The Effects of Deleting Medical Debt from Consumer Credit Reports*

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Abstract

One in seven Americans carry medical debt, with $88 billion reported on consumer credit reports. In April 2023, the three major credit bureaus stopped reporting medical debts below $500. We study the effects of this information deletion on consumer credit scores, credit limits and utilization, repayment behavior, and payday borrowing. Contrary to expectations that removing this negative credit information would improve credit access for affected individuals, we find no evidence of benefits. Regression discontinuity estimates comparing individuals just above and below the $500 threshold rule out even small effects. To help interpret these findings, we build credit scoring models using machine learning techniques and show that small medical debts are not meaningfully predictive of defaults, indicating that they contribute little to credit risk assessment. Finally, we show that larger medical debts ($\geq$ $500) are also not meaningfully predictive of default, suggesting that eliminating medical debts entirely from credit reports, as planned under a January 2025 decision by the Consumer Financial Protection Bureau, is unlikely to affect credit outcomes.

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1 Introduction

One in seven Americans carry medical debt (U.S. Census Bureau, 2022). Unpaid medical bills are often sent to collection agencies and subsequently reported to credit bureaus, resulting in $88 billion in medical debt appearing on consumer credit reports as of 2021 (Consumer Financial Protection Bureau, 2022). Policymakers have raised growing concerns that making medical debt visible to lenders could impair access to credit following unexpected medical shocks. In response, the three major U.S. credit bureaus announced in April 2023 that they were no longer including medical debt collections below $500 in credit reports. Building on this change, the Consumer Financial Protection Bureau (CFPB) issued a final rule in January 2025 to eliminate all remaining medical debt collections from credit reports.

Basic economic theory suggests that removing negative credit information should improve credit access for affected individuals. However, medical debt may be a poor signal of credit risk. These debts are often inaccurate—frequently reflecting bills that were already paid or should have been covered by insurance—and are seldom repaid in full (Consumer Financial Protection Bureau, 2023). They are typically sold at steep discounts on secondary markets and may offer limited value for predicting default risk (Consumer Financial Protection Bureau, 2024). As a result, it remains unclear whether removing medical debt information from credit reports should impact lending decisions.

This paper uses a regression discontinuity design to estimate the effects of deleting medical debt collections from credit reports on credit access and financial health. Our empirical strategy exploits the $500 threshold introduced by the April 2023 policy change, comparing individuals whose medical debts were just above or below the reporting cutoff prior to deletion. Using 2019–2024 data from the Gies Consumer and Small Business Credit Panel (GCCP), we find no evidence that removing these debts affected credit scores, credit limits or utilization, repayment behavior, payday borrowing, or other related outcomes. Our null estimates are precise: the 95% confidence intervals rule out increases in credit scores greater than 6.03 points (0.97%) and decreases in the balance-to-limit ratio of revolving credit exceeding 1.54 percentage points (4.80%).

To help interpret these findings, we build credit scoring models using machine learning

techniques and evaluate whether small medical debt collections helped predict default risk prior to 2023. We compare two models: one trained on borrower credit histories that include medical debts below $500, and another trained on histories excluding these small medical debts. We find no meaningful difference in predictive accuracy between the models, indicating that small medical debts contribute little to risk assessment. Furthermore, we show that larger medical debts ($\geq$ $500) are similarly uninformative, suggesting that eliminating all medical debts from credit reports would also have little effect on lending decisions.

Finally, we use a difference-in-differences approach to estimate the indirect effects of removing small medical debt collections from credit reports on consumers who, as a result, are reclassified as higher default risk. Using our two credit scoring models—one incorporating medical debts below $500 and the other excluding them—we identify two groups: consumers whose predicted probability of default increases by at least 2 percentage points (the 95th percentile of the distribution) when medical debts are removed from the model, and those whose predicted probability falls by at least 2 percentage points. We show that these two groups are observationally similar across key characteristics and exhibited parallel trends prior to the 2023 information deletion.[1] Consistent with our RD results, we find no evidence of negative spillover effects from deleting small medical debts, with precise estimates that again rule out small effects.

Overall, we conclude that the 2023 decision to delete small medical debt collections from credit reports produced no measurable benefits for affected consumers and no harms to others reclassified as higher risk. Our findings suggest that information deletion is an inadequate solution for those burdened by medical debt, underscoring the need for alternative policies that address its underlying causes.

We make several contributions to the literature. First, we investigate the effects of information deletion in a novel context: medical debt. Liberman et al. (2019) study the deletion of credit default information in Chile and, like us, use credit scoring models to assess how changes in predicted probabilities affect credit access. They find that deletion increases bor-

[1]Both groups consist primarily of low-income consumers with thin credit files. As shown in the main text, when reliable information is scarce, even random noise can influence default predictions. Thus, an uninformative predictor like medical debt serves as a noisy partitioning mechanism, effectively creating two randomly assigned groups.

rowing for consumers whose predicted default risk declines, but reduces borrowing for those reclassified as higher-risk. Similarly, Jansen et al. (2024) find that removing bankruptcy flags lowers interest rates for affected consumers while raising them for those with no history of bankruptcy, resulting in a small decline in social surplus.[2] Beyond credit markets, Agan and Starr (2017) find that removing criminal history information from job applications reduces callbacks for Black applicants, and Bartik and Nelson (2024) show that bans on employers' use of credit reports lower job-finding rates and increase involuntary separations for Black workers. Unlike these studies, we show that the deleted information in our setting—small medical debts—has minimal predictive value. As a result, we find neither direct benefits for affected consumers nor indirect harms to others. A unique feature of our setting is the presence of a cutoff value for information deletion, which allows us to estimate direct effects using a rigorous RD design.

Second, we contribute to the literature on medical debt forgiveness, a policy often discussed alongside information deletion. Kluender et al. (2024) conduct two large-scale randomized experiments and find that forgiveness modestly improves credit access for consumers whose medical debts were reported to credit bureaus, but has no effect for others.[3] Their results suggest that whether a debt appears on a credit report plays a key role in determining the impact of debt relief. However, our analysis—which focuses specifically on medical debts that were reported—fails to detect any meaningful effects on credit access. Taken together, these findings suggest that neither deleting medical debt information from credit reports nor forgiving the debt itself alleviates financial distress. These results contrast with evidence from other debt relief contexts, which generally show positive results (Dobbie and Song, 2015; Di Maggio et al., 2020; Cespedes et al., 2025).

Third, we advance the literature on machine learning in credit markets. We are the first to demonstrate that medical debt collections are poor predictors of default risk.[4] However, we

[2]For studies examining the direct (but not indirect) effects of removing bankruptcy flags and other unpaid debts from credit reports, see Musto (2004), Bos et al. (2018), Dobbie et al. (2020), Gross et al. (2020), and Herkenhoff et al. (2021).

[3]Kluender et al. (2024) find no effect of debt relief on credit scores or credit limits in their two main experiments ($N = 12,998$ and $N = 65,968$ treated). In a smaller credit reporting subexperiment ($N = 1,423$ treated), they do detect effects, concentrated among the subset of consumers with no other debts in collections ($N = 234$).

[4]Brevoort and Kambara (2014) show that medical debt collections are less predictive of future credit

also show that even unreliable information like medical debt can still influence credit scores, particularly for consumers with thin credit files—a phenomenon previously documented by Blattner and Nelson (2022). Prior studies have used machine learning to study information deletion (Liberman et al., 2019) and to develop credit scoring models (e.g. Khandani et al., 2010; Frost et al., 2020; Sadhwani et al., 2020; Fuster et al., 2022; Meursault et al., 2022; Agarwal et al., 2023; Blattner et al., 2024; Chioda et al., 2024). Building on this body of work, we construct a credit scoring model using XGBoost, a state-of-the-art prediction algorithm, and achieve substantially better performance than prior studies across multiple metrics.

Finally, we contribute to a growing literature on debts in collections and the debt collection industry (e.g. Fedaseyeu and Hunt, 2018; Fedaseyeu, 2020; Cheng et al., 2020; Kluender et al., 2021; Batty et al., 2022; Guttman-Kenney et al., 2022; Keys et al., 2022; Fonseca, 2023; Lin, 2024). The study most closely related to ours is Batty et al. (2022), who show that expanding health insurance coverage reduces medical debts in collection but does not improve other financial outcomes. Like Fonseca (2023), we study both mainstream and subprime credit outcomes by linking traditional credit reports from a major credit bureau to reports from a bureau specializing in alternative financial services. This linkage provides a more comprehensive set of credit market outcomes, particularly for consumers with limited access to traditional credit.

The remainder of this paper is structured as follows. Section 2 describes the data used in our analysis. Section 3 presents RD estimates of the direct effects of deleting medical debt collections. Section 4 investigates whether medical debt is predictive of default. Section 5 concludes.

performance than non-medical debt collections, but do not directly quantify the predictive power of medical debt.

2 Background and Data

2.1 Background

Medical debt arises when patients are unable to pay the out-of-pocket portions of their medical bills. Typically, healthcare providers first attempt to recover unpaid amounts directly from patients. If these efforts fail, they may enlist third-party collection agencies, which use a variety of tactics to recover payment, include filing lawsuits to obtain court judgments and reporting unpaid debts to credit bureaus.[5] In some cases, medical debts are sold to debt buyers, who assume responsibility for future collection efforts.

There are three major consumer reporting agencies in the United States: Equifax, Experian, and TransUnion. On March 18, 2022, these agencies jointly announced a series of changes to the treatment of medical debt on credit reports. Effective July 1, 2022, paid medical debts in collection would no longer appear on consumer credit files. In addition, the waiting period before unpaid medical debt could be reported was extended from six months to one year, providing consumers more time to resolve billing disputes or secure insurance coverage.

As part of that same announcement, the bureaus also committed to removing all medical collection debts with an initial reported balance under $500 by the "first half of 2023" (Business Wire, 2022). On April 11, 2023, the agencies confirmed that these small medical debts had been removed from consumer credit reports. Although the exact timing of the deletions is uncertain, Quinn (2023) reports that they occurred in March and April 2023. In addition to making this information unavailable to lenders, the policy also reduced the leverage of debt collectors, who could no longer use credit reporting as a threat during collection.[6]

The consequences of medical debt are complex and challenging to quantify, in part because payment rates are exceedingly low—medical debt can be purchased for pennies on the dollar (Kluender et al., 2024). This contrasts sharply with other forms of unsecured debt,

[5] While hospitals can report unpaid medical bills directly to credit bureaus, this practice is uncommon (Brevoort and Kambara, 2014).

[6] The Fair Debt Collection Practices Act prohibits abusive or deceptive practices by third-party debt collectors.

such as student loans and credit card debt. Unlike medical debt, student loans are not easily dischargeable in bankruptcy; eliminating them typically requires proving "undue hardship," a demanding legal standard. Credit card debt also has much higher repayment rates, as issuers can threaten to restrict future access to credit for delinquent borrowers. Additionally, many states provide consumer protections specific to medical debt, including limits on wage garnishment and prohibitions on home foreclosure (Robertson et al., 2022).

Media discussions frequently highlight the relationship between medical debt and personal bankruptcies. While many bankruptcy filers do carry medical debt, this correlation does not necessarily imply causation. To assess causality, Dobkin et al. (2018) examine the impact of hospitalizations on the likelihood of filing for bankruptcy within four years of admission. They find that hospitalizations account for approximately 4 percent of personal bankruptcies among non-elderly adults and about 6 percent among uninsured non-elderly adults. These results suggest that medical debt may be a helpful predictor of future defaults. However, whether it provides predictive value beyond other credit variables remains an open question.

2.2 Data

Our study uses the Gies Consumer and Small Business Credit Panel (GCCP), a panel dataset of anonymized credit record data for consumers and small businesses, obtained from a major credit bureau. The GCCP features a one-percent random sample of individuals with a credit report, linked to alternative credit records and business credit records for individuals who own a business.[7] The dataset covers the years 2004–2024, with annual snapshots of credit records taken at the end of the first quarter of each year. Consumers are randomly sampled based on the last two digits of their Social Security numbers. This sampling method accounts for natural flows into the panel as new Social Security numbers are issued, as well as outflows due to death or prolonged inactivity, ensuring that the sample remains representative of the broader population over time.

[7] Alternative credit records include information not reported to the major credit bureaus, such as payday loans and title loans. See Fonseca (2023) and Correia et al. (2023) for a discussion of the link between mainstream and alternative credit records in the GCCP, Fonseca and Wang (2023) on the link between consumer and business credit records, and Fonseca and Liu (2024), Howard and Shao (2022), and Fonseca et al. (2024) for other papers using the GCCP.

The GCCP provides detailed debt information at the credit account ("tradeline") level, including outstanding balances and payment histories for mortgages, car loans, student loans, and credit cards. It also includes individuals' VantageScore credit scores, public records such as bankruptcies and judgments, debt in collections, and demographic variables such as age, gender, and 5-digit zip code. We classify a collection as medical debt if the associated creditor is labeled as Medical/Health Care or if the furnisher is identified as a business operating in the medical or health-related sector.[8] As shown in Table A.2, this classification produces estimates of medical debt prevalence that closely align with those from two external benchmarks.

We restrict the sample to the years 2019–2024 and to consumers aged 18 or older. We exclude people with missing data on age, credit score, or income, as well as those whose reported age increases by 10 years or more within a 12-month period. The final sample includes 15,313,700 observations, summarized in Table 1. The first three columns present statistics for the full sample: about half is female, the average credit score is 702, average annual income is $51,960, and the average total balance across all credit products is $76,460. Approximately 20 percent of consumers have an alternative credit record, and the average number of medical collections is 0.25.

The next three columns of Table 1 present statistics for individuals with at least one medical debt collection listed on their credit report. This group has, on average, lower credit scores, lower income, and lower balances compared to the full sample. They are also more likely to have subprime credit records. On average, they have 2.44 medical debt collections, of which 1.45 are for amounts below $500.

Figure 1 shows the share of consumers with medical debt collections from 2019 to 2024, which declines from roughly 16 percent to 4 percent over this period. The drop is largely driven by a sharp reduction in medical debts under $500, which fall from 10 percent in 2022 to zero by 2024—reflecting the credit bureaus' decision to stop reporting small medical debts. As noted earlier, the GCCP snapshots are taken at the end of March each year. The marked decline in small medical debts visible in the 2023 data suggests that much of the

[8]Furnisher categories include Dentists, Chiropractors, Doctors, Medical group, Hospitals and clinics, Osteopaths, Pharmacies and drugstore, Optometrists and optical outlets, and Medical and related health-nonspecific.

removal occurred prior to the official April 11, 2023 announcement, consistent with reports that deletions were implemented in both March and April.

2.3 Regression discontinuity sample

For our RD analysis, we further restrict the sample to consumers with at least one medical debt collection in 2022 and a non-missing credit score between 2022 and 2024. The resulting sample includes 271,305 consumers, totaling 813,915 observations across the three years. Table 2 presents summary statistics for this sample as of 2022, the year prior to the deletion of medical collections under $500 from credit reports. On average, these consumers had 3.53 debts in collections, including 1.56 small medical debts below $500.

3 Main Results: Regression Discontinuity

3.1 Empirical strategy

We employ an RD design to identify the direct effect of medical debt deletion on consumer credit outcomes. We first estimate the following first-stage model at the account level:

$$Y_{ij}^{2024} = \alpha_1 \text{DEBT}_{ij}^{2022} + \beta_1 \text{ABOVE}_{ij}^{2022} + \gamma_1 (\text{ABOVE}_{ij}^{2022} \times \text{DEBT}_{ij}^{2022}) + \epsilon_{ij} \tag{1}$$

The dependent variable, Y_{ij}^{2024}, represents an outcome in 2024 for account j belonging to consumer i. The running variable, DEBT_{ij}^{2022}, is defined as the account's balance relative to the $500 cutoff in 2022, the year prior to the deletion of small medical debt collections. The indicator variable ABOVE_{ij}^{2022} is equal to one if $\text{DEBT}_{ij}^{2022} \geq 0$. We approximate the conditional expectation function with a local linear regression, allowing the slope to vary on either side of the cutoff.[9]

Our second-stage outcomes are measured at the consumer level. We therefore aggregate the running variable by taking the maximum debt amount across all the consumer's accounts.

[9]Colorado and New York banned reporting of all medical debt collections from credit reports in August and December of 2023, respectively. Our first-stage regression discontinuity estimates remain robust when we exclude these states.

We then estimate the following model at the consumer level:

$$Y_i^{2024} = \alpha \text{MAXDEBT}_i^{2022} + \beta \text{ABOVE}_i^{2022} + \gamma(\text{ABOVE}_i^{2022} \times \text{MAXDEBT}_i^{2022}) + \epsilon_i \quad (2)$$

The running variable, MAXDEBT_i^{2022}, is defined as the largest medical debt for consumer i, relative to the \$500 cutoff, i.e., $\text{MAXDEBT}_i^{2022} = \max_j\{\text{DEBT}_{ij}^{2022}\}$, where j indexes consumer i's medical debt collection accounts. Our focal parameter of interest is β, which we interpret as the intent-to-treat effect of having at least one account not deleted. Equivalently, $-\beta$ measures the effect of having all accounts deleted. In the appendix, we estimate a model using the minimum rather than the maximum debt value across all accounts, as well as a model estimated at the account level instead of the individual level. While these models estimate different treatment effects, the qualitative conclusions remain the same.

Our main identifying assumption is that assignment around the \$500 threshold is effectively random. This assumption is plausible because medical debt balances are typically determined by fixed and often opaque pricing, leaving consumers with limited ability to manipulate their placement relative to the threshold. Additionally, our data come from administrative records, reducing concerns about measurement error or sample selection bias. We assess manipulation by examining the continuity of predetermined covariates and the density of the running variable around the cutoff (Lee, 2008; McCrary, 2008).

The main threat to identification is the potential for other policies to coincide with the \$500 threshold. For instance, if hospitals implement policies that restrict services to individuals once their unpaid medical bills exceed \$500, then any observed discontinuities could reflect hospital practices rather than credit bureau reporting rules. To evaluate this possibility, we estimate placebo RD specifications using data from before 2023, prior to the removal of small medical debts from credit reports.

A related concern is that debt collectors may have systematically treated medical collections differently at the \$500 threshold even before the 2023 policy change. For example, if debt collectors routinely refrained from reporting medical debts under \$500 to credit bureaus, then any observed effects could stem from debt collector behavior rather than changes in credit bureau policies. We assess this possibility using the same approach as above: estimat-

ing RD specifications using pre-2023 data to test for evidence of pre-existing discontinuities.

We use a triangular kernel in all RD regressions. Our preferred specification uses a mean-squared error optimal bandwidth that remains constant on either side of the cutoff but can vary across outcomes. We report robust bias-corrected confidence intervals to account for potential misspecification of the estimating equation (Calonico et al., 2014).

3.2 Results

We begin by estimating the first-stage effect of the 2023 deletion on medical collections accounts. Panel A of Figure 2 shows that by 2024, nearly all accounts with balances below $500 in 2022 had been removed from credit reports, whereas more than 10 percent of accounts with balances above $500 remained. Panel B demonstrates that this effect is also evident at the consumer level. After aggregating the running variable by taking the maximum debt amount across all accounts, the intervention reduced the number of medical debt collections per person in 2024 by 0.30 (107%).[10]

Figure 3 shows the direct effect of the 2023 deletion on credit access. We find no evidence of discontinuities around the $500 threshold. Table 3 presents formal estimates. The 95% confidence intervals rule out improvements in credit scores greater than 6.03 points (0.97%), increases in balances exceeding $2,602 (5.05%), increases in new credit accounts greater than 0.09 (17.65%), and decreases in revolving utilization larger than 1.54 (4.80%).[11] Figure 4 presents analogous results for delinquency, bankruptcy, and alternative credit use. Here, the 95% confidence intervals rule out reductions in delinquent balances greater than $802 (42.36%), decreases in the probability of bankruptcy larger than 1.19 percentage points (37.42%), decreases in the probability of holding an alternative credit balance greater than 0.29 percentage points (7.51%), and increases in the number of alternative credit accounts exceeding 0.04 (22.60%).

Figure A.1 shows results for additional credit outcomes, including the number of ac-

[10] A consumer whose largest medical collection account was under $500 in 2022 but subsequently acquired new medical collection accounts exceeding $500 in 2023 or 2024 will still be recorded as having medical collections in 2024. These newly acquired accounts explain the positive values plotted to the left of the cutoff in Panel (b).

[11] Medical collections have not been included in the VantageScore model since January 2023; therefore, there is no mechanical relationship between debt deletion and credit scores in this analysis.

counts 90+ days past due, the number of new inquiries, revolving limits, total balance in alternative credit accounts, and the number of new mortgage accounts. We again detect no significant effects. Our null estimates remain precise, with 95% confidence intervals ruling out meaningful changes across all outcomes.

In Table A.7, we focus on the subsample of consumers whose debts in collections consist solely of medical debts—a group for which Kluender et al. (2024) found modest positive effects of debt relief, including a 13.8 point (2.3%) increase in average credit scores. However, we find no such benefits, instead ruling out a credit score increase of 9.91 points (1.52%) at the 95% confidence level. One possible reason for this discrepancy is that the two major credit scoring models—VantageScore and FICO—stopped using medical debt as a predictor in 2023, after the period analyzed in Kluender et al. (2024) but before our post-policy outcome window. Thus, while removing medical debt from credit reports may have affected credit scores in the earlier period, it no longer has a direct effect on them in our setting.[12]

Our analysis assumes that individuals cannot manipulate their debt balances to remain below the cutoff. That assumption in turn implies continuity in predetermined outcomes at the threshold. Figure A.2 confirms this prediction, showing no discontinuities in covariates such as income, age, and gender. To further probe manipulation directly, we examine the density of the running variable around the cutoff. If individuals were strategically adjusting balances, we would expect excess mass just below the $500 threshold. However, Figure A.3 shows no such evidence. Instead, the distribution exhibits bunching just above the cutoff, a pattern consistent with rounding behavior. This pattern could also reflect hospital or provider reporting practices, if some systematically refrain from reporting debts under $500. Such practices do not threaten our design so long as they are unrelated to outcomes of interest. The covariate smoothness documented in Figure A.2 supports this view, suggesting no systematic differences between individuals just above and below the cutoff.

