code the dependent variable $y_{i,t}$ as 1 if individual *i* died in period *t* or before, and 0 otherwise. Equation (6) assumes that $y_{i,t}$ can increase/decrease at any period *t* independently of its previous values, but this is not possible for mortality because it is an absorbing state. Hence, we are unable to estimate the $\theta_{\boldsymbol{\tau}}^{\boldsymbol{TOT}}$ parameters for mortality and focus on the $\theta_{\boldsymbol{\tau}}^{\boldsymbol{ITT}}$ parameters for cumulative mortality risk.

Finally, we also investigate the robustness of our dynamic RD estimates for mortality assessing sensitivity to (i.) controlling for individual characteristics (age, sex, region of residence, and insurer type), (ii.) restricting our sample to those at retirement-ineligible ages (ages 18-62 for men and ages 18-57 for women) in every month in our study period, and (iii.) using the same bandwidth (1 MMW) for all lags. These robustness analyses are shown in Figure 7 Panel A. Additionally, Panel B also shows that our results are robust to using restricted subsamples of workers continuously in the workforce for 24, 48, and 72 consecutive months (shown with purple, yellow, and gray dots, respectively).

1.5.3. Duration Analysis of Mortality

Following the approach of Bor et al. (2014), (Bor et al., 2014), we also use a complementary duration model to study the relationship between outpatient cost-sharing and mortality risk. The Bor et al.(2014), (Bor et al., 2014) approach uses a semiparametric regression model to specify the mortality hazard (i.e., the instantaneous probability of death at time t, conditional on survival up to time t) as a function of the 'running variable' (in our case, earnings in the previous month) and time. We use a parametric model (instead of the semi-parametric Cox model) because we find that the proportional hazards assumption does not hold in our case, and we selected a Weibull distribution among other possible parametric distributions using Akaike and Bayesian information criteria. Specifically, we estimate the causal hazard ratio (CHR), following Bor et al. (2014), (Bor et al., 2014) as:

$$CHR = \frac{h\left(b_{i,t} = 1, X_i, w_{i,t-1} \uparrow c\right)}{h\left(b_{i,t} = 0, X_i, w_{i,t-1} \downarrow c\right)}, \tag{8}$$

[viii] Original implementation of the dynamic RD described by Cellini et al. (2010) (Cellini et al., 2010) calculated standard errors by stacking the regression estimators to obtain standard errors, however, our main analysis uses (2), (3), and (4), making stacking impossible.

where:

$$h_{i,t}(t; b_{i,t}, X_i, w_{i,t-1}) = h_0(t) g(w_{i,t-1}^q, X_i, b_{i,t}) \tag{9}$$

$h_i(.)$ is the 8-year mortality hazard for individual i; $w_{i,t-1}$is individual i's earnings in the previous month t; $b_{it}$is an indicator variable taking value 1 if $w_{i,t-1}$ is equal to or greater than the threshold c (5 MMWs) and 0 otherwise; X_i is a vector of time-invariant individual characteristics (age in 2011, sex, enrollment in a public (vs. private) insurer, and geographic region of residence – there are 5 in Colombia). We also include quadratic polynomials of earnings in the previous month. The parameter accompanying $b_{i,t}$ captures the effect of higher (vs. lower) outpatient cost-sharing on the 8-year mortality hazard. We restrict the sample to individuals within a bandwidth h (0.5 MMW) in the earnings distribution ($w_{i,t-1} - h \leq w_{i,t-1} \leq w_{i,t-1} + h$). We also use restricted samples according to the minimum number of months that workers had a salary within a given bandwidth h (at least 1, 6, 12 and 18 months). Following Austin (2010) (Austin, 2010), we estimate the absolute difference in 8-year mortality risk for both copayment thresholds using a Weibull survival model.

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Figure S1. Outpatient Service Copayment Requirements for Formal-Sector Employees in Colombia.

Contributory Regime enrollees face a step-function copayment for outpatient services that varies with earnings (measured in Monthly Minimum Wages (MMWs)). There are two copayment tiers of interest for this research; CT1: 46.1% of a daily minimum wage, which roughly corresponds to COP $ 13,500 (USD $ 3.65) in 2020; and CT2: 121.5% of a daily minimum wage, which roughly corresponds to COP $ 35,600 (USD $ 9.62) in 2020.

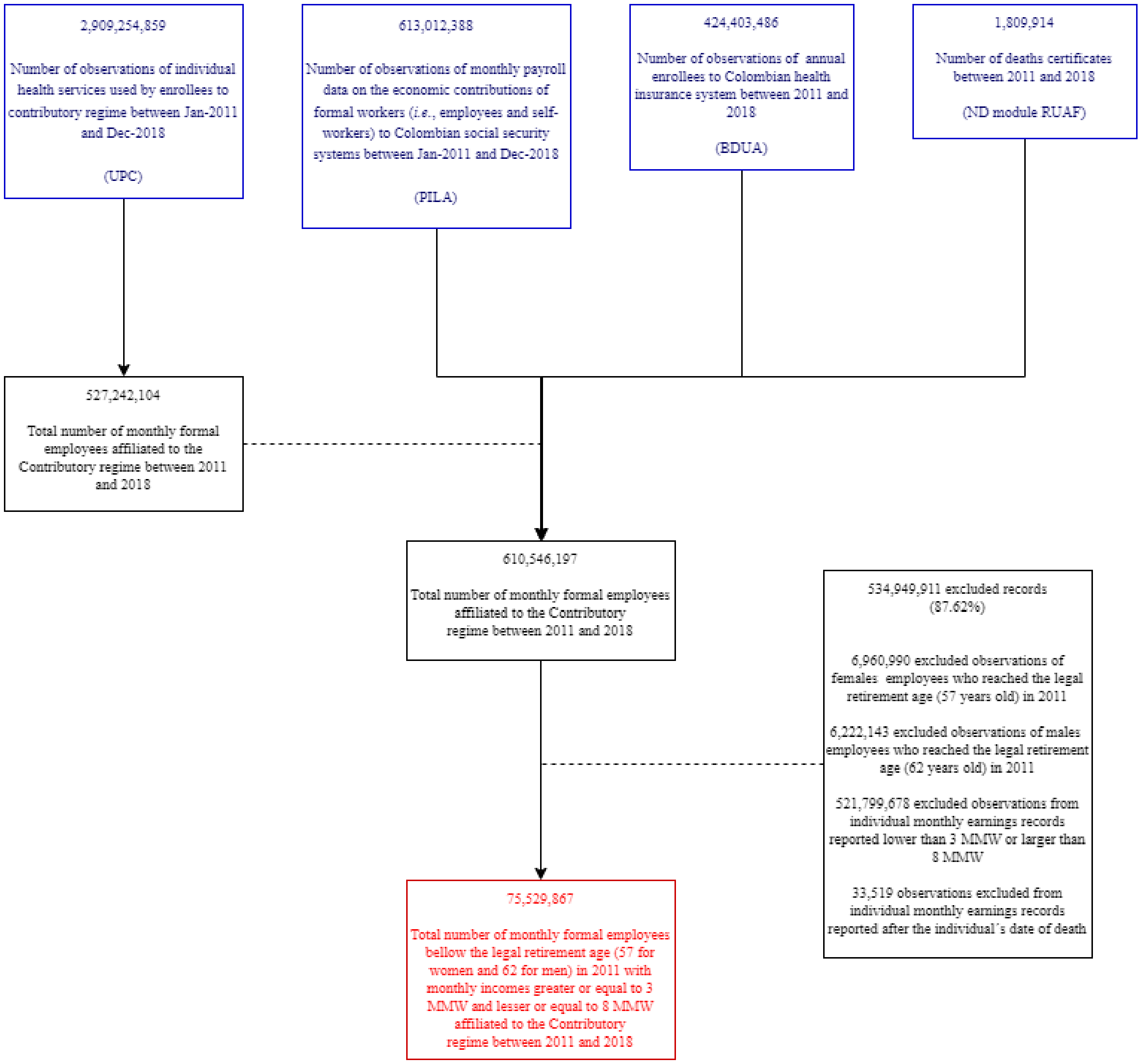

Figure S2. Sample Construction Flow Diagram

Construction of our sample from primary sources (shown in blue boxes) to final linked database (shown in red boxes). We used one final linked database in long format for all analyses.

Appendix 2
Supporting Information for

"Cost-Sharing in Medical Care Can Increase Adult Mortality: Evidence from Colombia"

Giancarlo Buitrago, Javier Amaya, Grant Miller,* and Marcos Vera-Hernández

Supplementary Text

2.1. Descriptive Statistics

Table 1 in the paper shows summary statistics of Contributory Regime enrollees in our sample, both overall and by copayment tier.

Among 2,785,679 individuals meeting the inclusion criteria (i.e., all employees enrolled in the Contributory Regime for at least one month between January 2011 and December 2018, excluding those who reached the legal retirement age (57 for women and 62 for men) by 2011), there were 2,140,081 individuals with a mean monthly minimum wage (MMWs) [i] between 3 and 5, and 645,598 individuals with a mean MMW above 5 MMWs. Table 1 shows summary statistics for our sample, both overall and by copayment tier.

Because individuals in our sample can move across the cost-sharing threshold month-to-month, we illustrate the extent of movement across the threshold over time among individuals within 4-6 MMWs in the earnings distribution. Specifically, Figure S3 shows the cumulative share of individuals who: (i.) never cross the threshold, (ii.) who cross the threshold from above, and (iii.) who cross the threshold from below, for each month over our entire 8-year study period. In general, there is substantial movement across the threshold. For example, among individuals in our sample at the beginning of the study period, 50% of these individuals had already crossed the threshold in both directions by January 2012. By the end of the study period, about 55% of individuals had crossed the threshold in both directions at least once, and about 20% had not crossed the threshold in either direction. These results are consistent with our estimates of the effect of being above the cost-sharing threshold in a given month on the probability of being above the cost-sharing threshold in future months, as shown in Figure S4.

2.2. Evaluation of RDD Assumptions

2.2.1. McCrary Density Test for Sorting Around the Thresholds

[i] Monthly minimum wages (MMWs) are workers' earnings divided by Colombia's official minimum wage (a worker earning the minimum wage therefore earns 1 MMW). For formal sector workers, the Colombian health care system requires different copayments for workers earning less than 2 MMWs, 2-5 (exclusive) MMWs, and 5+ MMWs. Because there are other public subsidy programs in Colombia (a transportation program and a housing program) that use the 2 MMW threshold for benefit assignment, we focus on the 5 MMW threshold.

Our static RD estimation (and the dynamic RD estimation frameworks which build on them – described in detail in Section 1) assume no manipulation of the 'running variable' (in our case, that individuals do not manipulate reported earnings in the PILA system to face lower outpatient cost-sharing requirements). Such manipulation would be evident as a mass-point of individuals just below the 5 MMW threshold in the distribution of $w_{i,m}$. To investigate this possibility, Figure S7 shows the histogram of observations across the earnings distribution. In general, there are numerous mass points at focal nominal earnings amounts (for example, CO$ 2,000,000; CO$ 2,500,000; CO$ 3,000,000, …, etc.) in different years. Among the 12 mass points, two are close to the 5MMW threshold – one corresponding CO$ 3,000,000 in 2014 and at CO$ 3,000,000 in 2013. Given this, it is perhaps unsurprising that the McCrary density test (McCrary, 2008) formally rejects the null hypotheses of distribution continuity at the 5 MMW threshold, but it seems unlikely to be due to actual manipulation of earnings in the PILA system given the clear pattern of multiple mass points at round focal levels of earnings – as well as the fact that the mass point closest to the threshold is to its right (above the threshold) rather than to its left (if there were manipulations, individuals would presumably prefer to fall below rather than above the threshold, all else equal).

2.2.2 Tests for Covariate Continuity/Balance

Because our individual characteristics are time invariant, we randomly selected one observation per individual and use our static RD model (estimated with local lineal regression) to test for imbalance in the distribution of the time-invariant individual characteristics across the outpatient cost-sharing threshold. Specifically, Figure S5 shows RD estimates for all available covariates: age, sex, region of residence, and insurer type (which can only change annually at the time of "open enrollment"). Figure S6 summarizes p-values from these RD analyses, showing balance in all covariates other than an indicator for individuals residing in the Bogotá region. This finding appears due to the fact that individuals in Bogotá are relatively more likely to have focal earnings levels (see Figure S8 showing the proportion of individuals in Bogotá at different points in the monthly earnings distribution).

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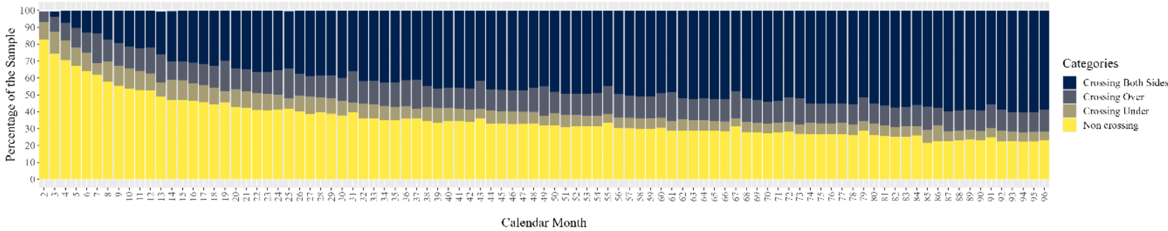
McCrary, J. (2008). Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of Econometrics*, *142*(2), 698–714. https://doi.org/10.1016/j.jeconom.2007.05.005

A. Cumulative Treatment Assignment Changes



B. Subjects With no Information About Salary in each calendar month

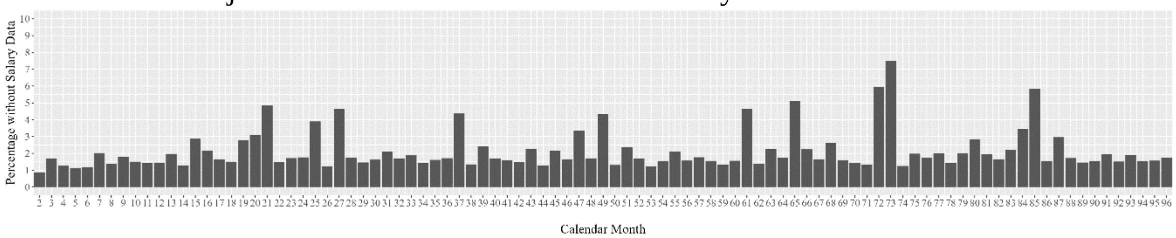


Figure S3. Changes in Treatment Assignment Over Time
Panel A. Cumulative changes in treatment assignment by month among individuals with earnings between 4 and 6 monthly minimum wages (MMWs) in four categories: (i) individuals who have not crossed the cost-sharing threshold (yellow); ii) individuals who have crossed the cost-sharing threshold at least once from below (dark yellow); iii) individuals who have crossed the cost-sharing threshold at least once from above (light blue); and iv) individuals who have crossed the cost-sharing threshold at least once in both directions (dark blue). Panel B. The share of individuals with no earnings information by month.

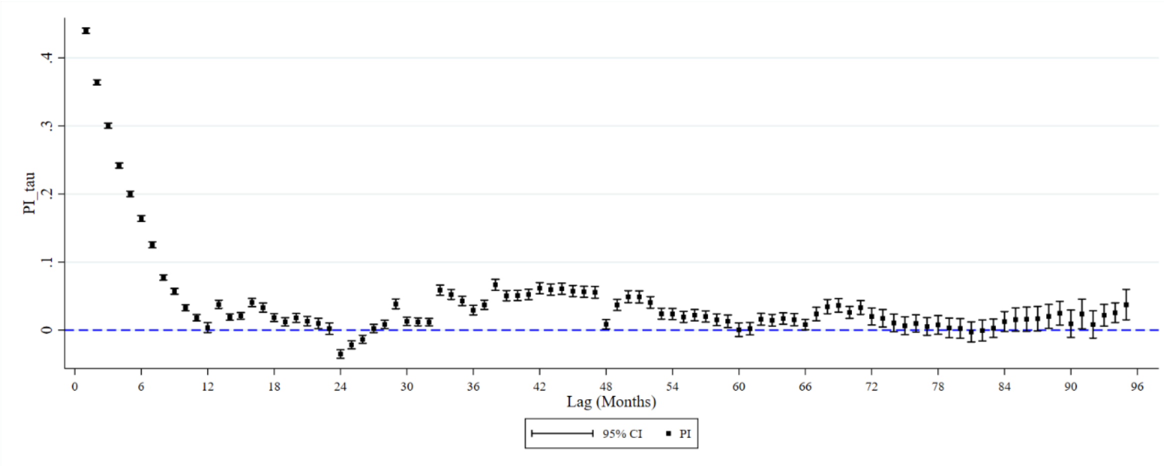


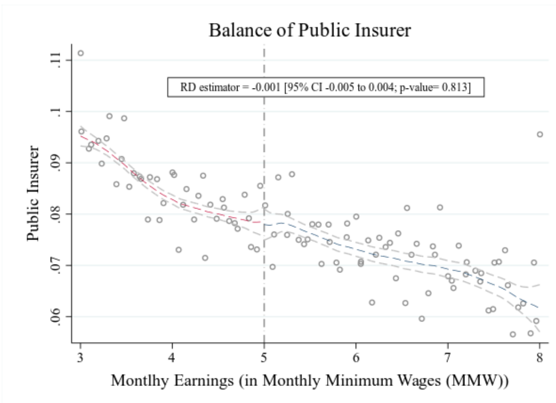
Figure S4. Estimates of the Effect of Being above the Cost-Sharing Threshold in a Given Month on the Probability of Being above the Cost-Sharing Threshold in Subsequent Months

The figure shows estimates of (π_τ), or the effect of being above the cost-sharing threshold at time t on the probability of being above the threshold at time $t+\tau$ (estimated using local linear regression). These values are used in the recursive relationship shown in Appendix 1 Equation 7 to recover the θ_{τ}^{TOT} parameters (following Cellini et al. (Cellini et al., 2010)).

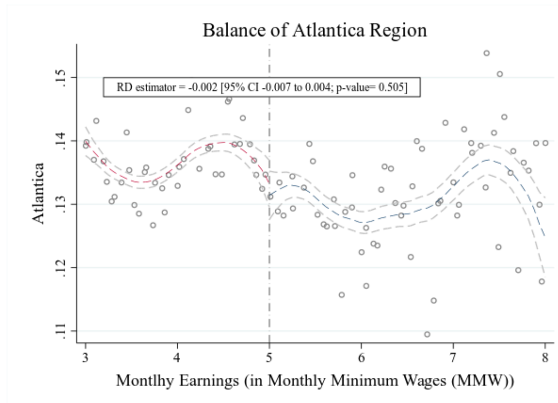
Panel A.

