The Effects of Deleting Medical Debt from Consumer Credit Reports*

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Abstract

One in seven Americans carry medical debt, with $69 billion reported on consumer credit reports. In April 2023, the three major credit bureaus stopped reporting medical debt collections below $500. We study the effects of this information deletion on consumer credit scores, credit access, repayment behavior, and payday borrowing. Regression discontinuity estimates comparing individuals just above and below the $500 threshold show that the deletion reduced the reported number of medical debt collections by 61 percent. Despite expectations that removing negative credit information would improve credit outcomes for affected individuals, we find no evidence of benefits over the subsequent two years, ruling out even small effects. To interpret these findings, we build credit scoring models and show that medical debts, regardless of size, add minimal incremental information for default prediction beyond standard credit report variables, implying that they contribute negligibly to credit risk assessment. Our results suggest that eliminating medical debt collections entirely from credit reports would be 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 $69 billion in medical debt appearing on consumer credit reports as of 2022.[1] Nearly one-fifth of this total comes from balances under $500. While credit reporting can reduce information frictions and adverse selection, policymakers increasingly worry that the visibility of medical debt on credit reports—often reflecting health shocks—could impair access to credit. 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 reform, the Consumer Financial Protection Bureau (CFPB) finalized a rule in January 2025 to eliminate all remaining medical debt collections above $500 from credit reports. However, a federal court struck down the rule in July 2025, leaving the regulatory future of medical-debt reporting in doubt. Thirty U.S. senators criticized the policy reversal, arguing that keeping medical debt on credit reports "blocks working families from access to credit" (Warnock et al., 2025).

Basic economic theory suggests that removing negative information from credit reports should improve credit access for the individuals whose information is deleted. For these consumers, deletion may increase credit supply by raising commercial credit scores used by some lenders or by reducing predicted default risk in proprietary models that incorporate credit-report information (Braunstein, 2010). 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 (CFPB, 2023). They are typically sold at steep discounts on secondary markets and may offer limited incremental value for predicting default risk beyond standard credit-report variables, which would limit any lending response to their removal (CFPB, 2024). Thus, the ultimate effect of removing medical debt information on lending is uncertain and remains an open empirical question.

This paper uses a regression discontinuity (RD) design to estimate the effects of deleting

[1] Unless otherwise specified, our use of the term "medical debt" refers to medical debt collections that appear on consumer credit reports, which represent a subset of consumers' total medical liabilities.

medical debt collections from credit reports on a comprehensive set of credit outcomes. Our empirical strategy exploits the \$500 threshold introduced by the April 2023 policy change, comparing individuals whose medical debts in 2022 were just above or below the reporting cutoff prior to deletion. Using data from the Gies Consumer and Small Business Credit Panel (GCCP), we show that the April 2023 deletion reduced the number of medical debt collections per consumer by 0.30 (61%) by 2024. However, we find no evidence that removing these debts affected credit scores, credit limits or utilization, repayment behavior, payday borrowing, or other related outcomes in the year following removal. Our null estimates are precise: for example, the 95% confidence intervals rule out increases in credit scores greater than 6.03 points (0.98%) and decreases in the balance-to-limit ratio of revolving credit exceeding 2.8 percentage points (5.28%). We find no evidence of strategic manipulation of the running variable around the \$500 threshold, and our placebo and falsification tests show that outcomes exhibited no discontinuities at the cutoff prior to the April 2023 deletion, supporting the validity of our RD design. We obtain similarly null results when extending the analysis to 2025, two years after the deletion.

To help interpret these null findings, we investigate whether medical debt collections contained incremental predictive information for default risk prior to 2023. We first show, in simple parametric specifications, that medical debt contains some information in isolation, but that this signal attenuates rapidly once other credit-report variables are included. We then evaluate incremental predictive content using a flexible, high-dimensional classification model, estimating otherwise identical models on rich credit histories with and without medical debt variables. We compare two models: one trained on borrower credit histories that include medical debts below \$500, and another trained on histories excluding these debts. The models perform nearly identically, suggesting that small medical debts contribute minimally to risk assessment, a conclusion reinforced by our placebo tests showing that they behave similarly to a randomly generated noise predictor. Consistent with these results, we show that even when medical debt contains little incremental information about default risk, its inclusion can still affect predicted risk by injecting noise into credit risk models, particularly for borrowers with thin credit files.

Furthermore, we show that larger medical debts ($\geq$ \$500) are similarly uninformative:

excluding all medical debt from the model produces only negligible changes in classification performance, with no meaningful deterioration in the model's ability to identify defaulters. These results suggest that eliminating *all* medical debts from credit reports would be unlikely to materially affect lending decisions.

Our results also help interpret a recent change in VantageScore, one of the two most widely used commercial credit scoring models, regarding its treatment of medical debt. In January 2023, VantageScore removed all medical debt collections from its model and estimated that the change would raise scores by up to 20 points for some consumers.[2] These predicted gains may appear inconsistent with our finding that medical debt collections are not meaningfully predictive of default, but they can be understood by considering model specification. Commercial models pool medical and non-medical debt collections into a single, "total collections" variable (Brevoort and Kambara, 2015). If non-medical debt collections are sufficiently predictive of default, removing medical collections from this composite variable could raise scores even when medical collections contain little information about risk. Because medical collections had already been excluded from the VantageScore model before the April 2023 deletion, any effects of deletion on VantageScores could arise only indirectly through behavioral responses. By contrast, FICO credit scores and many proprietary models continued to incorporate medical collections directly, so the April 2023 reporting change could in principle affect lending directly through those channels. Our null findings demonstrate that any such effects were small in practice.

Our study contributes to research on debt relief and financial outcomes, which has examined contexts including residential mortgages (Agarwal et al., 2017; Cherry et al., 2021; Ganong and Noel, 2020; Cespedes et al., 2025), credit cards (Dobbie and Song, 2020), bankruptcy (Dobbie and Song, 2015), student debt (Di Maggio et al., 2020; Dinerstein et al., 2025), and medical debt (Adams et al., 2022). The work most closely related to ours is Kluender et al. (2024), who conduct two large-scale randomized experiments to evaluate the effects of medical debt forgiveness—a policy often discussed alongside information deletion. They find that debt forgiveness modestly improves credit scores and credit card limits for

[2]Because this change affected all consumers, including those above and below the $500 threshold, it does not affect the internal validity of our RD analysis. For consumers with scores below 640, a 20-point difference in scores corresponds to roughly a 2 percentage point difference in observed 90-day delinquency rates.

consumers whose medical debts were reported to credit bureaus, but has no effect for others.[3] Their results highlight the central role of information visibility—specifically, whether a debt appears on a credit report—in determining the effectiveness of debt relief. Our study tests this mechanism directly by isolating the information channel itself. Using a much larger sample of consumers with reported medical debts and exploiting the 2023 reporting cutoff, we show that deleting medical debts from credit reports has no detectable effects across a broad set of credit outcomes, including payday borrowing, an important margin rarely examined alongside mainstream credit outcomes. Together, these findings suggest that policies targeting the visibility of medical debt, like policies targeting the debt itself, are unlikely to alleviate financial distress.