We also conduct a series of falsification and placebo tests. Our falsification tests, shown in Figures A.4, A.5, and A.6, replicate our RD specification but use 2022 outcomes instead

[12]While we find that medical debt is not a significant predictor in our credit scoring model, older models may have treated it differently for two reasons. First, medical debt may have historically been a stronger predictor of default risk. Second, if earlier models used fewer variables or less sophisticated algorithms than ours, they may have assigned greater importance to medical debt.

of 2024 outcomes. As expected, we find no evidence of treatment effects, including for the first-stage outcomes. Similarly, our placebo tests, presented in Figures A.7 and A.8, replicate our RD analysis using the 2020–2022 period in place of 2022–2024. Once again, we find no significant effects, further reinforcing the credibility of our research design.

4 Mechanism: Medical Debt and Credit Scoring

Section 3 finds that deleting medical debt collections from credit reports provides no measurable improvements in access to credit and financial health for consumers with medical debt, suggesting that this information is not relevant for loan origination. In this section, we provide evidence that medical debts are not predictive of future default, which helps explain why their deletion has no meaningful impact on lending decisions.

4.1 Are medical debts relevant for loan origination?

When originating consumer loans, lenders typically use granular information to estimate the probability that a borrower will default, relying on credit scoring models described in Section 4.2.[13] The major credit bureaus provide scores from commercial credit scoring models, such as VantageScore and FICO, which are used by most lenders to some extent. These scores were likely not substantially affected by the deletion of small medical debts: VantageScore stopped including medical collections in its model in January 2023, while FICO removed information on medical collections below $500 and downweighted those above $500 a few months later.[14] While we do not observe FICO scores, in Section 3 we showed that the deletion had no detectable impact on VantageScores and ruled out even small effects. Thus, for lenders that rely solely on these scores, the absence of changes in loan origination is unsurprising.

[13] In addition to default probabilities, lenders estimate two other components that determine their expected credit losses: the loss given default (LGD) and the exposure at default (EAD). Unlike default probabilities, LGD and EAD are rarely estimated at the borrower level; instead, they are typically based on product characteristics or historical averages (Federal Reserve Board, 2013).

[14] See announcements at https://www.vantagescore.com/major-credit-score-news-vantagescore-removes-medical-debt-collection-records-from-latest-scoring -models/ and https://www.myfico.com/credit-education/blog/medical-collections-removal.

However, the largest lenders, which account for most of the loan volume in consumer credit markets, use in-house proprietary models to estimate default risk (e.g., Braunstein, 2010). These lenders often employ simple and transparent approaches to credit scoring, such as logistic regression, since compliance with the Equal Credit Opportunity Act and other federal regulations requires lenders to articulate the reasons for the denial of an application for credit upon request. At the same time, lenders are increasingly incorporating machine learning methods alongside logistic regression, using them as a supplement to improve predictive performance (e.g., Brainard, 2021).

For lenders developing their own models, the decision to use information on small medical debt collections should depend on whether these data help predict defaults. To examine this, we train two credit scoring models: one that includes data on medical collections below $500 and another that excludes it. While our models do not exactly replicate any specific lender's approach, they rely on similar data and algorithms, and—as we show—they outperform existing models in the literature. Our approach assumes that a well-designed credit scoring model such as ours should be able to detect the predictive power of medical debt collections, if any exists.

As we demonstrate below, medical debt collections below $500 provide no meaningful predictive value beyond other variables available in credit reports. This finding suggests that lenders developing in-house credit scoring models should not have relied on this information, helping to explain why the April 2023 intervention had no effects on access to credit. Finally, we show that medical debts above $500 also fail to predict default, suggesting that the CFPB's 2025 final rule to delete all remaining medical debt collections from credit reports is also unlikely to affect credit access or financial health.

4.2 Credit scoring with and without medical collections

Credit scoring models estimate the likelihood that a borrower will default based on their financial and credit history. Formally, these models take the form:

$$Y = f(X_1, X_2, ...X_n) + e \tag{3}$$

where Y is a credit outcome, X_i are borrower characteristics, and e captures irreducible noise. The function $f(\cdot)$ represents the mapping from borrower attributes to a predicted outcome, which may be specified parametrically or estimated flexibly using machine learning techniques.

Traditional credit scoring models, such as FICO and VantageScore, are typically logit models estimated on consumer-level data and segmented into groups based on repayment history, commonly referred to as "scorecards" (Federal Reserve Board, 2007). Within each scorecard, a separate logistic regression is estimated, so that model parameters differ across groups. These models generally aim to predict "default," defined as any credit account becoming 90 or more days past due within the next 18–24 months. Predictors typically include variables related to payment history, amounts owed, length of credit history, new credit activity, and credit mix. To capture nonlinear relationship, predictors are often binned into discrete categories, which can improve model performance (Federal Reserve Board, 2007).

Rather than relying on binning and group-specific estimation, our baseline model uses XGBoost, a state-of-the-art machine learning algorithm well-suited for classification problems. This flexible, tree-based ensemble method is designed to capture complex, nonlinear interactions between predictors and typically outperforms standard parametric models in predictive accuracy. Nevertheless, we show in Section 4.5 that our conclusions are robust to using a traditional logit approach.

Our model includes $n = 46$ predictors that capture a broad set of credit-related information: accounts and balances past due, the number of medical and non-medical collections, the number of bankruptcies and other public records, balances and accounts of different credit types, average account age, age of oldest account, and the number of new credit inquiries and accounts.[15] Consistent with prior work, our model excludes variables prohibited by the Equal Credit Opportunity Act—such as sex and marital status—as well as variables that may proxy for them, such as geographic identifiers (Federal Reserve Board, 2007; Blattner and Nelson, 2022).

[15]For more information on the predictors included in traditional credit scoring models, see https://www.myfico.com/credit-education/whats-in-your-credit-score.

We train two person-level credit scoring models: one including the number of medical debt collections below $500 and one excluding this information. Both models include information on the number of medical debts above $500.[16] Using data from 2019 to 2021—prior to the removal of information on medical collections below $500—we predict the probability of a default occurring between 2020 and 2021, based on borrower characteristics measured in 2019. We define default as any account becoming 90 or more days past due in 2020–2021, excluding collections. The dataset contains records for over 2.4 million consumers. We allocate 90% of these observations for training and reserve 10% for out-of-sample performance evaluation. Predicted default probabilities are converted into binary predictions using a threshold of 50%.

We report model performance in Table 4. The first column shows results for the model including medical collections below $500; the second column presents results for the model excluding them. Because default is a relatively rare event, the accuracy score—the share of correct predictions—provides limited insight. For example, a model that predicts no consumers will default achieves an accuracy score of 86.69%, reflecting the share of consumers in the sample who did not default. Similarly, the area under the Receiver Operating Characteristic curve (AUC), which measures the probability that the model assigns a higher default probability to a true defaulter than to a non-defaulter, is less informative in imbalanced classification settings. Instead, we focus on precision and recall, which better capture a model's ability to predict rare events (Davis and Goadrich, 2006).

Precision and recall are defined as:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \tag{4}$$

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \tag{5}$$

Precision measures the proportion of predicted defaulters who actually defaulted, while recall measures the proportion of actual defaulters who were correctly identified. Both metrics

[16] We also investigated the effect of including information on the balance amounts of medical collections. Surprisingly, incorporating these data worsened the predictive accuracy of the model, even for balances over $500. We therefore don't include balance information in this analysis.

are important in our setting: high precision minimizes the misclassification of creditworthy borrowers, helping lenders avoid missed profitable opportunities, while high recall ensures that the model identifies high-risk borrowers, reducing the likelihood of inadvertently lending to high-risk borrowers. To balance these goals, we also compute the F1 score, which is the harmonic mean of precision and recall:

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{6}$$

Table 4 shows that our algorithm performs well in predicting default, achieving an F1 Score of 0.557. To assess this result, we focus on its components, precision and recall, which are more commonly reported in other papers. Our recall of 0.448 ranks among the highest, with prior studies typically reporting values between 0.35 and 0.41 (e.g., Butaru et al. (2016), Agarwal et al. (2023)). Two exceptions are Khandani et al. (2010) and Chioda et al. (2024), who achieve recalls of 0.654 and 0.749, respectively, but over shorter prediction horizons of 3 and 6 months.[17] Shorter prediction windows generally yield higher precision and recall, helping explain the stronger performance in these studies. Moreover, Chioda et al. (2024) use a 20% threshold—substantially lower than our 50% threshold—which further boosts recall but reduces precision.

Our precision score of 0.736 also compares favorably with the literature, where reported values typically range from 0.06 to 0.50 (e.g., Butaru et al. (2016), Fuster et al. (2022), Agarwal et al. (2023), Chioda et al. (2024)). The sole exception is Khandani et al. (2010), who achieve a higher precision of 0.853 but, again, over a much shorter 3-month horizon. Although precision and recall are more informative than AUC in settings with rare outcomes, our model's AUC of 0.712 further demonstrates its effectiveness, falling well within the typical range of 0.66 to 0.88 reported in the literature.

Comparing the first two columns in Table 4 shows that removing information on medical collections below $500 has no measurable impact on model performance. All metrics remain unchanged up to the third decimal, except for accuracy, which slightly *increases* by 0.001 when small medical collections are removed. This result provides strong evidence that

[17] We compute recall and precision for Khandani et al. (2010) using the confusion matrix for the December 2008 3-month forecast with a 50% classification threshold.

medical collections below $500 contribute no meaningful predictive value. The third column shows that even deleting information on all medical collections, including those exceeding $500, has no measurable impact on model performance. These results suggest that the CFPB's 2025 final rule to eliminate all remaining medical collections from credit reports is unlikely to affect the accuracy of credit scoring models.

To further examine the role of medical collections, Figure 5 reports variable importance measures based on average SHAP values, ranking variables in order of predictive importance.[18] Small medical collections rank third from the bottom, with an average SHAP value of 0.0011, compared to an average value of 0.278 for the 10 most important features. Figure A.13 further shows that removing information on medical collections below $500 has minimal effect on predicted default probabilities: only about 10% of consumers experience a change greater than 2 percentage points.[19]

Although Figure A.13 suggests that small medical debt collections might improve predictive performance for a subset of individuals represented in the tails of that distribution, these effects are more likely driven by noise than by meaningful differences in default risk. To investigate this further, we categorize consumers into three groups based on the changes in their predicted default probabilities across the two models:

> **Negatively treated**: Consumers in the top 5 percent of the distribution, whose predicted probability of default increases by approximately 2 percentage points or more when small medical debts are removed from the model.
>
> **Positively treated**: Consumers in the bottom 5 percent of the distribution, whose predicted probability of default decreases by approximately 2 percentage points or more when small medical debts are removed from the model.
>
> **Unaffected**: Consumers between the 25th and 75th percentiles, who experience a change in predicted default probabilities of no more than 0.002 percentage points.

[18] A feature's SHAP value quantifies its contribution to a specific model prediction, indicating how much the feature shifts the prediction relative to the mean. The average SHAP value reflects the feature's mean contribution across all predictions.

[19] For context, 2 percentage points corresponds to the difference in 2022Q2–2024Q1 90-day delinquency rates between consumers with a VantageScore of 300–500 and those with scores of 501–520 (https://www.vantagescore.com/lenders/risk-ratio/).

If small medical debts were truly predictive of default, we would expect clear differences between these groups. For instance, positively treated consumers—those whose predicted risk falls when small medical debts are excluded—should have more small medical debts on average than negatively treated consumers.

However, we do not observe this pattern. Table 5 shows summary statistics for all three groups. While both the positively and negatively treated groups differ significantly from the unaffected group, they are remarkably similar to each other. Figure 6 illustrates these results using balancing regressions. All variables are standardized and each dot represents the regression coefficient of the variable labeled on the y-axis, regressed on either the positive (blue) or negatively treated (red) group indicator. If small medical debts were strongly predictive of default, we would expect a pronounced sorting effect along relevant characteristics—particularly the number of medical debts. However, Figure 6 reveals no such pattern: positively and negatively treated consumers appear statistically indistinguishable across a wide range of characteristics, including the presence of medical debts.

The similarity between these two groups, despite their substantial divergence from the unaffected group, suggests that the changes in predicted risk are driven by estimation noise. As shown in Blattner and Nelson (2022), default probabilities are estimated with considerable noise for low-income consumers with thin credit files. In such settings, even uninformative predictors like small medical debts can receive non-zero weights during model training.[20] As a result, excluding an uninformative feature may shift predictions for noisy cases, creating two groups with large changes in predicted risk but no meaningful underlying differences. This process effectively assigns consumers randomly to the positively or negatively treated groups, while separating them from the more stable, unaffected group. To validate this interpretation, Section 4.3 introduces a randomly generated variable into the model and shows that excluding it produces a nearly identical pattern to the one observed when excluding small medical collections debts.

[20] In theory, machine-learning algorithms such as XGBoost should assign zero weight to uninformative variables. In practice, however, finite sample noise in the training data can lead to spurious associations.

4.3 Placebo test: credit scoring with and without random noise

As a placebo test, we compare the effect of removing medical collections below $500 to that of removing a randomly generated variable. Specifically, we train a version of our model that includes a predictor drawn randomly from a uniform distribution and compare its performance to our baseline model, which excludes this random variable.

Table A.9 presents the performance metrics. Columns (1)–(2) replicate the estimates from the first two columns of Table 4, confirming that removing small medical collections has no discernible impact on model performance. Comparing Column (3) to Column (1) shows a nearly identical pattern when a random variable is included and then removed.[21] Figure A.14 reinforces this result by overlaying the distribution of probability changes from Figure A.13 with the corresponding distribution obtained after removing the noise variable. The two distributions are nearly indistinguishable.

Figure A.15 further supports this interpretation by showing that removing the random variable sorts consumers into our three groups—unaffected, positively treated, and negatively treated—in the same way as removing medical collections under $500. Panel A reproduces the balance plot from Figure 6, where each dot represents the coefficient from a regression of the standardized variable labeled (y-axis) on either the positively treated (blue) or negatively treated (red) group indicator. Panel B presents the same analysis using the random variable instead of medical collections. In both panels, "treated" consumers have, on average, lower credit scores, lower income, and lower balances, reinforcing the conclusion that default probability estimates are substantially noisier for these consumers (Blattner and Nelson, 2022).

One potential concern with this placebo test is that removing any variable—regardless of its predictive power—might fail to generate systematic differences between the positively and negatively treated groups. To address this concern, Figure A.16 examines the impact of removing a clearly informative piece of information: credit history length, as measured by average account age, the age of the oldest account, and the age of the oldest account that

[21] Comparing Column (3) to Column (1), we find that removing the random variable increases the F1 Score by 0.002, suggesting a slight improvement in prediction due to reduced overfitting. In contrast, there is no change in the F1 Score when comparing Column (2) to Column (1), indicating that small medical collections may have minimal but nonzero predictive power in the credit scoring model.

was never delinquent or derogatory. Credit history length is widely used in credit scoring models as a predictor of default (Federal Reserve Board, 2007) and average account age is one of the most important features in our model as measured by SHAP values (Figure 5). When we exclude these variables, we observe clear sorting patterns: the positively treated group is younger and has a shorter credit history, as measured by average account age, than the negatively treated group. In contrast to the removal of small medical collections or a random variable, excluding a truly predictive predictor produces meaningful differences between the groups. This contrast underscores that our placebo test is meaningful: removing uninformative variables leads to random sorting, while removing valuable predictors results in systematic differences across groups.

4.4 Spillover Effects: Difference-in-differences

Next, we use a differences-in-differences research design to rule out negative spillover effects of deleting small medical debt collections from credit reports. To isolate consumers most exposed to these negative spillovers, we define the treatment group as consumers whose predicted probability of default increases by about two percentage points or more when small medical debts are excluded from our credit scoring model (the "negatively treated" group described in Section 4.2). Because this classification is based on 2019 characteristics, we restrict our analysis to 2020–2024.

A natural control group would be consumers whose predicted default risk remains unchanged ("unaffected" consumers).[22] However, as shown in Table 5, these consumers differ significantly from the "negatively treated" group across observables. Instead, we use the "positively treated" group—consumers whose predicted probability of default decreases when small medical debts are removed—as the control group. These individuals are more comparable in terms of observables, and because small medical debts have minimal predictive power, the assignment to the "negatively" and "positively" treated groups is effectively random (as shown in Sections 4.2 and 4.3). This randomness lends credibility to our key identifying assumption: in the absence of the information deletion, outcomes for the two

[22]This is the control group used in Liberman et al. (2019), who implement a similar difference-in-differences analysis.

groups would have followed similar trends.[23]

We estimate the following regression model at the individual level:

$$Y_{ict} = \alpha + \beta \text{TREATED}_i \times \text{POST}_t + \lambda_i + \delta_{ct} + \epsilon_{it}, \tag{7}$$

where Y_{ict} is an outcome for consumer i, residing in county c, in year t; TREATED_i is an indicator equal to one if the consumer belongs to the "negatively treated" group and zero if they belong to the "positively treated" group; POST_t is an indicator equal to one beginning in 2023, the year of information deletion; and λ_i and δ_{ct} denote consumer and county-year fixed effects, respectively.

Because treatment is defined by the change in predicted default probability (with versus without small medical debts), we sort the full sample into 1,000 equal-sized bins based on this difference and cluster standard errors at the bin level. Together, the negative and positively treated groups comprise 10 percent of the full sample, resulting in 100 clusters.

Our coefficient of interest, β, captures the average effect of deleting medical debt collections for the treatment group—consumers whose predicted default probability increases when medical debts are removed—relative to the control group. To assess the validity of the parallel trends assumption, we also estimate an event-study version of Equation (7):

$$Y_{ict} = \alpha + \sum_{\substack{\tau=2020, \\ \tau \neq 2022}}^{2024} \beta_\tau \text{TREATED}_i \times \mathbb{I}_{t=\tau} + \lambda_i + \delta_{ct} + \epsilon_{it}, \tag{8}$$

where $\mathbb{I}_{t=\tau}$ is an indicator for year $t = \tau$ and zero otherwise. We use 2022, the year prior to information deletion, as the reference period so that β_τ captures the differential change in outcomes between the treatment and control groups relative to 2022.

4.4.1 Results

Figure A.17 in the Appendix presents event-study estimates of the indirect effect of information deletion (Equation (8)) on credit-access outcomes: credit scores (panel A), total balance

[23] If small medical debts did have any predictive power, their deletion would be expected to positively affect the treatment group and negatively affect the control group, providing an upper bound for the estimated effects.

across all credit products (panel B), number of accounts opened in the last 6 months (panel C), and revolving utilization (panel D). Outcome trends are similar between the treatment and control groups prior to 2023, with no statistically significant differences. We observe no significant trend changes after 2023, consistent with the absence of any indirect effects.

Figure A.18 shows similar results for measures of payment history and subprime borrowing, including the total balance 90+ days past due (panel A), whether a consumer had a bankruptcy in the last 7 years (panel B), whether a consumer has an alternative credit balance (panel C), and the number of alternative credit records (panel D). We again find no evidence of pre-trends or of any significant effects.[24]

Table A.8 in the Appendix presents estimates from Equation (7), which assumes a constant treatment effect over time and aggregates years to increase statistical power. Across all 8 outcomes, estimated effects are small and generally insignificant. The only significant estimate—a 0.721-point increase in credit scores—is economically small, representing just 0.12% of the sample mean (617.13). Overall, our estimates are precise and consistently point to null effects, allowing us to rule out even small negative spillovers from the deletion of small medical debts. This is consistent with the evidence presented in Section 4.2 that changes in predicted risk are driven by estimation noise, and alleviates concerns that consumers reclassified as higher default risk are unobservably different and differentially exposed to the information deletion.

4.5 Robustness: Logit Model

As a robustness check, we show that our conclusions are unchanged when employing the traditional logit scorecard approach described briefly in Section 4.2 and in detail in Federal Reserve Board (2007). Specifically, we follow the industry practice of estimating separate models (scorecards) for three groups of consumers: major derogatory files, thin files, and clean files. The major derogatory scorecard is estimated on consumers who have at least one account 90 or more days past due, an account in collections, or a public record (such as a bankruptcy or foreclosure). The thin scorecard covers consumers not in the major derogatory scorecard who have fewer than three accounts. The clean scorecard applies to consumers

[24] We show additional outcomes in Appendix Figure A.19.

with three or more accounts who are not classified as major derogatory.

We use 2019 data to measure the same 46 predictors as in our baseline model, along with the characteristics used to segment consumers into the three scorecards. In 2019, 32.4% of consumers fell into the major derogatory scorecard, 12.7% into the thin scorecard, and 54.9% into the clean scorecard. Each predictor is binned separately within each scorecard using the OptBinning Python library, which applies a mixed-integer programming model that balances information gains with interpretability constraints, such as monotonicity and statistically significant differences between bins.

We report the performance of this model in Table A.10. The first column shows results including medical collections, the second column excludes medical collections below $500, and the third column excludes all medical collections. Although the logit model underperforms our baseline model on all metrics other than AUC (Table 4), its predictive accuracy still compares favorably to the literature summarized in Section 4.2.

Consistent with our baseline results (Table 4), the exclusion of small medical collections has no meaningful effect: all metrics remain unchanged up to the third decimal, except for a 0.001 *increase* in recall (column 1 vs. 2 of Table A.10). Likewise, dropping all medical collections leaves results virtually unaffected: relative to Column (1), the only difference is a 0.001 decline in the F1 score, driven by a 0.001 decline in recall.

4.6 Do medical collections predict default in the absence of better information?

The previous results suggest that medical collections are not meaningfully predictive of default in the presence of other credit variables. This finding may seem surprising: Dobkin et al. (2018) find that hospitalizations account for 4–6% of personal bankruptcies, suggesting that medical debt could serve as a useful signal of financial distress. However, it is possible that other credit report variables offer a more accurate signal than medical debt alone.

To test whether medical debt predicts default in the absence of stronger predictors, we train a restricted version of our baseline XGBoost model using only four predictors. These predictors include the number of medical debts below and above $500, and two of the least

important predictors in our model (as measured by the SHAP values shown in Figure 5): bankruptcy trades and bankruptcy trades in the past 24 months. Thus, this restricted model relies solely on medical debt and variables with even less predictive power.