Panel B.

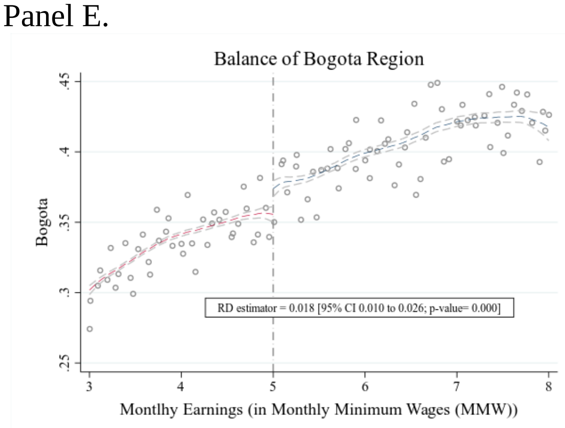
Panel C.



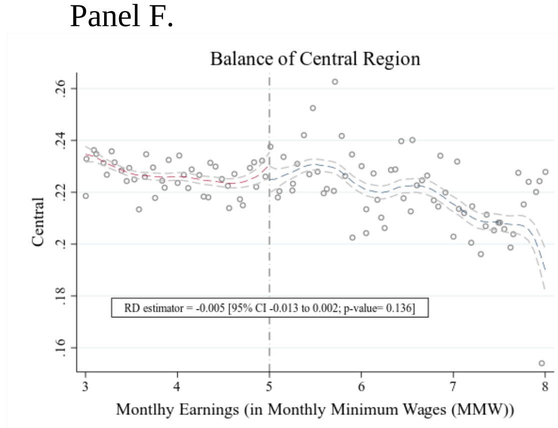
Panel D.



Panel E.

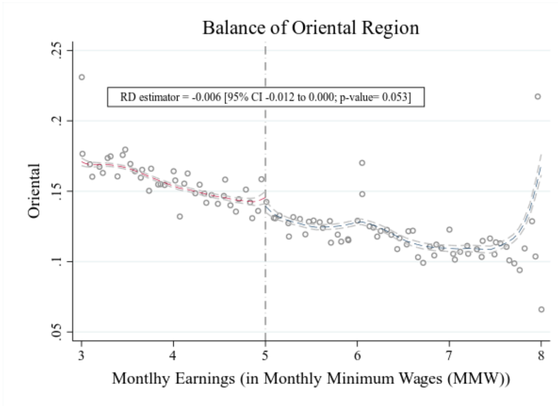


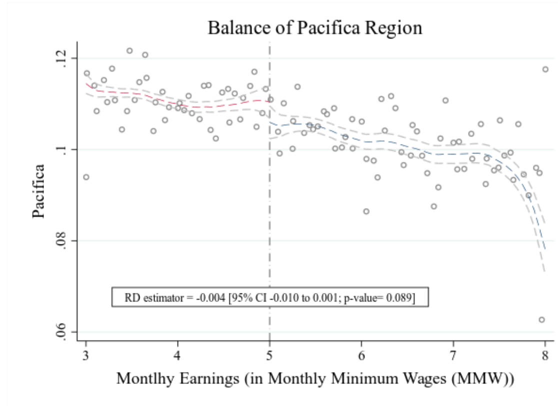
Panel F.



Panel G.

Panel H.





Panel I.

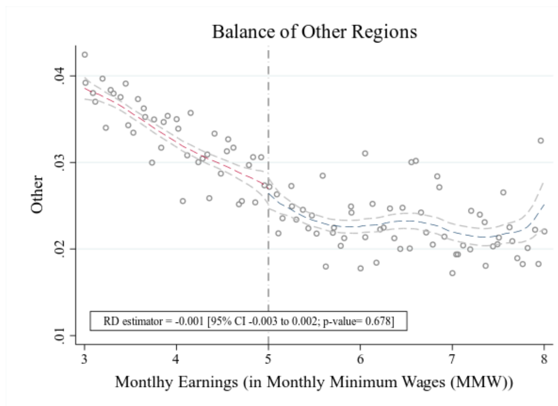


Figure S5. Balance in Individual Characteristics Across the Cost-Sharing Threshold. Individual characteristics by earnings (in units of monthly minimum wages (MMWs)) among formal sector workers in Colombia between 2011 and 2018, with local linear smoothing on each side of the 5 MMW threshold. Static regression discontinuity (RD) estimates obtained by local linear regression using SI Appendix 1 Equation (2) with robust bias-corrected 'optimal' sample bandwidths; standard errors adjusted for heteroskedasticity and clustered at the individual level (Calonico et al., 2020; Fan & Gijbels, 1996; Hahn et al., 2001).

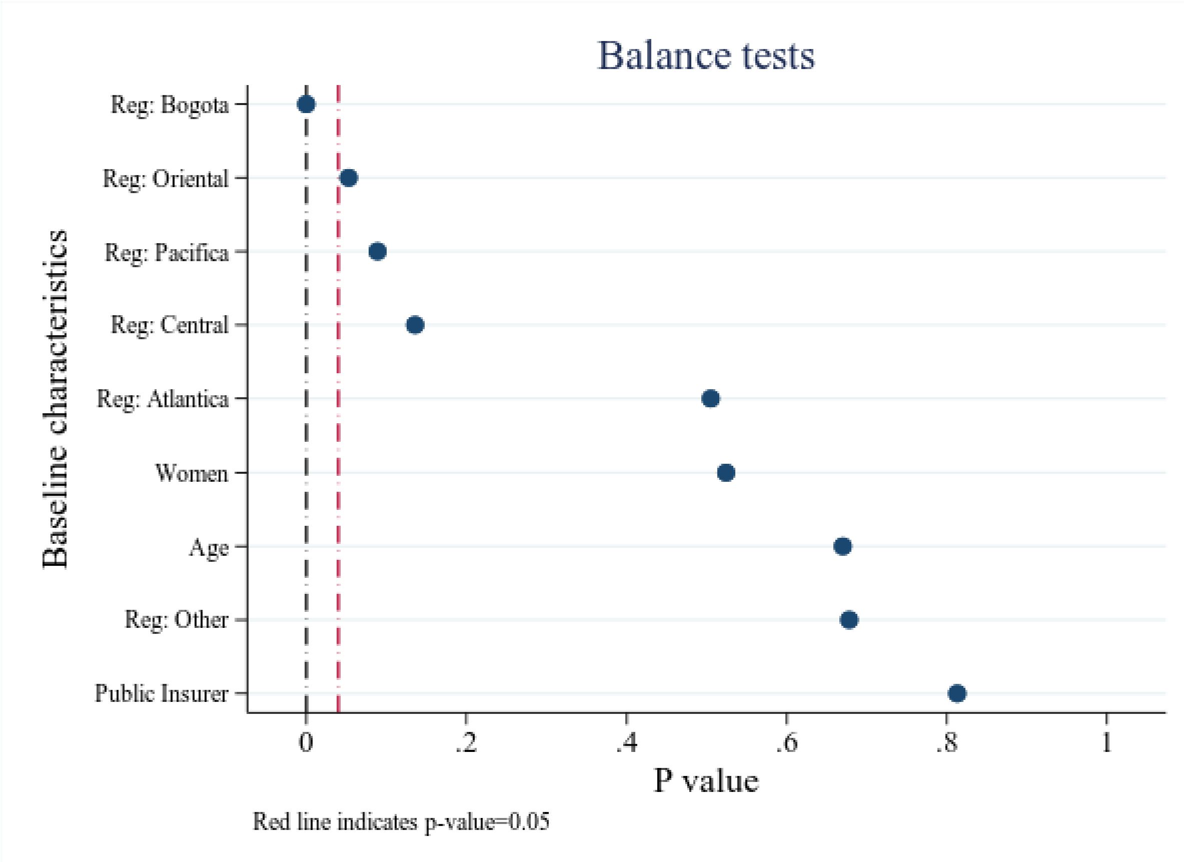
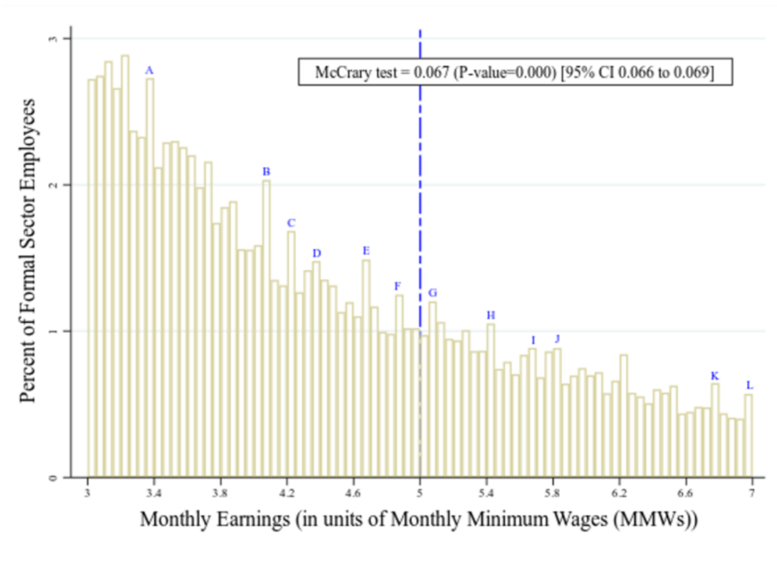


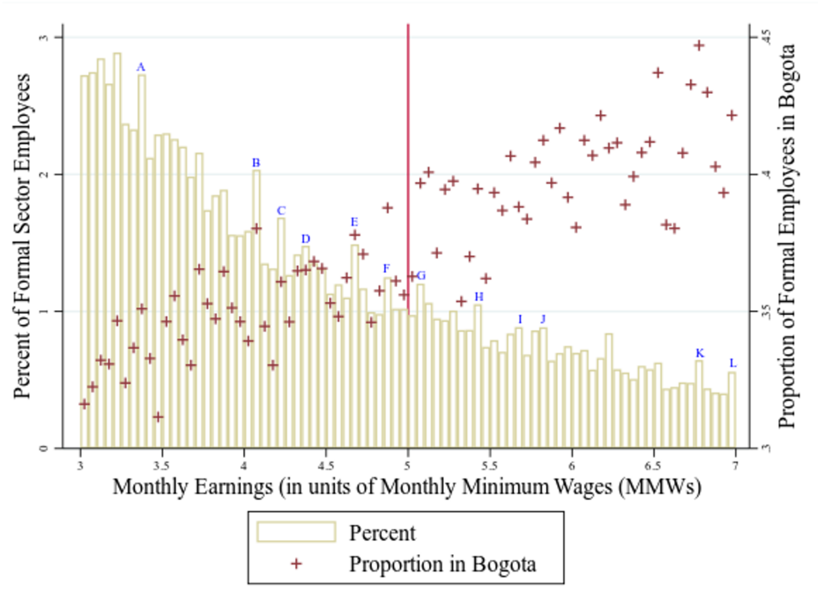
Figure S6. Covariate Balance Test p-values.

P-values from tests of continuity of baseline covariates at the 5 Monthly Minimum Wage (MMW) threshold among formal sector workers in Colombia between 2011 and 2018, with local linear smoothing on each side of the 5 MMW threshold. Static regression discontinuity (RD) estimates obtained by local linear regression using SI Appendix 1 Equation (2) with robust bias-corrected 'optimal' sample bandwidths; standard errors adjusted for heteroskedasticity and clustered at the individual level (Calonico et al., 2020; Fan & Gijbels, 1996; Hahn et al., 2001).



Marker	Earnings /MMW	Year	Earnings (COP in Millions)
A	3.39	2013	2
B	4.06	2017	3
C	4.24	2013	2.5
D	4.35	2016	3
E	4.65	2015	3
F	4.87	2014	3
G	5.08	2013	3
H	5.43	2015	3.5
I	5.76	2018	4.5
J	5.81	2016	4
K	6.78	2013	4
L	6.98	2015	4.5

Figure S7. McCrary (2008) Density Test for Running Variable Manipulation.
Density of observations across the distribution of monthly earnings (in units of monthly minimum wages (MMWs)), with a McCrary (2008) density test for continuity at the outpatient cost-sharing threshold at 5 MMWs.



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A	3.39	2013	2
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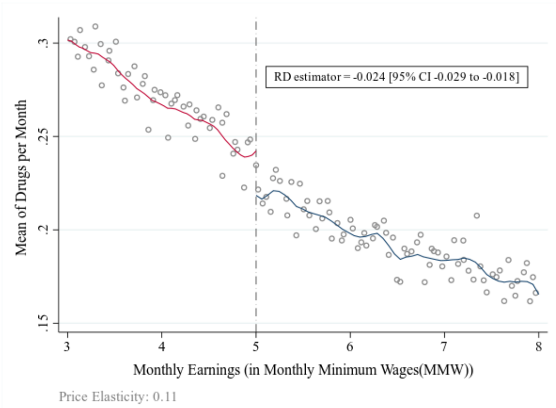
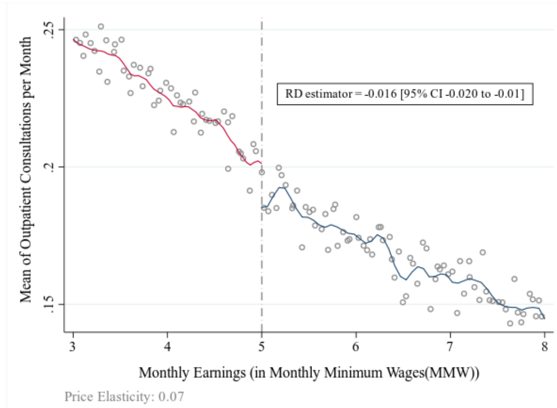
F	4.87	2014	3
G	5.08	2013	3
H	5.43	2015	3.5
I	5.76	2018	4.5
J	5.81	2016	4
K	6.78	2013	4
L	6.98	2015	4.5

Figure S8. Distribution of Monthly Earnings Overlaid with the Proportion of Formal Sector Workers in Bogotá.
Density of observations by monthly earnings (in units of monthly minimum wages (MMWs)) and the proportion of individuals in Bogotá at each earnings amount.

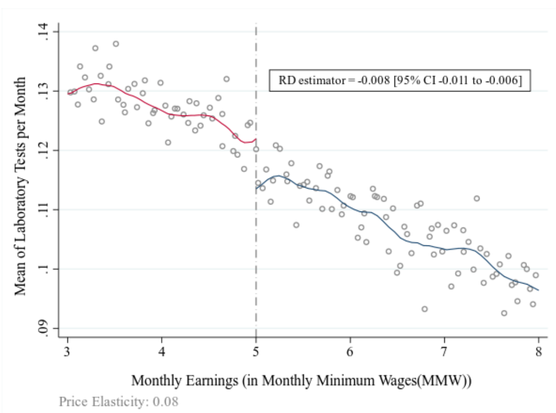
Panel A.



Panel B.



Panel C.



Panel D.

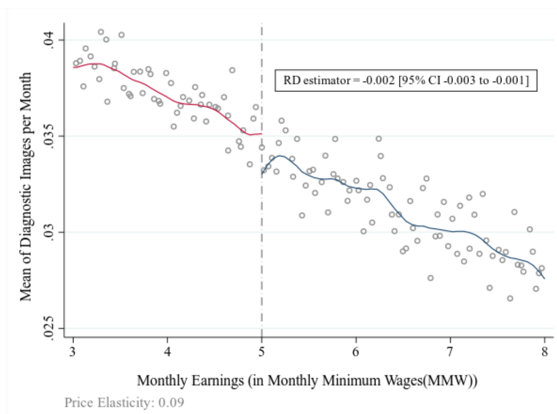
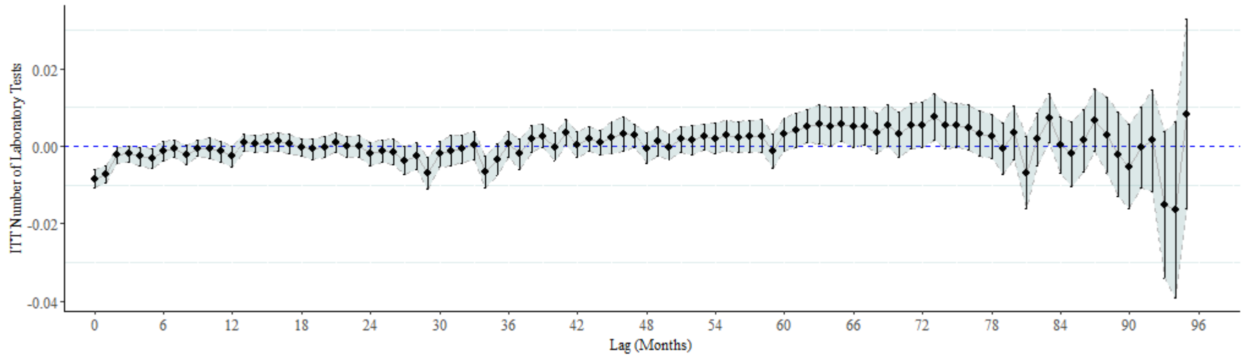
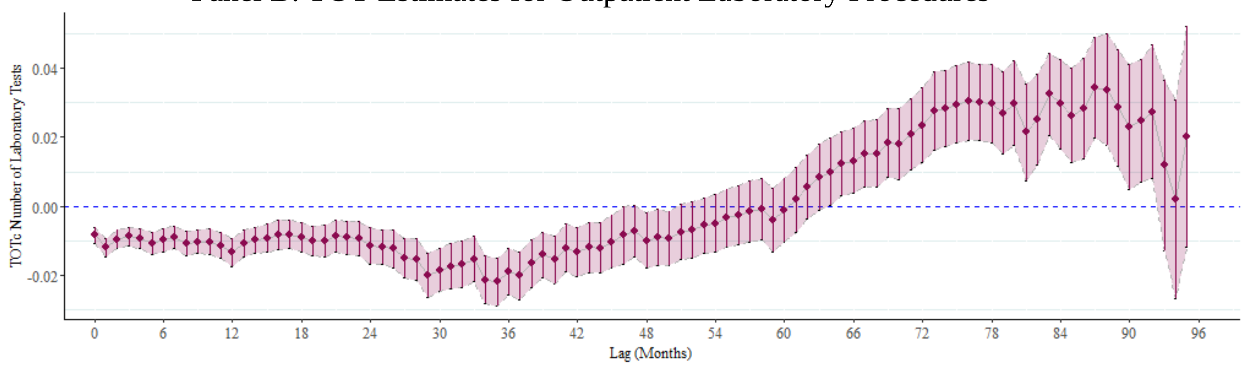


Figure S9. The Contemporaneous Effect of Higher Outpatient Cost-Sharing on Outpatient Service Use by Type. Outpatient service use per month by earnings (in units of monthly minimum wages (MMWs)) and type among formal sector workers in Colombia between 2011 and 2018, with local linear smoothing on each side of the 5 MMW threshold. (A) Drugs. (B) Consultations. (C) Laboratory Tests. (D) Diagnostic Images. Static regression discontinuity estimates by local linear regression with robust bias-corrected ‘optimal’ sample bandwidths and standard errors adjusted for heteroskedasticity and clustered at the individual level.