We also extend the literature on information deletion by studying a novel context: medical debt. Prior work has studied the effects of removing bankruptcy flags and unpaid debts from credit reports on borrowing or labor market outcomes (Musto, 2004; Bos et al., 2018; Liberman et al., 2019; Dobbie et al., 2020; Gross et al., 2020; Herkenhoff et al., 2021; Jansen et al., 2024), as well as the effect of expanding lenders' access to borrower credit histories (Miller, 2015). Beyond credit markets, related studies examine the removal of criminal history or credit-report information in employer screening, highlighting how information deletion can affect screening incentives and produce unintended labor market effects (Agan and Starr, 2017; Bartik and Nelson, 2025; Agan et al., 2026). A distinctive feature of our setting is that lending decisions are explicitly based on predicting default using a well-defined, observable set of credit-report variables, allowing us to evaluate directly whether the information being removed contributes to default prediction. We show that small medical debts have minimal incremental predictive value for default risk and that their removal therefore yields no detectable benefits for affected consumers. More broadly, our results suggest that in settings like credit scoring—where researchers can observe the underlying information set—evaluating the predictive content of the information slated for removal is informative about the likely effects of deletion.

[3] Kluender et al. (2024) find no average effect of debt relief on credit scores in their two main samples, which include many consumers whose forgiven medical debts never appeared on credit reports. In their credit reporting sub-experiment—which focuses on consumers whose medical debts would otherwise have appeared on their credit reports—they detect improvements in credit scores and limits. This discrepancy may be due to a modeling change in VantageScore, as we discuss in Section 2.

Third, we relate to 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 also show that even unreliable information like medical debt can still influence predicted default probabilities, particularly for consumers with thin credit files—not because it contains meaningful signal, but because it injects noise into prediction models when reliable information is scarce—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; Guttman-Kenney et al., 2022; Keys et al., 2022; Fonseca, 2023; Lin, 2024). Consistent with our RD estimates, Batty et al. (2022) and Goldsmith-Pinkham et al. (2023) find that expanded health insurance coverage reduces medical debt collections but does not improve other financial outcomes. Our results help explain this pattern by showing that medical debt collections contain little incremental information about default risk relative to standard credit-report variables, so changes to the reporting of medical debt are unlikely to meaningfully affect lending decisions or borrower behavior. 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 provides background on medical debt, credit reports, and credit scoring models. Section 3 describes the data used in our analysis. Section 4 presents RD estimates of the direct effects of deleting medical debt

[4] Brevoort and Kambara (2014) show that medical debt collections are less predictive of future credit performance than non-medical debt collections, but do not directly quantify the predictive power of medical debt.

collections. Section 5 investigates whether medical debt is predictive of default. Section 6 concludes.

2 Background

2.1 Medical debt

Medical debt arises when patients are unable to pay the out-of-pocket portions of their medical bills. Healthcare providers typically first attempt to collect unpaid amounts directly from patients. If these efforts fail, they often turn to third-party collection agencies, which may pursue repayment through calls, letters, and lawsuits; they also frequently report unpaid debts to credit bureaus.[5] Because not all medical debts are reported to credit bureaus, the balances observed on credit reports represent only a subset of total medical debt and should be interpreted as a lower bound on consumers' overall medical liabilities.

The consequences of medical debt are complex and challenging to quantify, in part because repayment 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, such as student loans and credit card debt. Unlike medical debt, student loans are rarely dischargeable in bankruptcy—elimination typically requires proving "undue hardship," a demanding legal standard—while credit card debt 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).[6]

Popular commentary frequently highlights 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 how hospitalizations affect the likelihood of filing for bankruptcy within four years of admission.

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

[6]Colorado and New York prohibited reporting of all medical debt collections in August and December 2023, respectively, several months after the nationwide deletion of small medical debts. Our results are robust to excluding these states from the analysis (Table A.12).

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 indicate that health shocks can trigger financial distress, but whether medical debt itself adds predictive value beyond standard credit variables remains an open question.

2.2 Credit reports

When a consumer applies for credit, the lender's underwriting system typically requests a credit report from one or more of the three national credit bureaus: Equifax, Experian, and TransUnion. By making borrowers' prior credit histories observable at the point of application, credit reports reduce information frictions and adverse selection. The bureau locates the borrower's credit file and returns both the credit report and, often, a credit score such as FICO or VantageScore. The lender then incorporates this information into its internal credit decision process, which may rely primarily on the bureau-provided credit score or, for more sophisticated institutions, combine it with proprietary risk models that draw on the underlying credit-report data.

A credit report summarizes a consumer's credit accounts, including revolving credit lines (e.g., credit cards) and installment loans (auto, student, mortgage). It records balances and limits, use of available credit, payment history, and negative marks such as late payments, debt collections, and bankruptcies. Debt collection entries include information on the number and total balance of medical collection accounts.

Over the past several years, credit bureaus have substantially revised how medical debts are treated in credit reporting. On March 18, 2022, the three national credit bureaus jointly announced several reforms. Beginning July 1, 2022, paid medical debts in collection were removed from consumer credit files, and the waiting period for reporting unpaid medical debt was extended from six months to one year, giving consumers more time to resolve billing disputes or secure insurance coverage.

As part of that same announcement, the bureaus also pledged to delete all medical debt collections with an initial reported balance under $500 by the "first half of 2023" (Business Wire, 2022). On April 11, 2023, they confirmed completion of these deletions. Although the exact timing of the deletions is uncertain, Quinn (2023) reports that they occurred in March and April 2023. By removing this information from lenders' view, the policy also potentially reduced the leverage of debt collectors, since they could no longer use credit reporting as a tool to pressure repayment.[7]

Medical debt collections can influence credit decisions through lenders' internal underwriting models or through commercial credit scores that summarize credit-report information. Section 5 evaluates how removing medical debt information may influence lenders' internal underwriting models; here, we describe its treatment in commercial credit scoring models.

The precise treatment of medical debt collections in commercial credit scoring systems is not publicly disclosed. Historically, these models appear to have treated medical and nonmedical collections similarly, aggregating them into a single "total collections" variable (Brevoort and Kambara, 2015). However, in January 2023, VantageScore removed all medical debt collection data from its model and stated that the change would have "minimal" impact on predictive performance (VantageScore, 2022).[8] Consequently, the April 2023 deletion of small medical debts from credit reports could not mechanically affect VantageScores, since medical debt had already been excluded from the model. By contrast, FICO scores continued incorporating all unpaid medical collections through April 2023 and currently include those with balances exceeding $500. Even when score formulas do not change mechanically, deletion may still matter through behavioral responses: if removal affects credit access or repayment behavior, subsequent credit performance may change and indirectly influence all credit scores over time.