Table A.11 presents the performance metrics for the restricted model. As expected, Column (1) shows that this model performs very poorly. Its accuracy is 0.8669—identical to that of a naive model that predicts no defaults. The recall score is just 0.0008, meaning that it correctly identifies only 0.08 percent of true defaulters. Among borrowers classified as defaulters, only 34.62 percent are correctly classified, and the model achieves an F1 Score of just 0.0016, far below our baseline of 0.557.

Column (2) reports metrics for the restricted model when we exclude medical debts below $500. The model's performance drops by 50 percent according to our preferred metric—the F1 Score. Column (3) shows that removing all medical debts from the restricted model leads to a further 75 percent drop in the F1 Score. These results indicate that medical debts have some limited predictive power in isolation, but add little value when more informative credit report variables are included.

5 Conclusion

This paper studies the effects of deleting medical debt collections from credit reports using a combination of regression discontinuity, machine-learning credit scoring models, and differences-in-differences analysis. Contrary to stated policy goals, we find that deleting medical debts from credit reports has no meaningful impact on credit access or financial health.

Our analysis focuses on small medical debts under $500, which were removed from credit reports by all three major credit bureaus in 2023. Using a regression discontinuity design, we find no evidence that consumers benefit from the removal of this information in terms of credit access, repayment behavior, or payday borrowing, ruling out even small effects.

To help interpret these findings, we show that this information has little predictive value for default, based on a comparison of two credit scoring models: one that includes small medical debts and one that excludes them. Finally, we analyze potential spillover effects

using a differences-in-differences framework. We compare consumers whose predicted default probability rises when small medical debts are removed to observably similar consumers whose predicted default probability declines. We find no evidence of negative spillover effects, again ruling out small effects.

Our findings contribute to the ongoing policy debate on how to best alleviate the burden of medical debt. While economic theory emphasizes ex-ante solutions such as expanding health insurance coverage, these are difficult to implement: about 30 million Americans remain uninsured, and many insured individuals face substantial out-of-pocket costs (Einav and Finkelstein, 2023). Recent policy efforts have shifted toward ex-post solutions, such as debt forgiveness and the removal of medical debt from credit reports. However, Kluender et al. (2024) find that forgiving medical debt has little impact, and we find that deleting medical debt from credit reports has no measurable effect. Together, these results suggest that alternative strategies are needed to more effectively address the burden of medical debt.

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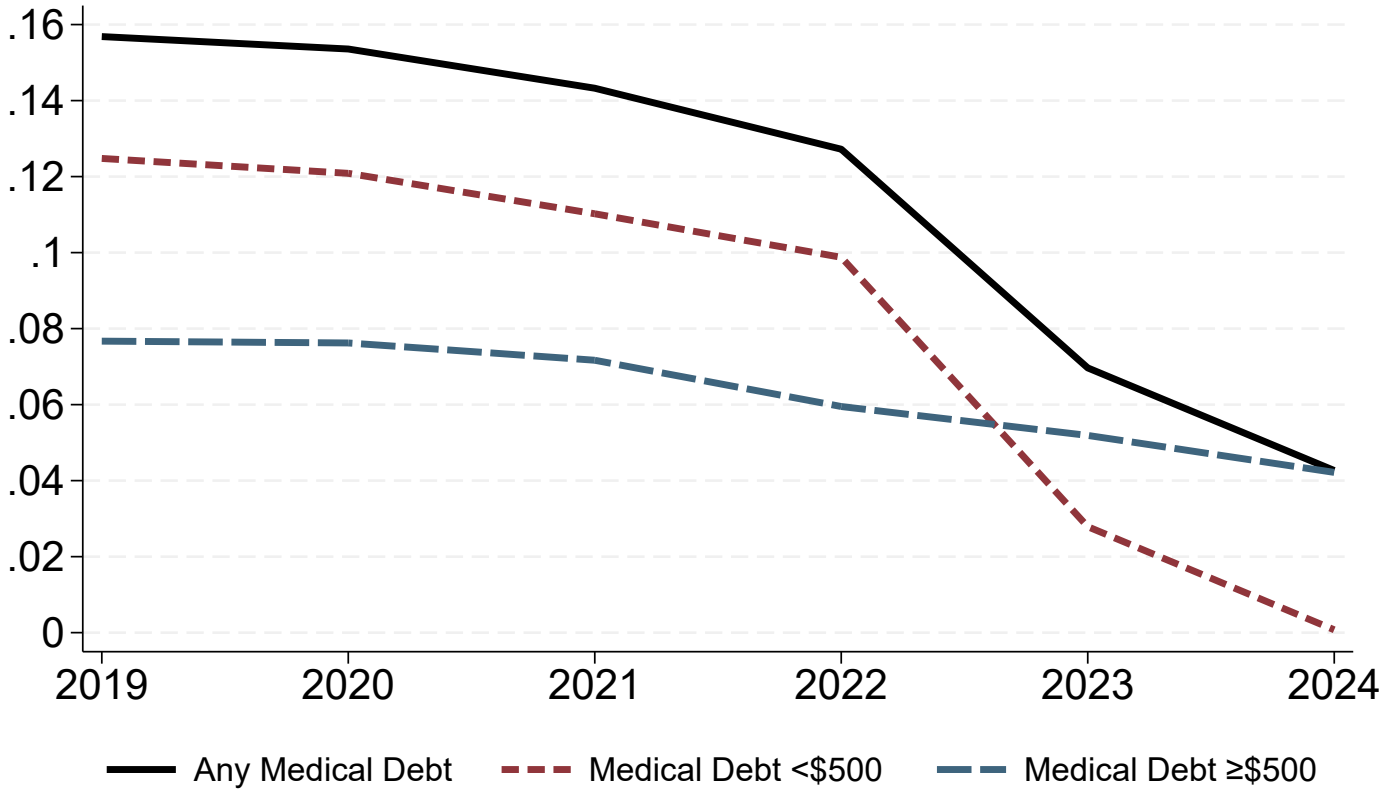
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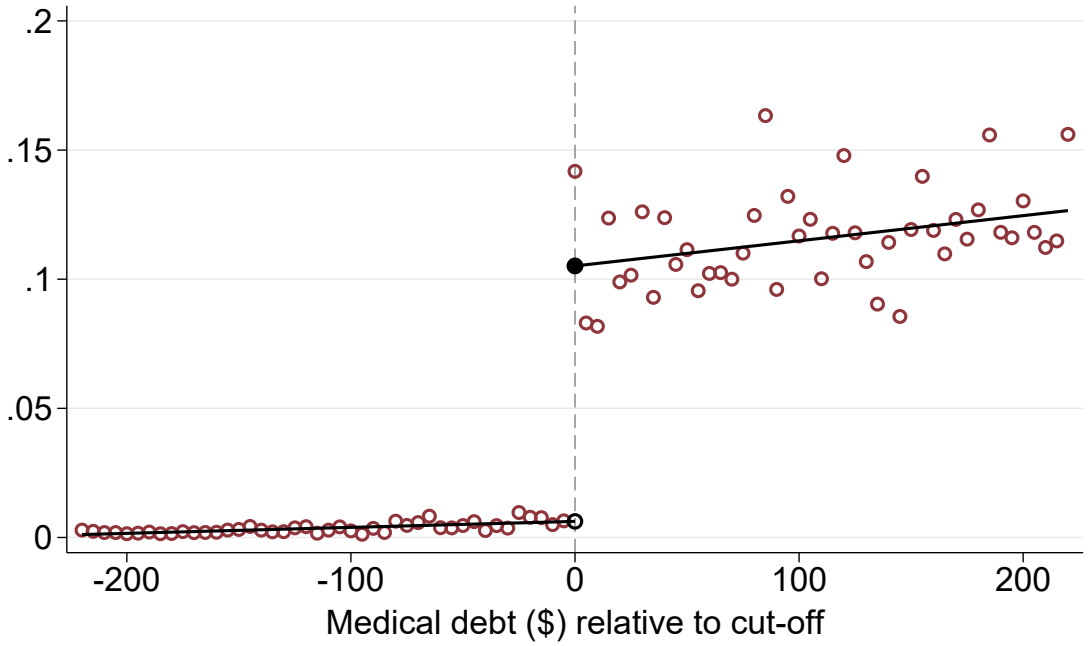
Figure 1: Share of Consumers with Medical Debt Collections, 2019–2024



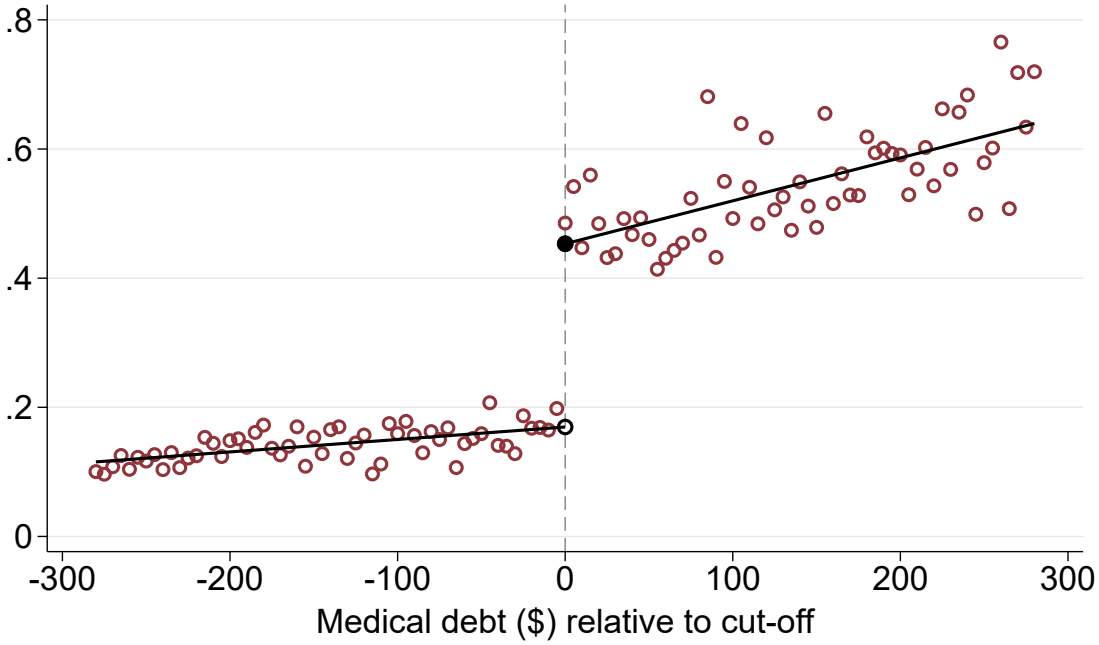
Notes: This figure shows the share of consumers with medical debt collections appearing on credit reports from 2019 to 2024. The black solid line plots the share with any medical debt in collections. The red dash line plots the share with debt below $500, while the blue long dash line plots the share with debt above $500.

Figure 2: Two-Year Evolution of 2022 Medical Collections Accounts

(a) Share of Surviving Accounts

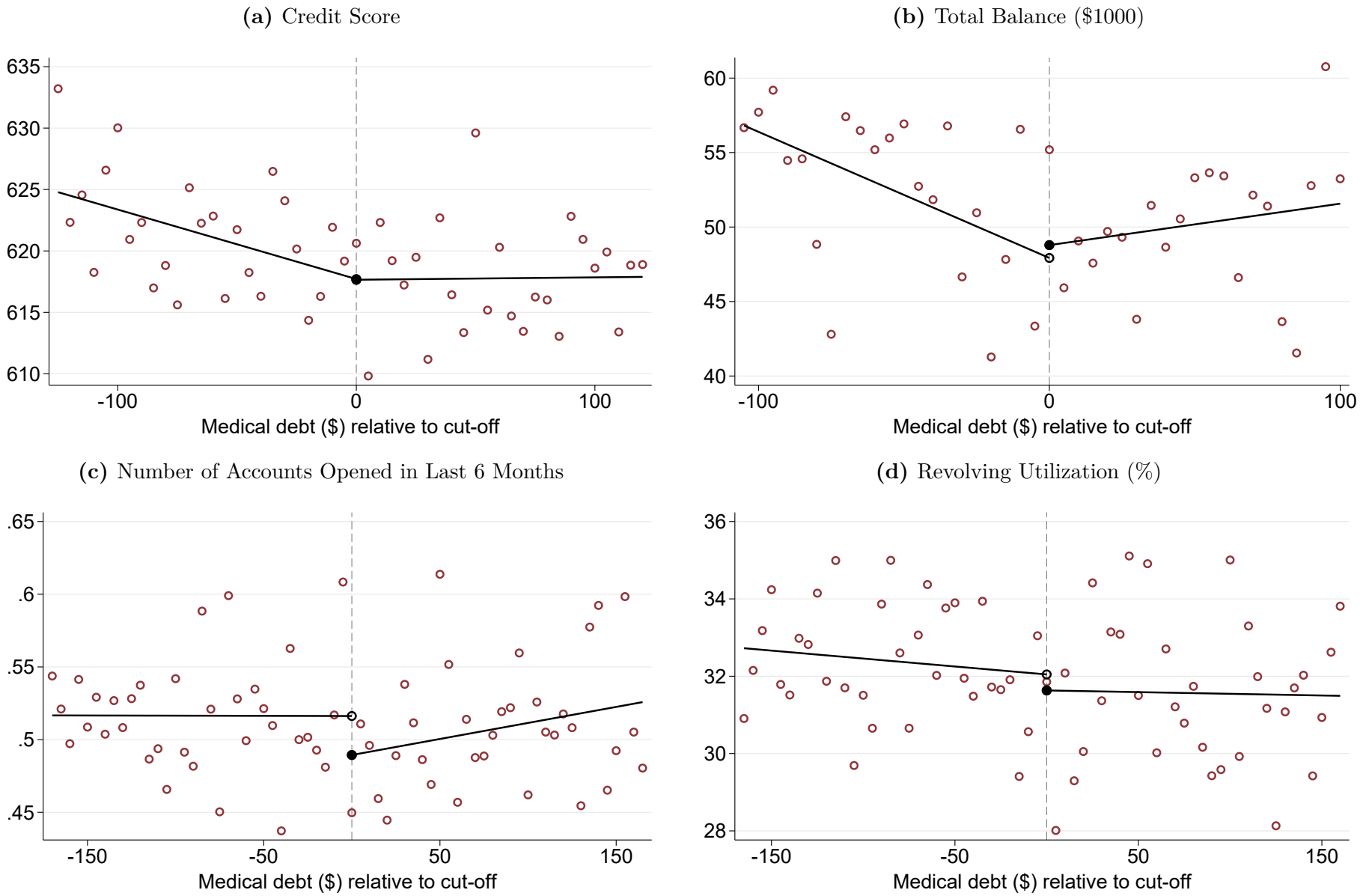


(b) Average Number of Accounts per Person



Notes: Panel (a) shows the proportion of 2022 medical debt collection accounts that remain on credit reports in 2024 by account amount, where the amount is measured as distance from the $500 threshold. Panel (b) shows the average number of medical debt collections accounts per person in 2024, where the running variable is the maximum value of the consumer's 2022 medical collections accounts. The fitted lines are estimated using Equation (1) for Panel (a) and Equation (2) for Panel (b). The RD estimate for Panel (a) is reported in Column (11) of Table A.1, and the estimate for Panel (b) appears in Column (2) of Table 3.

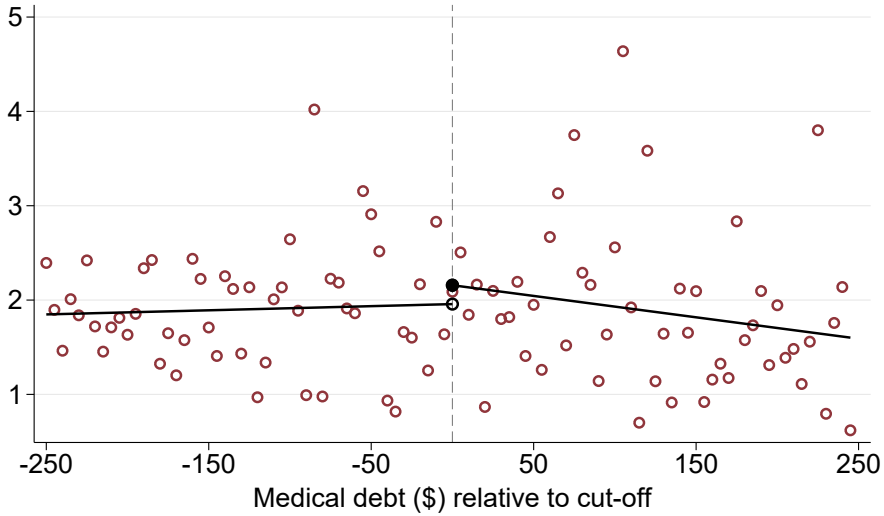
Figure 3: Access to Credit, 2024



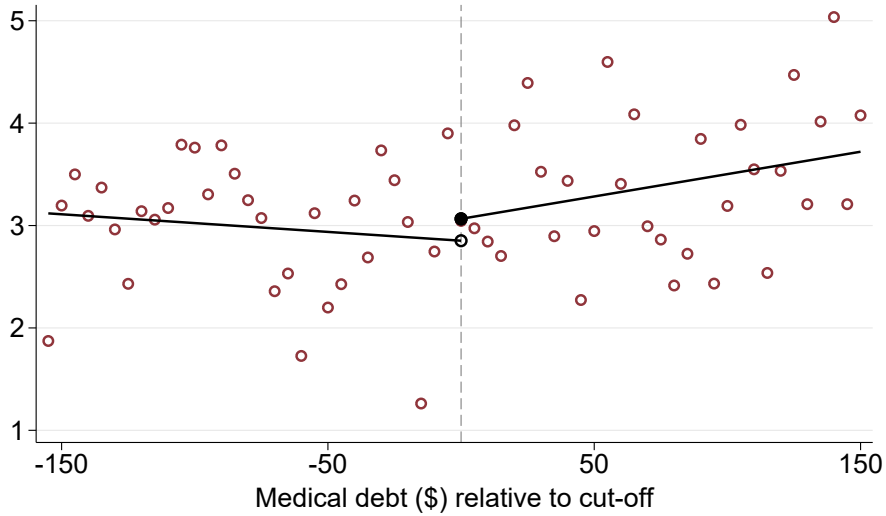
Notes: This figure shows the relationship between medical debt in 2022 and four different measures of credit access in 2024. Medical debt is defined as the maximum value of the consumer's 2022 medical collections accounts, measured relative to the $500 threshold. The corresponding RD estimates from Equation (2) are reported in Table 3.

Figure 4: Financial Distress and Access to Alternative Credit, 2024

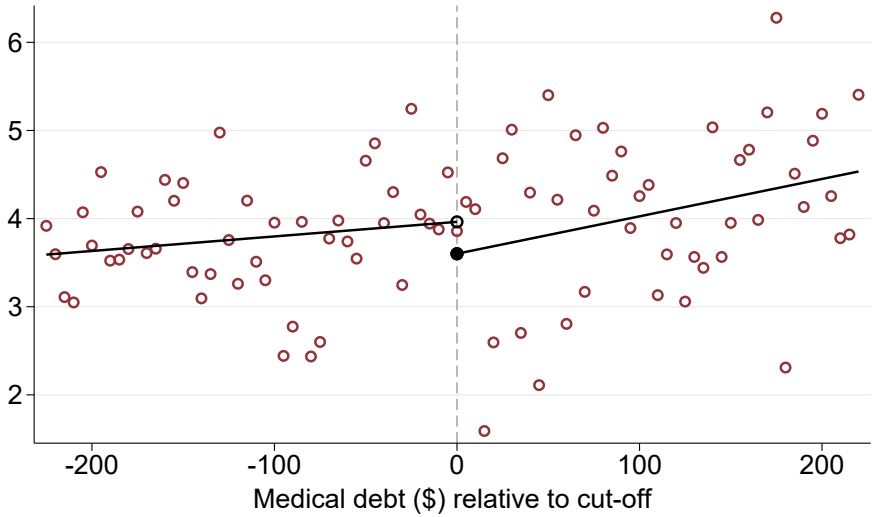
(a) Total Balance 90+ Days Past Due ($1000)



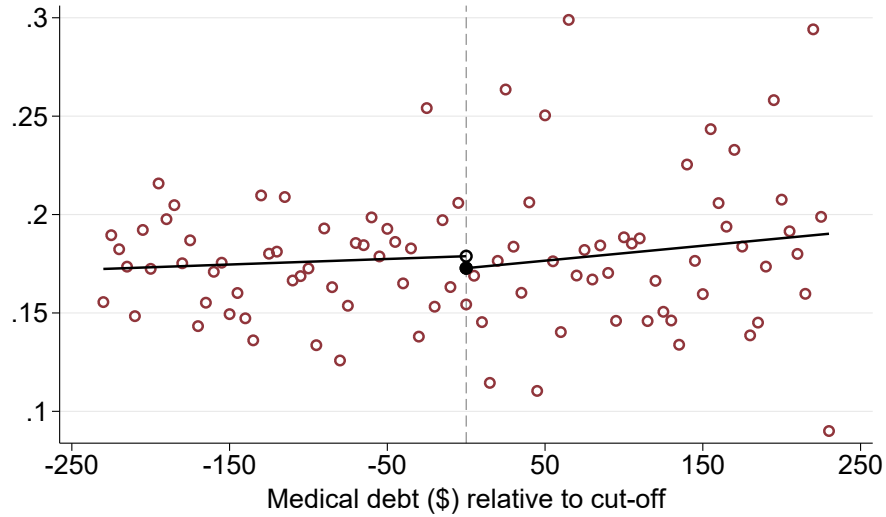
(b) Bankruptcy in Last 7 Years (%)



(c) Has Alternative Credit Balance (%)