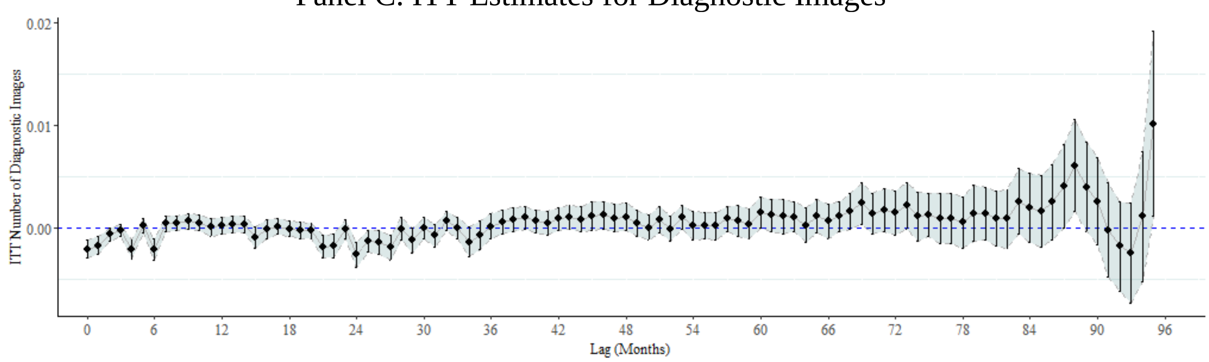
Panel A. ITT Estimates for Outpatient Laboratory Procedures



Panel B. TOT Estimates for Outpatient Laboratory Procedures



Panel C. ITT Estimates for Diagnostic Images



Panel D. TOT Estimates for Diagnostic Images

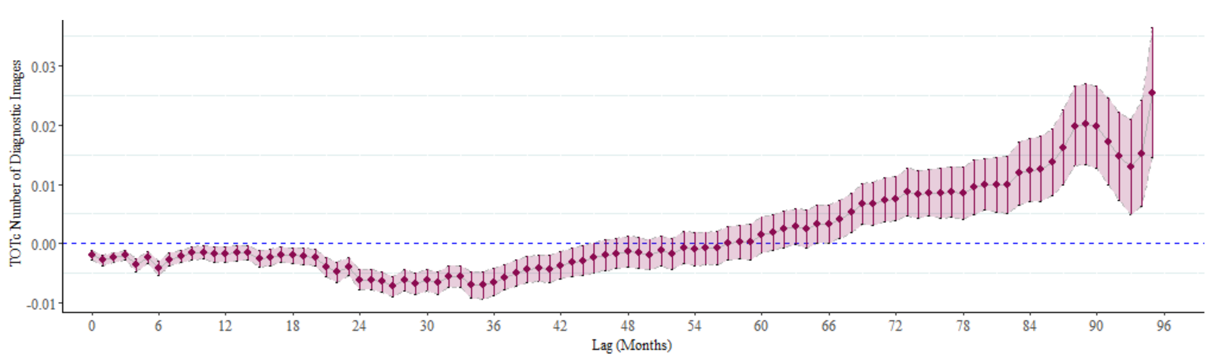
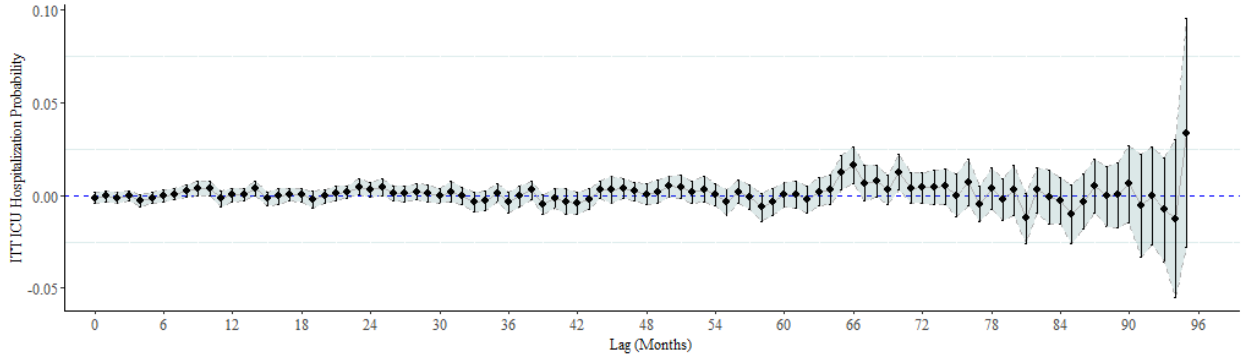


Figure S10. The Dynamic Effect of Higher Outpatient Cost-Sharing on Outpatient Laboratory Procedures and Diagnostic Images. Intention-to-treat (ITT) (Panel A and C) and cumulative **treatment-on-treated (TOT)** (Panel B and D) dynamic regression discontinuity (RD) estimates obtained by local linear regression using the methods described in Section 5.2 of the Appendix 1) with robust bias-corrected 'optimal' sample bandwidths; standard errors adjusted for heteroskedasticity and clustered at the individual-level (Cellini et al., 2010; Enami et al., 2023; Fan & Gijbels, 1996; Hahn et al., 2001; Hsu & Shen, 2022).

Panel A. ITT Estimates for the Probability of Intensive Care Use



Panel B. TOT Estimates for the Probability of Intensive Care Use

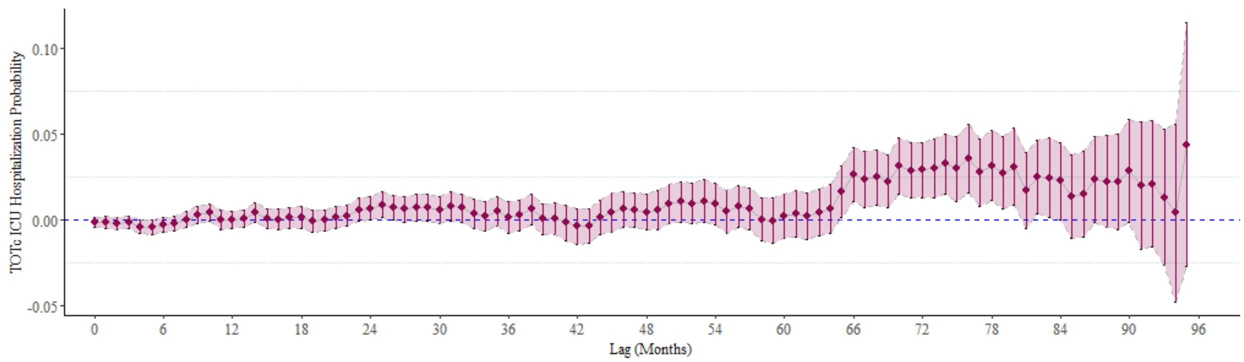


Figure S11. The Dynamic Effect of Higher Outpatient Cost-Sharing on the Probability of Intensive Care Use. Intention-to-treat (ITT) (Panel A) and cumulative **treatment-on-treated (TOT)** (Panel B) dynamic regression discontinuity (RD) estimates obtained by local linear regression using the methods described in Section 5.2 of the Appendix 1 with robust bias-corrected 'optimal' sample bandwidths; standard errors adjusted for heteroskedasticity and clustered at the individual-level (Cellini et al., 2010; Enami et al., 2023; Fan & Gijbels, 1996; Hahn et al., 2001; Hsu & Shen, 2022)

Disease	ICD-10 Codes
Acute myocardial infarction	I21, I22, I252
Congestive heart failure	I50
Peripheral vascular disease	I71, I790, I739, R02, Z958, Z959
Cerebral vascular accident	I60, I61, I62, I63, I65, I66, G450, G451, G452, G458, G459, G46, I64, G454, I670, I671, I672, I674, I675, I676, I677, I678, I679, I681, I682, I688, I69
Dementia	F00, F01, F02, F051
Pulmonary disease	J40, J41, J42, J44, J43, J45, J46, J47, J67, J44, J60, J61, J62, J63, J66, J64, J65
Connective tissue disorder	M32, M34, M332, M053, M058, M059, M060, M063, M069, M050, M052, M051, M353
Peptic ulcer	K25, K26, K27, K28
Liver disease	K702, K703, K73, K717, K740, K742, K746, K743, K744, K745
Diabetes	E109, E119, E139, E149, E101, E111, E131, E141, E105, E115, E135, E145
Diabetes complications	E102, E112, E132, E142 E103, E113, E133, E143 E104, E114, E134, E144
Paraplegia	G81, G041, G820, G821, G822
Renal disease	N03, N052, N053, N054, N055, N056, N072, N073, N074, N01, N18, N19, N25
Cancer	C0, C1, C2, C3, C40, C41, C43, C45, C46, C47, C48, C49, C5, C6, C70, C71, C72, C73, C74, C75, C76, C80, C81, C82, C83, C84, C85, C883, C887, C889, C900, C901, C91, C92, C93, C940, C941, C942, C943, C9451, C947, C95, C96
Metastatic cancer	C77, C78, C79, C80
Severe liver disease	K729, K766, K767, K721
Human Immunodeficiency Virus	B20, B21, B22, B23, B24
Arterial hypertension	I10, I11, I12, I13, I14, I15

Table S1. ICD-10 Codes Used to Identify Chronic Disease Diagnosis in *Base del Estudio de Suficiencia de la Unidad Por Capitación* (the UPC Database). Arterial hypertension codes are not included in the Charlson comorbidities index. However, we include them due to the high prevalence of patients with hypertension. ICD-10: International Classification of Diseases, 10th Revision.

Model	AIC	BIC
Weibull	498621.8	498806.9
Log-logistic	498650.2	498835.3
Lognormal	500507.9	500693
Exponential	503434.1	503604.9

Table S2. Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) for Candidate Parametric Survival Models.
Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) for Weibull, log-logistic, log-normal, and exponential models using a sample of subjects with monthly earnings between 4.5 MMW and 5.5 MMW for at least 12 months.

Outpatient Services Use	(1) Total Outpatient	(2) Drugs	(3) Consultations	(4) Diagnostic Images	(5) Laboratory Tests
Outpatient Cost-sharing effect	-0.0463***	-0.0237***	-0.0160***	-0.00202***	-0.00839***
	(0.00582)	(0.00286)	(0.00193)	(0.000421)	(0.00129)
Observations	4,984,140	6,328,294	10,565,972	4,593,323	9,552,324
Optimal Bandwidth	0.17	0.22	0.35	0.15	0.33
Mean below threshold	0.60	0.24	0.04	0.20	0.12
Mean above threshold	0.56	0.22	0.03	0.19	0.11
Elasticity	-0.09	-0.11	-0.07	-0.09	-0.08

*** p<0.01, ** p<0.05, * p<0.1

Table S3. The Effect of Cost-Sharing on Outpatient Service Use, Total and by Type (at the 5 Monthly Minimum Wage (MMW) Threshold).
Local linear regression (LLR) estimates using Equation (2). We use all individuals enrolled in Contributory Regime for at least one month between January 2011 and December 2018, excluding individuals who reached the legal retirement age (57 for women and 62 for men) by 2011, robust bias-corrected 'optimal' sample bandwidths, standard errors adjusted for heteroskedasticity clustered at the individual level.

Month lag	ITT Estimate	95% Confidence Interval		Subsample size
		Low	High	
0	-0.046***	-0.058	-0.035	4,984,140
1	-0.053***	-0.065	-0.041	4,708,576
2	-0.042***	-0.054	-0.030	4,649,685
3	-0.049***	-0.061	-0.037	4,851,558
4	-0.045***	-0.056	-0.033	4,825,584
5	-0.043***	-0.056	-0.031	4,197,249
6	-0.045***	-0.057	-0.032	4,077,017
7	-0.046***	-0.059	-0.033	4,164,459
8	-0.045***	-0.057	-0.033	4,870,738
9	-0.042***	-0.053	-0.030	5,346,714
10	-0.049***	-0.062	-0.037	4,551,745
11	-0.046***	-0.058	-0.033	4,599,376
12	-0.045***	-0.058	-0.032	4,189,717
13	-0.041***	-0.053	-0.028	4,768,507
14	-0.039***	-0.051	-0.026	4,592,197
15	-0.039***	-0.052	-0.026	3,986,465
16	-0.024***	-0.036	-0.013	5,564,648
17	-0.036***	-0.050	-0.023	4,019,870
18	-0.036***	-0.049	-0.023	4,022,444
19	-0.034***	-0.047	-0.022	4,633,177
20	-0.034***	-0.048	-0.021	3,972,676
21	-0.032***	-0.044	-0.019	4,447,443
22	-0.036***	-0.049	-0.022	3,959,848
23	-0.041***	-0.055	-0.026	3,533,427
24	-0.046***	-0.060	-0.031	3,615,546
25	-0.038***	-0.052	-0.024	3,714,442
26	-0.033***	-0.047	-0.019	3,736,681
27	-0.037***	-0.052	-0.022	3,323,922
28	-0.033***	-0.047	-0.018	3,525,490
29	-0.034***	-0.049	-0.019	3,218,976
30	-0.026***	-0.040	-0.011	3,654,341
31	-0.022***	-0.036	-0.008	3,727,016
32	-0.020***	-0.034	-0.006	3,662,116
33	-0.006	-0.019	0.008	4,335,906
34	-0.028***	-0.043	-0.013	3,262,475
35	-0.006	-0.020	0.007	4,453,977
36	-0.008	-0.022	0.006	4,310,567
37	-0.002	-0.015	0.012	4,460,091
38	0.009	-0.004	0.021	5,974,168
39	0.007	-0.005	0.020	6,127,172
40	0.008	-0.004	0.021	5,786,019
41	0.012*	-0.001	0.025	5,462,317

42	0.008	-0.003	0.020	7,769,142
43	0.008	-0.005	0.021	5,493,076
44	0.011*	-0.002	0.023	6,365,765
45	0.010	-0.004	0.024	4,638,743
46	0.012*	-0.002	0.026	4,565,601
47	0.009	-0.005	0.023	4,549,995
48	0.006	-0.007	0.019	6,524,065
49	0.002	-0.012	0.016	4,574,867
50	-0.019**	-0.036	-0.002	2,680,761
51	0.002	-0.014	0.018	3,382,012
52	-0.003	-0.019	0.014	2,900,730
53	-0.013	-0.031	0.005	2,267,608
54	-0.008	-0.025	0.010	2,504,180
55	-0.012	-0.031	0.006	2,222,828
56	-0.003	-0.021	0.014	2,410,994
57	-0.003	-0.021	0.015	2,294,180
58	-0.001	-0.018	0.017	2,542,122
59	-0.031***	-0.053	-0.010	1,624,867
60	-0.011	-0.031	0.010	1,919,932
61	-0.006	-0.026	0.014	1,902,076
62	-0.001	-0.020	0.018	2,109,447
63	0.009	-0.009	0.027	2,463,948
64	0.000	-0.020	0.020	1,973,209
65	-0.001	-0.021	0.019	1,857,311
66	0.005	-0.014	0.025	2,178,172
67	0.004	-0.016	0.024	1,860,287
68	0.009	-0.012	0.029	1,819,278
69	0.020**	0.000	0.040	1,948,176
70	0.017	-0.003	0.038	1,873,981
71	0.023**	0.002	0.044	1,741,498
72	0.026**	0.004	0.049	1,648,817
73	0.031***	0.009	0.053	1,694,896
74	0.030***	0.009	0.051	1,844,720
75	0.020*	-0.002	0.043	1,519,851
76	0.017	-0.006	0.039	1,423,842
77	0.015	-0.008	0.037	1,473,448
78	0.018	-0.005	0.040	1,367,623
79	0.009	-0.014	0.043	1,363,504
80	0.009	-0.015	0.046	1,042,329
81	-0.015	-0.041	0.034	772,219
82	-0.006	-0.031	0.039	929,815
83	0.020*	-0.003	0.056	1,125,700
84	0.015	-0.008	0.044	1,219,998
85	0.019	-0.006	0.048	1,001,380
86	0.018	-0.008	0.055	756,570

87	0.025*	-0.002	0.057	677,401
88	0.021	-0.008	0.057	549,056
89	0.021	-0.010	0.052	456,179
90	0.010	-0.019	0.033	496,704
91	0.016	-0.013	0.054	434,935
92	-0.009	-0.049	0.034	214,644
93	-0.044*	-0.094	0.028	109,250
94	-0.053*	-0.115	0.011	66,474
95	0.013	-0.048	0.072	57,452

*** p<0.01, ** p<0.05, * p<0.1

Table S4. **The Dynamic Effect of Higher Outpatient Cost-Sharing on Total Outpatient Service Use.**

Effect of greater outpatient cost-sharing on the total monthly use of outpatient services at the 5 MMW threshold using **intention-to-treat (ITT)** parameters. Dynamic regression discontinuity (RD) estimates by local linear regression with robust bias-corrected ‘optimal’ sample bandwidths; standard errors adjusted for heteroskedasticity and clustered at the individual level (Cellini et al., 2010; Enami et al., 2023; Fan & Gijbels, 1996; Hahn et al., 2001; Hsu & Shen, 2022).