3 Data

Our study uses the Gies Consumer and Small Business Credit Panel (GCCP), a panel dataset of anonymized credit records 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,

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

[8]Because this change affected all consumers, it does not threaten the internal validity of our empirical analysis, which exploits the removal of small medical debts under $500 from credit reports.

linked to alternative credit records and business credit records for individuals who own a business.[9] The dataset spans 2004–2025 and contains annual snapshots measured at the close of the first quarter of each year. Sampling is based on the last two digits of 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.

Each GCCP record includes all reported debt obligations, or "tradelines," with information on credit type (mortgage, auto, student, or credit card), balances and limits, and payment history. The data also include VantageScores, public records such as bankruptcies and judgments, debts in collections, and demographic variables such as age, sex, income, and 5-digit zip code. Demographic variables are administrative or modeled: age is computed from date of birth, sex is a bureau-provided name-based classification, and income is a bureau-provided estimate based on credit-report variables.

We classify a debt collection as medical if the creditor is labeled as Medical/Health Care or if the furnisher operates in a medical or health-related sector.[10] Using this classification, we compute estimates of the prevalence and aggregate balances of medical debt collections in the GCCP. As shown in Tables A.1 and A.2, these GCCP-based estimates closely match corresponding benchmarks from external sources. In 2022, our GCCP data indicate that \$69 billion in medical debt appeared on consumer credit reports, of which \$12 billion came from balances under \$500. As in previous studies, our measure does not capture medical spending paid using credit cards, which cannot be identified in the data.

We restrict the main analysis to the years 2019–2024 and to consumers aged 18 or older. We drop records with missing age, credit score, or income, as well as those in which reported age increases by 10 years or more in a single year. The final sample includes 15,313,700 observations, summarized in Table 1. In the full sample, about half of consumers are female,

[9]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.

[10]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.

the average credit score is 702, average annual income is $51,960, and average total balances across all credit products is $76,460. About 20 percent of consumers have an alternative credit record, and their average number of medical collections is 0.25. In an extension, we incorporate 2025 data to examine whether longer-run patterns differ from the one-year effects studied in our primary analysis.

The next three columns of Table 1 describe consumers with at least one medical debt collection. This group has lower credit scores, lower income, and lower balances than the full sample and is more likely to have subprime credit. Among these consumers, the average number of medical debt collections is 2.44, of which 1.45 involve balances below $500.

Figure 1 shows that the share of consumers with medical debt collections fell from 16 percent in 2019 to 4 percent in 2024. This decline is driven by the disappearance of medical debts under $500, which fall from 10 percent in 2022 to zero by 2024 after the credit bureaus stopped reporting them. Because the GCCP snapshots are taken at the end of March each year, the marked decline already evident in the 2023 data implies that many deletions occurred before the April 11, 2023 public announcement, consistent with reports that the deletions occurred in March and April.

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

4 Regression Discontinuity Design and Results

4.1 Empirical strategy

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

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

We refer to this account-level specification as a "first stage," since it documents the effect of deletion on the reporting of individual medical debt collection accounts. 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.

We then estimate a separate specification at the consumer level that aggregates the running variable by taking the maximum debt amount across all the consumer's medical debt collection accounts:

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

The running variable is defined as the largest medical debt for consumer i, relative to the \$500 cutoff: $\text{MAXDEBT}_i^{2022} = \max_j \text{DEBT}_{ij}^{2022}$. 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. Appendix B.1 reports results from alternative specifications that use the minimum rather than the maximum debt balance, as well as specifications estimated at the account level instead of the individual level. Although these designs target different treatment effects, they yield qualitatively similar results.

Our main analysis considers a set of ten consumer credit outcomes spanning credit access, repayment behavior, and payday borrowing. These outcome variables are defined in Table A.4. In addition, our supplementary analysis, reported in the appendix, examines a broader set of outcomes, including credit inquiries, revolving credit limits, alternative credit balances, and mortgage origination.

Our main identifying assumption is that assignment around the \$500 threshold is effectively random. This assumption is plausible because medical charges are typically set by providers using fixed and often opaque pricing, leaving consumers with little opportunity to strategically adjust balances. Additionally, our data come from administrative records, reducing concerns about measurement error or sample selection bias. We assess manipulation by testing for continuity in predetermined covariates and by examining the density of the running variable around the cutoff (Lee, 2008; McCrary, 2008).

The main threat to identification is that other policies or practices might also depend on the $500 threshold. For instance, if hospitals restrict services once unpaid bills exceed $500, then any observed discontinuities could reflect hospital practices rather than credit bureau reporting rules. A related concern is that debt collectors may have treated debts below $500 differently even before the 2023 policy change—for example, by routinely choosing not to report them. To assess these possibilities, we estimate placebo RD specifications with outcomes measured before 2023, prior to the removal of small medical debts from credit reports.

All RD regressions use a triangular kernel. Our preferred specification uses a mean-squared error optimal bandwidth that is symmetric around the cutoff and allowed to vary across outcomes. We report robust bias-corrected confidence intervals to account for potential misspecification of the estimating equation (Calonico et al., 2014).

4.2 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 above the cutoff remained. Panel B shows similar patterns after aggregating to the consumer level: the deletion reduced the number of medical debt collections per person in 2024 by 0.30 (61.4%).[11]

We next turn to credit access. Figure 3 shows no evidence of discontinuities in credit scores, balances, new accounts, or revolving utilization (balance-to-limit ratio). Table 3 presents formal estimates. The 95 percent confidence intervals rule out improvements in credit scores greater than 6.03 points (0.98%), increases in balances exceeding $2,602 (5.21%), increases in new credit accounts greater than 0.09 (17.90%), and decreases in revolving

[11] Consumers whose largest 2022 medical collection account was under $500 may still have medical collections in 2024 if they acquired new ones above 500 dollars in 2023 or 2024. These new accounts generate the positive values to the left of the cutoff in Panel (b).

utilization larger than 2.8 percentage points (5.28%).[12]

Figure 4 presents analogous results for delinquency, bankruptcy, and alternative credit use. The estimates again show no evidence of discontinuities at the cutoff, and for several outcomes the confidence intervals rule out economically meaningful effects. In particular, they rule out decreases in the probability of holding an alternative credit balance greater than 0.29 percentage points (7.53%) and increases in the number of alternative credit accounts exceeding 0.04 (25.45%). Estimates for delinquent balances and bankruptcy are less precise, but still rule out large effects, including reductions in delinquent balances greater than $802 (40.1%) and decreases in the probability of bankruptcy larger than 1.19 percentage points (37.07%).

Figure A.1 shows results for additional outcomes, including the number of accounts 90+ days past due, the number of new inquiries, revolving limits, total balance in alternative credit accounts, and the number of new mortgage accounts. Again, we find no detectable effects, and the estimates are sufficiently precise to rule out meaningful changes in most outcomes.