(d) Number of Alternative Credit Accounts



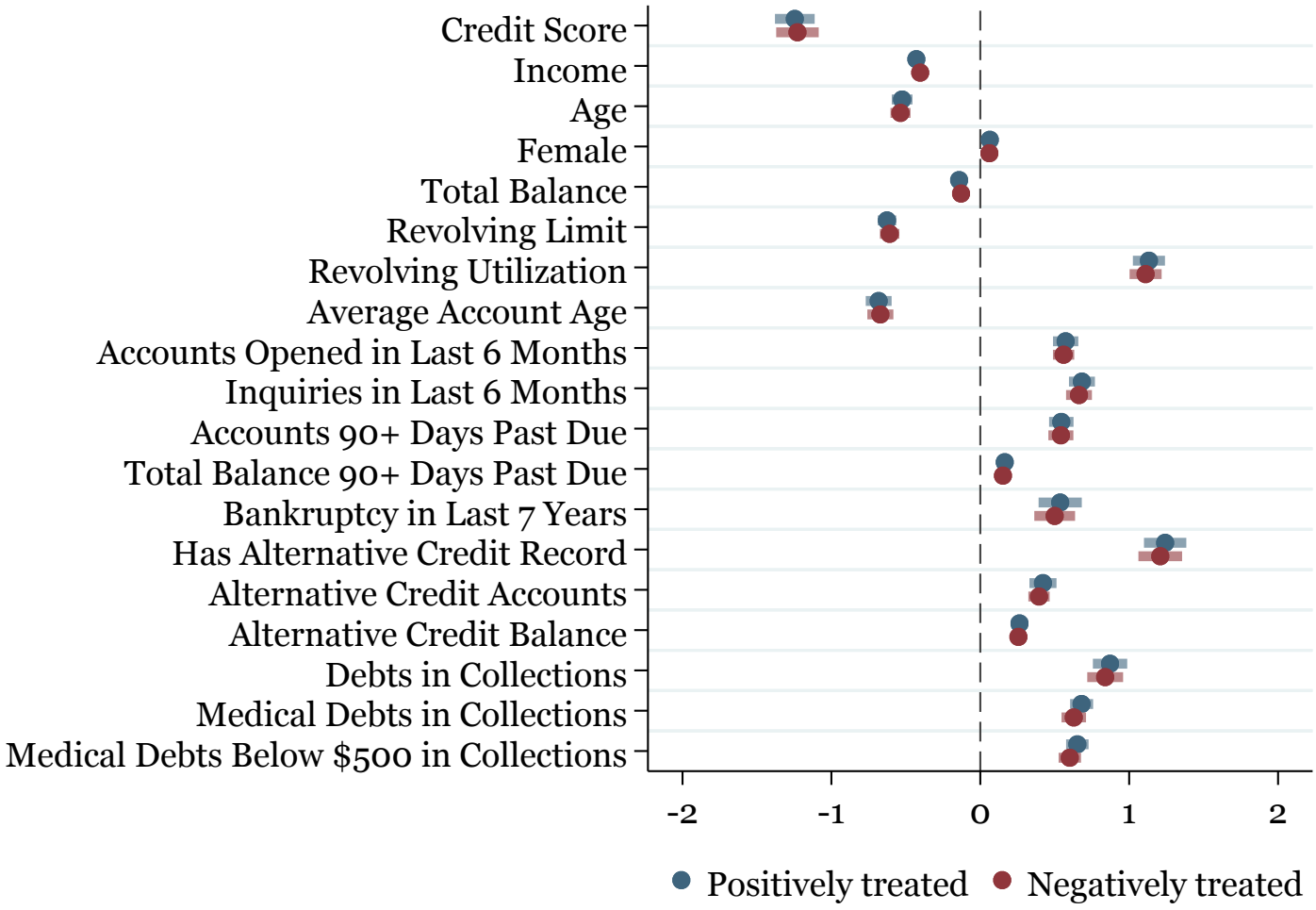
Notes: This figure shows the relationship between medical debt in 2022 and measures of financial distress and access to alternative credit in 2024. Medical debt is defined as the maximum value of the consumer's 2022 medical collections accounts, measured relative to the $500 threshold. The corresponding RD estimates from Equation (2) are reported in Table 3.

Figure 5: Variable Importance in the Credit Scoring Model



Notes: This figure displays variable importance measures, expressed as average SHAP values, for the credit scoring model presented in Section 4. The model, trained on 2019 data, predicts defaults occurring in 2020–2021 and is estimated using XGBoost. It incorporates 46 predictors, including medical collections under $500. Predictors ("features") are listed from top to bottom based on their average contribution to the model's predictions (average absolute SHAP value). Each row shows the distribution of SHAP values for individual observations, with the predictor's value (X_i) color-coded according to the heat map on the right. Narrow horizontal lines centered around 0 indicate that the predictor has little effect on predictions.

Figure 6: Covariate Balance by Changes in Default Probabilities



Notes: This figure shows estimates from balancing regressions for selected outcomes. Each balancing regression compares positively or negatively treated consumers to unaffected consumers in 2022. Negatively treated consumers are those whose predicted probability of default increases by 2 percentage points or more when small medical collections are removed from the credit scoring model described in Section 4. Positively treated consumers are those whose predicted default probability decreases by at least two percentage points. Unaffected consumers experience changes of less than 0.002 percentage points. All variables are standardized, and each dot represents the regression coefficient of the variable labeled on the y-axis, regressed on either the positive (blue) or negatively treated (red) group indicator. We divide consumers in the full sample into 100 equal-sized bins based on changes in predicted default probability and cluster standard errors at the bin level.

Table 1: Summary Statistics, 2019–2024

	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample			Medical Debt Subsample		
	Mean	St. Dev.	Median	Mean	St. Dev.	Median
A. Demographics						
Income ($1,000)	51.96	32.81	41.00	38.69	19.51	34.00
Age (years)	50.56	19.41	49.00	44.90	15.16	43.00
Female (%)	50.02	50.00	100.00	54.06	49.83	100.00
B. Access to Credit						
Credit Score	702.26	100.85	715.00	611.21	86.69	601.00
Total Balance ($1,000)	76.46	140.15	10.14	41.91	86.90	6.75
Revolving Limit ($1,000)	21.47	33.72	6.42	4.92	14.46	0.00
Revolving Utilization (%)	28.09	32.84	13.00	49.86	39.50	47.00
Average Account Age (months)	105.15	77.05	94.00	73.39	51.58	66.00
Number of Accounts Opened in Last 6 Months	0.41	0.83	0.00	0.47	0.95	0.00
Number of Inquiries in Last 6 Months	0.41	0.74	0.00	0.62	0.90	0.00
Number of New Mortgages in Last 6 Months	0.02	0.16	0.00	0.01	0.11	0.00
C. Access to Alternative Credit						
Has Alternative Credit Record (%)	19.99	39.99	0.00	47.93	49.96	0.00
Has Alternative Credit Balance (%)	1.02	10.05	0.00	2.60	15.92	0.00
Number of Alternative Credit Accounts	0.05	0.43	0.00	0.13	0.68	0.00
Alternative Credit Balance ($1,000)	0.05	0.79	0.00	0.13	1.19	0.00
D. Financial Distress						
Number of Accounts 90+ Days Past Due	0.19	0.90	0.00	0.46	1.33	0.00
Total Balance 90+ Days Past Due ($1,000)	0.81	12.16	0.00	1.95	15.90	0.00
Bankruptcy in Last 7 Years (%)	2.84	16.60	0.00	4.79	21.35	0.00
E. Debt in Collections						
Total Debts ($1,000)	0.56	3.65	0.00	3.14	9.90	1.39
Total Medical Debts ($1,000)	0.16	2.46	0.00	1.55	7.51	0.75
Number of Debts	0.60	1.87	0.00	3.81	4.11	3.00
Number of Medical Debts	0.25	1.02	0.00	2.44	2.17	2.00
Number of Medical Debts Below $500	0.15	0.66	0.00	1.45	1.53	1.00
Observations	15,313,700			1,585,485		

Notes: This table presents summary statistics from the 2019–2024 Gies Consumer and Small Business Credit Panel. The first three columns show statistics for the full sample, while the last three focus on consumers with at least one medical collection during the reported year.

Table 2: Summary Statistics for Consumers with Medical Collections, 2022 (RD sample)

	(1)	(2)	(3)
	Mean	St. Dev.	Median
A. Demographics			
Income ($1,000)	40.70	20.53	35.00
Age (years)	45.11	15.19	43.00
Female (%)	55.28	49.72	100.00
B. Access to Credit			
Credit Score	625.38	87.95	618.00
Total Balance ($1,000)	48.89	94.40	10.66
Revolving Limit ($1,000)	6.03	15.79	0.23
Revolving Utilization (%)	29.51	38.58	6.00
Average Account Age (months)	73.74	49.08	66.00
Number of Accounts Opened in Last 6 Months	0.60	1.09	0.00
Number of Inquiries in Last 6 Months	0.67	0.93	0.00
Number of New Mortgages in Last 6 Months	0.02	0.13	0.00
C. Access to Alternative Credit			
Has Alternative Credit Record (%)	51.72	49.97	100.00
Has Alternative Credit Balance (%)	3.20	17.59	0.00
Number of Alternative Credit Accounts	0.14	0.67	0.00
Alternative Credit Balance ($1,000)	0.18	1.45	0.00
D. Financial Distress			
Number of Accounts 90+ Days Past Due	0.31	0.91	0.00
Total Balance 90+ Days Past Due ($1,000)	1.31	13.17	0.00
Bankruptcy in Last 7 Years (%)	4.11	19.86	0.00
E. Debt in Collections			
Total Debts ($1,000)	2.69	6.51	1.09
Total Medical Debts ($1,000)	1.22	1.55	0.57
Number of Debts	3.53	3.77	2.00
Number of Medical Debts	2.37	2.00	1.00
Number of Medical Debts Below $500	1.56	1.43	1.00
Observations	271,305		

Notes: This table presents summary statistics from the Gies Consumer and Small Business Credit Panel. The statistics are based on data from 2022, the year preceding the removal of information on medical collections below $500. The unit of observation is the consumer. The sample is limited to consumers with a non-missing credit score from 2022–2024 who had at least one medical collection account in 2022.

Table 3: RD Estimates of the Direct Effect of Medical Debt Deletion

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Number of Debts	Number of Medical Debts	Credit Score	Total Balance ($1,000)	Number of Accounts Opened in Last 6 Months	Revolving Utilization (%)	Total Balance 90+ Days Past Due ($1,000)	Bankruptcy in Last 7 Years (%)	Has Alternative Credit Balance (%)	Number of Alternative Credit Accounts
ABOVE^{2024}	–0.226*** [–0.324, –0.145]	–0.299*** [–0.322, –0.267]	0.683 [–3.63, 6.03]	–2.23 [–8.59, 2.60]	0.0386* [–0.000785, 0.0895]	0.393 [–1.54, 2.38]	–0.0926 [–0.802, 0.510]	–0.367 [–1.19, 0.542]	0.381 [–0.293, 1.28]	0.0109 [–0.0153, 0.0453]
Sample mean	1.31	0.279	620	51.5	0.510	32.1	1.89	3.18	3.86	0.177
% of Mean	–17.3	–107	0.110	–4.34	7.55	1.22	–4.89	–11.6	9.87	6.15
Bandwidth	146	281	122	104	167	161	246	152	223	230
Observations	271,305	271,305	271,305	271,305	271,305	271,305	271,305	271,305	271,305	271,305

Notes: This table presents the estimated coefficient ($-\beta$) and 95% confidence intervals from Equation (2). The running variable for medical debt corresponds to the highest debt amount across the consumer's medical collections accounts. We report MSE-optimal estimates with robust, bias-corrected 95% confidence intervals in brackets. Sample Mean reports the mean of the dependent variable in 2024. A ***, **, and * indicate significance at the 1%, 5%, and 10% level respectively, using conventional inference.

Table 4: Performance Metrics for Credit Scoring Models With and Without Medical Collections

	(1)	(2)	(3)
	All Predictors	Exclude Medical Debts < $500	Exclude All Medical Debts
Accuracy	0.905	0.906	0.906
Recall	0.448	0.448	0.448
Precision	0.736	0.736	0.737
F1 Score	0.557	0.557	0.557
AUC	0.712	0.712	0.712

Notes: This table reports performance metrics for a credit scoring model predicting defaults occurring between 2020 and 2021, based on borrower characteristics from 2019. Column (1) presents metrics for the baseline model, which includes 46 predictors and is estimated using XGBoost. Column (2) reports metrics when small (under $500) medical collections are excluded from the predictors. Column (3) shows metrics when all medical collections are excluded. The accuracy score represents the share of correct predictions. For comparison, a naive model predicting no defaults achieves an accuracy of 0.867. Precision is the proportion of predicted defaults that were correctly classified. Recall is the proportion of actual defaults correctly classified. F1 score is the harmonic mean of Precision and Recall. The AUC (Area Under the Receiver Operating Characteristic Curve) indicates the probability that the model assigns a higher default probability to a true defaulter than to a non-defaulter.

Table 5: Summary Statistics by Treatment Groups Based on Changes in Default Probabilities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Unaffected			Positively Treated			Negatively Treated		
	Mean	St. Dev.	Median	Mean	St. Dev.	Median	Mean	St. Dev.	Median
A. Demographics									
Income ($1,000)	60.00	36.31	50.00	44.00	22.68	38.00	44.84	24.00	38.00
Age (years)	57.06	19.42	58.00	45.77	14.95	44.00	45.59	15.08	44.00
Female (%)	50.03	50.00	100.00	53.52	49.88	100.00	53.35	49.89	100.00
B. Access to Credit									
Credit Score	750.49	85.44	787.00	611.01	80.44	609.00	612.67	82.00	610.00
Total Balance ($1,000)	88.24	154.59	7.82	65.33	115.15	17.97	67.43	118.42	18.33
Revolving Limit ($1,000)	31.79	38.96	19.11	6.06	15.52	0.43	6.72	17.30	0.49
Revolving Utilization (%)	16.09	23.16	6.00	54.68	38.61	55.00	54.06	38.76	55.00
Average Account Age (months)	136.56	83.72	123.00	77.00	46.49	68.00	77.43	46.31	69.00
Number of Accounts Opened in Last 6 Months	0.28	0.64	0.00	0.70	1.19	0.00	0.70	1.19	0.00
Number of Inquiries in Last 6 Months	0.26	0.57	0.00	0.78	1.00	0.00	0.76	0.99	0.00
Number of New Mortgages in Last 6 Months	0.03	0.17	0.00	0.02	0.13	0.00	0.02	0.14	0.00
C. Access to Alternative Credit									
Has Alternative Credit Record (%)	6.90	25.35	0.00	54.01	49.84	100.00	52.86	49.92	100.00
Has Alternative Credit Balance (%)	0.22	4.72	0.00	3.88	19.32	0.00	3.76	19.03	0.00
Number of Alternative Credit Accounts	0.01	0.19	0.00	0.19	0.86	0.00	0.18	0.85	0.00
Alternative Credit Balance ($1,000)	0.01	0.35	0.00	0.22	1.59	0.00	0.21	1.55	0.00
D. Financial Distress									
Number of Accounts 90+ Days Past Due	0.05	0.44	0.00	0.64	1.68	0.00	0.64	1.67	0.00
Total Balance 90+ Days Past Due ($1,000)	0.22	6.42	0.00	2.85	22.81	0.00	2.64	21.64	0.00
Bankruptcy in Last 7 Years (%)	0.95	9.68	0.00	9.61	29.48	0.00	9.17	28.85	0.00
E. Debt in Collections									
Total Debts ($1,000)	0.17	1.71	0.00	1.69	4.88	0.11	1.67	4.53	0.08
Total Medical Debts ($1,000)	0.06	0.67	0.00	0.44	1.90	0.00	0.41	1.53	0.00
Number of Debts	0.20	1.07	0.00	1.78	3.01	1.00	1.73	2.96	1.00
Number of Medical Debts	0.09	0.60	0.00	0.71	1.66	0.00	0.66	1.60	0.00
Number of Medical Debts Below $500	0.05	0.39	0.00	0.42	1.09	0.00	0.39	1.05	0.00
Observations	6,914,163			691,413			691,415		

Notes: This table shows descriptive statistics between 2019 and 2024 for Unaffected consumers in the first three columns, Positively Treated consumers in the next three columns, and Negatively Treated consumers in the last three columns. Negatively Treated refers to consumers above the 95th percentile in the distribution of probability difference, whose predicted probability of default increases by approximately 2 p.p. or more when medical collections below $500 are removed from our baseline credit scoring model. Positively Treated refers to consumers below the 5th percentile in the distribution of probability difference, whose predicted probability of default decreases by approximately 2 p.p. or more when medical collections below $500 are removed from our baseline credit scoring model. Unaffected consists of consumers between the 25th and 75th percentiles. All variables come from the Gies Consumer and Small Business Credit Panel.

Online Appendix

"The Effects of Deleting Medical Debt from Consumer Credit Reports"

Victor Duarte, Julia Fonseca, Divij Kohli, Julian Reif

A Alternative RD specifications

The effect of deleting small medical debt collections on individual-level outcomes depends on the underlying treatment mechanism. We consider three possibilities:

1. **Account level**: Treatment scales with the proportion of deleted accounts.
2. **Person level (max)**: Treatment occurs only if all of an individual's medical debt collections are deleted.
3. **Person level (min)** Treatment occurs if any (i.e., at least one) medical debt collection is deleted.

The account-level specification can be estimated using Equation (1). First-stage estimates for this case are reported in Panel A of Figure 2. In this appendix, we extend this specification to estimate second-stage outcomes. Since outcomes such as an individual's credit score do not vary across accounts, we cluster standard errors at the individual level.

The person-level (max) specification, where treatment occurs only if all medical debts are deleted, is estimated using Equation (2), as reported in the main text. The person-level (min) specification, where treatment occurs if any medical collection is deleted, can be estimated using a variant of this approach, with the running variable MINDEBT_i^{2022} defined as the balance of the consumer's smallest medical debt relative to the \$500 cutoff:

$$Y_i^{2024} = \alpha \text{MINDEBT}_i^{2022} + \beta \text{ABOVE}_i^{2022} + \gamma(\text{ABOVE}_i^{2022} \times \text{MINDEBT}_i^{2022}) + \epsilon_i \qquad (9)$$

We present estimates for these three treatment definitions in Table A.1. Panel A replicates the main text estimates from Table 3, which correspond to the person-level (max) specification. Panel B reports estimates for the person-level (min) specification. The first-stage estimates in Columns (1) and (2) are slightly larger in magnitude, likely due to sample composition differences near the threshold. However, as in Panel A, all second-stage estimates in Columns (3)–(10) remain statistically insignificant. Panel C presents results for the account-level specification, showing a similar pattern. Overall, these findings suggest that our main estimates are robust to alternative RD specifications.

Table A.1: Direct Effect: Alternative RD Specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Number of Debts	Number of Medical Debts	Credit Score	Total Balance ($1,000)	Number of Accounts Opened in Last 6 Months	Revolving Utilization (%)	Total Balance 90+ Days Past Due ($1,000)	Bankruptcy in Last 7 Years (%)	Has Alternative Credit Balance (%)	Number of Alternative Credit Accounts	Share of Surviving Accounts
A. Running Variable is Maximum Debt											
ABOVE^{2024}	–0.226*** [–0.324, –0.145]	–0.299*** [–0.322, –0.267]	0.683 [–3.63, 6.03]	–2.23 [–8.59, 2.60]	0.0386* [–0.000785, 0.0895]	0.393 [–1.54, 2.38]	–0.0926 [–0.802, 0.510]	–0.367 [–1.19, 0.542]	0.381 [–0.293, 1.28]	0.0109 [–0.0153, 0.0453]	N/A
Sample mean	1.31	0.279	620	51.5	0.510	32.1	1.89	3.18	3.86	0.177	
% of Mean	–17.3	–107	0.110	–4.34	7.55	1.22	–4.89	–11.6	9.87	6.15	
Bandwidth	146	281	122	104	167	161	246	152	223	230	
Observations	271,305	271,305	271,305	271,305	271,305	271,305	271,305	271,305	271,305	271,305	
B. Running Variable is Minimum Debt											
ABOVE^{2024}	–0.409*** [–0.560, –0.293]	–0.432*** [–0.527, –0.367]	0.408 [–5.28, 6.13]	–2.59 [–9.64, 2.69]	0.00807 [–0.0379, 0.0597]	0.940 [–1.09, 3.46]	0.159 [–0.526, 0.745]	0.138 [–0.682, 1.08]	0.0149 [–0.709, 0.977]	–0.00692 [–0.0397, 0.0312]	N/A
Sample mean	1.54	0.521	616	46.7	0.477	29.7	1.93	2.69	3.63	0.165	
% of Mean	–26.5	–83.0	0.0663	–5.54	1.69	3.16	8.26	5.11	0.411	–4.19	
Bandwidth	121	121	123	104	192	151	248	162	261	283	
Observations	271,305	271,305	271,305	271,305	271,305	271,305	271,305	271,305	271,305	271,305	
C. Running Variable is Amount of Debt in Medical Account											
ABOVE^{2022}	–0.436*** [–0.642, –0.286]	–0.438*** [–0.628, –0.295]	2.85* [–0.149, 6.78]	0.160 [–3.61, 3.23]	0.014 [–0.014, 0.051]	0.98 [–0.448, 2.697]	0.078 [–0.342, 0.434]	0.038 [–0.535, 0.638]	0.284 [–0.288, 0.912]	0.009 [– 0.011,0.032]	-0.101*** [–0.104, 0.096]
Sample Mean	1.58	0.55	615	47.3	0.49	30.51	1.90	2.93	3.787	0.174	0.0586
% of Mean	-27.5	-79.5	0.46	0.34	2.80	3.21	4.12	1.30	7.50	5.20	-173
Bandwidth	93	90	103	100	175	140	232	151	249	243	221
Observations	723,088	723,088	723,088	723,088	723,088	723,088	723,088	723,088	723,088	723,088	723,088

Notes: This table shows the coefficient ($-\beta$) estimates and 95% confidence intervals of Equation (2). The running variable in Panel A corresponds to the highest debt amount across the consumer's medical collections accounts. The running variable in Panel B corresponds to the smallest debt amount across the consumer's medical collections accounts. Whereas, the running variable in Panel C corresponds to the debt amount in the consumer's medical collections account. "Share of Surviving Accounts" varies across accounts and is not reported for the person-level specifications presented in Panels A and B. We report MSE-optimal estimates with robust, bias-corrected 95% confidence intervals in brackets. Sample Mean reports the mean of the dependent variable in 2024. A ***, **, and * indicate significance at the 1%, 5%, and 10% level respectively, using conventional inference.

B Comparing GCCP Medical Collection Data to External Sources

To identify consumers with medical collections, we use credit account (tradeline) data from the GCCP. We classify a collection as medical if the creditor is categorized as Medical/Health Care or the furnisher is identified as a business in the medical or health-related sector.[1] To assess whether our sample accurately captures the proportion of consumers with medical collections, we conduct a benchmarking exercise.