Month lag	TOT Estimate	95% Confidence Interval		Subsample size
		Low	High	
0	-0.046***	-0.056	-0.037	4,984,140
1	-0.079***	-0.091	-0.067	4,708,576
2	-0.090***	-0.103	-0.077	4,649,685
3	-0.108***	-0.122	-0.095	4,851,558
4	-0.120***	-0.133	-0.107	4,825,584
5	-0.131***	-0.145	-0.117	4,197,249
6	-0.144***	-0.159	-0.129	4,077,017
7	-0.159***	-0.175	-0.143	4,164,459
8	-0.174***	-0.190	-0.158	4,870,738
9	-0.185***	-0.201	-0.169	5,346,714
10	-0.206***	-0.223	-0.189	4,551,745
11	-0.220***	-0.238	-0.202	4,599,376
12	-0.234***	-0.253	-0.216	4,189,717
13	-0.243***	-0.262	-0.225	4,768,507
14	-0.253***	-0.271	-0.234	4,592,197
15	-0.264***	-0.283	-0.245	3,986,465
16	-0.260***	-0.279	-0.241	5,564,648
17	-0.275***	-0.294	-0.257	4,019,870
18	-0.288***	-0.308	-0.268	4,022,444
19	-0.298***	-0.319	-0.278	4,633,177
20	-0.308***	-0.329	-0.288	3,972,676
21	-0.316***	-0.336	-0.296	4,447,443
22	-0.329***	-0.351	-0.308	3,959,848
23	-0.346***	-0.368	-0.324	3,533,427
24	-0.366***	-0.389	-0.344	3,615,546
25	-0.376***	-0.399	-0.353	3,714,442
26	-0.381***	-0.404	-0.359	3,736,681
27	-0.393***	-0.416	-0.371	3,323,922
28	-0.400***	-0.424	-0.375	3,525,490
29	-0.409***	-0.433	-0.385	3,218,976
30	-0.410***	-0.434	-0.386	3,654,341
31	-0.413***	-0.438	-0.388	3,727,016
32	-0.416***	-0.442	-0.391	3,662,116
33	-0.405***	-0.430	-0.380	4,335,906
34	-0.422***	-0.449	-0.396	3,262,475
35	-0.412***	-0.438	-0.386	4,453,977
36	-0.410***	-0.438	-0.383	4,310,567

37	-0.403***	-0.429	-0.377	4,460,091
38	-0.388***	-0.414	-0.361	5,974,168
39	-0.379***	-0.405	-0.353	6,127,172
40	-0.371***	-0.397	-0.345	5,786,019
41	-0.360***	-0.387	-0.334	5,462,317
42	-0.356***	-0.382	-0.330	7,769,142
43	-0.350***	-0.376	-0.323	5,493,076
44	-0.340***	-0.367	-0.314	6,365,765
45	-0.332***	-0.359	-0.305	4,638,743
46	-0.323***	-0.352	-0.293	4,565,601
47	-0.316***	-0.345	-0.288	4,549,995
48	-0.314***	-0.342	-0.286	6,524,065
49	-0.314***	-0.343	-0.286	4,574,867
50	-0.330***	-0.360	-0.300	2,680,761
51	-0.315***	-0.344	-0.286	3,382,012
52	-0.310***	-0.340	-0.281	2,900,730
53	-0.316***	-0.348	-0.285	2,267,608
54	-0.314***	-0.346	-0.282	2,504,180
55	-0.316***	-0.348	-0.285	2,222,828
56	-0.307***	-0.339	-0.275	2,410,994
57	-0.301***	-0.333	-0.268	2,294,180
58	-0.296***	-0.329	-0.263	2,542,122
59	-0.322***	-0.358	-0.286	1,624,867
60	-0.315***	-0.352	-0.279	1,919,932
61	-0.307***	-0.344	-0.271	1,902,076
62	-0.297***	-0.333	-0.262	2,109,447
63	-0.281***	-0.316	-0.245	2,463,948
64	-0.280***	-0.317	-0.244	1,973,209
65	-0.279***	-0.316	-0.242	1,857,311
66	-0.270***	-0.307	-0.234	2,178,172
67	-0.266***	-0.302	-0.230	1,860,287
68	-0.256***	-0.295	-0.217	1,819,278
69	-0.237***	-0.275	-0.200	1,948,176
70	-0.228***	-0.265	-0.191	1,873,981
71	-0.214***	-0.251	-0.177	1,741,498
72	-0.200***	-0.240	-0.160	1,648,817
73	-0.184***	-0.227	-0.142	1,694,896
74	-0.174***	-0.214	-0.134	1,844,720
75	-0.173***	-0.214	-0.131	1,519,851
76	-0.171***	-0.214	-0.129	1,423,842

77	-0.170***	-0.211	-0.130	1,473,448
78	-0.164***	-0.206	-0.121	1,367,623
79	-0.166***	-0.209	-0.124	1,363,504
80	-0.166***	-0.211	-0.121	1,042,329
81	-0.186***	-0.233	-0.139	772,219
82	-0.189***	-0.237	-0.141	929,815
83	-0.165***	-0.212	-0.118	1,125,700
84	-0.159***	-0.204	-0.113	1,219,998
85	-0.150***	-0.197	-0.103	1,001,380
86	-0.142***	-0.192	-0.092	756,570
87	-0.129***	-0.179	-0.078	677,401
88	-0.122***	-0.174	-0.071	549,056
89	-0.119***	-0.172	-0.065	456,179
90	-0.125***	-0.183	-0.067	496,704
91	-0.118***	-0.174	-0.061	434,935
92	-0.135***	-0.197	-0.072	214,644
93	-0.176***	-0.249	-0.103	109,250
94	-0.207***	-0.288	-0.126	66,474
95	-0.160***	-0.246	-0.074	57,452

Table S5. The Dynamic Effect of Higher Outpatient Cost-Sharing on Total Outpatient Service Use.

Effect of greater outpatient cost-sharing on the total monthly use of outpatient services at the 5 MMW threshold using and **treatment-on-treated (TOT)** parameters. Dynamic regression discontinuity (RD) estimates by local linear regression with robust bias-corrected 'optimal' sample bandwidths; standard errors adjusted for heteroskedasticity and clustered at the individual level (Cellini et al., 2010; Enami et al., 2023; Fan & Gijbels, 1996; Hahn et al., 2001; Hsu & Shen, 2022).

Month lag	ITT Estimate	95% Confidence Interval		Subsample size
		Low	High	
0	-0.024***	-0.029	-0.018	6,328,294
1	-0.028***	-0.034	-0.022	5,899,383
2	-0.022***	-0.028	-0.016	6,007,919
3	-0.023***	-0.029	-0.017	6,220,503
4	-0.021***	-0.027	-0.016	6,245,819
5	-0.022***	-0.028	-0.016	5,759,124
6	-0.023***	-0.029	-0.017	5,499,554
7	-0.021***	-0.027	-0.015	5,637,775
8	-0.019***	-0.025	-0.013	6,759,700
9	-0.018***	-0.023	-0.012	6,834,051
10	-0.020***	-0.026	-0.014	6,180,365
11	-0.017***	-0.023	-0.011	6,545,950
12	-0.015***	-0.021	-0.009	6,704,705
13	-0.015***	-0.021	-0.009	6,592,608
14	-0.016***	-0.022	-0.009	5,802,608
15	-0.014***	-0.021	-0.008	5,693,339
16	-0.010***	-0.016	-0.004	7,084,950
17	-0.011***	-0.017	-0.005	6,666,991
18	-0.012***	-0.018	-0.006	5,478,524
19	-0.009***	-0.015	-0.003	6,617,264
20	-0.010***	-0.016	-0.004	5,903,555
21	-0.009***	-0.015	-0.003	6,195,477
22	-0.010***	-0.017	-0.003	5,505,176
23	-0.014***	-0.021	-0.007	4,737,933
24	-0.011***	-0.018	-0.005	5,447,511
25	-0.009***	-0.016	-0.003	5,452,979
26	-0.008**	-0.014	-0.001	5,768,258
27	-0.008**	-0.014	-0.001	5,299,777
28	-0.004	-0.011	0.002	6,080,745
29	0.000	-0.006	0.006	6,998,030
30	0.001	-0.006	0.007	6,733,370
31	0.001	-0.005	0.007	6,867,343
32	0.005	-0.002	0.011	6,785,071
33	0.003	-0.004	0.009	6,586,191
34	0.003	-0.003	0.010	6,530,098
35	0.004	-0.003	0.010	6,336,690
36	0.004	-0.002	0.010	8,466,657
37	0.007**	0.000	0.013	7,746,526
38	0.004	-0.003	0.011	5,806,385
39	0.005	-0.002	0.012	5,629,099
40	0.005	-0.002	0.012	5,656,075
41	0.007*	0.000	0.014	5,260,776

42	0.003	-0.004	0.011	4,917,064
43	0.003	-0.004	0.011	4,505,262
44	0.007*	-0.001	0.014	4,919,051
45	0.007*	-0.001	0.014	4,726,942
46	0.004	-0.004	0.013	3,729,362
47	0.004	-0.005	0.012	3,961,044
48	0.003	-0.006	0.011	4,130,097
49	-0.001	-0.010	0.008	3,306,541
50	-0.007	-0.016	0.003	2,762,820
51	-0.003	-0.013	0.007	2,645,028
52	0.001	-0.009	0.010	2,800,251
53	-0.004	-0.013	0.006	2,420,559
54	-0.004	-0.014	0.006	2,366,369
55	-0.005	-0.015	0.005	2,334,491
56	-0.001	-0.011	0.009	2,388,462
57	-0.002	-0.013	0.008	2,309,199
58	-0.005	-0.015	0.006	2,204,873
59	-0.011*	-0.023	0.001	1,807,577
60	-0.010*	-0.022	0.001	1,950,243
61	-0.006	-0.018	0.006	1,873,062
62	-0.005	-0.016	0.007	1,899,854
63	0.001	-0.010	0.012	2,068,760
64	-0.003	-0.015	0.008	1,836,974
65	-0.005	-0.017	0.007	1,699,123
66	-0.003	-0.015	0.008	1,742,076
67	-0.005	-0.017	0.007	1,554,792
68	0.000	-0.012	0.012	1,611,031
69	0.007	-0.005	0.018	1,891,070
70	0.008	-0.004	0.020	1,740,404
71	0.009	-0.003	0.021	1,650,170
72	0.012*	0.000	0.025	1,614,732
73	0.012*	0.000	0.025	1,568,888
74	0.012*	-0.001	0.025	1,489,127
75	0.009	-0.004	0.021	1,466,707
76	0.007	-0.006	0.020	1,379,400
77	0.007	-0.006	0.019	1,407,387
78	0.008	-0.005	0.021	1,223,086
79	0.005	-0.007	0.018	1,268,852
80	0.004	-0.009	0.017	1,062,678
81	0.002	-0.012	0.015	1,054,505
82	-0.014*	-0.030	0.002	628,959
83	-0.004	-0.019	0.011	720,294
84	-0.013	-0.030	0.004	552,407
85	-0.002	-0.018	0.014	616,427
86	0.005	-0.010	0.021	629,675

87	0.007	-0.007	0.022	678,757
88	0.005	-0.011	0.020	565,496
89	0.006	-0.011	0.022	430,970
90	0.002	-0.014	0.019	405,770
91	0.011	-0.005	0.028	376,622
92	-0.015	-0.037	0.008	173,368
93	-0.015	-0.038	0.007	151,133
94	-0.020	-0.052	0.011	64,256
95	-0.011	-0.043	0.021	61,454

*** p<0.01, ** p<0.05, * p<0.1

Table S6. The Dynamic Effect of Higher Outpatient Cost-Sharing on Drug Purchases. Effect of greater outpatient cost-sharing on the total monthly use of outpatient services at the 5 MMW threshold using **intention-to-treat (ITT)** parameters. Dynamic regression discontinuity (RD) estimates by local linear regression with robust bias-corrected ‘optimal’ sample bandwidths; standard errors adjusted for heteroskedasticity and clustered at the individual level (Cellini et al., 2010; Enami et al., 2023; Fan & Gijbels, 1996; Hahn et al., 2001; Hsu & Shen, 2022).

Month lag	TOT Estimate	95% Confidence Interval		Subsample size
		Low	High	
0	-0.024***	-0.029	-0.019	6,328,294
1	-0.041***	-0.047	-0.035	5,899,383
2	-0.047***	-0.053	-0.040	6,007,919
3	-0.054***	-0.060	-0.047	6,220,503
4	-0.059***	-0.065	-0.053	6,245,819
5	-0.066***	-0.072	-0.060	5,759,124
6	-0.073***	-0.080	-0.066	5,499,554
7	-0.078***	-0.086	-0.071	5,637,775
8	-0.083***	-0.090	-0.075	6,759,700
9	-0.087***	-0.095	-0.080	6,834,051
10	-0.095***	-0.103	-0.088	6,180,365
11	-0.100***	-0.108	-0.091	6,545,950
12	-0.103***	-0.112	-0.095	6,704,705
13	-0.107***	-0.115	-0.098	6,592,608
14	-0.112***	-0.121	-0.103	5,802,608
15	-0.115***	-0.124	-0.107	5,693,339
16	-0.115***	-0.123	-0.106	7,084,950
17	-0.117***	-0.126	-0.108	6,666,991
18	-0.121***	-0.131	-0.112	5,478,524
19	-0.122***	-0.132	-0.113	6,617,264
20	-0.125***	-0.135	-0.116	5,903,555
21	-0.128***	-0.137	-0.118	6,195,477
22	-0.131***	-0.141	-0.121	5,505,176
23	-0.138***	-0.148	-0.127	4,737,933
24	-0.142***	-0.153	-0.131	5,447,511
25	-0.143***	-0.154	-0.133	5,452,979
26	-0.144***	-0.155	-0.134	5,768,258
27	-0.146***	-0.156	-0.135	5,299,777
28	-0.144***	-0.155	-0.132	6,080,745
29	-0.140***	-0.150	-0.129	6,998,030
30	-0.137***	-0.148	-0.126	6,733,370
31	-0.136***	-0.147	-0.125	6,867,343
32	-0.132***	-0.143	-0.120	6,785,071
33	-0.130***	-0.141	-0.119	6,586,191
34	-0.127***	-0.139	-0.116	6,530,098
35	-0.125***	-0.137	-0.113	6,336,690
36	-0.123***	-0.135	-0.111	8,466,657

37	-0.118***	-0.130	-0.106	7,746,526
38	-0.115***	-0.128	-0.103	5,806,385
39	-0.112***	-0.124	-0.100	5,629,099
40	-0.108***	-0.121	-0.096	5,656,075
41	-0.103***	-0.116	-0.090	5,260,776
42	-0.102***	-0.115	-0.089	4,917,064
43	-0.100***	-0.113	-0.087	4,505,262
44	-0.093***	-0.106	-0.080	4,919,051
45	-0.089***	-0.102	-0.076	4,726,942
46	-0.087***	-0.102	-0.073	3,729,362
47	-0.085***	-0.099	-0.071	3,961,044
48	-0.084***	-0.098	-0.070	4,130,097
49	-0.086***	-0.101	-0.071	3,306,541
50	-0.091***	-0.106	-0.076	2,762,820
51	-0.089***	-0.104	-0.073	2,645,028
52	-0.083***	-0.099	-0.068	2,800,251
53	-0.084***	-0.100	-0.069	2,420,559
54	-0.085***	-0.102	-0.068	2,366,369
55	-0.086***	-0.102	-0.070	2,334,491
56	-0.082***	-0.099	-0.065	2,388,462
57	-0.082***	-0.099	-0.065	2,309,199
58	-0.084***	-0.102	-0.066	2,204,873
59	-0.092***	-0.111	-0.073	1,807,577
60	-0.096***	-0.115	-0.076	1,950,243
61	-0.094***	-0.113	-0.075	1,873,062
62	-0.093***	-0.112	-0.074	1,899,854
63	-0.087***	-0.106	-0.068	2,068,760
64	-0.088***	-0.107	-0.068	1,836,974
65	-0.090***	-0.111	-0.070	1,699,123
66	-0.091***	-0.111	-0.070	1,742,076
67	-0.092***	-0.113	-0.072	1,554,792
68	-0.088***	-0.110	-0.066	1,611,031
69	-0.080***	-0.101	-0.059	1,891,070
70	-0.074***	-0.095	-0.053	1,740,404
71	-0.070***	-0.090	-0.049	1,650,170
72	-0.063***	-0.085	-0.041	1,614,732
73	-0.058***	-0.082	-0.034	1,568,888
74	-0.055***	-0.078	-0.032	1,489,127
75	-0.055***	-0.079	-0.031	1,466,707
76	-0.055***	-0.079	-0.030	1,379,400

77	-0.054***	-0.077	-0.030	1,407,387
78	-0.051***	-0.075	-0.027	1,223,086
79	-0.051***	-0.076	-0.027	1,268,852
80	-0.051***	-0.076	-0.027	1,062,678
81	-0.053***	-0.079	-0.028	1,054,505
82	-0.070***	-0.097	-0.042	628,959
83	-0.069***	-0.097	-0.041	720,294
84	-0.079***	-0.108	-0.049	552,407
85	-0.074***	-0.103	-0.045	616,427
86	-0.065***	-0.095	-0.035	629,675
87	-0.058***	-0.087	-0.029	678,757
88	-0.057***	-0.085	-0.028	565,496
89	-0.055***	-0.085	-0.024	430,970
90	-0.057***	-0.089	-0.025	405,770
91	-0.048***	-0.079	-0.018	376,622
92	-0.068***	-0.104	-0.033	173,368
93	-0.079***	-0.115	-0.042	151,133
94	-0.090***	-0.133	-0.046	64,256
95	-0.086***	-0.133	-0.040	61,454

Table S7. The Dynamic Effect of Higher Outpatient Cost-Sharing on Drugs Purchases. Effect of greater outpatient cost-sharing on the total monthly use of outpatient services at the 5 MMW threshold using and **treatment-on-treated (TOT)** parameters. Dynamic regression discontinuity (RD) estimates by local linear regression with robust bias-corrected ‘optimal’ sample bandwidths; standard errors adjusted for heteroskedasticity and clustered at the individual level (Cellini et al., 2010; Enami et al., 2023; Fan & Gijbels, 1996; Hahn et al., 2001; Hsu & Shen, 2022).