Table A.9 focuses on consumers whose collections consist solely of medical debts. We again find no robust evidence of effects for our outcomes, although we do find a reduction in revolving utilization (balance-to-limit ratio) of 3.0 percentage points (6.3%) that is statistically significant under conventional inference but not after adjustment for multiple hypothesis testing.[13] By contrast, Kluender et al. (2024) found modest benefits of medical debt relief for this group, including a 13.8 point (2.3%) increase in average VantageScores. We find no comparable gains. Instead, the 95 percent confidence interval rules out a credit score increase larger than 9.91 points (1.52%). A key difference is that our outcomes are measured after January 2023, when the VantageScore model removed medical debt collections from its inputs. One explanation for this discrepancy is therefore that the score gains documented in earlier work reflect mechanical effects of credit scoring models that are no

[12] Medical collections were removed from the VantageScore model in January 2023, so the deletion cannot directly affect our credit score measure. However, indirect effects remain possible, as discussed in Section 2.2.

[13] We control the family-wise error rate using the Sidak-Holm step-down procedure (Huh and Reif, 2021). The family consists of the 8 outcomes reported in columns (3)–(10). For revolving utilization, the conventional (unadjusted) p-value is 0.009 and the Sidak-Holm adjusted p-value is 0.07.

longer operational in our setting (see Section 2.2). Brevoort and Kambara (2014) note that commercial credit scoring models often aggregate medical and non-medical collections into a single "total collections" variable. If non-medical collections are sufficiently informative about default risk, removing medical collections from this composite measure could mechanically raise credit scores, even if medical collections themselves contain little independent predictive power. Our null effects across a broad set of outcomes are consistent with this interpretation.

We evaluate the no-manipulation assumption by testing whether predetermined outcomes are continuous at the cutoff. Figure A.2 shows no significant discontinuities in income, age, or sex. We also examine the density of the running variable. Strategic manipulation would generate excess mass just below the $500 threshold. However, Figure A.3 shows no such pattern. Instead, we observe slight bunching above the cutoff, consistent with rounding behavior or provider reporting practices rather than strategic manipulation. Taken together, the smoothness of predetermined covariates and the absence of excess mass below the cutoff support the validity of the no-manipulation assumption.

Our sample is restricted to consumers with non-missing credit scores. This restriction could bias our estimates if the deletion of small medical debts affected the probability that a consumer is scorable. Although this seems unlikely—VantageScore removed medical debts from its inputs in January 2023—medical debts could still influence scorable status or indirectly affect reporting behavior. To address this concern, Appendix B.2 presents a supplementary analysis showing no evidence that the deletion of small medical debts affected the number of scorable consumers in our data (Table A.11). For completeness, we also estimate difference-in-discontinuities models for our other main outcomes using this unrestricted sample; the resulting coefficients closely match our baseline RD estimates, suggesting that the null findings are not driven by pre-existing discontinuities at the cutoff.

We also conduct a series of falsification and placebo tests. Figures A.4, A.5, and A.6 replicate our RD specification using 2022 outcomes instead of 2024 outcomes. As expected, we observe no evidence of discontinuities, including for first-stage outcomes. Figures A.7 and A.8 repeat our analysis for 2020–2022 in place of 2022–2024 and likewise find no significant effects. Together, these results show that the $500 threshold was not associated with spurious breaks in outcomes prior to the April 2023 deletion, supporting the internal validity of our RD design.

Finally, Table A.10 examines 2025 outcomes to assess longer-run effects. The first-stage effect on the number of debts persists and remains large, but the estimates for credit access and financial health remain near zero and statistically insignificant. The confidence intervals continue to rule out economically meaningful effects. Overall, the evidence indicates that deleting small medical debt collections had no discernible short- or medium-term impact on credit access, repayment behavior, or broader financial outcomes.

5 The Predictive Value of Medical Debt

As outlined in Section 3, medical debt information could influence lending decisions either through its contribution to commercial credit scores such as FICO or through lenders' proprietary risk models. Yet our RD analysis showed that deleting small medical debt collections from credit reports produced no measurable improvements in credit access or financial health for affected consumers. This absence of effects suggests that information on small medical debts carries little value for underwriting. If these debts contained meaningful information about default risk, their removal would have altered the inputs to lenders' risk assessment models and, in turn, altered loan approval and pricing decisions.

In this section, we test this implication directly by evaluating whether medical debt collections predict default. We train credit scoring models that are identical except for whether they include information on medical collections below $500, and we repeat the analysis excluding all medical collections. While our model does not replicate any specific lender's proprietary approach, sophisticated lenders deploy cutting-edge risk models and face strong incentives to extract any variable with genuine predictive content (Braunstein, 2010). Thus, if a state-of-the-art model such as ours detects no predictive value in medical debt collections, it is reasonable to infer that lenders' proprietary models are likewise unlikely to extract meaningful signal from them.

We show below that medical debt collections provide no meaningful incremental predictive power beyond standard credit-report variables. We demonstrate this result in several complementary ways: removing medical collections has a negligible effect on different measures of classification error; medical debt variables rank near the bottom of standard measures of variable importance; and excluding them produces only minimal changes in the distribution of predicted default probabilities.

5.1 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.[14] Formally, these models take the form:

$$\Pr(Y = 1 \mid X) = f(X) \tag{3}$$

where Y is a binary default indicator and X denotes a vector of borrower characteristics. The function $f(\cdot)$ represents the mapping from borrower attributes to a predicted default probability, 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 relationships, predictors are 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 widely used in classification settings (Chen and Guestrin, 2016). This flexible, tree-based ensemble method captures complex,

[14] In addition to default probabilities, lenders estimate two other components of expected credit losses: loss given default (LGD) and 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).

nonlinear interactions and typically outperforms standard parametric models, making it a natural choice for assessing whether medical collections contain any predictive signal. Its structure also resembles the advanced modeling approaches likely employed by sophisticated lenders. Section 5.3 shows that our conclusions do not hinge on this specification: a traditional logit approach yields similar results.

Our model includes $n = 46$ predictors that capture a broad set of credit-related characteristics. In addition to the number of medical debt collections, the model includes detailed measures of delinquency (counts and balances of past-due accounts across multiple horizons, derogatory indicators, and recency measures); counts and balances of non-medical collections; indicators of bankruptcies and other public records; balances and account counts across major credit types; credit utilization measures; account-age characteristics; and recent inquiries and new accounts.[15] Consistent with prior work, our model excludes variables prohibited by the Equal Credit Opportunity Act (ECOA)—such as race, 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). Although age is not prohibited under ECOA, its inclusion requires special documentation and validation under fair-lending regulations (Federal Reserve Board, 2007). We therefore exclude it from our model, consistent with the approach used in FICO scores (FICO, 2025).

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 retain 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 whether a consumer experiences default 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 split the data into a 10% holdout test set and a 90% train and validation set, then further split

[15] "Derogatory" events refer to serious negative credit outcomes, such as repossessions, but do not include collections or bankruptcies, which we model separately. The recency measure captures the time elapsed since the most recent derogatory event. For more information on the predictors included in traditional credit scoring models, see FICO (2025).