Table A.2 compares the share of consumers with medical collections in the GCCP to estimates from other sources. Column (1) reports the annual share of consumers with at least one medical collection in the GCCP from 2018 to 2023, showing a decline from 16.8% in 2018 to 7.1% in 2023. This decline reflects policy changes made during this period, including the removal of paid medical collections, the extension of the reporting delay for medical collections from six months to one year, and the removal of medical collections below $500).

A similar trend appears in columns (2) and (3), which report estimates from Blavin et al. (2023) (Urban Institute) and Sandler and Nathe (2022) (CFPB), respectively. The Urban Institute data show a slightly lower share of consumers with medical collections than the GCCP, while the CFPB data report a slightly higher share. These small differences might reflect differences in reporting timelines: the GCCP data are measured in March, the Urban Institute data in August, and the CFPB data in January. Overall, the GCCP data aligns well with these external benchmarks.

[1] Furnisher categories include Dentists, Chiropractors, Doctors, Medical group, Hospitals and clinics, Osteopaths, Pharmacies and drugstore, Optometrists and optical outlets, and Medical and related health-nonspecific.

Table A.2: Comparing GCCP Medical Collection Data to External Sources

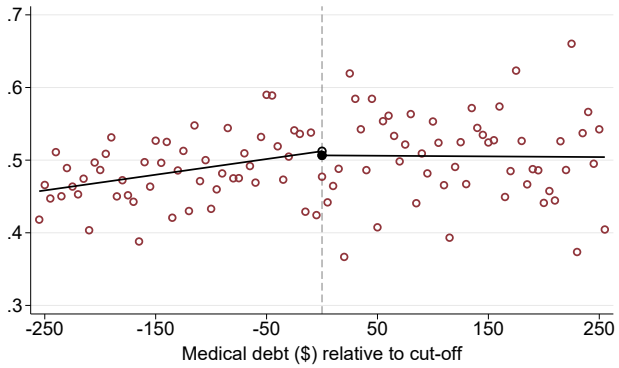
	(1)	(2)	(3)
Year	GCCP	Urban Institute	CFPB
2019	15.9%	16%	17.5%
2020	15.6%	15%	16%
2021	14.6%	14%	15.5%
2022	12.9%	12%	14%
2023	7.1%	5%	

Notes: This table compares the share of individuals with medical collections in the GCCP to estimates from other sources. Column (1) reports the share of consumers with at least one account in medical collections. Columns (2) and (3) present estimates from Blavin et al. (2023) and Sandler and Nathe (2022), respectively. The GCCP data are measured in March, the Urban Institute data in August, and the CFPB data in January.

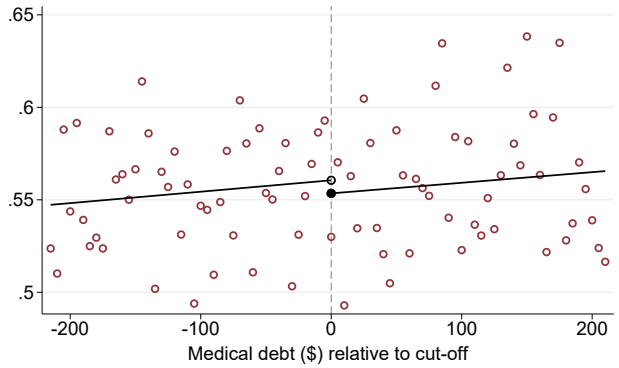
C Additional Figures and Tables

Figure A.1: Additional Credit Outcomes for RD Analysis, 2024

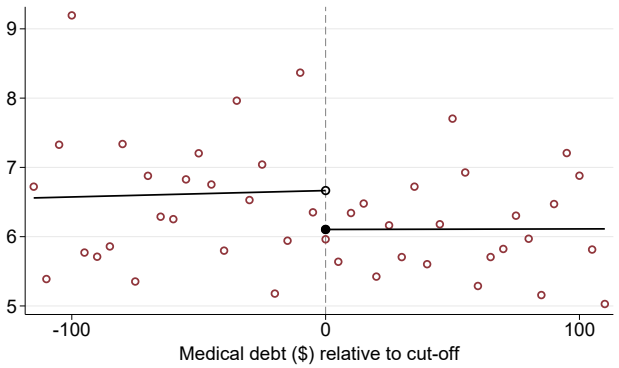
(a) Number of Accounts 90+ Days Past Due



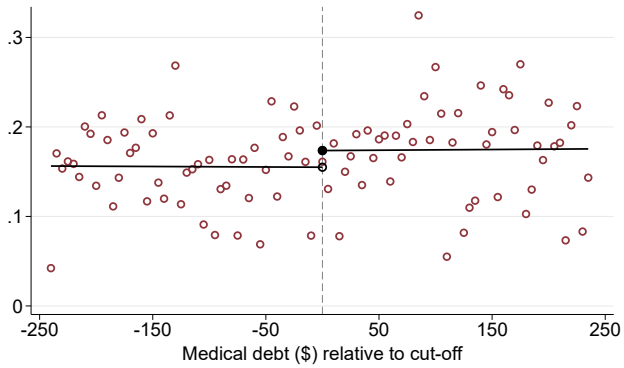
(b) Number of Inquiries in Last 6 Months



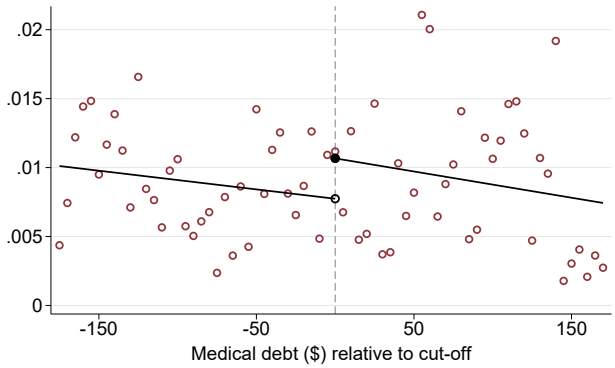
(c) Revolving Limit ($1,000)



(d) Alternative Credit Balance ($1,000)

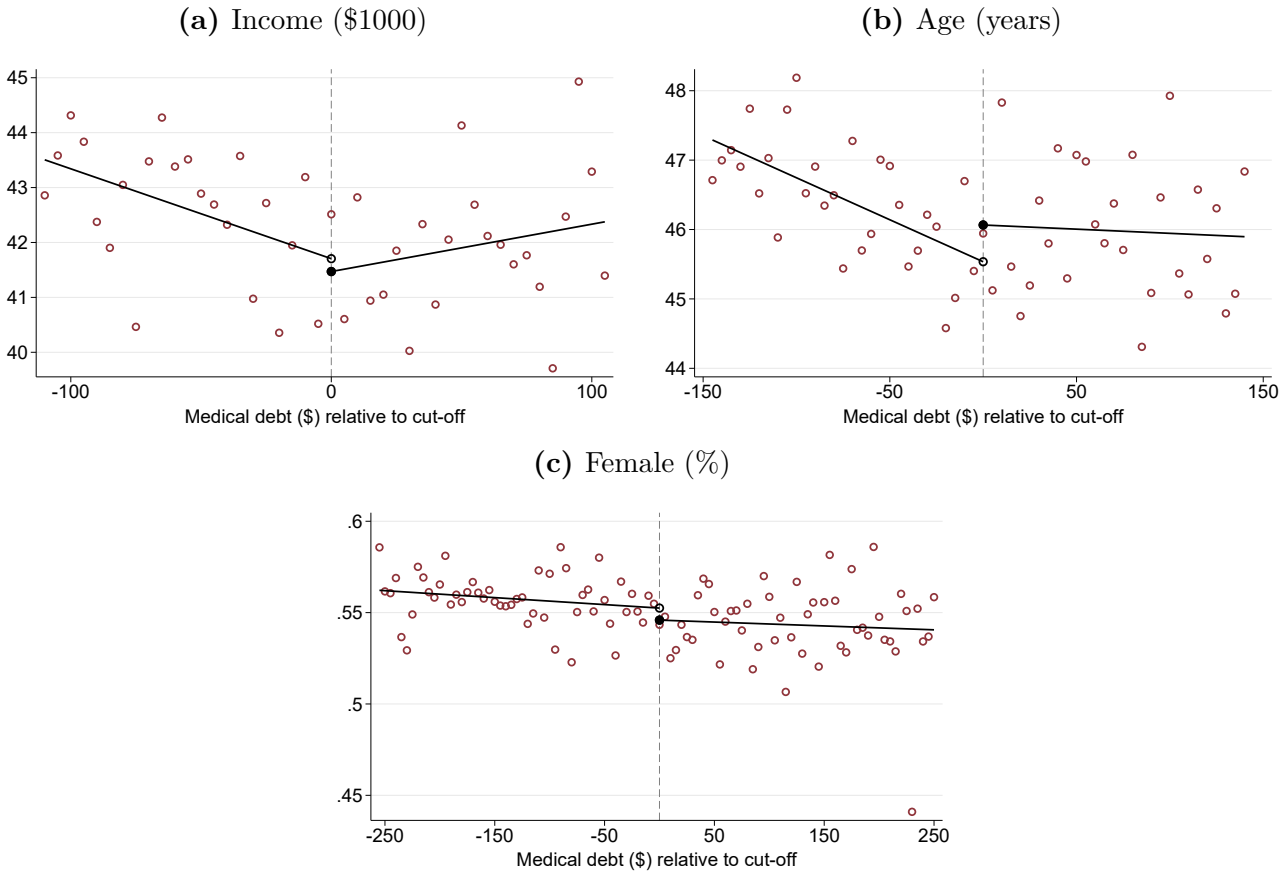


(e) Number of New Mortgages in Last 6 Months



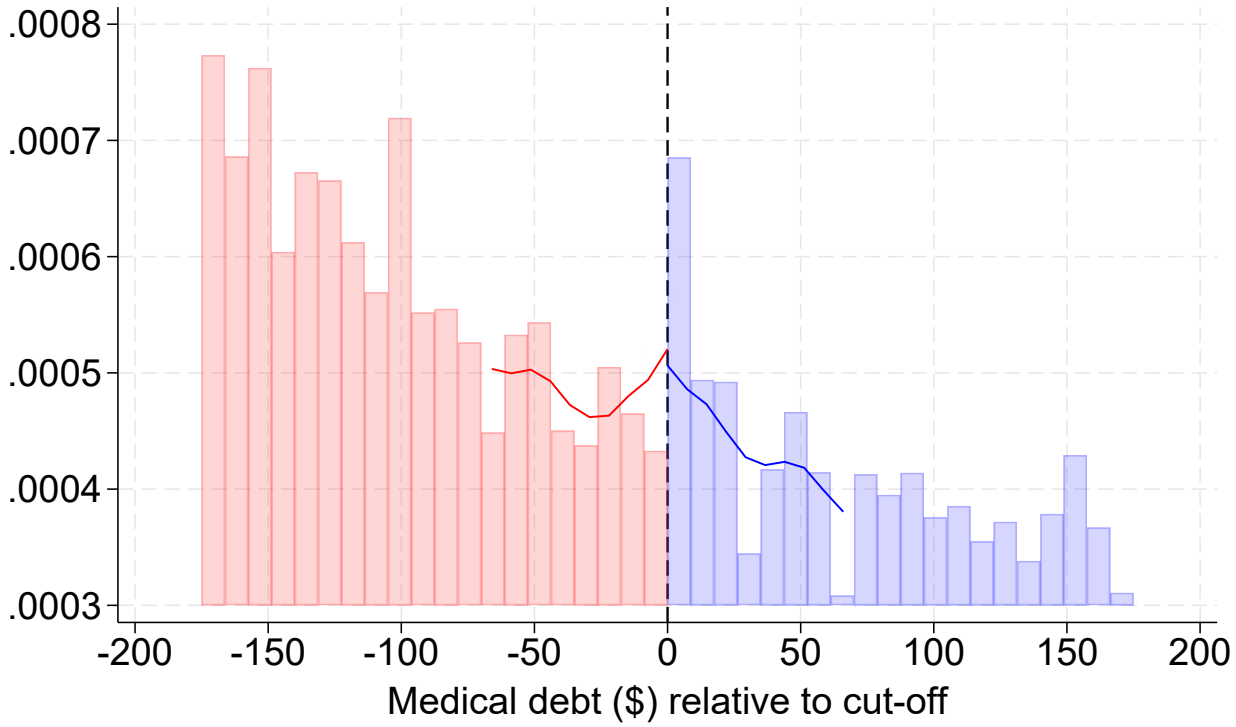
Notes: This figure shows the relationship between 2022 medical debt and five supplementary credit outcomes in 2024. Medical debt is defined as the maximum value of the consumer's 2022 medical collections accounts, measured relative to the $500 threshold. RD estimates from Equation (2) are reported in Table A.4.

Figure A.2: Covariate Smoothness Test: Demographics



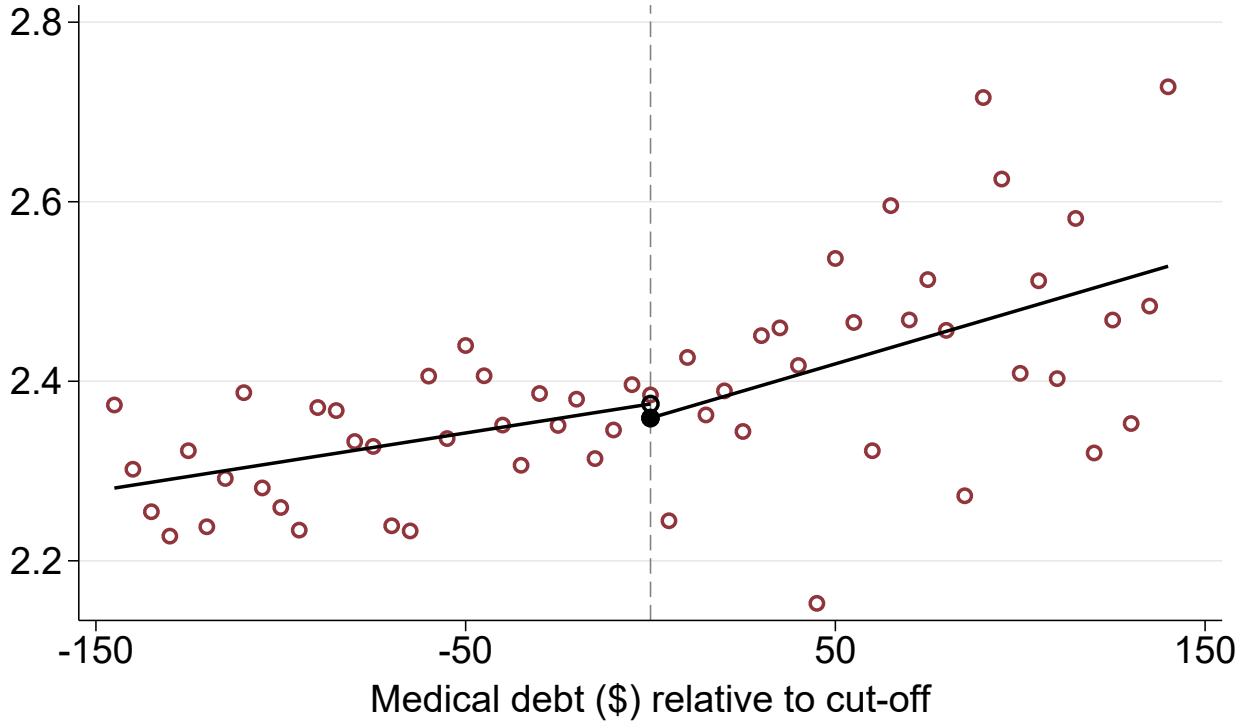
Notes: This figure shows the relationship between 2022 medical debt and three demographic variables in 2024. Medical debt is defined as the maximum value of the consumer's 2022 medical collections accounts, measured relative to the $500 threshold. RD estimates from Equation (2) are reported in Table A.3.

Figure A.3: Density Test of the Running Variable (Medical Debt), 2022



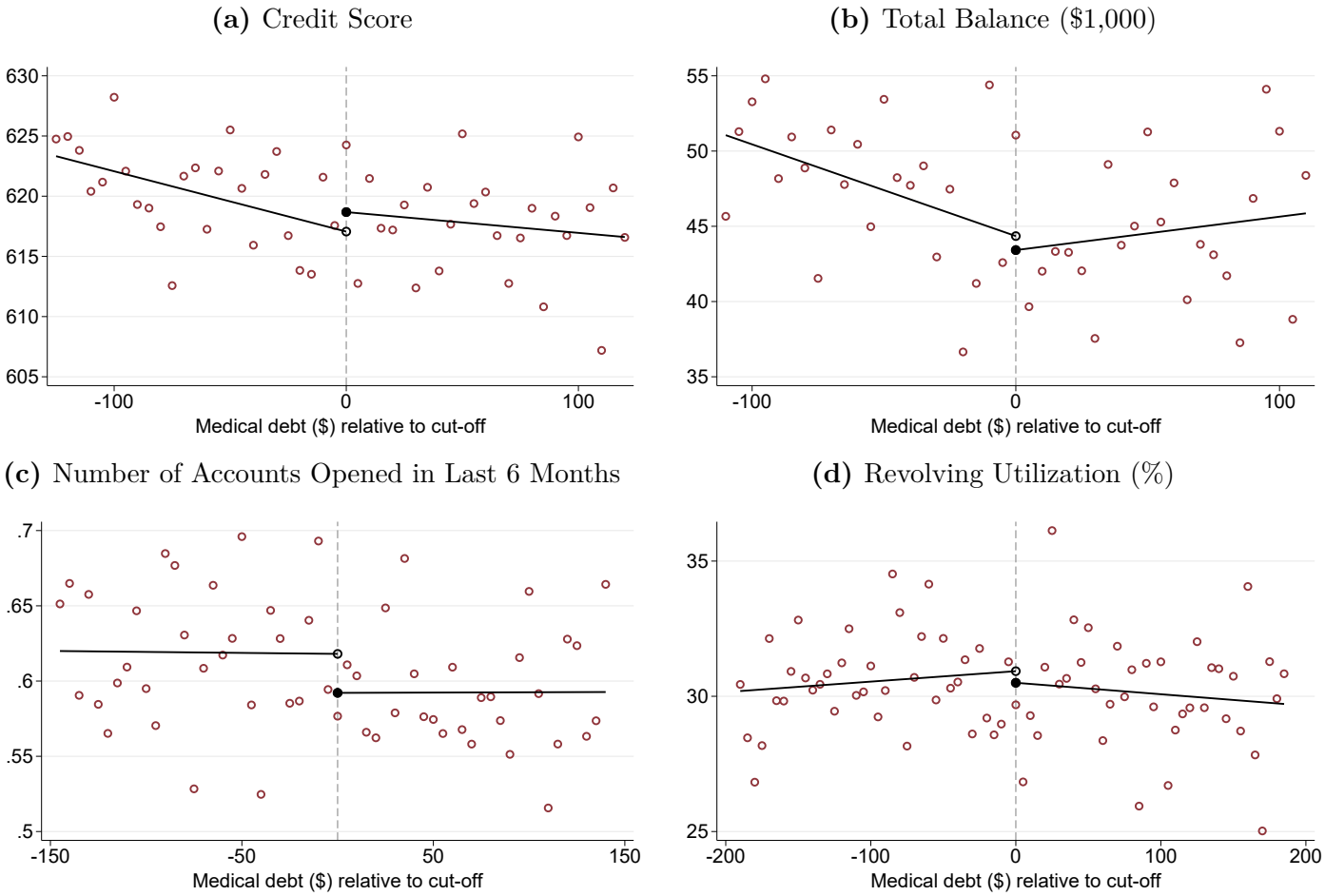
Notes: This figure shows the results of the McCrary density test for a discontinuity in the distribution of medical debt at the $500 cutoff (normalized to zero on the x-axis). The running variable is defined as the maximum value of the consumer's 2022 medical collections accounts, measured relative to the $500 threshold. The distribution shows no evidence of bunching below the cutoff, which would be consistent with strategic manipulation to qualify for deletion. Instead, the pattern is consistent with rounding behavior or reporting practices if some providers systematically refrain from reporting debts under $500.

Figure A.4: Falsification test: Average Number of Accounts per Person, 2022



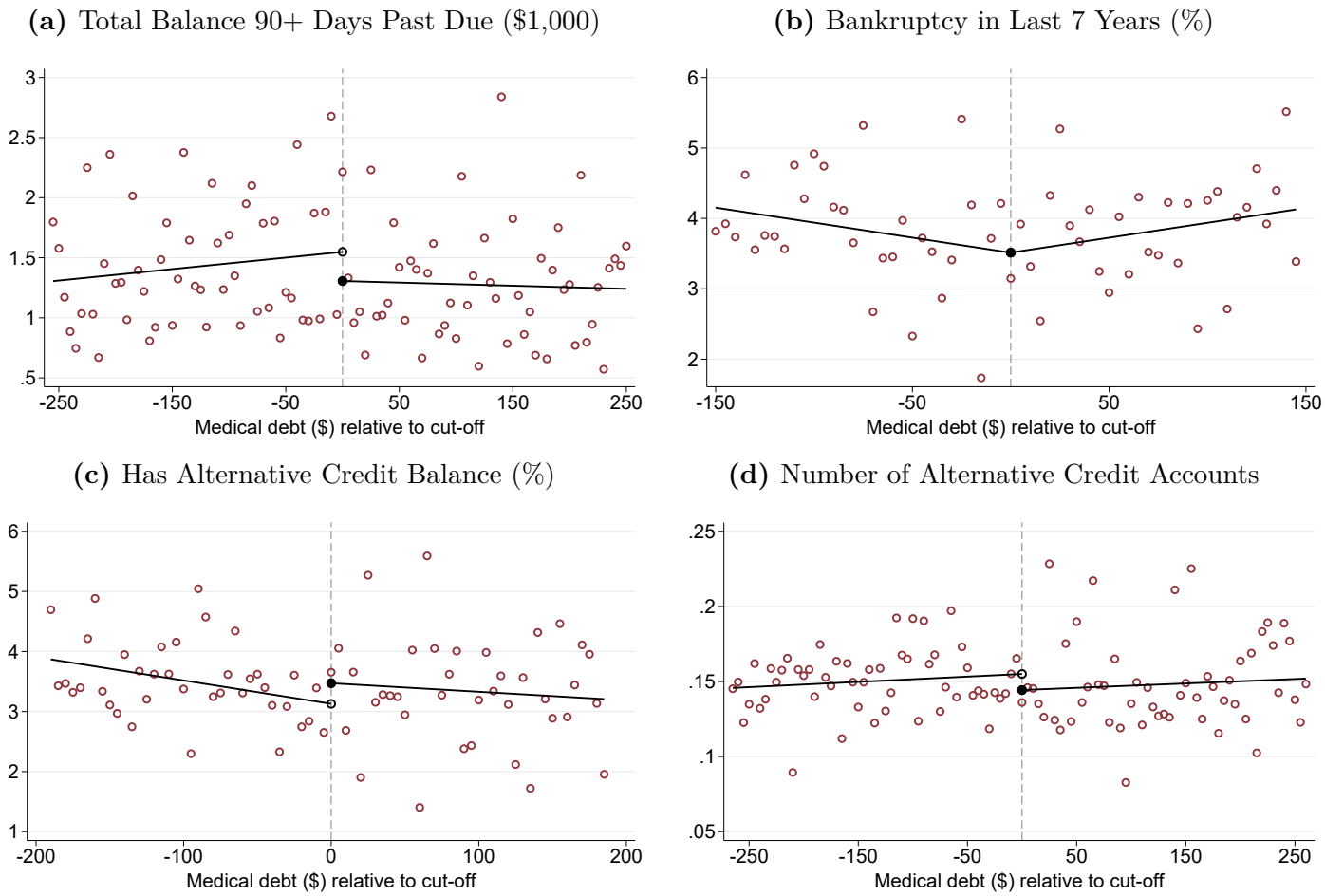
Notes: This figure shows the relationship between the medical debt running variable and the average number of medical collections accounts per person in 2022. The medical debt running variable is defined as the maximum value of the consumer's 2022 medical collections accounts, measured relative to the $500 threshold. RD estimates from Equation (2) are reported in Table 3.