Month lag	ITT Estimate	95% Confidence Interval		Subsample size
		Low	High	
0	-0.016***	-0.020	-0.012	4,593,323
1	-0.018***	-0.022	-0.014	4,491,041
2	-0.015***	-0.019	-0.011	4,258,162
3	-0.016***	-0.020	-0.012	4,038,359
4	-0.015***	-0.019	-0.011	3,999,205
5	-0.014***	-0.019	-0.010	3,869,907
6	-0.016***	-0.020	-0.012	3,746,048
7	-0.017***	-0.022	-0.013	3,649,677
8	-0.016***	-0.020	-0.012	4,217,011
9	-0.015***	-0.019	-0.012	4,561,648
10	-0.018***	-0.023	-0.014	4,175,801
11	-0.016***	-0.021	-0.012	3,775,476
12	-0.016***	-0.021	-0.012	3,545,341
13	-0.018***	-0.022	-0.014	3,839,233
14	-0.016***	-0.020	-0.012	3,786,096
15	-0.015***	-0.019	-0.010	3,276,936
16	-0.012***	-0.016	-0.007	4,020,584
17	-0.015***	-0.020	-0.010	3,160,279
18	-0.013***	-0.018	-0.009	3,389,950
19	-0.015***	-0.019	-0.010	3,767,993
20	-0.013***	-0.017	-0.008	3,564,361
21	-0.013***	-0.018	-0.009	3,658,801
22	-0.013***	-0.017	-0.009	3,604,478
23	-0.014***	-0.019	-0.009	3,176,430
24	-0.015***	-0.020	-0.011	3,352,672
25	-0.012***	-0.017	-0.007	3,367,401
26	-0.013***	-0.017	-0.008	3,241,412
27	-0.013***	-0.018	-0.008	2,956,265
28	-0.012***	-0.017	-0.007	3,090,040
29	-0.014***	-0.019	-0.009	2,672,611
30	-0.013***	-0.018	-0.008	2,857,302
31	-0.010***	-0.015	-0.005	3,119,912
32	-0.014***	-0.019	-0.009	2,731,176
33	-0.009***	-0.014	-0.005	3,341,468
34	-0.012***	-0.017	-0.007	2,953,136
35	-0.011***	-0.016	-0.006	2,971,023
36	-0.011***	-0.016	-0.006	3,136,631
37	-0.006**	-0.011	-0.001	3,329,559
38	-0.005**	-0.009	0.000	3,475,597
39	-0.005**	-0.009	0.000	3,519,606
40	-0.003	-0.007	0.002	3,643,045
41	-0.005**	-0.009	0.000	3,400,513
42	-0.010***	-0.015	-0.005	2,960,614

43	0.000	-0.003	0.004	6,015,567
44	-0.001	-0.005	0.003	5,473,507
45	0.000	-0.004	0.004	4,522,150
46	0.001	-0.003	0.005	5,123,950
47	0.000	-0.004	0.005	4,401,611
48	-0.001	-0.006	0.003	4,118,941
49	-0.002	-0.006	0.002	5,329,410
50	-0.003	-0.007	0.002	4,729,518
51	0.001	-0.003	0.004	6,071,597
52	0.000	-0.004	0.004	5,037,819
53	0.000	-0.004	0.004	4,625,651
54	0.000	-0.004	0.004	4,330,888
55	-0.005	-0.011	0.001	2,097,424
56	-0.002	-0.007	0.003	2,687,105
57	0.000	-0.006	0.005	2,209,420
58	0.001	-0.004	0.006	2,968,200
59	-0.012***	-0.018	-0.005	1,481,682
60	-0.006*	-0.013	0.001	1,636,249
61	-0.007*	-0.013	0.000	1,518,144
62	-0.004	-0.011	0.002	1,727,470
63	0.002	-0.003	0.007	2,888,633
64	-0.002	-0.007	0.004	2,122,476
65	-0.004	-0.010	0.003	1,511,417
66	0.003	-0.003	0.008	2,590,362
67	0.002	-0.005	0.008	1,976,157
68	0.005*	0.000	0.011	2,365,581
69	0.006*	0.000	0.012	2,146,337
70	0.004	-0.002	0.011	2,019,841
71	0.007**	0.001	0.014	1,877,143
72	0.008**	0.001	0.014	1,746,848
73	0.009***	0.002	0.015	1,842,083
74	0.008**	0.002	0.015	1,533,038
75	0.006*	0.000	0.012	2,185,884
76	0.005*	-0.001	0.012	1,880,611
77	0.004	-0.002	0.011	1,983,595
78	0.006	-0.002	0.013	1,390,220
79	0.003	-0.004	0.009	1,861,592
80	0.005	-0.002	0.011	1,606,593
81	0.001	-0.006	0.008	1,320,300
82	0.001	-0.006	0.009	1,012,902
83	0.007*	-0.001	0.014	1,027,652
84	-0.001	-0.012	0.010	436,874
85	0.001	-0.008	0.011	635,334
86	0.006	-0.002	0.015	762,941
87	0.004	-0.006	0.015	511,779

88	0.008	-0.002	0.018	507,803
89	0.006	-0.005	0.017	391,465
90	0.005	-0.005	0.015	520,274
91	0.007	-0.003	0.018	415,772
92	0.006	-0.007	0.019	247,496
93	-0.005	-0.022	0.011	134,701
94	-0.006	-0.022	0.010	117,511
95	0.025*	-0.002	0.053	31,520

*** p<0.01, ** p<0.05, * p<0.1

Table S8. The Dynamic Effect of Higher Outpatient Cost-Sharing on Outpatient Consultations.

Effect of greater outpatient cost-sharing on the total monthly use of outpatient services at the 5 MMW threshold using **intention-to-treat (ITT**) parameters. Dynamic regression discontinuity (RD) estimates by local linear regression with robust bias-corrected 'optimal' sample bandwidths; standard errors adjusted for heteroskedasticity and clustered at the individual level (Cellini et al., 2010; Enami et al., 2023; Fan & Gijbels, 1996; Hahn et al., 2001; Hsu & Shen, 2022).

Month lag	TOT Estimate	95% Confidence Interval		Subsample size
		Low	High	
0	-0.016***	-0.020	-0.012	4,593,323
1	-0.027***	-0.031	-0.023	4,491,041
2	-0.031***	-0.036	-0.027	4,258,162
3	-0.037***	-0.041	-0.032	4,038,359
4	-0.040***	-0.045	-0.036	3,999,205
5	-0.044***	-0.049	-0.039	3,869,907
6	-0.050***	-0.055	-0.044	3,746,048
7	-0.056***	-0.061	-0.051	3,649,677
8	-0.061***	-0.066	-0.055	4,217,011
9	-0.065***	-0.071	-0.060	4,561,648
10	-0.073***	-0.079	-0.068	4,175,801
11	-0.078***	-0.084	-0.072	3,775,476
12	-0.083***	-0.089	-0.077	3,545,341
13	-0.089***	-0.096	-0.083	3,839,233
14	-0.093***	-0.100	-0.087	3,786,096
15	-0.097***	-0.103	-0.090	3,276,936
16	-0.097***	-0.104	-0.091	4,020,584
17	-0.103***	-0.110	-0.097	3,160,279
18	-0.107***	-0.114	-0.100	3,389,950
19	-0.112***	-0.119	-0.105	3,767,993
20	-0.115***	-0.122	-0.108	3,564,361
21	-0.119***	-0.126	-0.112	3,658,801
22	-0.123***	-0.130	-0.115	3,604,478
23	-0.128***	-0.135	-0.120	3,176,430
24	-0.134***	-0.142	-0.126	3,352,672
25	-0.136***	-0.145	-0.128	3,367,401
26	-0.140***	-0.148	-0.132	3,241,412
27	-0.144***	-0.152	-0.136	2,956,265
28	-0.147***	-0.156	-0.139	3,090,040
29	-0.152***	-0.160	-0.143	2,672,611
30	-0.155***	-0.164	-0.146	2,857,302
31	-0.156***	-0.165	-0.147	3,119,912
32	-0.162***	-0.172	-0.153	2,731,176
33	-0.162***	-0.171	-0.153	3,341,468
34	-0.166***	-0.175	-0.157	2,953,136
35	-0.168***	-0.177	-0.159	2,971,023
36	-0.171***	-0.180	-0.161	3,136,631

37	-0.168***	-0.178	-0.159	3,329,559
38	-0.167***	-0.176	-0.157	3,475,597
39	-0.166***	-0.175	-0.156	3,519,606
40	-0.164***	-0.173	-0.154	3,643,045
41	-0.165***	-0.175	-0.155	3,400,513
42	-0.171***	-0.181	-0.161	2,960,614
43	-0.163***	-0.173	-0.154	6,015,567
44	-0.161***	-0.170	-0.151	5,473,507
45	-0.158***	-0.167	-0.148	4,522,150
46	-0.155***	-0.164	-0.145	5,123,950
47	-0.153***	-0.162	-0.143	4,401,611
48	-0.153***	-0.162	-0.144	4,118,941
49	-0.153***	-0.163	-0.144	5,329,410
50	-0.153***	-0.162	-0.144	4,729,518
51	-0.149***	-0.158	-0.139	6,071,597
52	-0.146***	-0.155	-0.137	5,037,819
53	-0.145***	-0.154	-0.135	4,625,651
54	-0.143***	-0.152	-0.134	4,330,888
55	-0.146***	-0.156	-0.136	2,097,424
56	-0.144***	-0.154	-0.134	2,687,105
57	-0.141***	-0.151	-0.131	2,209,420
58	-0.138***	-0.148	-0.128	2,968,200
59	-0.148***	-0.159	-0.137	1,481,682
60	-0.148***	-0.159	-0.137	1,636,249
61	-0.148***	-0.160	-0.137	1,518,144
62	-0.146***	-0.157	-0.134	1,727,470
63	-0.139***	-0.150	-0.127	2,888,633
64	-0.138***	-0.149	-0.126	2,122,476
65	-0.139***	-0.151	-0.128	1,511,417
66	-0.134***	-0.145	-0.123	2,590,362
67	-0.131***	-0.143	-0.120	1,976,157
68	-0.125***	-0.136	-0.114	2,365,581
69	-0.120***	-0.131	-0.109	2,146,337
70	-0.118***	-0.129	-0.107	2,019,841
71	-0.113***	-0.124	-0.101	1,877,143
72	-0.108***	-0.121	-0.096	1,746,848
73	-0.104***	-0.116	-0.091	1,842,083
74	-0.099***	-0.112	-0.087	1,533,038
75	-0.098***	-0.110	-0.086	2,185,884
76	-0.096***	-0.109	-0.084	1,880,611

77	-0.095***	-0.107	-0.083	1,983,595
78	-0.092***	-0.106	-0.079	1,390,220
79	-0.093***	-0.105	-0.080	1,861,592
80	-0.090***	-0.103	-0.077	1,606,593
81	-0.092***	-0.105	-0.078	1,320,300
82	-0.091***	-0.105	-0.077	1,012,902
83	-0.086***	-0.100	-0.072	1,027,652
84	-0.090***	-0.106	-0.075	436,874
85	-0.090***	-0.106	-0.074	635,334
86	-0.084***	-0.100	-0.067	762,941
87	-0.082***	-0.099	-0.065	511,779
88	-0.076***	-0.093	-0.059	507,803
89	-0.075***	-0.092	-0.057	391,465
90	-0.075***	-0.093	-0.057	520,274
91	-0.071***	-0.089	-0.053	415,772
92	-0.068***	-0.088	-0.048	247,496
93	-0.077***	-0.100	-0.054	134,701
94	-0.081***	-0.106	-0.057	117,511
95	-0.053***	-0.085	-0.021	31,520

Table S9. The Dynamic Effect of Higher Outpatient Cost-Sharing on Outpatient Consultations.

Effect of greater outpatient cost-sharing on the total monthly use of outpatient services at the 5 MMW threshold using and **treatment-on-treated (TOT)** parameters. Dynamic regression discontinuity (RD) estimates by local linear regression with robust bias-corrected ‘optimal’ sample bandwidths; standard errors adjusted for heteroskedasticity and clustered at the individual level (Cellini et al., 2010; Enami et al., 2023; Fan & Gijbels, 1996; Hahn et al., 2001; Hsu & Shen, 2022).

Month lag	ITT Estimate	95% Confidence Interval		Subsample size
		Low	High	
0	-0.008***	-0.011	-0.006	9,552,324
1	-0.007***	-0.009	-0.003	10,761,652
2	-0.002**	-0.006	0.001	13,828,307
3	-0.002*	-0.007	0.000	14,685,026
4	-0.003**	-0.005	0.001	11,275,654
5	-0.003**	-0.005	0.002	9,068,035
6	-0.001	-0.003	0.004	10,557,630
7	0.000	-0.003	0.004	11,005,323
8	-0.002*	-0.004	0.002	9,573,297
9	0.000	-0.004	0.002	12,826,827
10	-0.001	-0.004	0.003	9,847,689
11	-0.001	-0.004	0.003	10,040,440
12	-0.003*	-0.005	0.002	7,799,691
13	0.001	-0.003	0.004	11,601,977
14	0.001	-0.003	0.004	12,731,650
15	0.001	-0.004	0.004	10,383,849
16	0.001	-0.003	0.004	11,241,442
17	0.001	-0.003	0.004	8,613,263
18	0.000	-0.003	0.004	10,835,630
19	-0.001	-0.003	0.005	9,222,266
20	0.000	-0.004	0.004	7,903,430
21	0.001	-0.002	0.005	8,701,195
22	0.000	-0.001	0.006	7,493,059
23	0.000	-0.003	0.005	8,345,711
24	-0.002	-0.004	0.004	7,412,256
25	-0.001	-0.003	0.004	7,028,087
26	-0.001	-0.001	0.007	5,739,802
27	-0.004*	-0.002	0.006	4,581,728
28	-0.002	-0.002	0.007	4,625,514
29	-0.007***	-0.001	0.007	3,561,385
30	-0.002	0.001	0.009	4,461,532
31	-0.001	0.000	0.009	4,517,855
32	-0.001	0.002	0.010	4,471,477
33	0.000	0.001	0.009	4,667,652
34	-0.007***	-0.002	0.007	3,448,142
35	-0.003	-0.001	0.007	3,874,359
36	0.001	0.001	0.010	5,063,594
37	-0.002	-0.002	0.007	3,734,392
38	0.002	0.001	0.010	5,452,249

39	0.003*	-0.002	0.007	7,789,820
40	0.000	-0.001	0.008	4,053,578
41	0.004*	0.000	0.010	5,027,793
42	0.000	-0.005	0.005	5,217,941
43	0.002	-0.003	0.007	6,056,896
44	0.001	-0.003	0.007	6,568,023
45	0.002	-0.002	0.008	4,570,341
46	0.003	-0.003	0.008	4,208,831
47	0.003	-0.001	0.009	6,229,055
48	-0.001	-0.005	0.005	4,537,076
49	0.001	-0.002	0.009	4,979,327
50	0.000	-0.003	0.007	5,639,651
51	0.002	0.000	0.010	5,925,503
52	0.002	-0.002	0.009	4,671,318
53	0.002	-0.001	0.010	5,865,387
54	0.002	-0.003	0.008	3,842,198
55	0.003	0.000	0.011	4,190,659
56	0.002	0.001	0.012	4,062,580
57	0.003	0.000	0.012	3,242,308
58	0.003	-0.002	0.010	3,509,512
59	-0.001	-0.003	0.009	3,303,449
60	0.003	-0.005	0.008	3,916,978
61	0.004*	-0.001	0.011	3,569,124
62	0.005**	0.001	0.013	3,463,380
63	0.006**	-0.002	0.011	2,409,937
64	0.005*	0.002	0.015	2,416,292
65	0.006**	0.001	0.014	3,115,537
66	0.005*	0.002	0.015	2,291,257
67	0.005*	0.000	0.013	2,419,703
68	0.003	0.000	0.014	2,055,458
69	0.005*	0.002	0.016	1,951,262
70	0.003	0.001	0.016	1,881,651
71	0.005*	0.000	0.015	2,081,125
72	0.006*	0.005	0.020	1,741,997
73	0.008**	0.007	0.022	1,631,610
74	0.005*	0.003	0.019	1,677,620
75	0.005*	-0.001	0.015	1,798,309
76	0.005	0.001	0.017	1,781,972
77	0.003	-0.002	0.015	1,870,028
78	0.003	0.001	0.018	1,835,251
79	-0.001	-0.003	0.014	1,413,100

80	0.004	-0.001	0.017	1,215,743
81	-0.007	-0.009	0.009	692,437
82	0.002	-0.003	0.015	1,235,429
83	0.007**	0.003	0.022	1,395,100
84	0.000	-0.008	0.013	1,075,493
85	-0.002	-0.005	0.017	768,945
86	0.002	-0.002	0.021	855,132
87	0.007	0.002	0.025	839,987
88	0.003	0.000	0.024	543,005
89	-0.002	-0.005	0.020	343,798
90	-0.005	-0.015	0.012	401,194
91	0.000	-0.011	0.019	457,533
92	0.001	-0.016	0.018	280,015
93	-0.015	-0.029	0.009	116,281
94	-0.016	-0.056	-0.011	82,909
95	0.008	-0.017	0.049	58,677

*** p<0.01, ** p<0.05, * p<0.1

Table S10. The Dynamic Effect of Higher Outpatient Cost-Sharing on Laboratory Procedures.

Effect of greater outpatient cost-sharing on the total monthly use of outpatient services at the 5 MMW threshold using **intention-to-treat (ITT)** parameters. Dynamic regression discontinuity (RD) estimates by local linear regression with robust bias-corrected ‘optimal’ sample bandwidths; standard errors adjusted for heteroskedasticity and clustered at the individual level (Cellini et al., 2010; Enami et al., 2023; Fan & Gijbels, 1996; Hahn et al., 2001; Hsu & Shen, 2022).