[16] We also investigated the effect of including the balance amounts of medical collections. Incorporating these data worsened predictive accuracy, even for balances over \$500, consistent with substantial noise in reported medical collection balances. We therefore omit balance information from our analysis.

the train and validation set into 90% training and 10% validation (so the validation set is 9% of the full sample). We tune hyperparameters via Bayesian optimization using a tree-structured Parzen estimator (TPE) (Bergstra et al., 2011), fitting the XGBoost classifier on the training set at each iteration and choosing parameters that maximize performance in the validation set, measured using the F1 score—a standard metric that balances precision and recall and is described below. We then fit the final model on the combined train and validation data before evaluating model performance out-of-sample on the holdout test set. Predicted default probabilities are converted into binary predictions using a threshold of 50%. We provide more detail on the hyperparameter tuning and fitting procedure in Appendix C.

We measure model performance through several metrics. We report accuracy—the share of correct predictions—given its broad usage and ease of interpretation, though it provides limited insight in our setting: a model that predicts no defaults achieves an accuracy score of 86.69%, matching the share of consumers who did not default. We also compute 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. We provide precise definitions of accuracy and AUC in Appendix C.4.

Our preferred metrics are precision and recall, which better capture a model's ability to predict rare events than either accuracy or AUC (Davis and Goadrich, 2006). Precision and recall are defined as:

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

$$\text{Recall} = 1 - \text{False Negative Rate} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

Precision is the share of predicted defaulters who actually defaulted, while recall is the share of actual defaulters who were correctly identified. High precision minimizes the misclassification of creditworthy borrowers, helping lenders avoid missed profitable opportunities. High recall ensures that true high-risk borrowers are identified, reducing the likelihood of inadvertently lending to borrowers who are unlikely to repay. To balance these objectives, we also compute the F1 score, which is the harmonic mean of precision and recall:

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

Finally, for ease of interpretation, we also report the false positive rate, which captures the share of non-defaulters incorrectly classified as defaulters:

$$\text{False Positive Rate} = \frac{\text{False Positives}}{\text{False Positives} + \text{True Negatives}}$$

5.1.1 Results

As a benchmark, we begin by estimating a linear probability model relating the number of medical debt collections to two-year default rates (Table A.13). Column (1) shows a statistically significant association between medical debt and default, but this relationship attenuates sharply as additional credit-report controls are introduced. Across debt categories, the estimated coefficients decline by 60–80 percent once standard credit-report controls are included, and decline further after introducing flexible polynomial terms.[17] This pattern suggests that the predictive content of medical debt largely reflects correlations with other credit-report variables rather than independent signal. Although richer parametric specifications—such as spline-based models or models with extensive interaction terms—could further increase flexibility within this framework, linear probability models are not well suited to classification and are limited in their ability to capture complex nonlinearities. We therefore turn to a flexible, high-dimensional classification approach to assess whether medical debt retains any incremental predictive value once nonlinearities and interactions are allowed for more generally.

Table 4 reports out-of-sample model performance for our XGBoost model. Column (1) shows that our baseline model with the full set of predictors performs exceptionally well in predicting default. For instance, we achieve an AUC of 0.902, exceeding the typical range of 0.66 to 0.88 reported in prior work (e.g., Butaru et al., 2016; Fuster et al., 2022; Agarwal et al., 2023; Blattner and Nelson, 2022; Chioda et al., 2024). Our F1 Score of 0.560 also

[17] Appendix Table A.14 shows a similar attenuation pattern when medical debt is measured by balance amounts rather than counts, using the maximum medical collection balance across accounts.

compares favorably to the literature and significantly exceeds the corresponding metric from our linear probability model.[18] To interpret this value, we focus on its components, precision and recall, which are more commonly reported. Our recall of 0.452 ranks among the highest reported values, with most prior studies finding recalls 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 report recalls of 0.654 and 0.749, respectively, but both use substantially shorter prediction horizons of 3 and 6 months.[19] Shorter prediction windows generally yield higher precision and recall, helping explain the stronger performance in these studies. In addition, Chioda et al. (2024) use a 20% threshold—much lower than our 50% threshold—which further boosts recall at the expense of 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 prediction horizon.

Comparing the first two columns of Table 4 shows that removing information on medical collections below \$500 has no meaningful impact on model performance. Our preferred metric, the F1 score, together with accuracy and AUC, remains unchanged up to the third decimal. Decomposing the F1 score down into its two components, we observe a negligible decrease of 0.001 in recall and an *increase* of 0.002 in precision when small medical collections are removed. The third column further shows that deleting information on *all* medical collections, including those exceeding \$500, likewise has a negligible effect. Removing all medical collections increases the false negative rate by 0.2 percentage points—economically small—and actually *improves* the false positive rate by 0.01 percentage points. 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.

[18] The comparison should be interpreted with caution, as the linear probability model metrics are computed in-sample, whereas the XGBoost results are evaluated out-of-sample. Out-of-sample evaluation provides the appropriate benchmark for assessing predictive performance. The linear probability model is included solely as a benchmark and is not intended as a competing classification approach.

[19] 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.

To shed light on the limited impact of medical collections on model performance, Figure 5 reports average absolute SHAP values, which summarize each predictor's contribution to the model's predictions. The most important predictors are Number of Accounts Never Past-Due or Derogatory and Credit Amount in Last 6 Months; on average, they shift the model's predicted log-odds of default by 0.334, corresponding to roughly a 4 percentage point change relative to an average default probability of 13 percent.[20] By contrast, medical collections below $500 rank near the bottom of the importance distribution, with an average SHAP value of 0.004—nearly 100 times smaller than the top predictors. Medical collections above $500 are similarly unimportant, with an average SHAP value of just 0.008. Together, these two variables account for less than 0.4 percent of the total SHAP mass, meaning that excluding medical collections would change predicted default risk for the average borrower by a trivial amount relative to standard credit-report information.

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.[21] Although the tails of Figure A.13 suggest that small medical debt collections might improve predictive performance for a narrow set of borrowers, these changes are far more likely to reflect estimation noise than meaningful differences in default risk. To investigate this further, we categorize consumers into three groups based on the change in their predicted default probabilities across the two models:

Higher risk: Consumers in the top 5 percent of the distribution, whose predicted probabilities increase by approximately 2 percentage points or more when small medical debts are removed from the model.

Lower risk: Consumers in the bottom 5 percent of the distribution, whose predicted probabilities decrease by approximately 2 percentage points or more when small medical debts are removed from the model.

[20] An average default probability of 13 percent implies odds of $0.13/(1-0.13) = 0.149$. A log-odds shift of 0.334 multiplies these odds by $\exp(0.334) \approx 1.37$, corresponding to a change in the predicted default probability of about 4 percentage points.