Figure A.5: Falsification Test: Access to Credit, 2022



Notes: This figure shows the relationship between 2022 medical debt and four credit measures in 2022. Medical debt is defined as the maximum value of the consumer's 2022 medical collections accounts, measured relative to the $500 threshold. RD estimates from Equation (2) are reported in Table A.5.

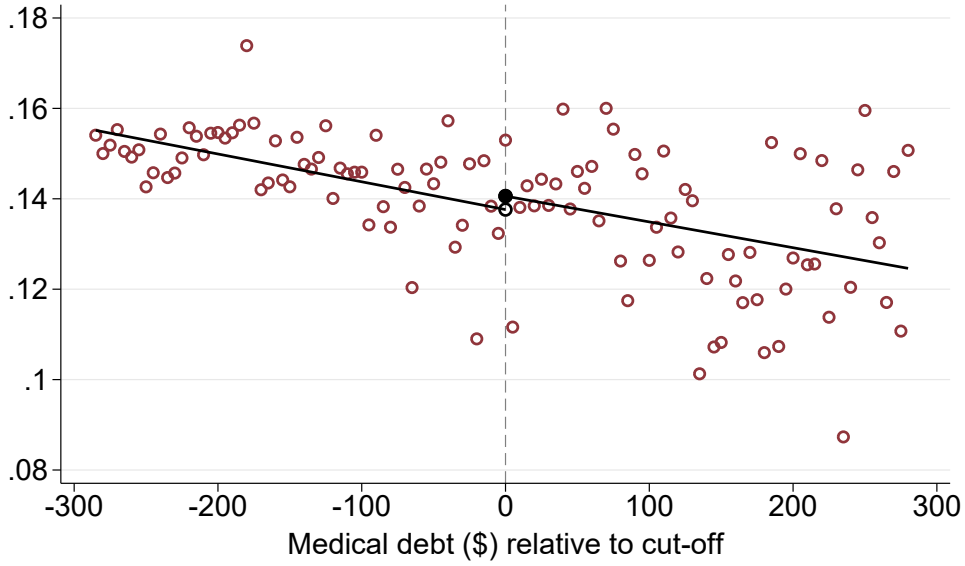
Figure A.6: Falsification Test: Financial Distress and Access to Alternative Credit, 2022



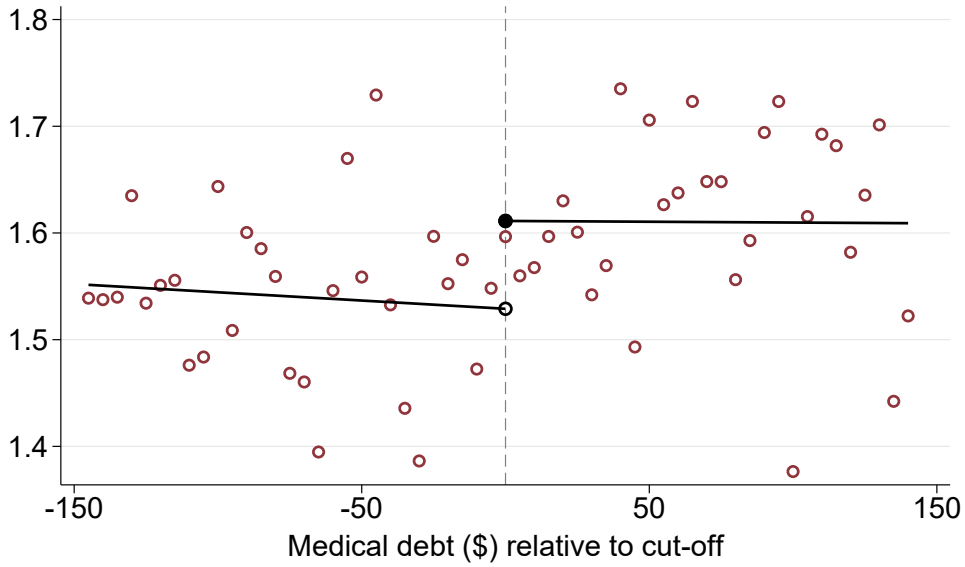
Notes: This figure shows the relationship between medical debt in 2022 and measures of financial distress and access to alternative credit in 2022. Medical debt is defined as the maximum value of the consumer's 2022 medical collections accounts, measured relative to the $500 threshold. RD estimates from Equation (2) are reported in Table A.5.

Figure A.7: Placebo Test: Two-Year Evolution of 2020 Medical Collections Accounts

(a) Share of Surviving Accounts

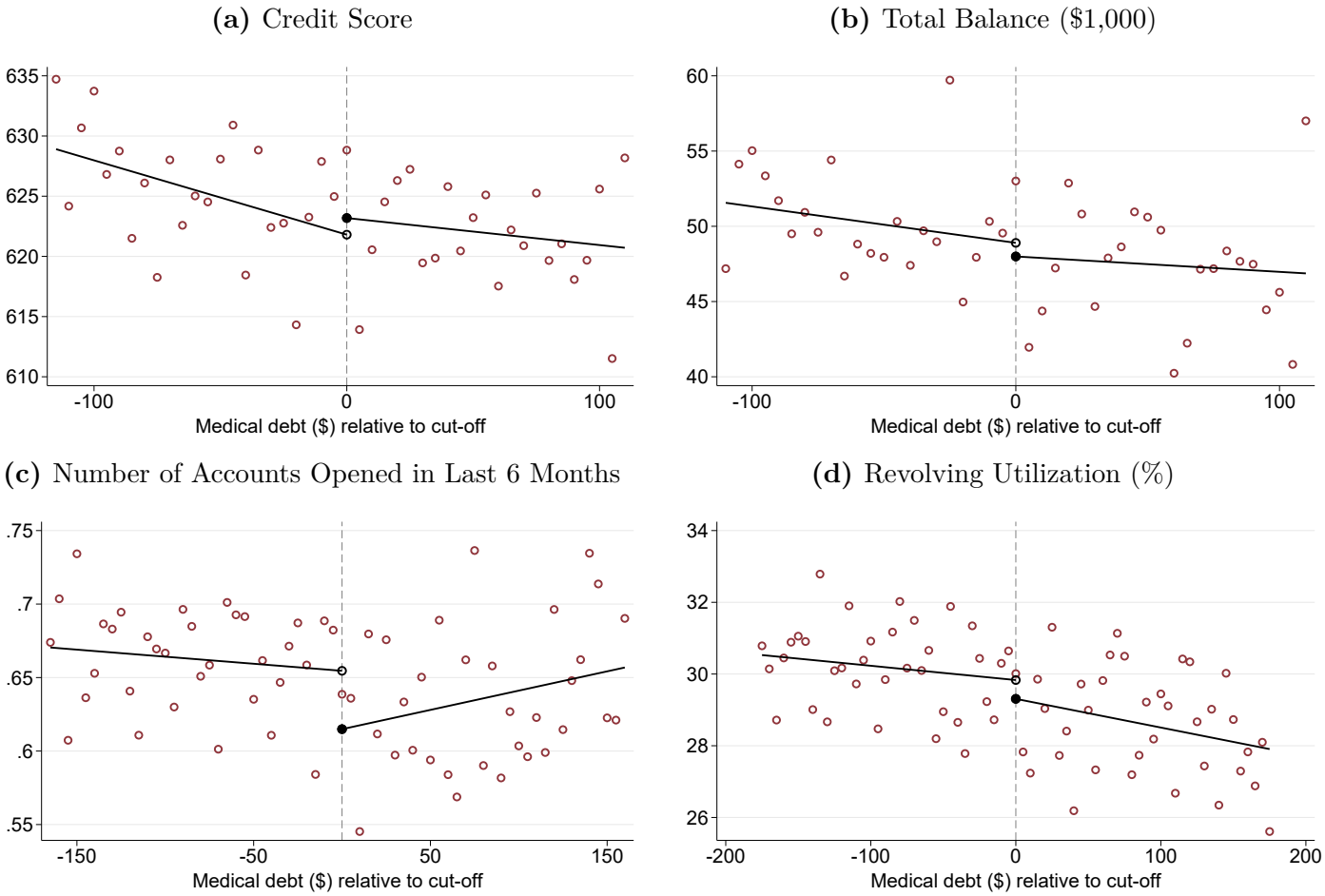


(b) Average Number of Accounts per Person



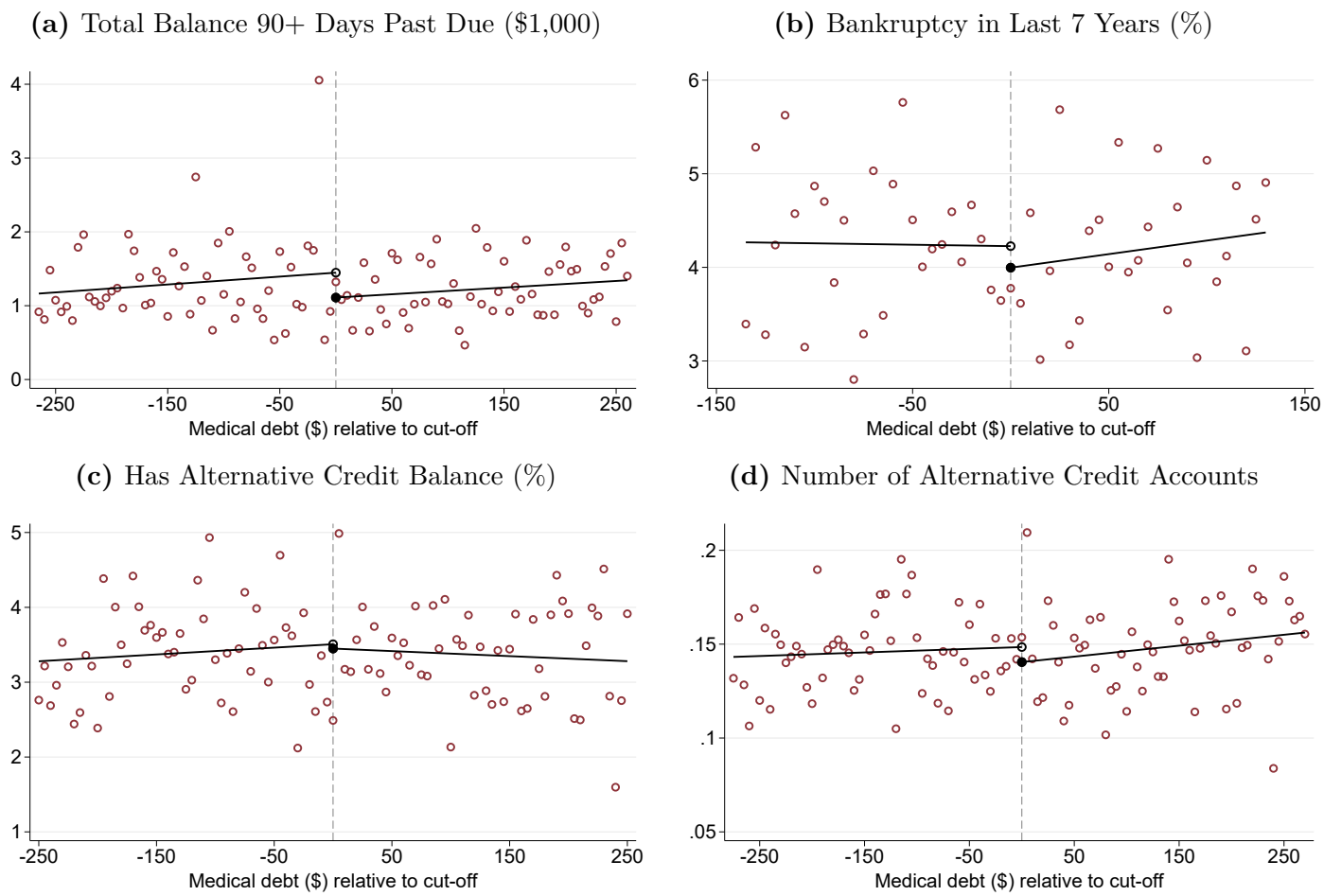
Notes: Panel (a) shows the proportion of 2020 medical collection accounts which remain present on 2022 credit reports by account amount, where the amount is measured as distance from the $500 threshold. Panel (b) shows the average number accounts per person. In panel (b), the running variable is equal to the maximum value of the consumer's medical collections accounts. RD estimates from Equation (2) are reported in Table A.6.

Figure A.8: Placebo Test: Access to Credit



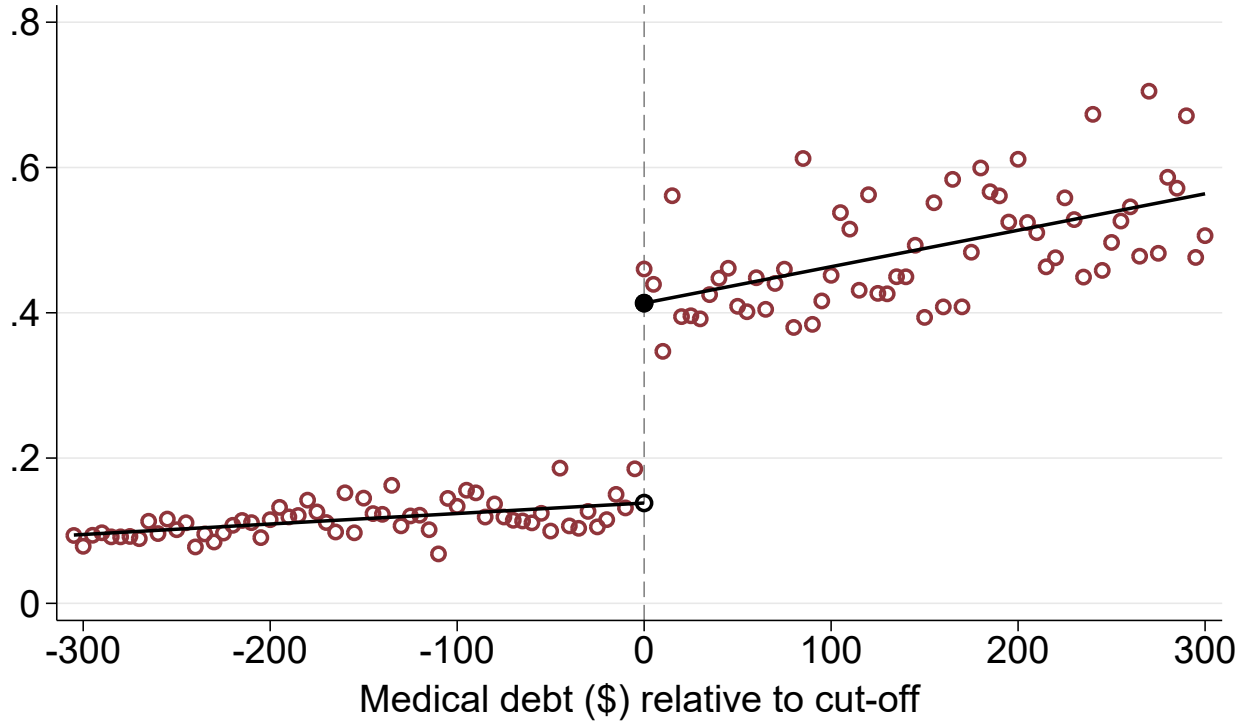
Notes: This figure shows the relationship between 2022 medical debt and five supplementary credit outcomes in 2022. Medical debt is defined as the maximum value of the consumer's 2022 medical collections accounts, measured relative to the $500 threshold. RD estimates from Equation (2) are reported in Table A.6.

Figure A.9: Placebo Test: Financial Distress and Access to Alternative Credit



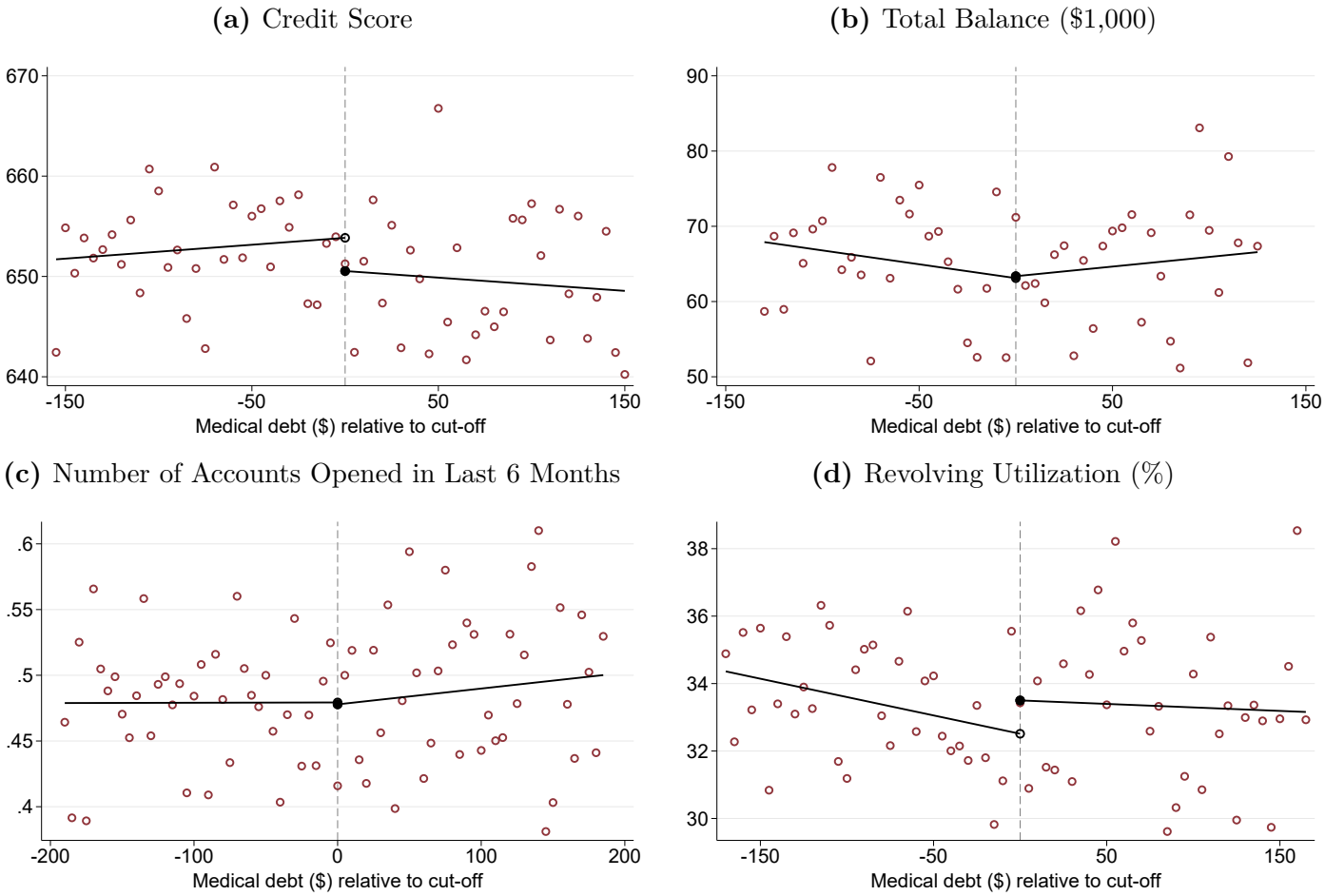
Notes: This figure shows the relationship between medical debt in 2022 and measures of financial distress and access to alternative credit in 2022. Medical debt is defined as the maximum value of the consumer's 2022 medical collections accounts, measured relative to the $500 threshold. RD estimates from Equation (2) are reported in Table A.6.