Month lag	TOT Estimate	95% Confidence Interval		Subsample size
		Low	High	
0	-0.008***	-0.011	-0.006	9,552,324
1	-0.012***	-0.015	-0.009	10,761,652
2	-0.010***	-0.012	-0.007	13,828,307
3	-0.009***	-0.011	-0.006	14,685,026
4	-0.010***	-0.012	-0.007	11,275,654
5	-0.011***	-0.014	-0.007	9,068,035
6	-0.010***	-0.013	-0.007	10,557,630
7	-0.009***	-0.012	-0.006	11,005,323
8	-0.011***	-0.014	-0.007	9,573,297
9	-0.010***	-0.014	-0.007	12,826,827
10	-0.010***	-0.014	-0.007	9,847,689
11	-0.011***	-0.015	-0.008	10,040,440
12	-0.013***	-0.017	-0.009	7,799,691
13	-0.011***	-0.015	-0.007	11,601,977
14	-0.010***	-0.014	-0.006	12,731,650
15	-0.009***	-0.013	-0.005	10,383,849
16	-0.008***	-0.013	-0.004	11,241,442
17	-0.008***	-0.012	-0.004	8,613,263
18	-0.009***	-0.013	-0.005	10,835,630
19	-0.010***	-0.014	-0.006	9,222,266
20	-0.010***	-0.015	-0.005	7,903,430
21	-0.009***	-0.013	-0.004	8,701,195
22	-0.009***	-0.014	-0.004	7,493,059
23	-0.009***	-0.014	-0.004	8,345,711
24	-0.012***	-0.017	-0.006	7,412,256
25	-0.012***	-0.017	-0.007	7,028,087
26	-0.012***	-0.018	-0.007	5,739,802
27	-0.015***	-0.021	-0.009	4,581,728
28	-0.015***	-0.021	-0.009	4,625,514
29	-0.020***	-0.027	-0.014	3,561,385
30	-0.018***	-0.025	-0.012	4,461,532
31	-0.017***	-0.024	-0.011	4,517,855
32	-0.017***	-0.023	-0.010	4,471,477
33	-0.015***	-0.022	-0.009	4,667,652
34	-0.021***	-0.028	-0.015	3,448,142
35	-0.022***	-0.029	-0.015	3,874,359
36	-0.019***	-0.026	-0.012	5,063,594

37	-0.020***	-0.027	-0.013	3,734,392
38	-0.017***	-0.024	-0.010	5,452,249
39	-0.014***	-0.021	-0.007	7,789,820
40	-0.015***	-0.022	-0.009	4,053,578
41	-0.012***	-0.019	-0.005	5,027,793
42	-0.013***	-0.020	-0.006	5,217,941
43	-0.012***	-0.019	-0.005	6,056,896
44	-0.012***	-0.019	-0.005	6,568,023
45	-0.010***	-0.018	-0.003	4,570,341
46	-0.008**	-0.017	0.000	4,208,831
47	-0.007**	-0.015	0.000	6,229,055
48	-0.010***	-0.018	-0.002	4,537,076
49	-0.009**	-0.017	-0.001	4,979,327
50	-0.009**	-0.017	-0.001	5,639,651
51	-0.008**	-0.016	0.000	5,925,503
52	-0.007*	-0.015	0.001	4,671,318
53	-0.006*	-0.014	0.002	5,865,387
54	-0.005	-0.013	0.004	3,842,198
55	-0.003	-0.012	0.005	4,190,659
56	-0.003	-0.011	0.006	4,062,580
57	-0.002	-0.010	0.007	3,242,308
58	-0.001	-0.010	0.008	3,509,512
59	-0.004	-0.013	0.005	3,303,449
60	-0.001	-0.011	0.008	3,916,978
61	0.002	-0.008	0.011	3,569,124
62	0.005	-0.004	0.015	3,463,380
63	0.008**	-0.001	0.018	2,409,937
64	0.010**	0.000	0.020	2,416,292
65	0.012***	0.003	0.021	3,115,537
66	0.013***	0.004	0.023	2,291,257
67	0.015***	0.006	0.025	2,419,703
68	0.015***	0.006	0.025	2,055,458
69	0.018***	0.008	0.028	1,951,262
70	0.018***	0.008	0.028	1,881,651
71	0.021***	0.011	0.031	2,081,125
72	0.023***	0.013	0.034	1,741,997
73	0.028***	0.016	0.039	1,631,610
74	0.028***	0.017	0.039	1,677,620
75	0.030***	0.018	0.041	1,798,309
76	0.031***	0.019	0.042	1,781,972

77	0.030***	0.019	0.041	1,870,028
78	0.030***	0.019	0.041	1,835,251
79	0.027***	0.015	0.039	1,413,100
80	0.030***	0.018	0.042	1,215,743
81	0.022***	0.007	0.036	692,437
82	0.025***	0.012	0.038	1,235,429
83	0.032***	0.020	0.045	1,395,100
84	0.030***	0.017	0.043	1,075,493
85	0.026***	0.013	0.040	768,945
86	0.028***	0.014	0.043	855,132
87	0.034***	0.020	0.049	839,987
88	0.034***	0.018	0.050	543,005
89	0.029***	0.012	0.046	343,798
90	0.023***	0.005	0.041	401,194
91	0.025***	0.007	0.043	457,533
92	0.027***	0.008	0.047	280,015
93	0.012	-0.013	0.037	116,281
94	0.002	-0.027	0.031	82,909
95	0.020	-0.012	0.052	58,677

Table S11. The Dynamic Effect of Higher Outpatient Cost-Sharing on Laboratory Procedures.

Effect of greater outpatient cost-sharing on the total monthly use of outpatient services at the 5 MMW threshold using and **treatment-on-treated (TOT)** parameters. Dynamic regression discontinuity (RD) estimates by local linear regression with robust bias-corrected 'optimal' sample bandwidths; standard errors adjusted for heteroskedasticity and clustered at the individual level (Cellini et al., 2010; Enami et al., 2023; Fan & Gijbels, 1996; Hahn et al., 2001; Hsu & Shen, 2022).

Month lag	ITT Estimate	95% Confidence Interval		Subsample size
		Low	High	
0	-0.002***	-0.0028	-0.0012	10,565,972
1	-0.002***	-0.0026	-0.0008	8,881,589
2	-0.001*	-0.0013	0.0001	15,540,492
3	0.000	-0.0009	0.0004	16,862,950
4	-0.002***	-0.0030	-0.0011	7,362,079
5	0.000	-0.0005	0.0010	14,206,568
6	-0.002***	-0.0031	-0.0011	6,701,396
7	0.000	-0.0004	0.0012	12,420,543
8	0.000	-0.0003	0.0012	13,622,707
9	0.001	-0.0002	0.0015	11,944,401
10	0.001	-0.0003	0.0013	13,001,262
11	0.000	-0.0008	0.0010	9,805,174
12	0.000	-0.0006	0.0010	12,832,088
13	0.000	-0.0005	0.0012	11,382,304
14	0.000	-0.0005	0.0011	11,870,411
15	-0.001	-0.0019	0.0002	6,529,529
16	0.000	-0.0010	0.0008	8,671,424
17	0.000	-0.0007	0.0010	10,795,285
18	0.000	-0.0009	0.0008	11,541,331
19	0.000	-0.0011	0.0006	9,881,013
20	0.000	-0.0012	0.0006	8,607,514
21	-0.002***	-0.0030	-0.0007	4,966,397
22	-0.002***	-0.0029	-0.0006	4,940,288
23	0.000	-0.0010	0.0009	7,544,782
24	-0.003***	-0.0038	-0.0014	4,567,445
25	-0.001**	-0.0024	-0.0001	5,581,582
26	-0.001**	-0.0026	-0.0002	4,647,025
27	-0.002***	-0.0031	-0.0006	4,302,879
28	0.000	-0.0013	0.0011	5,098,594
29	-0.001*	-0.0024	0.0001	4,506,596
30	0.000	-0.0012	0.0012	5,312,035
31	-0.001	-0.0019	0.0004	5,547,495
32	0.001	-0.0004	0.0017	7,179,523
33	0.000	-0.0011	0.0012	5,738,305
34	-0.001*	-0.0028	0.0000	3,609,654
35	-0.001	-0.0021	0.0007	3,746,729
36	0.000	-0.0012	0.0015	4,396,498
37	0.001	-0.0007	0.0018	5,022,540
38	0.001	-0.0005	0.0021	4,840,241
39	0.001*	-0.0002	0.0022	5,798,912
40	0.001	-0.0005	0.0019	5,211,310
41	0.000	-0.0008	0.0017	5,076,089
42	0.001	-0.0003	0.0021	5,270,838

43	0.001	-0.0002	0.0023	4,819,457
44	0.001	-0.0004	0.0021	4,776,577
45	0.001*	-0.0002	0.0025	4,465,693
46	0.001*	-0.0001	0.0027	4,016,905
47	0.001	-0.0004	0.0024	3,867,737
48	0.001	-0.0003	0.0025	3,914,266
49	0.001	-0.0009	0.0019	4,098,885
50	0.000	-0.0013	0.0014	3,898,603
51	0.001	-0.0006	0.0022	3,893,104
52	0.000	-0.0014	0.0013	3,882,650
53	0.001*	-0.0002	0.0023	5,344,147
54	0.000	-0.0013	0.0017	3,371,407
55	0.000	-0.0011	0.0016	3,929,174
56	0.000	-0.0012	0.0016	3,921,389
57	0.001	-0.0004	0.0022	4,896,708
58	0.001	-0.0009	0.0024	2,931,546
59	0.000	-0.0012	0.0019	3,427,714
60	0.001*	-0.0001	0.0031	3,110,433
61	0.001	-0.0004	0.0029	2,980,931
62	0.001	-0.0006	0.0029	2,675,267
63	0.001	-0.0004	0.0026	4,019,303
64	0.000	-0.0014	0.0020	3,103,171
65	0.001	-0.0006	0.0030	2,627,004
66	0.001	-0.0011	0.0024	2,689,019
67	0.001	-0.0006	0.0028	3,102,925
68	0.002*	-0.0001	0.0034	2,842,615
69	0.002**	0.0003	0.0045	1,914,770
70	0.001	-0.0005	0.0034	2,192,465
71	0.002	-0.0004	0.0040	1,732,466
72	0.001	-0.0007	0.0036	1,893,951
73	0.002*	-0.0001	0.0044	1,596,241
74	0.001	-0.0012	0.0035	1,431,058
75	0.001	-0.0009	0.0035	1,653,293
76	0.001	-0.0015	0.0034	1,264,857
77	0.001	-0.0016	0.0035	1,207,692
78	0.001	-0.0020	0.0031	1,176,702
79	0.001	-0.0011	0.0040	1,096,848
80	0.001	-0.0012	0.0041	1,062,677
81	0.001	-0.0015	0.0034	1,214,230
82	0.001	-0.0018	0.0037	913,269
83	0.003	-0.0006	0.0058	714,992
84	0.002	-0.0012	0.0052	717,565
85	0.002	-0.0018	0.0050	650,100
86	0.003	-0.0011	0.0061	584,805
87	0.004**	0.0000	0.0081	413,813

88	0.006***	0.0016	0.0105	335,798
89	0.004*	-0.0003	0.0083	359,324
90	0.003	-0.0017	0.0069	360,578
91	0.000	-0.0048	0.0044	312,661
92	-0.002	-0.0064	0.0028	315,806
93	-0.002	-0.0073	0.0025	244,148
94	0.001	-0.0052	0.0074	142,808
95	0.010**	0.0013	0.0190	56,808

*** p<0.01, ** p<0.05, * p<0.1

Table S12. The Dynamic Effect of Higher Outpatient Cost-Sharing on Diagnostic Images.

Effect of greater outpatient cost-sharing on the total monthly use of outpatient services at the 5 MMW threshold using **intention-to-treat (ITT)** parameters. Dynamic regression discontinuity (RD) estimates by local linear regression with robust bias-corrected 'optimal' sample bandwidths; standard errors adjusted for heteroskedasticity and clustered at the individual level (Cellini et al., 2010; Enami et al., 2023; Fan & Gijbels, 1996; Hahn et al., 2001; Hsu & Shen, 2022).

Month lag	TOT Estimate	95% Confidence Interval		Subsample size
		Low	High	
0	-0.002***	-0.0029	-0.0012	10,565,972
1	-0.003***	-0.0038	-0.0019	8,881,589
2	-0.002***	-0.0032	-0.0015	15,540,492
3	-0.002***	-0.0027	-0.0011	16,862,950
4	-0.004***	-0.0047	-0.0026	7,362,079
5	-0.002***	-0.0033	-0.0014	14,206,568
6	-0.004***	-0.0053	-0.0029	6,701,396
7	-0.003***	-0.0038	-0.0016	12,420,543
8	-0.002***	-0.0032	-0.0011	13,622,707
9	-0.002***	-0.0028	-0.0005	11,944,401
10	-0.001***	-0.0026	-0.0004	13,001,262
11	-0.002***	-0.0031	-0.0005	9,805,174
12	-0.002***	-0.0031	-0.0006	12,832,088
13	-0.002***	-0.0029	-0.0003	11,382,304
14	-0.002***	-0.0027	-0.0003	11,870,411
15	-0.003***	-0.0040	-0.0011	6,529,529
16	-0.002***	-0.0037	-0.0009	8,671,424
17	-0.002***	-0.0032	-0.0005	10,795,285
18	-0.002***	-0.0033	-0.0007	11,541,331
19	-0.002***	-0.0035	-0.0008	9,881,013
20	-0.002***	-0.0037	-0.0009	8,607,514
21	-0.004***	-0.0055	-0.0024	4,966,397
22	-0.005***	-0.0065	-0.0032	4,940,288
23	-0.004***	-0.0054	-0.0023	7,544,782
24	-0.006***	-0.0078	-0.0045	4,567,445
25	-0.006***	-0.0078	-0.0044	5,581,582
26	-0.006***	-0.0082	-0.0048	4,647,025
27	-0.007***	-0.0091	-0.0055	4,302,879
28	-0.006***	-0.0080	-0.0043	5,098,594
29	-0.007***	-0.0087	-0.0049	4,506,596
30	-0.006***	-0.0081	-0.0043	5,312,035
31	-0.007***	-0.0085	-0.0047	5,547,495
32	-0.006***	-0.0074	-0.0037	7,179,523
33	-0.006***	-0.0075	-0.0037	5,738,305
34	-0.007***	-0.0093	-0.0047	3,609,654
35	-0.007***	-0.0094	-0.0047	3,746,729
36	-0.007***	-0.0088	-0.0043	4,396,498

37	-0.006***	-0.0079	-0.0035	5,022,540
38	-0.005***	-0.0073	-0.0027	4,840,241
39	-0.004***	-0.0065	-0.0022	5,798,912
40	-0.004***	-0.0063	-0.0020	5,211,310
41	-0.004***	-0.0065	-0.0020	5,076,089
42	-0.004***	-0.0060	-0.0014	5,270,838
43	-0.003***	-0.0056	-0.0008	4,819,457
44	-0.003**	-0.0053	-0.0004	4,776,577
45	-0.002**	-0.0050	0.0001	4,465,693
46	-0.002*	-0.0045	0.0006	4,016,905
47	-0.002*	-0.0042	0.0009	3,867,737
48	-0.001	-0.0040	0.0012	3,914,266
49	-0.002	-0.0042	0.0010	4,098,885
50	-0.002*	-0.0044	0.0007	3,898,603
51	-0.001	-0.0038	0.0013	3,893,104
52	-0.002*	-0.0044	0.0008	3,882,650
53	-0.001	-0.0034	0.0020	5,344,147
54	-0.001	-0.0037	0.0018	3,371,407
55	-0.001	-0.0036	0.0019	3,929,174
56	-0.001	-0.0036	0.0021	3,921,389
57	0.000	-0.0028	0.0029	4,896,708
58	0.000	-0.0026	0.0032	2,931,546
59	0.000	-0.0028	0.0032	3,427,714
60	0.001	-0.0015	0.0044	3,110,433
61	0.002	-0.0012	0.0050	2,980,931
62	0.002*	-0.0007	0.0056	2,675,267
63	0.003**	-0.0002	0.0058	4,019,303
64	0.002*	-0.0008	0.0057	3,103,171
65	0.003**	0.0001	0.0065	2,627,004
66	0.003**	0.0001	0.0065	2,689,019
67	0.004***	0.0009	0.0072	3,102,925
68	0.005***	0.0019	0.0085	2,842,615
69	0.007***	0.0032	0.0102	1,914,770
70	0.007***	0.0030	0.0103	2,192,465
71	0.007***	0.0036	0.0112	1,732,466
72	0.008***	0.0038	0.0114	1,893,951
73	0.009***	0.0047	0.0127	1,596,241
74	0.008***	0.0042	0.0124	1,431,058
75	0.009***	0.0046	0.0126	1,653,293
76	0.009***	0.0043	0.0127	1,264,857

77	0.009***	0.0045	0.0130	1,207,692
78	0.009***	0.0042	0.0129	1,176,702
79	0.009***	0.0048	0.0141	1,096,848
80	0.010***	0.0056	0.0144	1,062,677
81	0.010***	0.0053	0.0145	1,214,230
82	0.010***	0.0050	0.0148	913,269
83	0.012***	0.0065	0.0171	714,992
84	0.012***	0.0071	0.0177	717,565
85	0.013***	0.0071	0.0181	650,100
86	0.014***	0.0080	0.0195	584,805
87	0.016***	0.0099	0.0225	413,813
88	0.020***	0.0131	0.0266	335,798
89	0.020***	0.0134	0.0271	359,324
90	0.020***	0.0127	0.0267	360,578
91	0.017***	0.0099	0.0247	312,661
92	0.015***	0.0074	0.0221	315,806
93	0.013***	0.0048	0.0210	244,148
94	0.015***	0.0063	0.0242	142,808
95	0.025***	0.0146	0.0364	56,808

Table S13. The Dynamic Effect of Higher Outpatient Cost-Sharing on Diagnostic Images.

Effect of greater outpatient cost-sharing on the total monthly use of outpatient services at the 5 MMW threshold using and **treatment-on-treated (TOT)** parameters. Dynamic regression discontinuity (RD) estimates by local linear regression with robust bias-corrected ‘optimal’ sample bandwidths; standard errors adjusted for heteroskedasticity and clustered at the individual level (Cellini et al., 2010; Enami et al., 2023; Fan & Gijbels, 1996; Hahn et al., 2001; Hsu & Shen, 2022).