[21] 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/).

Unaffected: Consumers between the 25th and 75th percentiles, whose predicted probabilities change by no more than approximately 0.2 percentage points.

If small medical debts were truly predictive of default, these groups should exhibit clear differences. For instance, consumers reclassified as lower risk should, on average, hold more small medical debts than those reclassified as higher risk.

However, we do not observe this pattern. Table 5 shows summary statistics for all three groups. While both the higher and lower risk groups differ significantly from the unaffected group, they are remarkably similar to each other. Figure 6 illustrates their similarity using balancing regressions. Each dot plots the coefficient from a regression of a standardized variable on an indicator for either the lower risk (blue) or higher risk (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: consumers in the higher and lower risk groups appear statistically indistinguishable across a wide range of characteristics, including the presence of medical debts.

The similarity between the positively and negatively treated groups, despite their substantial divergence from the unaffected group, suggests that the changes in predicted risk are driven by estimation noise rather than meaningful differences in underlying credit risk. 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 can receive non-zero weights during model training.[22] Consequently, excluding an uninformative feature can shift predicted probabilities for noisy cases in largely random ways, producing two groups with sizeable—but economically meaningless—changes in predicted risk. This process effectively assigns consumers quasi-randomly to the higher and lower risk groups, while separating them from the more stable, unaffected group. To validate this interpretation, Section 5.2 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 debt collections.

[22] 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.

5.2 Placebo Test Using a Random Noise Predictor

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

Table A.15 reports the performance metrics for this placebo exercise. Column (1) adds a purely random noise variable to the baseline set of predictors. Column (2) reproduces the baseline model; the comparison between columns (1) and (2) thus isolates the effect of removing the noise predictor. Column (3) removes small medical debt collections from this same baseline model, reproducing column (2) of Table 4. Strikingly, the negligible changes in model performance induced by excluding small medical debt collections closely mirror those induced by excluding the random noise variable. Figure A.14 reinforces this comparison, showing that the distribution of changes in predicted default probabilities after removing the random predictor is nearly indistinguishable from the distribution obtained after removing small medical debt collections.

Figure A.15 provides additional evidence. Panel A reproduces the balance plot from Figure 6, showing that removing small medical collections assigns consumers to the positively and negatively treated groups in a way that yields no systematic differences across observable characteristics. Panel B performs the same exercise for the random variable and produces a similar pattern. In both panels, the consumers reclassified as higher or lower "risk" have lower credit scores, lower income, and lower balances, consistent with the conclusion that predicted default probabilities are substantially noisier for these borrowers (Blattner and Nelson, 2022).

One potential concern with this placebo exercise 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 predictor: credit history length, as measured by average account age, the age of the oldest account, and the age of the oldest account that was never delinquent or derogatory. Credit history length is widely used in credit scoring models as a predictor of default (Federal Reserve Board, 2007), with longer credit histories generally associated with lower default risk, 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 pronounced and intuitive sorting: consumers reclassified as lower risk are younger and have a shorter credit history, as measured by average account age, consistent with the removal of a predictor that assigns higher risk to borrowers with limited credit histories. In contrast to the effects of removing small medical collections or a random variable, removing a genuinely predictive predictor produces clear and systematic differences across groups. This contrast confirms the validity of our placebo test: removing uninformative variables produces random sorting, whereas removing valuable predictors yields meaningful differences.

5.3 Robustness Using a Traditional Logit Model

As a robustness check, we show that our conclusions are unchanged when we replace the XGBoost model with a traditional logit scorecard approach, described briefly in Section 5.1 and in detail in Federal Reserve Board (2007). Following industry practice, we estimate separate models (scorecards) for three groups of consumers: major derogatory files, thin files, and clean files. The major derogatory scorecard includes consumers with 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 group who have fewer than three accounts. The clean scorecard applies to consumers with three or more accounts who are not classified as major derogatory.

We use 2019 data to construct the same 46 predictors as in our baseline model, along with the variables needed 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. Within each scorecard, we bin predictors using the OptBinning Python library, which applies a mixed-integer programming model to create monotonic and statistically meaningful bins—an approach consistent with traditional industry scorecard construction (Federal Reserve Board, 2007).

Table A.16 reports the performance of this logit scorecard model. Column (1) shows results including medical collections, Column (2) excludes medical collections below \$500, and Column (3) excludes all medical collections. Although the logit model underperforms our baseline model on all metrics except the False Positive Rate (see Table 4), its predictive accuracy still compares favorably to the prior literature summarized in Section 5.1.

Consistent with our baseline results (Table 4), removing small medical collections has no meaningful effect: all metrics remain unchanged up to the third decimal, except for a 0.001 *increase* in recall when we exclude medical collections below \$500 (column 1 vs. 2 of Table A.16). Likewise, dropping all medical collections produces virtually no change relative to the full model: the only difference is a 0.001 decline in the F1 score, driven by a 0.001 decline in recall. These results reinforce the conclusion that medical debt collections—whether below or above \$500—offer little, if any, incremental value for predicting default.

6 Conclusion

This paper studies the effects of deleting small medical debt collections from credit reports. Contrary to stated policy goals, we find that removing this information has no meaningful impact on credit access or financial health for affected consumers. Our analysis focuses on credit outcomes; we do not study how medical debt or its removal may affect other domains, such as mental or physical health, or other dimensions of hardship.

Leveraging the nationwide removal of medical debts under \$500 from credit reports in 2023, we use a regression discontinuity design to estimate the causal effects of information deletion. We find no evidence that consumers benefit from the removal of this information in terms of credit access, repayment behavior, or payday borrowing, and we rule out even small effects. To interpret these null findings, we show that medical debt collections—both small *and* large—carry little incremental predictive value for default by comparing credit scoring models with and without medical debt variables. The negligible performance difference between these models underscores that medical debt information provides little value to lenders' risk assessment.

These results are directly relevant to recent proposals to remove all medical debt collections from credit reports, including the CFPB's rule finalized in 2025 and later struck down. While that policy debate often assumes that deleting medical debt would expand credit access, our evidence suggests that eliminating medical collections—small or large—is unlikely to materially affect credit outcomes.

More broadly, our results inform ongoing debates about how best to alleviate the burden of medical debt. While economic theory emphasizes the importance of ex-ante solutions, such as expanding health insurance coverage, these approaches remain difficult to implement: about 30 million Americans are uninsured, and many insured individuals face substantial out-of-pocket costs (Einav and Finkelstein, 2023). Recent policy efforts have therefore shifted toward ex-post interventions, including debt forgiveness and information deletion. Taken together, results from our study and Kluender et al. (2024) indicate that neither of these interventions has detectable effects on credit access or financial health. These findings suggest that more effective approaches will likely require addressing the underlying drivers of medical debt.