Figure A.10: Medical Collections Sub-Sample: Average Number of Accounts per Person, 2022



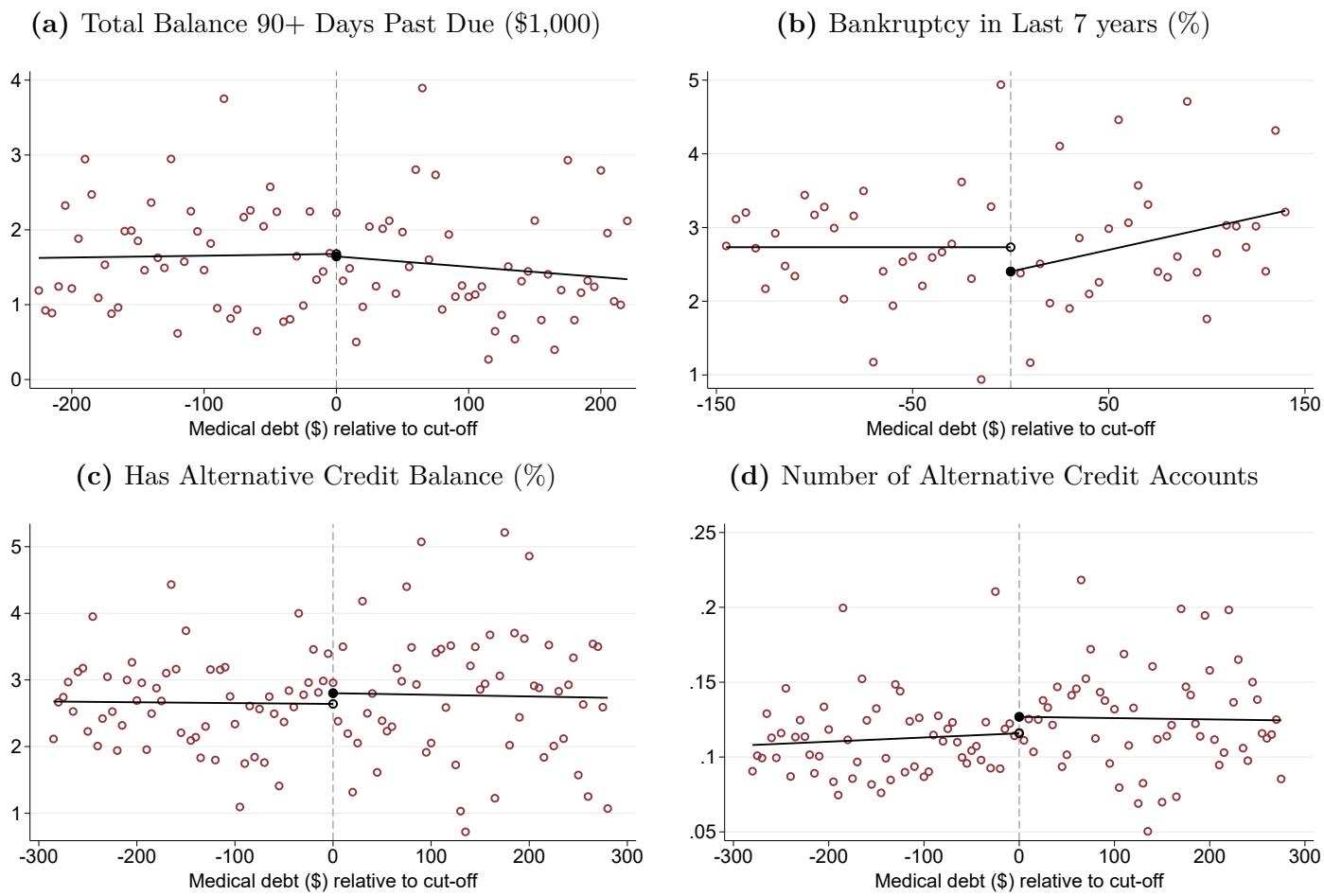
Notes: This figure shows the average number of medical collections accounts per person in 2024, where the running variable is the maximum value of the consumer's 2022 medical collections account, measured relative to the $500 threshold. The medical collections sub-sample restricts the RD sample to consumers for whom the total number of accounts in collection is same as the total number of medical collections accounts. RD estimates from Equation (2) are reported in Table A.7.

Figure A.11: Medical Collections Sub-Sample: Access to Credit



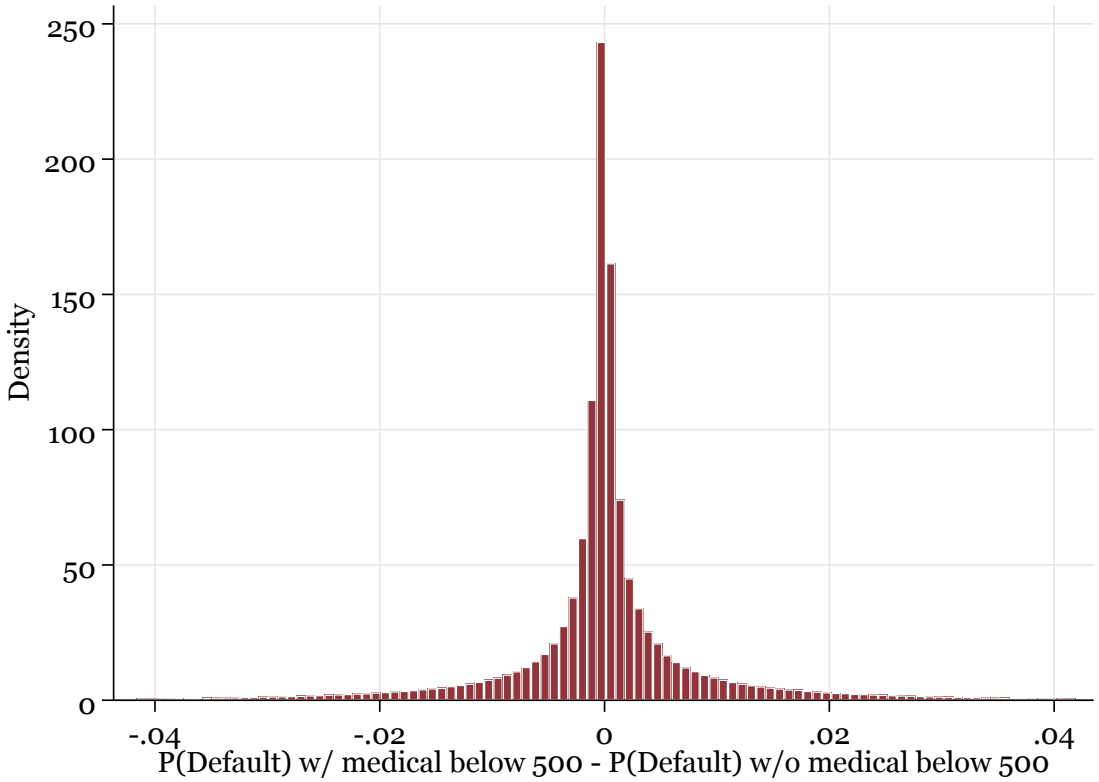
Notes: This figure shows the relationship between medical debt in 2022 and four different measures of credit access in 2024. The medical collections sub-sample restricts the RD sample to consumers for whom the total number of accounts in collections is same as the total number of medical collection accounts. Medical debt is defined as the maximum value of the consumer's 2022 medical collections accounts, measured relative to the $500 threshold. RD estimates from Equation (2) are reported in Table A.7.

Figure A.12: Medical Collections Sub-Sample: Financial Distress and Access to Alternative Credit



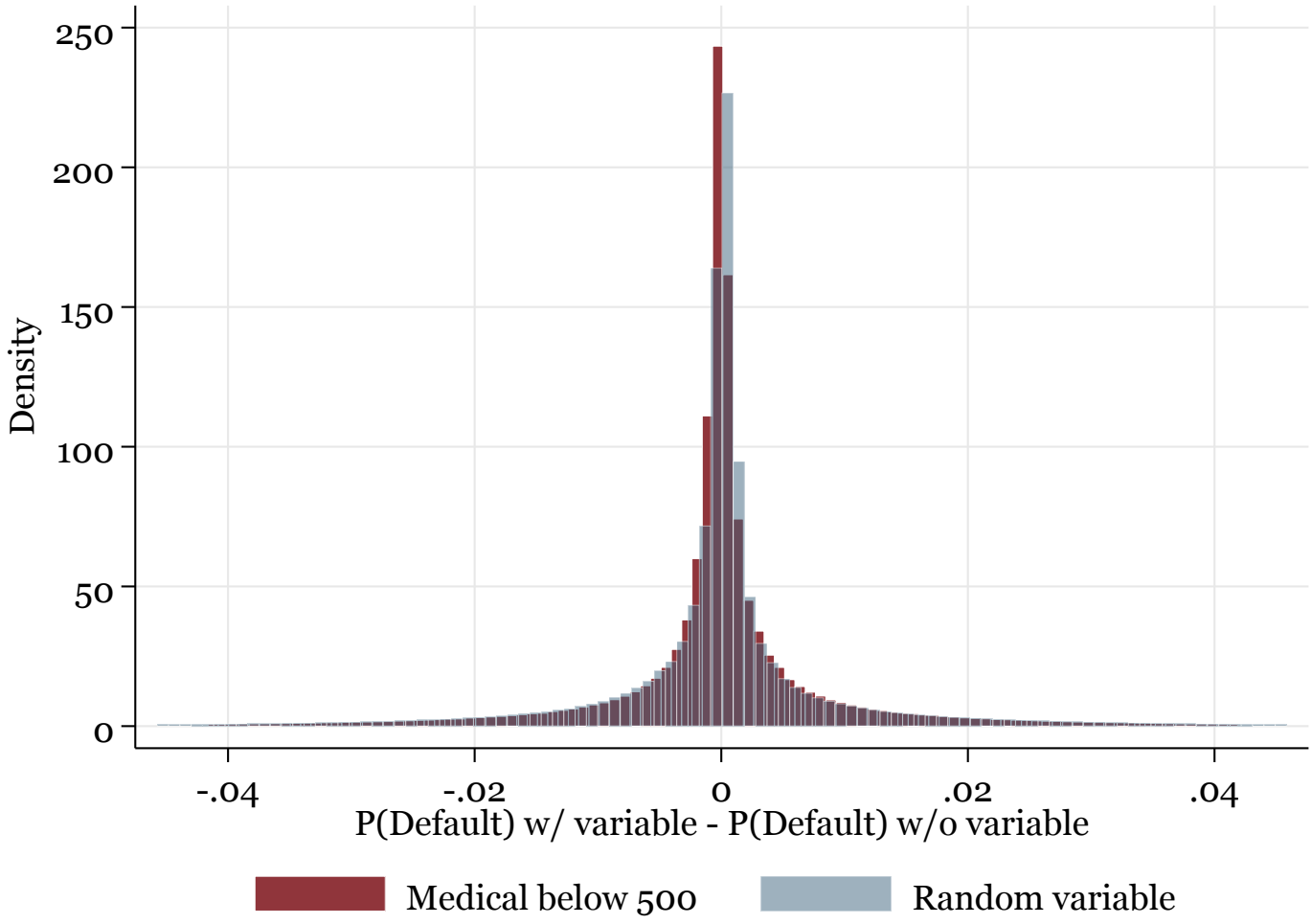
Notes: This figure shows the relationship between medical debt in 2022 and measures of financial distress and access to alternative credit in 2024. The medical collections sub-sample restricts the RD sample to consumers for whom the total number of accounts in collections is the same as the total number of medical collection accounts. Medical debt is defined as the maximum value of the consumer's 2022 medical collections accounts, measured relative to the $500 threshold. RD estimates from Equation (2) are reported in Table A.7.

Figure A.13: Effect of Removing Small Medical Collections on Predicted Default Probabilities



Notes: This figure shows the change in the predicted probability of default over 24 months following the removal of small (< $500) medical collections for 2.8 million consumers in the GCCP. Predictions, generated using the credit scoring model described in Section 4, are based on 2019 data.

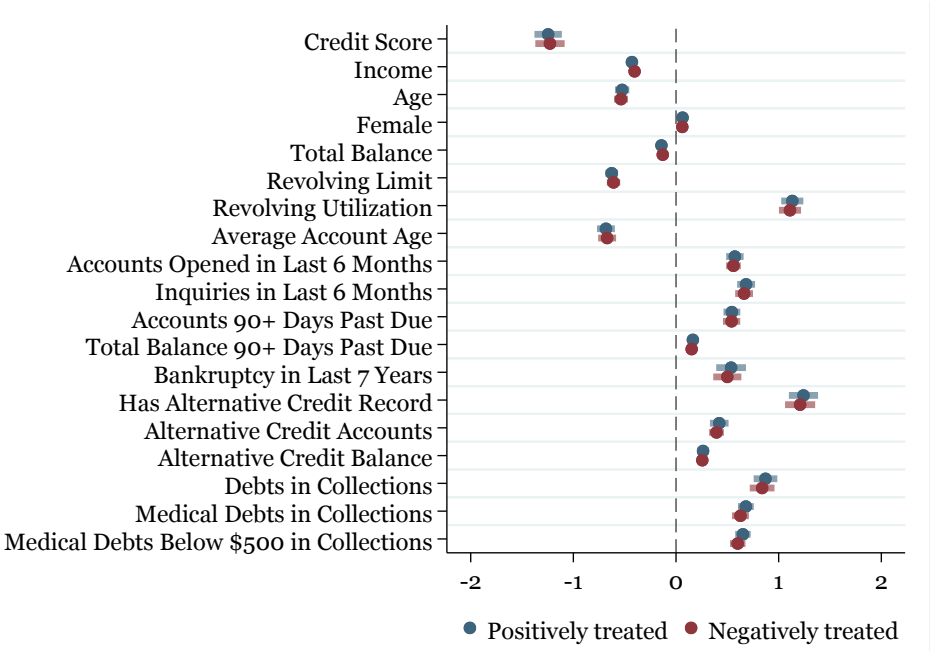
Figure A.14: Effect of Removing Small Medical Collections vs. Removing Noise



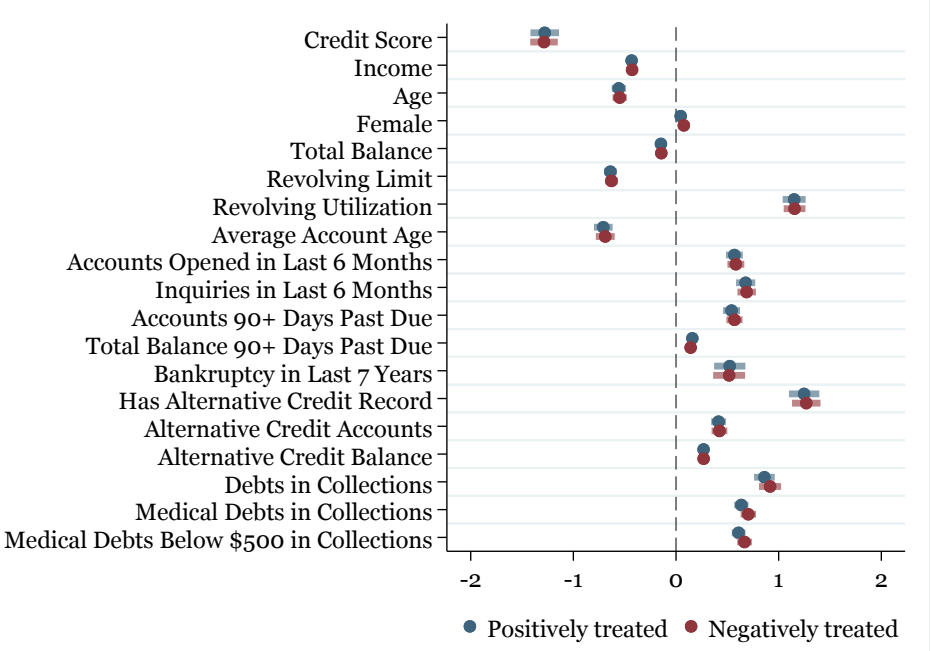
Notes: This figure shows the change in the predicted probability of default over 24 months following the removal of a variable from the credit scoring model described in Section 4. The red histogram reproduces the plot from Figure A.13, showing the effect of removing small (< $500) medical collections. The blue histogram shows the effect of removing a random noise predictor that was drawn randomly from a uniform distribution.

Figure A.15: Covariate Balance by Changes in Default Probabilities: Small Medical Collections vs. Noise

(a) Small (< $500) Medical Collections

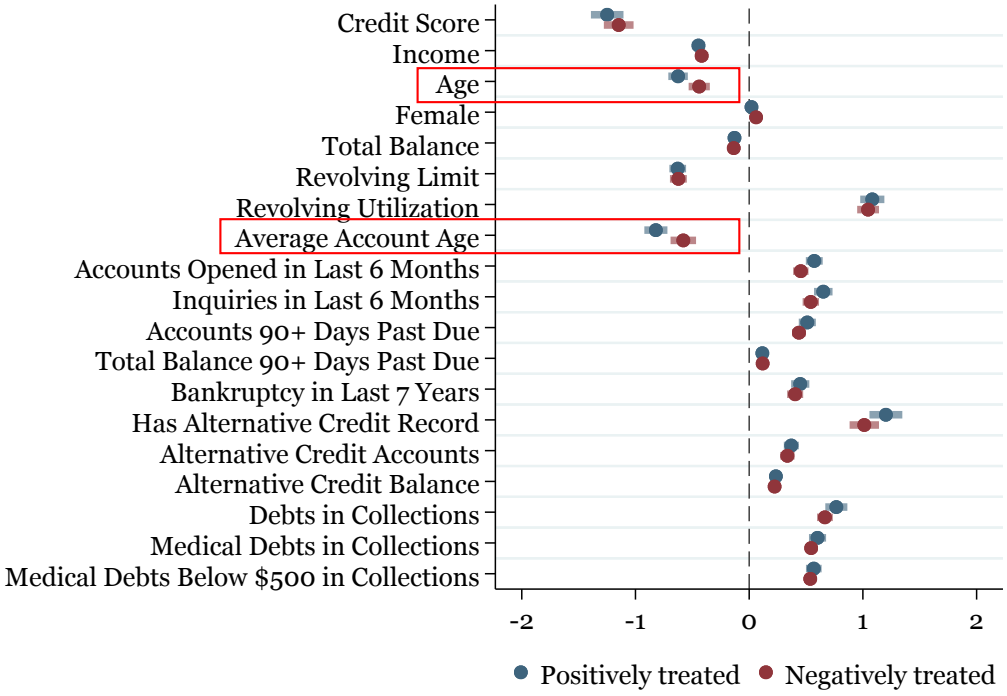


(b) Random Variable



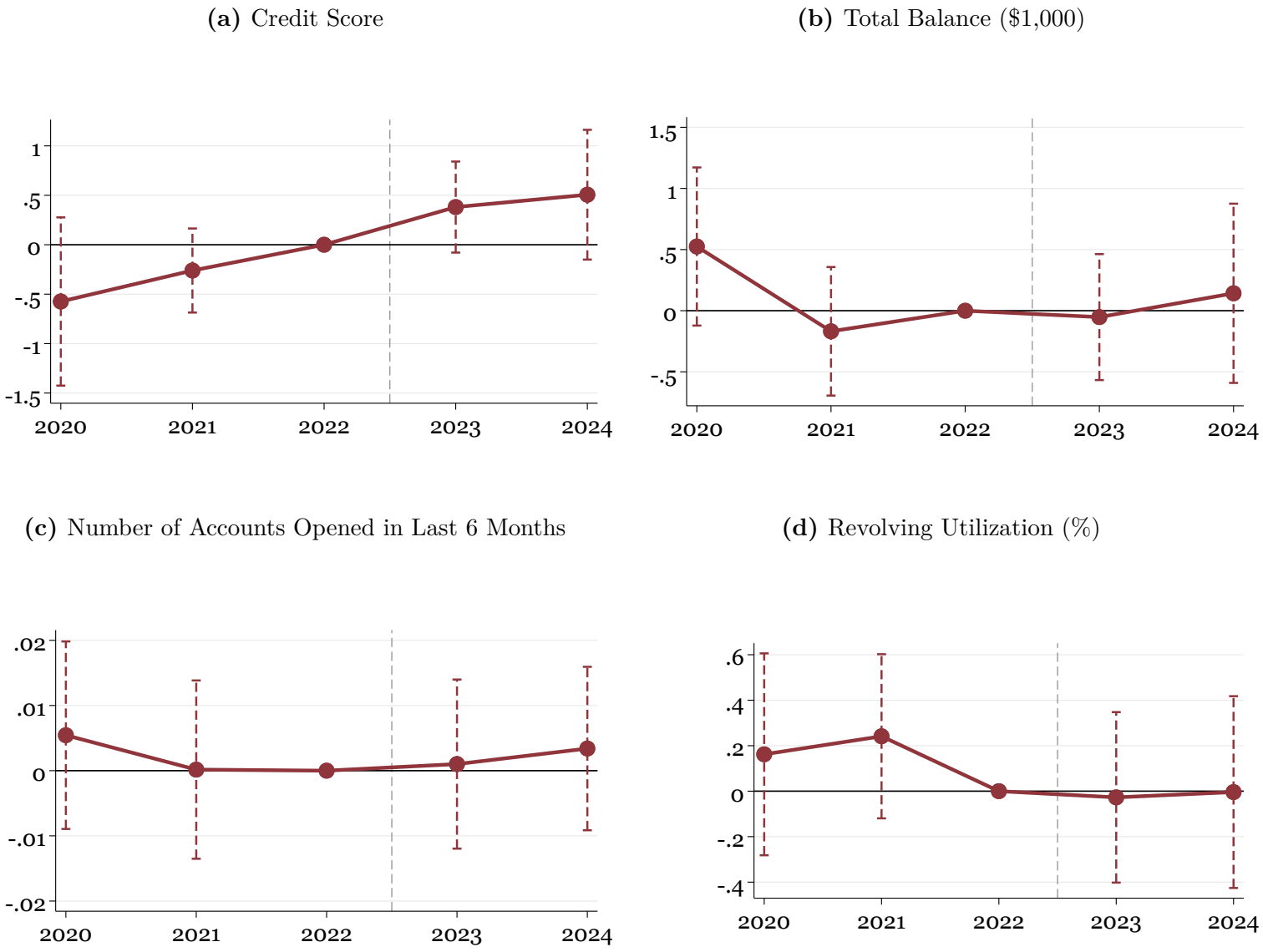
Notes: This figure shows estimates from balancing regressions for selected outcomes. Each balancing regression compares positively or negatively treated consumers to unaffected consumers in 2022. Negatively treated consumers are those whose predicted probability of default increases by 2 percentage points or more when small medical collections (Panel a) or a randomly generated predictor (Panel b) are removed from the credit scoring model described in Section 4. Positively treated consumers are those whose predicted default probability decreases by at least two percentage points. Unaffected consumers experience changes of less than 0.002. All variables are standardized, and each dot represents the regression coefficient of the variable labeled on the y-axis, regressed on either the positive (blue) or negatively treated (red) group indicator. We divide consumers in the full sample into 100 equal-sized bins based on changes in predicted default probability and cluster standard errors at the bin level.