Month lag	ITT Estimate	95% Confidence Interval		Subsample size
		Low	High	
0	-0.030***	-0.039	-0.022	4,734,313
1	-0.032***	-0.041	-0.023	4,603,188
2	-0.032***	-0.041	-0.023	4,571,560
3	-0.031***	-0.040	-0.022	4,559,124
4	-0.030***	-0.039	-0.021	4,523,511
5	-0.030***	-0.039	-0.020	4,569,420
6	-0.028***	-0.037	-0.018	4,312,248
7	-0.028***	-0.037	-0.018	4,386,098
8	-0.028***	-0.038	-0.019	4,317,294
9	-0.028***	-0.038	-0.018	4,356,314
10	-0.028***	-0.038	-0.018	4,381,733
11	-0.026***	-0.036	-0.016	4,363,541
12	-0.026***	-0.036	-0.016	4,220,127
13	-0.026***	-0.036	-0.016	4,048,662
14	-0.028***	-0.038	-0.017	3,950,449
15	-0.027***	-0.037	-0.016	4,118,948
16	-0.027***	-0.037	-0.017	4,017,904
17	-0.024***	-0.034	-0.014	4,151,781
18	-0.027***	-0.037	-0.017	4,022,381
19	-0.029***	-0.039	-0.019	3,982,679
20	-0.029***	-0.040	-0.019	3,986,178
21	-0.031***	-0.041	-0.020	3,898,349
22	-0.033***	-0.044	-0.022	3,706,076
23	-0.034***	-0.046	-0.023	3,523,263
24	-0.036***	-0.047	-0.025	3,577,980
25	-0.040***	-0.052	-0.028	3,083,514
26	-0.041***	-0.053	-0.029	3,099,506
27	-0.039***	-0.050	-0.027	3,090,896
28	-0.041***	-0.053	-0.029	2,799,234
29	-0.040***	-0.053	-0.028	2,690,269
30	-0.043***	-0.055	-0.030	2,631,004
31	-0.042***	-0.055	-0.030	2,585,355
32	-0.043***	-0.056	-0.030	2,534,132
33	-0.042***	-0.055	-0.030	2,609,093
34	-0.042***	-0.055	-0.029	2,573,620
35	-0.041***	-0.054	-0.027	2,540,646
36	-0.045***	-0.059	-0.031	2,382,739
37	-0.041***	-0.055	-0.027	2,475,658
38	-0.037***	-0.050	-0.024	2,738,896
39	-0.036***	-0.049	-0.023	2,749,846
40	-0.024***	-0.036	-0.012	3,126,998
41	-0.020***	-0.033	-0.008	3,136,938
42	-0.017***	-0.029	-0.005	3,262,917

43	-0.012**	-0.024	0.000	3,286,464
44	-0.005	-0.016	0.007	3,810,511
45	-0.004	-0.015	0.008	4,209,584
46	-0.004	-0.015	0.008	4,100,381
47	-0.004	-0.016	0.007	3,987,082
48	-0.008	-0.020	0.004	4,059,112
49	-0.006	-0.018	0.006	4,108,827
50	-0.003	-0.015	0.009	4,257,985
51	-0.001	-0.013	0.011	4,169,070
52	0.002	-0.009	0.014	4,524,752
53	0.003	-0.009	0.015	4,332,130
54	0.002	-0.010	0.014	4,150,568
55	0.003	-0.010	0.016	3,613,354
56	0.008	-0.005	0.021	3,487,251
57	0.010	-0.003	0.024	3,341,374
58	0.011	-0.004	0.025	2,841,231
59	0.009	-0.007	0.025	2,039,025
60	0.006	-0.011	0.023	1,905,754
61	0.009	-0.008	0.026	1,808,809
62	0.007	-0.010	0.024	1,733,982
63	0.009	-0.008	0.026	1,828,102
64	0.010	-0.006	0.027	2,070,972
65	0.008	-0.009	0.026	1,810,804
66	0.010	-0.007	0.027	1,966,658
67	0.014	-0.003	0.032	1,901,963
68	0.021**	0.004	0.038	2,160,578
69	0.025***	0.008	0.043	1,914,770
70	0.029***	0.011	0.047	1,844,881
71	0.033***	0.013	0.052	1,562,855
72	0.035***	0.015	0.055	1,672,270
73	0.034***	0.013	0.054	1,596,240
74	0.032***	0.011	0.052	1,524,836
75	0.031***	0.011	0.052	1,451,857
76	0.026**	0.005	0.048	1,276,120
77	0.027**	0.006	0.048	1,294,503
78	0.028**	0.006	0.050	1,144,795
79	0.026**	0.004	0.047	1,111,920
80	0.026**	0.005	0.047	1,172,744
81	0.026**	0.005	0.048	1,144,952
82	0.019*	-0.003	0.041	1,061,181
83	0.020*	-0.003	0.043	983,573
84	0.028**	0.004	0.053	895,952
85	0.029**	0.003	0.054	792,896
86	0.034**	0.008	0.059	701,939
87	0.030**	0.004	0.056	628,246

88	0.028**	0.003	0.054	573,250
89	0.033**	0.006	0.060	463,443
90	0.032**	0.004	0.059	394,768
91	0.026*	-0.003	0.055	301,053
92	0.021	-0.006	0.048	319,092
93	0.016	-0.013	0.046	196,736
94	-0.001	-0.035	0.032	119,126
95	0.007	-0.039	0.053	55,763

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table S14. The Dynamic Effect of Higher Outpatient Cost-Sharing on Charlson Comorbidity Index.

Effect of greater outpatient cost-sharing on the total monthly use of outpatient services at the 5 MMW threshold using **intention-to-treat (ITT)** parameters. Dynamic regression discontinuity (RD) estimates by local linear regression with robust bias-corrected ‘optimal’ sample bandwidths; standard errors adjusted for heteroskedasticity and clustered at the individual level (Cellini et al., 2010; Enami et al., 2023; Fan & Gijbels, 1996; Hahn et al., 2001; Hsu & Shen, 2022).

Month lag	TOT Estimate	95% Confidence Interval		Subsample size
		Low	High	
0	-0.030***	-0.038	-0.023	4,734,313
1	-0.049***	-0.057	-0.041	4,603,188
2	-0.062***	-0.071	-0.053	4,571,560
3	-0.071***	-0.080	-0.062	4,559,124
4	-0.079***	-0.088	-0.070	4,523,511
5	-0.088***	-0.097	-0.078	4,569,420
6	-0.094***	-0.104	-0.084	4,312,248
7	-0.102***	-0.112	-0.091	4,386,098
8	-0.111***	-0.123	-0.100	4,317,294
9	-0.120***	-0.132	-0.109	4,356,314
10	-0.130***	-0.143	-0.117	4,381,733
11	-0.138***	-0.150	-0.125	4,363,541
12	-0.146***	-0.158	-0.134	4,220,127
13	-0.154***	-0.167	-0.140	4,048,662
14	-0.163***	-0.176	-0.150	3,950,449
15	-0.171***	-0.184	-0.158	4,118,948
16	-0.179***	-0.193	-0.165	4,017,904
17	-0.183***	-0.197	-0.170	4,151,781
18	-0.193***	-0.207	-0.178	4,022,381
19	-0.204***	-0.219	-0.189	3,982,679
20	-0.214***	-0.229	-0.199	3,986,178
21	-0.224***	-0.240	-0.209	3,898,349
22	-0.236***	-0.252	-0.220	3,706,076
23	-0.249***	-0.265	-0.232	3,523,263
24	-0.262***	-0.279	-0.246	3,577,980
25	-0.279***	-0.297	-0.261	3,083,514
26	-0.294***	-0.311	-0.277	3,099,506
27	-0.305***	-0.322	-0.287	3,090,896
28	-0.318***	-0.336	-0.300	2,799,234
29	-0.329***	-0.348	-0.311	2,690,269
30	-0.343***	-0.363	-0.324	2,631,004
31	-0.357***	-0.376	-0.337	2,585,355
32	-0.370***	-0.390	-0.350	2,534,132
33	-0.382***	-0.403	-0.361	2,609,093
34	-0.393***	-0.414	-0.372	2,573,620
35	-0.403***	-0.425	-0.382	2,540,646
36	-0.419***	-0.441	-0.397	2,382,739

37	-0.428***	-0.450	-0.406	2,475,658
38	-0.434***	-0.457	-0.411	2,738,896
39	-0.441***	-0.465	-0.417	2,749,846
40	-0.437***	-0.460	-0.414	3,126,998
41	-0.435***	-0.458	-0.412	3,136,938
42	-0.434***	-0.457	-0.410	3,262,917
43	-0.430***	-0.453	-0.407	3,286,464
44	-0.422***	-0.445	-0.399	3,810,511
45	-0.418***	-0.440	-0.395	4,209,584
46	-0.415***	-0.439	-0.391	4,100,381
47	-0.414***	-0.436	-0.391	3,987,082
48	-0.417***	-0.440	-0.394	4,059,112
49	-0.415***	-0.438	-0.392	4,108,827
50	-0.411***	-0.434	-0.388	4,257,985
51	-0.405***	-0.429	-0.381	4,169,070
52	-0.396***	-0.419	-0.373	4,524,752
53	-0.390***	-0.414	-0.366	4,332,130
54	-0.386***	-0.410	-0.361	4,150,568
55	-0.381***	-0.406	-0.356	3,613,354
56	-0.372***	-0.397	-0.348	3,487,251
57	-0.362***	-0.387	-0.338	3,341,374
58	-0.355***	-0.381	-0.328	2,841,231
59	-0.349***	-0.376	-0.322	2,039,025
60	-0.347***	-0.374	-0.319	1,905,754
61	-0.339***	-0.366	-0.311	1,808,809
62	-0.333***	-0.363	-0.303	1,733,982
63	-0.324***	-0.354	-0.295	1,828,102
64	-0.314***	-0.344	-0.285	2,070,972
65	-0.307***	-0.338	-0.276	1,810,804
66	-0.299***	-0.330	-0.268	1,966,658
67	-0.286***	-0.317	-0.255	1,901,963
68	-0.268***	-0.298	-0.238	2,160,578
69	-0.250***	-0.281	-0.219	1,914,770
70	-0.231***	-0.264	-0.199	1,844,881
71	-0.213***	-0.246	-0.179	1,562,855
72	-0.195***	-0.230	-0.161	1,672,270
73	-0.181***	-0.217	-0.146	1,596,240
74	-0.169***	-0.206	-0.133	1,524,836
75	-0.157***	-0.192	-0.121	1,451,857
76	-0.148***	-0.185	-0.112	1,276,120

77	-0.137***	-0.174	-0.101	1,294,503
78	-0.125***	-0.162	-0.088	1,144,795
79	-0.116***	-0.154	-0.078	1,111,920
80	-0.106***	-0.142	-0.069	1,172,744
81	-0.095***	-0.133	-0.057	1,144,952
82	-0.092***	-0.130	-0.053	1,061,181
83	-0.086***	-0.126	-0.046	983,573
84	-0.071***	-0.114	-0.029	895,952
85	-0.060***	-0.103	-0.018	792,896
86	-0.045**	-0.088	-0.001	701,939
87	-0.036*	-0.082	0.011	628,246
88	-0.027	-0.073	0.018	573,250
89	-0.014	-0.060	0.032	463,443
90	-0.004	-0.052	0.044	394,768
91	0.000	-0.050	0.051	301,053
92	0.002	-0.047	0.052	319,092
93	0.004	-0.047	0.055	196,736
94	-0.010	-0.062	0.043	119,126
95	-0.006	-0.070	0.058	55,763

Table S15. The Dynamic Effect of Higher Outpatient Cost-Sharing on Charlson Comorbidity Index.
Effect of greater outpatient cost-sharing on the total monthly use of outpatient services at the 5 MMW threshold using and **treatment-on-treated (TOT)** parameters. Dynamic regression discontinuity (RD) estimates by local linear regression with robust bias-corrected ‘optimal’ sample bandwidths; standard errors adjusted for heteroskedasticity and clustered at the individual level (Cellini et al., 2010; Enami et al., 2023; Fan & Gijbels, 1996; Hahn et al., 2001; Hsu & Shen, 2022).

Month lag	ITT Estimate	95% Confidence Interval		Subsample size
		Low	High	
0	-0.00131	-0.00415	0.00153	24,295,870
1	-0.00040	-0.00359	0.00279	18,654,768
2	-0.00136	-0.00428	0.00155	22,706,746
3	-0.00004	-0.00305	0.00297	22,111,204
4	-0.00288	-0.00637	0.00060	16,655,397
5	-0.00146	-0.00449	0.00157	22,764,789
6	-0.00008	-0.00351	0.00335	17,068,958
7	0.00063	-0.00295	0.00421	14,956,218
8	0.00239	-0.00080	0.00558	19,528,056
9	0.00356*	-0.00038	0.00750	12,984,509
10	0.00349*	-0.00040	0.00739	12,982,603
11	-0.00190	-0.00629	0.00249	10,940,435
12	0.00008	-0.00342	0.00358	17,058,173
13	0.00068	-0.00277	0.00413	17,215,819
14	0.00375*	-0.00027	0.00777	12,031,760
15	-0.00175	-0.00539	0.00190	15,733,561
16	-0.00054	-0.00446	0.00338	13,046,736
17	0.00039	-0.00323	0.00400	16,161,692
18	0.00023	-0.00338	0.00384	15,713,060
19	-0.00200	-0.00677	0.00277	8,835,614
20	-0.00037	-0.00408	0.00334	15,041,860
21	0.00103	-0.00279	0.00485	14,202,367
22	0.00156	-0.00237	0.00550	13,476,382
23	0.00449**	0.00026	0.00873	10,774,068
24	0.00292	-0.00112	0.00695	12,080,457
25	0.00437*	-0.00041	0.00915	8,720,900
26	0.00108	-0.00325	0.00541	11,197,624
27	0.00071	-0.00335	0.00477	11,941,233
28	0.00199	-0.00232	0.00629	10,606,086
29	0.00075	-0.00395	0.00546	8,327,364
30	-0.00031	-0.00442	0.00380	11,718,787
31	0.00200	-0.00322	0.00721	6,933,361
32	-0.00050	-0.00525	0.00425	8,235,085
33	-0.00375	-0.00888	0.00137	7,262,452
34	-0.00293	-0.00842	0.00256	6,507,056
35	0.00133	-0.00372	0.00638	7,891,158
36	-0.00382	-0.00938	0.00174	6,018,070
37	-0.00045	-0.00583	0.00493	6,650,239
38	0.00276	-0.00206	0.00759	8,557,411
39	-0.00486*	-0.00994	0.00022	7,619,955
40	-0.00154	-0.00716	0.00408	6,028,809
41	-0.00340	-0.01037	0.00357	4,326,581
42	-0.00412	-0.01003	0.00179	5,755,086

43	-0.00198	-0.00734	0.00338	6,376,797
44	0.00295	-0.00225	0.00815	7,499,545
45	0.00315	-0.00344	0.00975	4,230,093
46	0.00350	-0.00211	0.00911	6,070,363
47	0.00217	-0.00299	0.00733	7,351,273
48	0.00055	-0.00573	0.00682	5,032,708
49	0.00188	-0.00474	0.00851	4,005,349
50	0.00484*	-0.00084	0.01051	6,020,859
51	0.00463	-0.00177	0.01102	4,860,564
52	0.00180	-0.00393	0.00752	6,227,255
53	0.00324	-0.00367	0.01014	3,749,086
54	0.00035	-0.00574	0.00644	5,223,225
55	-0.00382	-0.01077	0.00313	3,432,882
56	0.00195	-0.00409	0.00799	4,995,868
57	-0.00122	-0.00793	0.00548	4,284,721
58	-0.00628	-0.01399	0.00144	3,049,440
59	-0.00352	-0.01119	0.00415	2,798,084
60	0.00055	-0.00611	0.00721	4,631,223
61	0.00019	-0.00733	0.00771	3,244,411
62	-0.00210	-0.00943	0.00524	3,179,369
63	0.00187	-0.00624	0.00998	2,761,294
64	0.00302	-0.00514	0.01118	3,007,003
65	0.01214**	0.00284	0.02144	2,083,529
66	0.01607***	0.00603	0.02611	2,151,584
67	0.00654	-0.00320	0.01627	2,005,702
68	0.00735	-0.00167	0.01637	2,513,698
69	0.00311	-0.00542	0.01164	2,574,404
70	0.01235**	0.00240	0.02229	1,323,774
71	0.00377	-0.00531	0.01286	1,945,506
72	0.00416	-0.00441	0.01274	2,437,397
73	0.00418	-0.00569	0.01406	1,909,851
74	0.00489	-0.00553	0.01531	1,961,566
75	0.00005	-0.01137	0.01147	1,372,103
76	0.00693	-0.00576	0.01962	1,537,476
77	-0.00462	-0.01480	0.00556	2,025,766
78	0.00364	-0.00829	0.01556	1,464,523
79	-0.00233	-0.01389	0.00922	1,381,627
80	0.00275	-0.01038	0.01587	1,039,372
81	-0.01228*	-0.02566	0.00109	940,823
82	0.00285	-0.01017	0.01588	1,001,894
83	-0.00081	-0.01361	0.01199	832,147
84	-0.00300	-0.01536	0.00936	1,127,518
85	-0.01027	-0.02394	0.00340	921,354
86	-0.00353	-0.01825	0.01119	870,756
87	0.00521	-0.00904	0.01946	846,056

88	-0.00041	-0.01541	0.01460	753,331
89	0.00015	-0.01558	0.01587	684,764
90	0.00610	-0.01455	0.02675	358,649
91	-0.00567	-0.03029	0.01896	259,548
92	-0.00008	-0.02582	0.02567	224,691
93	-0.00770	-0.03436	0.01895	197,153
94	-0.01248	-0.05820	0.03325	104,849
95	0.03341	-0.02860	0.09541	61,581

*** p<0.01, ** p<0.05, * p<0.1

Table S16. The Dynamic Effect of Higher Outpatient Cost-Sharing on the Probability of Hospitalization in the Intensive Care Unit.

Effect of greater outpatient cost-sharing on the total monthly use of outpatient services at the 5 MMW threshold using **intention-to-treat (ITT)** parameters. Dynamic regression discontinuity (RD) estimates by local linear regression with robust bias-corrected ‘optimal’ sample bandwidths; standard errors adjusted for heteroskedasticity and clustered at the individual level (Cellini et al., 2010; Enami et al., 2023; Fan & Gijbels, 1996; Hahn et al., 2001; Hsu & Shen, 2022).