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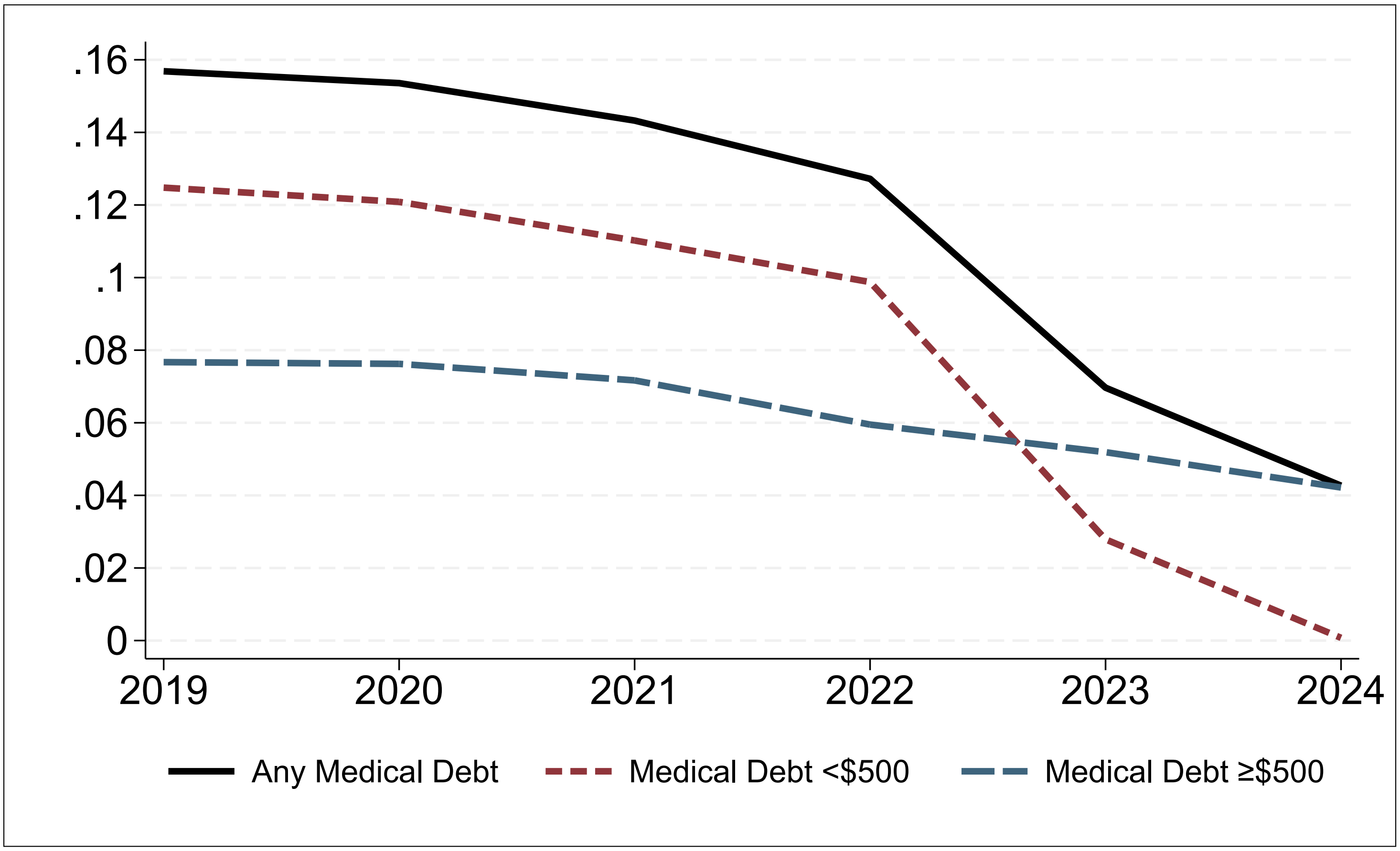
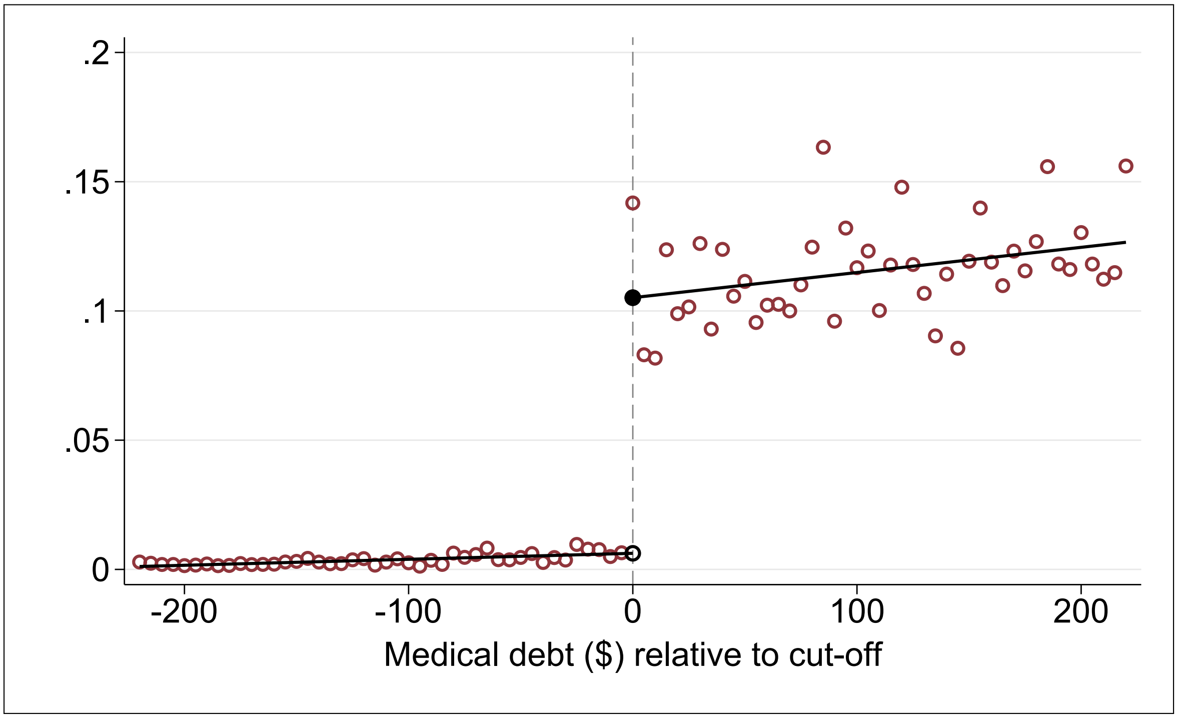
Figure 1: Share of Consumers with Medical Debt Collections, 2019–2024