Figure A.16: Covariate Balance by Changes in Default Probabilities: Length of Credit History



Notes: This figure shows estimates from balancing regressions for selected outcomes. Each balancing regression compares positively or negatively treated consumers to unaffected consumers in 2022. Negatively treated refers to consumers above the 95th percentile in the distribution of probability differences according to credit scoring models with and without information on credit history length. Positively treated refers to consumers below the 5th percentile in the distribution of probability differences. Unaffected refers to consumers between the 25th and 75th percentiles. All variables are standardized, and each dot represents the regression coefficient of the variable labeled on the y-axis, regressed on either the positive (blue) or negatively treated (red) group indicator. We divide consumers in the full sample into 100 equal-sized bins based on changes in predicted default probability and cluster standard errors at the bin level.

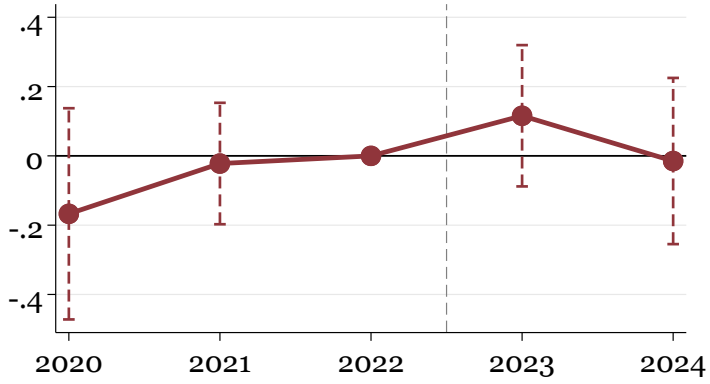
Figure A.17: Effect of Removing Medical Debts on Credit Access for Consumers Reclassified as Higher Risk



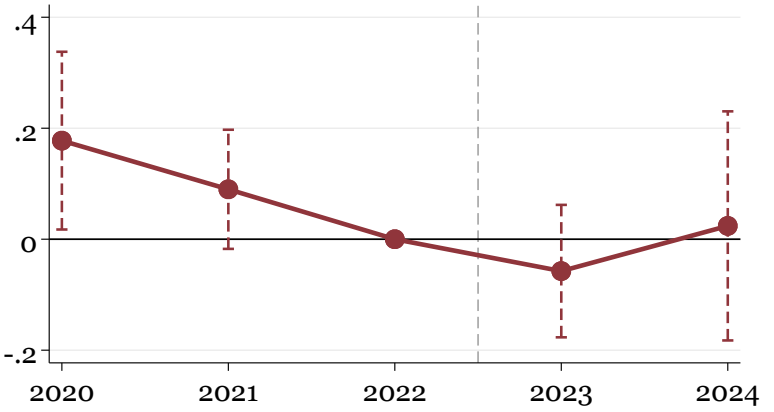
Notes: This figure presents difference-in-differences estimates based on Equation (8). The treatment group consists of consumers whose predicted probability of default increases by 2 percentage points or more when small medical collections are removed from the credit scoring model described in Section 4. The control group includes consumers whose predicted probability falls by at least 2 percentage points. The dashed vertical line indicates when small medical debts were removed from credit reports. Standard errors are clustered based on 100 bins of predicted default probabilities.

Figure A.18: Effect of Removing Medical Debts on Financial Distress and Alternative Credit for Consumers Reclassified as Higher Risk

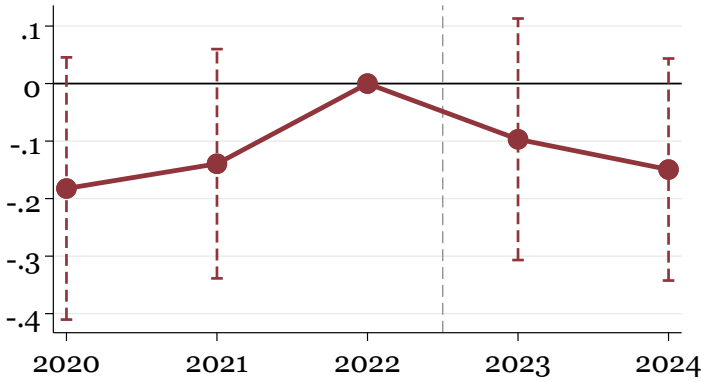
(a) Total Balance 90+ Days Past Due ($1,000)



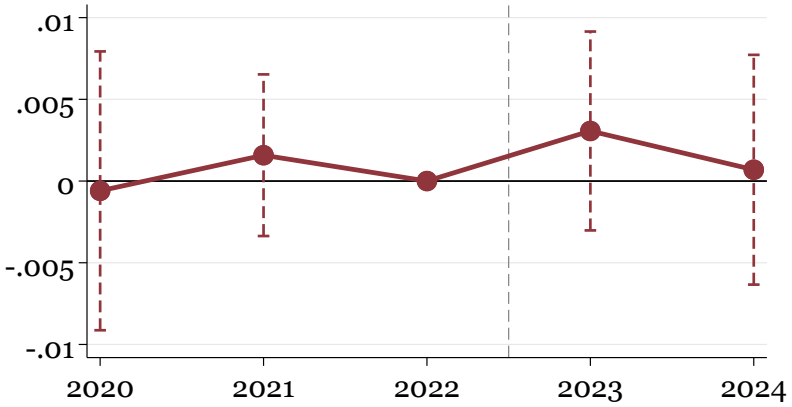
(b) Bankruptcy in Last 7 Years (%)



(c) Has Alternative Credit Balance (%)



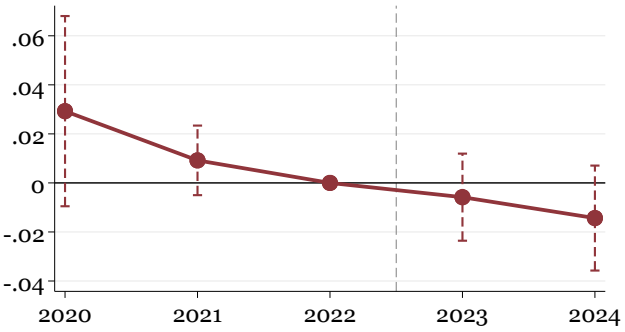
(d) Number of Alternative Credit Accounts



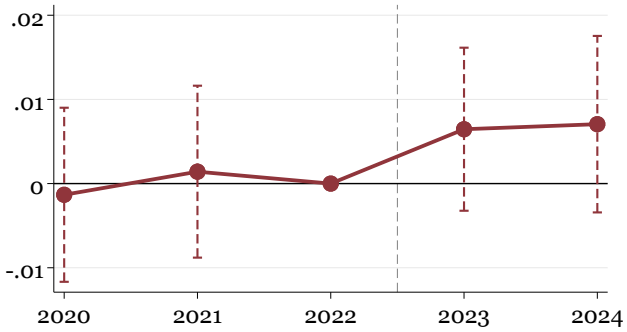
Notes: This figure presents difference-in-differences estimates based on Equation (8). The treatment group consists of consumers whose predicted probability of default increases by 2 percentage points or more when small medical collections are removed from the credit scoring model described in Section 4. The control group includes consumers whose predicted probability falls by at least 2 percentage points. The dashed vertical line indicates when small medical debts were removed from credit reports. Standard errors are clustered based on 100 bins of predicted default probabilities.

Figure A.19: Effect of Removing Small Medical Collections on Additional Outcomes

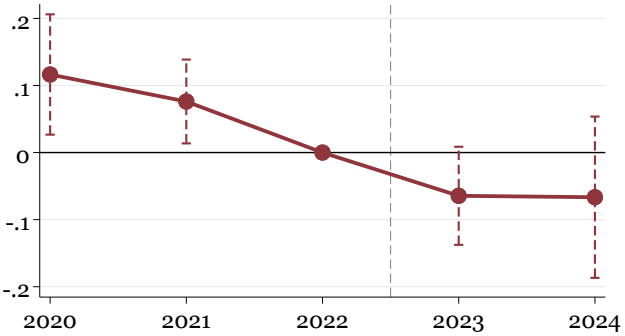
(a) Number of Accounts 90+ Days Past Due



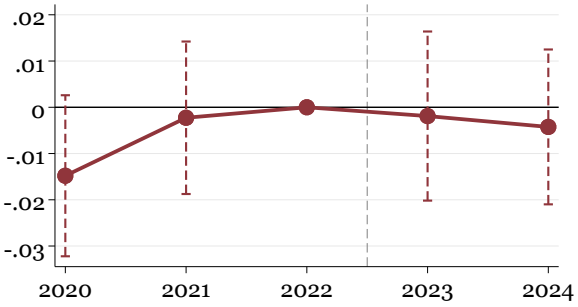
(b) Number of Inquiries in Last 6 Months



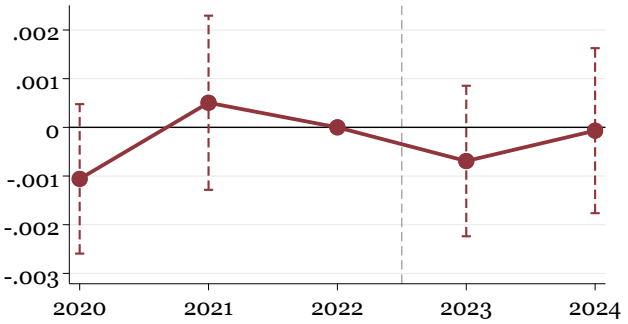
(c) Revolving Limit ($1,000)



(d) Alternative Credit Balance ($1,000)



(e) Number of New Mortgages in Last 6 Months



This figure shows coefficient estimates and 95% confidence intervals of Equation (8) for the outcomes denoted in panel captions. We create 1,000 equal-sized bins of the difference in predicted probability of default in our full sample and cluster our standard errors at the bin level. Our differences-in-differences sample corresponds to 10% of the full sample, and we are thus left with 100 clusters.

Table A.3: Covariate Smoothness: RD Estimates of the Direct Effect of Medical Debt Deletion

	(1)	(2)	(3)
	Income ($1,000)	Age (years)	Female (%)
$ABOVE^{2024}$	–0.0663	–0.512	0.00970
	[–1.44, 1.04]	[–1.17, 0.314]	[–0.00990, 0.0301]
Sample mean	42.3	46.3	0.552
% of Mean	–0.157	–1.11	1.76
Bandwidth	109	141	254
Observations	271,305	271,305	263,895

Notes: This table presents the estimated coefficient ($-\beta$) and 95% confidence intervals from Equation (2). The running variable for medical debt corresponds to the highest debt amount across the consumer's medical collections accounts. We report MSE-optimal estimates with robust, bias-corrected 95% confidence intervals in brackets. Sample Mean reports the mean of the dependent variable in 2024. A ***, **, and * indicate significance at the 1%, 5%, and 10% level respectively, using conventional inference.

Table A.4: Additional Credit Outcomes: RD Estimates of the Direct Effect of Medical Debt Deletion

	(1)	(2)	(3)	(4)	(5)
	Number of Accounts 90+ Days Past Due	Number of Inquiries in Last 6 Months	Revolving Limit ($1,000)	Alternative Credit Balance ($1,000)	Number of Mortgage Accounts Opened in Last 6 Months
$ABOVE^{2024}$	0.0146	0.0167	0.635	–0.00672	–0.000727
	[–0.0334, 0.0698]	[–0.0198, 0.0520]	[–0.204, 1.71]	[–0.0490, 0.0498]	[–0.00509, 0.00459]
Sample mean	0.490	0.556	6.39	0.164	0.00909
% of Mean	2.97	3.01	9.94	–4.09	–8.01
Bandwidth	255	212	114	236	174
Observations	271,305	271,305	271,305	271,305	271,305

Notes: This table presents the estimated coefficient ($-\beta$) and 95% confidence intervals from Equation (2). The running variable for medical debt corresponds to the highest debt amount across the consumer's medical collections accounts. We report MSE-optimal estimates with robust, bias-corrected 95% confidence intervals in brackets. Sample Mean reports the mean of the dependent variable in 2024. A ***, **, and * indicate significance at the 1%, 5%, and 10% level respectively, using conventional inference.

Table A.5: Falsification Test: RD Estimates of the Direct Effect of Medical Debt Deletion

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Number of Debts	Number of Medical Debts	Credit Score	Total Balance ($1,000)	Number of Accounts Opened in Last 6 Months	Revolving Utilization (%)	Total Balance 90+ Days Past Due ($1,000)	Bankruptcy in Last 7 Years (%)	Has Alternative Credit Balance (%)	Number of Alternative Credit Accounts
ABOVE^{2024}	0.0875	0.0310	–1.99	–0.427	0.0255	0.0617	0.141	–0.0906	–0.457	0.00521
	[–0.0644, 0.195]	[–0.0672, 0.128]	[–6.70, 2.85]	[–6.23, 4.04]	[–0.0285, 0.0840]	[–1.67, 1.95]	[–0.492, 0.677]	[–1.08, 0.809]	[–1.36, 0.174]	[–0.0240, 0.0302]
Sample mean	3.45	2.37	619	46.4	0.607	30.3	1.36	3.85	3.45	0.149
% of Mean	2.53	1.31	–0.321	–0.921	4.20	0.203	10.4	–2.35	–13.2	3.50
Bandwidth	193	143	124	111	144	187	251	150	188	264
Observations	271,305	271,305	271,305	271,305	271,305	271,305	271,305	271,305	271,305	271,305

Notes: This table presents the estimated coefficient ($-\beta$) and 95% confidence intervals from Equation (2). The running variable for medical debt corresponds to the highest debt amount across the consumer's medical collections accounts. We report MSE-optimal estimates with robust, bias-corrected 95% confidence intervals in brackets. Sample Mean reports the mean of the dependent variable in 2024. A ***, **, and * indicate significance at the 1%, 5%, and 10% level respectively, using conventional inference.

Table A.6: Placebo Test: RD Estimates of the Direct Effect of Medical Debt Deletion

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Number of Debts	Number of Medical Debts	Credit Score	Total Balance ($1,000)	Number of Accounts Opened in Last 6 Months	Revolving Utilization (%)	Total Balance 90+ Days Past Due ($1,000)	Bankruptcy in Last 7 Years (%)	Has Alternative Credit Balance (%)	Number of Alternative Credit Accounts
ABOVE^{2024}	–0.0287 [–0.184, 0.0775]	–0.0631 [–0.166, 0.00398]	–1.15 [–5.09, 3.78]	0.433 [–4.06, 5.95]	0.0333 [–0.0230, 0.0779]	0.660 [–1.04, 2.17]	0.322 [–0.168, 0.853]	0.260 [–0.575, 1.30]	–0.0933 [–0.803, 0.437]	0.000989 [–0.0268, 0.0242]
Sample mean	2.59	1.57	624	48.9	0.651	29.6	1.26	4.22	3.35	0.146
% of Mean	–1.11	–4.02	–0.185	0.886	5.11	2.23	25.5	6.17	–2.79	0.676
Bandwidth	154	145	111	110	164	176	264	134	250	274
Observations	322,756	322,756	322,756	322,756	322,756	322,756	322,756	322,756	322,756	322,756

Notes: This table presents the estimated coefficient ($-\beta$) and 95% confidence intervals from Equation (2). The running variable for medical debt corresponds to the highest debt amount across the consumer's medical collections accounts. We report MSE-optimal estimates with robust, bias-corrected 95% confidence intervals in brackets. Sample Mean reports the mean of the dependent variable in 2024. A ***, **, and * indicate significance at the 1%, 5%, and 10% level respectively, using conventional inference.

Table A.7: Medical Collections Sub-Sample: RD Estimates of the Direct Effect of Medical Debt Deletion

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Number of Debts	Number of Medical Debts	Credit Score	Total Balance ($1,000)	Number of Accounts Opened in Last 6 Months	Revolving Utilization (%)	Total Balance 90+ Days Past Due ($1,000)	Bankruptcy in Last 7 Years (%)	Has Alternative Credit Balance (%)	Number of Alternative Credit Accounts
ABOVE^{2024}	–0.256*** [–0.323, –0.198]	–0.282*** [–0.311, –0.246]	2.94 [–2.09, 9.91]	–3.34 [–12.5, 4.08]	0.00616 [–0.0457, 0.0663]	–1.04 [–3.77, 1.20]	–0.170 [–1.09, 0.493]	0.580 [–0.390, 1.87]	0.0289 [–0.804, 0.905]	–0.00981 [–0.0422, 0.0229]
Sample mean	0.570	0.230	652	65.5	0.481	33.4	1.59	2.76	2.69	0.116
% of Mean	–45.0	–123	0.452	–5.10	1.28	–3.12	–10.7	21.0	1.07	–8.47
Bandwidth	241	303	152	128	189	168	224	144	283	278
Observations	149,596	149,596	149,596	149,596	149,596	149,596	149,596	149,596	149,596	149,596

Notes: This table presents the estimated coefficient ($-\beta$) and 95% confidence intervals from Equation (2). The medical collections sub-sample restricts the RD sample to consumers for whom the total number of accounts in collections is same as the total number of medical collection accounts. The running variable for medical debt corresponds to the highest debt amount across the consumer's medical collections accounts. We report MSE-optimal estimates with robust, bias-corrected 95% confidence intervals in brackets. Sample Mean reports the mean of the dependent variable in 2024. A ***, **, and * indicate significance at the 1%, 5%, and 10% level respectively, using conventional inference.

Table A.8: Difference-in-Differences estimates of the Indirect Effect of Medical Debt Deletion

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Credit Score	Total Balance ($1,000)	Number of Accounts Opened in Last 6 Months	Revolving Utilization (%)	Total Balance 90+ Days Past Due ($1,000)	Bankruptcy in Last 7 Years (%)	Has Alternative Credit Balance (%)	Number of Alternative Credit Accounts
TREATED × POST	0.721***	–0.0745	0.000329	–0.144	0.114	–0.106	–0.0159	0.00156
	(0.271)	(0.302)	(0.00455)	(0.166)	(0.102)	(0.0957)	(0.0634)	(0.00309)
Sample mean	617	68.9	0.688	53.0	2.47	9.05	3.84	0.190
% of mean	0.117	–0.108	0.0478	–0.272	4.62	–1.17	–0.414	0.820
Observations	1,143,272	1,143,272	1,143,272	794,118	1,143,272	1,143,272	1,143,272	1,143,272

Notes: This table presents difference-in-differences estimates based on Equation (7). Standard errors are clustered based on 100 bins of predicted default probabilities. A ***, **, and * indicate significance at the 1%, 5%, and 10% level respectively.

Table A.9: Performance Metrics for Credit Scoring Models With and Without Medical Collections Versus a Random Variable

	(1)	(2)	(3)
	All Predictors	Exclude Medical Debts < $500	Include Random Variable
Accuracy	0.905	0.906	0.905
Recall	0.448	0.448	0.445
Precision	0.736	0.736	0.737
F1 Score	0.557	0.557	0.555
AUC	0.712	0.712	0.710

Notes: This table reports performance metrics for a credit scoring model predicting defaults occurring between 2020 and 2021, based on borrower characteristics from 2019. Column (1) presents metrics for the baseline model, which includes 46 predictors and is estimated using XGBoost. Column (2) reports metrics when small (under $500) medical collections are excluded from the predictors. Column (3) shows metrics when a random variable is included to the set of predictors. The accuracy score represents the share of correct predictions. For comparison, a naive model predicting no defaults achieves an accuracy of 0.867. Precision is the proportion of predicted defaults that were correctly classified. Recall is the proportion of actual defaults correctly classified. F1 score is the harmonic mean of Precision and Recall. The AUC (Area Under the Receiver Operating Characteristic Curve) indicates the probability that the model assigns a higher default probability to a true defaulter than to a non-defaulter.

Table A.10: Performance Metrics for Credit Scoring Models With and Without Medical Collections: Logit Model

	(1)	(2)	(3)
	All Predictors	Exclude Medical Debts < $500	Exclude All Medical Debts
Accuracy	0.897	0.897	0.897
Recall	0.375	0.376	0.374
Precision	0.726	0.726	0.726
F1 Score	0.495	0.495	0.494
AUC	0.890	0.890	0.890

Notes: This table reports performance metrics for a credit scoring model predicting defaults occurring between 2020 and 2021, based on borrower characteristics from 2019. Column (1) presents metrics for the model including 46 predictors and estimated using logistic regression. Column (2) reports metrics when small (under $500) medical collections are excluded from the predictors. Column (3) shows metrics when a random variable is included to the set of predictors. The accuracy score represents the share of correct predictions. For comparison, a naive model predicting no defaults achieves an accuracy of 0.867. Precision is the proportion of predicted defaults that were correctly classified. Recall is the proportion of actual defaults correctly classified. F1 score is the harmonic mean of Precision and Recall. The AUC (Area Under the Receiver Operating Characteristic Curve) indicates the probability that the model assigns a higher default probability to a true defaulter than to a non-defaulter.

Table A.11: Performance Metrics for Credit Scoring Models With and Without Medical Collections: Restricted Model

	(1)	(2)	(3)
	Restricted Model	Exclude Medical Debts < $500	Exclude All Medical Debts
Accuracy	0.8669	0.8670	0.8670
Recall	0.0008	0.0004	0.0001
Precision	0.3462	0.3250	0.5000
F1 Score	0.0016	0.0008	0.0002
AUC	0.5003	0.5001	0.5001

Notes: This table reports performance metrics for a credit scoring model predicting defaults occurring between 2020 and 2021, based on borrower characteristics from 2019. Column (1) presents metrics for the a model with six predictors—medical collections below and above $500, bankruptcy trades, bankruptcy trades in the past 24 months, tax liens in the past 24 months, and judgments trades in the past 24 months.—estimated using XGBoost. Column (2) reports metrics when small (under $500) medical collections are excluded from the set of six predictors. Column (3) shows metrics when all medical collections are excluded. The accuracy score represents the share of correct predictions. For comparison, a naive model predicting no defaults achieves an accuracy of 0.867. Precision is the proportion of predicted defaults that were correctly classified. Recall is the proportion of actual defaults correctly classified. F1 score is the harmonic mean of Precision and Recall. The AUC (Area Under the Receiver Operating Characteristic Curve) indicates the probability that the model assigns a higher default probability to a true defaulter than to a non-defaulter.