Month lag	TOT Estimate	95% Confidence Interval		Subsample size
		Low	High	
0	-0.001	-0.00409	0.00147	24,295,870
1	-0.001	-0.00458	0.00231	18,654,768
2	-0.002	-0.00567	0.00147	22,706,746
3	-0.001	-0.00497	0.00219	22,111,204
4	-0.004**	-0.00785	-0.00009	16,655,397
5	-0.004**	-0.00820	0.00010	22,764,789
6	-0.003*	-0.00725	0.00134	17,068,958
7	-0.002	-0.00615	0.00246	14,956,218
8	0.000	-0.00407	0.00486	19,528,056
9	0.003	-0.00216	0.00784	12,984,509
10	0.004*	-0.00091	0.00952	12,982,603
11	0.000	-0.00555	0.00567	10,940,435
12	0.000	-0.00515	0.00515	17,058,173
13	0.001	-0.00436	0.00566	17,215,819
14	0.004*	-0.00167	0.00981	12,031,760
15	0.001	-0.00510	0.00632	15,733,561
16	0.000	-0.00579	0.00629	13,046,736
17	0.001	-0.00471	0.00703	16,161,692
18	0.001	-0.00464	0.00762	15,713,060
19	-0.001	-0.00725	0.00589	8,835,614
20	0.000	-0.00636	0.00607	15,041,860
21	0.001	-0.00506	0.00779	14,202,367
22	0.003	-0.00376	0.00894	13,476,382
23	0.006**	-0.00083	0.01294	10,774,068
24	0.007**	-0.00006	0.01351	12,080,457
25	0.009***	0.00150	0.01623	8,720,900
26	0.007**	-0.00019	0.01443	11,197,624
27	0.006**	-0.00101	0.01352	11,941,233
28	0.007**	-0.00028	0.01512	10,606,086
29	0.007**	-0.00094	0.01495	8,327,364
30	0.006*	-0.00180	0.01355	11,718,787
31	0.008**	-0.00059	0.01666	6,933,361
32	0.007*	-0.00142	0.01543	8,235,085
33	0.004	-0.00513	0.01213	7,262,452
34	0.002	-0.00640	0.01076	6,507,056
35	0.005	-0.00316	0.01385	7,891,158
36	0.001	-0.00779	0.01074	6,018,070

37	0.003	-0.00646	0.01188	6,650,239
38	0.006*	-0.00275	0.01544	8,557,411
39	0.001	-0.00859	0.00960	7,619,955
40	0.001	-0.00862	0.01012	6,028,809
41	-0.002	-0.01220	0.00897	4,326,581
42	-0.004	-0.01426	0.00672	5,755,086
43	-0.003	-0.01354	0.00676	6,376,797
44	0.002	-0.00862	0.01164	7,499,545
45	0.004	-0.00734	0.01571	4,230,093
46	0.006	-0.00418	0.01662	6,070,363
47	0.006	-0.00411	0.01610	7,351,273
48	0.005	-0.00575	0.01514	5,032,708
49	0.006	-0.00543	0.01734	4,005,349
50	0.009*	-0.00202	0.02056	6,020,859
51	0.011**	-0.00103	0.02256	4,860,564
52	0.010*	-0.00224	0.02135	6,227,255
53	0.011**	-0.00129	0.02342	3,749,086
54	0.009*	-0.00266	0.02133	5,223,225
55	0.005	-0.00755	0.01725	3,432,882
56	0.008*	-0.00389	0.02013	4,995,868
57	0.006	-0.00584	0.01863	4,284,721
58	0.000	-0.01232	0.01303	3,049,440
59	0.000	-0.01343	0.01266	2,798,084
60	0.003	-0.01030	0.01545	4,631,223
61	0.004	-0.00969	0.01701	3,244,411
62	0.002	-0.01153	0.01550	3,179,369
63	0.004	-0.00935	0.01790	2,761,294
64	0.006	-0.00763	0.02051	3,007,003
65	0.017**	0.00177	0.03193	2,083,529
66	0.027***	0.01067	0.04244	2,151,584
67	0.024***	0.00738	0.03983	2,005,702
68	0.025***	0.00900	0.04102	2,513,698
69	0.023***	0.00732	0.03781	2,574,404
70	0.032***	0.01524	0.04802	1,323,774
71	0.029***	0.01284	0.04518	1,945,506
72	0.029***	0.01270	0.04547	2,437,397
73	0.030***	0.01282	0.04739	1,909,851
74	0.033***	0.01536	0.05017	1,961,566
75	0.030***	0.01097	0.04910	1,372,103
76	0.036***	0.01568	0.05596	1,537,476

77	0.028***	0.00806	0.04744	2,025,766
78	0.032***	0.01129	0.05235	1,464,523
79	0.028***	0.00679	0.04847	1,381,627
80	0.031***	0.00868	0.05368	1,039,372
81	0.018*	-0.00475	0.03976	940,823
82	0.025**	0.00335	0.04670	1,001,894
83	0.025**	0.00121	0.04830	832,147
84	0.023**	-0.00002	0.04539	1,127,518
85	0.014	-0.01070	0.03817	921,354
86	0.015	-0.00977	0.04039	870,756
87	0.024**	-0.00113	0.04856	846,056
88	0.023**	-0.00406	0.04931	753,331
89	0.022*	-0.00581	0.04996	684,764
90	0.028**	-0.00159	0.05847	358,649
91	0.020	-0.01726	0.05709	259,548
92	0.021	-0.01576	0.05792	224,691
93	0.013	-0.02653	0.05278	197,153
94	0.004	-0.04785	0.05609	104,849
95	0.044	-0.02698	0.11508	61,581

Table S17. The Dynamic Effect of Higher Outpatient Cost-Sharing on the Probability of Hospitalization in the Intensive Care Unit.
Effect of greater outpatient cost-sharing on the total monthly use of outpatient services at the 5 MMW threshold using and **treatment-on-treated (TOT)** parameters. Dynamic regression discontinuity (RD) estimates by local linear regression with robust bias-corrected 'optimal' sample bandwidths; standard errors adjusted for heteroskedasticity and clustered at the individual level (Cellini et al., 2010; Enami et al., 2023; Fan & Gijbels, 1996; Hahn et al., 2001; Hsu & Shen, 2022).

Month lag	ITT Estimate	95% Confidence Interval		Subsample size
		Low	High	
0	-0.00002	-0.00021	0.00017	15,517,817
1	-0.00001	-0.00020	0.00017	15,775,454
2	-0.00005	-0.00025	0.00015	14,010,269
3	-0.00016	-0.00035	0.00004	13,668,584
4	0.00000	-0.00021	0.00021	13,187,564
5	-0.00008	-0.00030	0.00013	13,191,822
6	-0.00001	-0.00023	0.00021	12,204,886
7	0.00005	-0.00017	0.00027	12,914,795
8	-0.00010	-0.00030	0.00011	15,367,812
9	0.00007	-0.00017	0.00030	11,766,919
10	0.00005	-0.00020	0.00029	10,862,076
11	0.00012	-0.00012	0.00036	11,690,479
12	-0.00027*	-0.00055	0.00001	7,524,454
13	0.00014	-0.00010	0.00038	10,114,228
14	-0.00001	-0.00026	0.00025	8,493,889
15	0.00001	-0.00023	0.00026	9,604,226
16	-0.00016	-0.00041	0.00010	8,413,137
17	-0.00026*	-0.00053	0.00001	6,488,838
18	0.00004	-0.00019	0.00028	9,436,076
19	-0.00018	-0.00041	0.00005	10,746,739
20	-0.00004	-0.00031	0.00022	8,693,957
21	0.00001	-0.00026	0.00028	8,060,841
22	-0.00010	-0.00036	0.00016	8,559,594
23	-0.00007	-0.00035	0.00021	7,276,440
24	-0.00014	-0.00040	0.00011	8,463,721
25	0.00003	-0.00024	0.00030	6,848,297
26	-0.00011	-0.00037	0.00014	7,801,218
27	-0.00007	-0.00031	0.00018	8,587,600
28	-0.00010	-0.00037	0.00017	7,246,377
29	-0.00001	-0.00028	0.00026	6,954,030
30	-0.00009	-0.00037	0.00019	7,094,726
31	0.00001	-0.00028	0.00029	6,674,648
32	-0.00001	-0.00031	0.00029	7,161,452
33	0.00004	-0.00027	0.00035	7,799,462
34	-0.00013	-0.00047	0.00020	8,017,364
35	0.00007	-0.00026	0.00040	7,733,608
36	0.00001	-0.00031	0.00033	7,114,110
37	-0.00002	-0.00031	0.00027	8,204,577
38	0.00009	-0.00018	0.00036	9,609,592

39	-0.00010	-0.00047	0.00028	5,713,882
40	-0.00017	-0.00055	0.00020	6,621,611
41	-0.00051**	-0.00091	-0.00010	4,555,463
42	-0.00017	-0.00052	0.00019	6,271,278
43	0.00004	-0.00030	0.00039	6,523,481
44	-0.00017	-0.00049	0.00015	5,473,514
45	-0.00012	-0.00046	0.00022	4,755,915
46	0.00017	-0.00018	0.00052	4,418,532
47	0.00018	-0.00014	0.00050	5,257,954
48	0.00002	-0.00032	0.00036	4,957,939
49	0.00000	-0.00036	0.00036	4,131,628
50	0.00013	-0.00021	0.00047	4,378,574
51	0.00017	-0.00018	0.00051	4,491,104
52	-0.00004	-0.00042	0.00034	3,569,423
53	0.00008	-0.00031	0.00047	3,419,464
54	-0.00003	-0.00039	0.00033	4,076,003
55	0.00011	-0.00023	0.00046	5,462,737
56	0.00018	-0.00018	0.00054	5,072,091
57	0.00002	-0.00038	0.00041	3,887,847
58	0.00026	-0.00016	0.00067	2,854,783
59	0.00020	-0.00021	0.00061	2,778,303
60	-0.00002	-0.00046	0.00042	2,956,783
61	0.00049**	0.00000	0.00098	2,304,377
62	0.00001	-0.00039	0.00041	3,526,576
63	0.00040	-0.00011	0.00091	2,078,095
64	0.00026	-0.00011	0.00064	3,880,636
65	0.00032	-0.00015	0.00078	2,337,657
66	0.00039	-0.00008	0.00085	2,389,611
67	0.00047**	0.00007	0.00087	3,280,811
68	0.00015	-0.00027	0.00057	2,957,213
69	0.00031	-0.00016	0.00078	2,370,929
70	0.00012	-0.00036	0.00061	1,884,473
71	0.00024	-0.00025	0.00072	1,903,014
72	0.00075***	0.00021	0.00129	1,590,614
73	0.00019	-0.00030	0.00067	2,070,078
74	0.00024	-0.00025	0.00072	2,110,902
75	0.00022	-0.00031	0.00075	1,870,487
76	0.00013	-0.00041	0.00066	1,846,767
77	-0.00046	-0.00106	0.00014	1,528,483
78	0.00000	-0.00049	0.00049	2,215,760
79	-0.00048	-0.00113	0.00017	1,226,122

80	-0.00011	-0.00073	0.00051	1,205,718
81	-0.00067*	-0.00135	0.00002	1,097,562
82	-0.00016	-0.00076	0.00045	1,084,915
83	-0.00055*	-0.00115	0.00005	1,002,636
84	-0.00018	-0.00083	0.00048	1,027,889
85	-0.00031	-0.00104	0.00042	668,249
86	0.00010	-0.00064	0.00084	753,192
87	-0.00017	-0.00091	0.00057	818,858
88	-0.00041	-0.00119	0.00038	789,034
89	-0.00063	-0.00154	0.00029	504,261
90	-0.00071	-0.00164	0.00022	441,507
91	-0.00039	-0.00153	0.00074	269,002
92	-0.00002	-0.00127	0.00124	216,343
93	0.00037	-0.00108	0.00182	218,110
94	-0.00025	-0.00185	0.00135	175,105
95	-0.00079	-0.00335	0.00178	67,705

*** p<0.01, ** p<0.05, * p<0.1

Table S18. The Dynamic Effect of Higher Outpatient Cost-Sharing on Number of General Hospitalizations.

Effect of greater outpatient cost-sharing on the total monthly use of outpatient services at the 5 MMW threshold using **intention-to-treat (ITT)** parameters. Dynamic regression discontinuity (RD) estimates by local linear regression with robust bias-corrected 'optimal' sample bandwidths; standard errors adjusted for heteroskedasticity and clustered at the individual level (Cellini et al., 2010; Enami et al., 2023; Fan & Gijbels, 1996; Hahn et al., 2001; Hsu & Shen, 2022).

Month lag	TOT Estimate	95% Confidence Interval		Subsample size
		Low	High	
0	-0.00002	-0.00021	0.00017	15,517,817
1	-0.00002	-0.00024	0.00020	15,775,454
2	-0.00006	-0.00030	0.00017	14,010,269
3	-0.00020*	-0.00044	0.00005	13,668,584
4	-0.00012	-0.00038	0.00015	13,187,564
5	-0.00017	-0.00045	0.00011	13,191,822
6	-0.00013	-0.00041	0.00014	12,204,886
7	-0.00006	-0.00035	0.00023	12,914,795
8	-0.00017	-0.00047	0.00013	15,367,812
9	-0.00006	-0.00038	0.00025	11,766,919
10	-0.00004	-0.00038	0.00031	10,862,076
11	0.00005	-0.00029	0.00039	11,690,479
12	-0.00028*	-0.00068	0.00011	7,524,454
13	-0.00006	-0.00044	0.00033	10,114,228
14	-0.00009	-0.00049	0.00032	8,493,889
15	-0.00007	-0.00046	0.00031	9,604,226
16	-0.00024	-0.00063	0.00015	8,413,137
17	-0.00043**	-0.00086	-0.00001	6,488,838
18	-0.00024	-0.00067	0.00018	9,436,076
19	-0.00039**	-0.00081	0.00004	10,746,739
20	-0.00035*	-0.00079	0.00010	8,693,957
21	-0.00028	-0.00073	0.00018	8,060,841
22	-0.00037*	-0.00081	0.00008	8,559,594
23	-0.00039*	-0.00086	0.00008	7,276,440
24	-0.00049**	-0.00096	-0.00003	8,463,721
25	-0.00038*	-0.00086	0.00011	6,848,297
26	-0.00048**	-0.00097	0.00000	7,801,218
27	-0.00051**	-0.00098	-0.00003	8,587,600
28	-0.00055**	-0.00105	-0.00004	7,246,377
29	-0.00049**	-0.00102	0.00003	6,954,030
30	-0.00055**	-0.00109	-0.00001	7,094,726
31	-0.00050**	-0.00104	0.00004	6,674,648
32	-0.00048**	-0.00101	0.00005	7,161,452
33	-0.00042*	-0.00101	0.00016	7,799,462
34	-0.00058**	-0.00118	0.00002	8,017,364
35	-0.00045*	-0.00105	0.00015	7,733,608
36	-0.00046*	-0.00108	0.00017	7,114,110

37	-0.00047*	-0.00106	0.00011	8,204,577
38	-0.00039*	-0.00095	0.00017	9,609,592
39	-0.00051**	-0.00111	0.00008	5,713,882
40	-0.00067**	-0.00131	-0.00002	6,621,611
41	-0.00107***	-0.00175	-0.00040	4,555,463
42	-0.00099***	-0.00162	-0.00037	6,271,278
43	-0.00077**	-0.00142	-0.00012	6,523,481
44	-0.00089***	-0.00153	-0.00025	5,473,514
45	-0.00090***	-0.00156	-0.00024	4,755,915
46	-0.00064**	-0.00133	0.00005	4,418,532
47	-0.00051*	-0.00119	0.00017	5,257,954
48	-0.00061**	-0.00130	0.00009	4,957,939
49	-0.00065**	-0.00136	0.00006	4,131,628
50	-0.00052*	-0.00122	0.00018	4,378,574
51	-0.00044	-0.00116	0.00028	4,491,104
52	-0.00058*	-0.00132	0.00016	3,569,423
53	-0.00051*	-0.00128	0.00026	3,419,464
54	-0.00055*	-0.00130	0.00019	4,076,003
55	-0.00041	-0.00116	0.00034	5,462,737
56	-0.00028	-0.00104	0.00047	5,072,091
57	-0.00033	-0.00107	0.00042	3,887,847
58	-0.00012	-0.00091	0.00068	2,854,783
59	-0.00004	-0.00083	0.00075	2,778,303
60	-0.00021	-0.00104	0.00061	2,956,783
61	0.00027	-0.00058	0.00111	2,304,377
62	0.00005	-0.00078	0.00087	3,526,576
63	0.00034	-0.00049	0.00118	2,078,095
64	0.00039	-0.00042	0.00120	3,880,636
65	0.00051	-0.00036	0.00137	2,337,657
66	0.00070*	-0.00018	0.00158	2,389,611
67	0.00094**	0.00007	0.00181	3,280,811
68	0.00081**	-0.00004	0.00166	2,957,213
69	0.00096**	0.00009	0.00184	2,370,929
70	0.00091**	0.00002	0.00180	1,884,473
71	0.00102**	0.00011	0.00192	1,903,014
72	0.00161***	0.00063	0.00259	1,590,614
73	0.00144***	0.00050	0.00239	2,070,078
74	0.00147***	0.00053	0.00241	2,110,902
75	0.00151***	0.00050	0.00253	1,870,487
76	0.00146***	0.00042	0.00249	1,846,767

77	0.00089*	-0.00017	0.00195	1,528,483
78	0.00106**	0.00004	0.00207	2,215,760
79	0.00066	-0.00044	0.00176	1,226,122
80	0.00078*	-0.00026	0.00183	1,205,718
81	0.00027	-0.00090	0.00144	1,097,562
82	0.00047	-0.00071	0.00165	1,084,915
83	0.00014	-0.00103	0.00130	1,002,636
84	0.00026	-0.00095	0.00148	1,027,889
85	0.00013	-0.00115	0.00141	668,249
86	0.00045	-0.00089	0.00179	753,192
87	0.00029	-0.00104	0.00162	818,858
88	-0.00008	-0.00144	0.00129	789,034
89	-0.00054	-0.00214	0.00106	504,261
90	-0.00087	-0.00245	0.00072	441,507
91	-0.00082	-0.00256	0.00093	269,002
92	-0.00051	-0.00232	0.00129	216,343
93	-0.00002	-0.00198	0.00195	218,110
94	-0.00039	-0.00259	0.00181	175,105
95	-0.00112	-0.00397	0.00172	67,705

Table S19. The Dynamic Effect of Higher Outpatient Cost-Sharing on Number of General Hospitalizations.

Effect of greater outpatient cost-sharing on the total monthly use of outpatient services at the 5 MMW threshold using and **treatment-on-treated (TOT)** parameters. Dynamic regression discontinuity (RD) estimates by local linear regression with robust bias-corrected ‘optimal’ sample bandwidths; standard errors adjusted for heteroskedasticity and clustered at the individual level (Cellini et al., 2010; Enami et al., 2023; Fan & Gijbels, 1996; Hahn et al., 2001; Hsu & Shen, 2022).

Restriction in the Sample	>1 Month	>6 Months	>12 Months	>18 Months
Hazard Ratio	1.099**	1.104**	1.133**	1.176**
	(0.0485)	(0.0551)	(0.0665)	(0.0799)
Number of Observations	14,717,423	13,207,346	11,298,888	9,494,674
8-year Mortality Risk Below Threshold (per 10000)	52.90	50.18	47.50	43.96
8-year Mortality Risk Above Threshold (per 10000)	53.75	52.31	52.17	52.05
Absolute Difference of Mortality Risk (per 10000)	0.85	2.13	4.67	8.09

Robust Standard Error Form in Parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table S20. Cumulative Effect of Higher Outpatient Cost-Sharing on Survival of Varying Durations. Hazard ratio estimates for the cumulative effect of higher outpatient cost-sharing on mortality risk at the 5 MMW threshold using a parametric Weibull model adjusted by covariates (age, sex, region, and public insurer) and a bandwidth of 0.5 monthly minimum wages (MMWs) among individuals remaining within the 0.5 MMW bandwidth for at least 1, 6, 12 and 18 months.