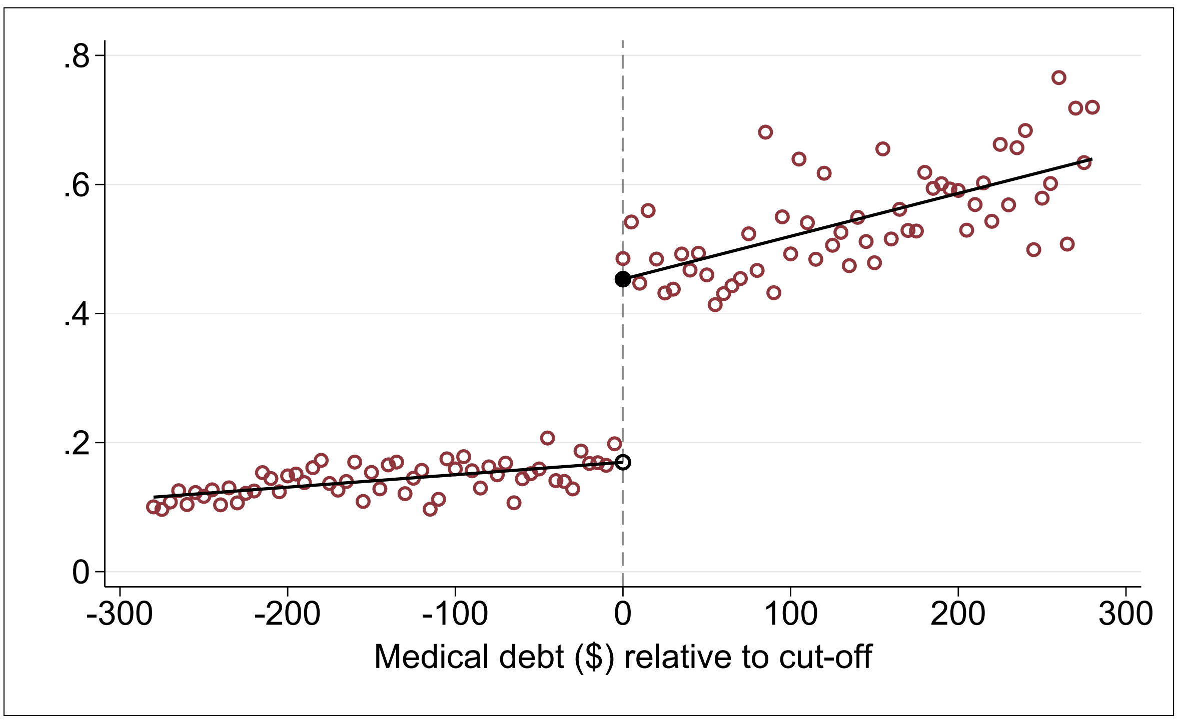
Notes: This figure shows the share of consumers with medical debt collections appearing on credit reports from 2019 to 2024. The black solid line plots the share with any medical debt in collections. The red dashed line plots the share with debt below $500, while the blue long-dashed line plots the share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

Figure 2: Two-Year Evolution of 2022 Medical Debt Collection Accounts

(a) Share of Surviving Accounts

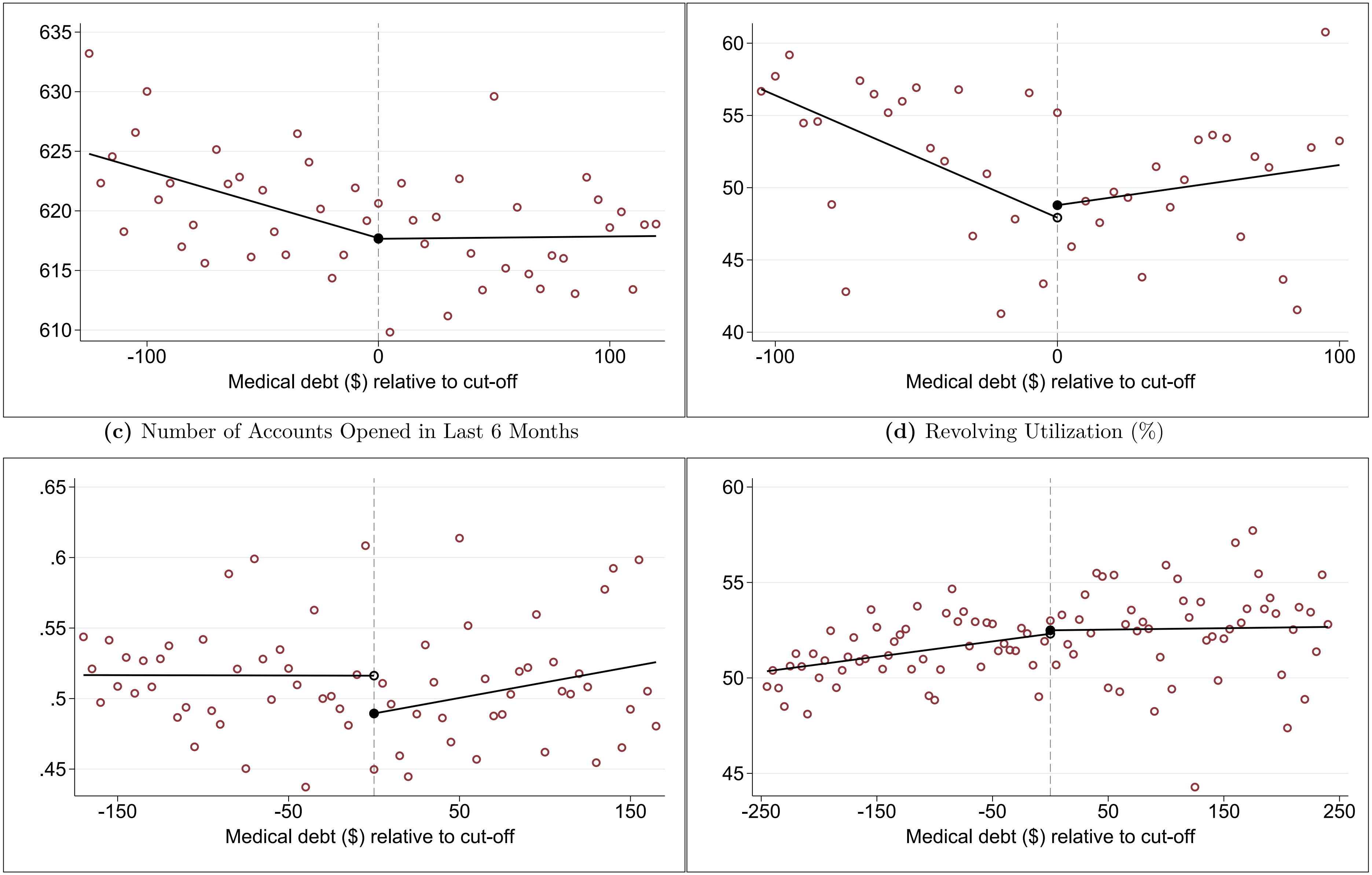


(b) Average Number of Accounts per Person



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.3, and the estimate for Panel (b) appears in Column (2) of Table 3.

Figure 3: Access to Credit, 2024



(a) Credit Score

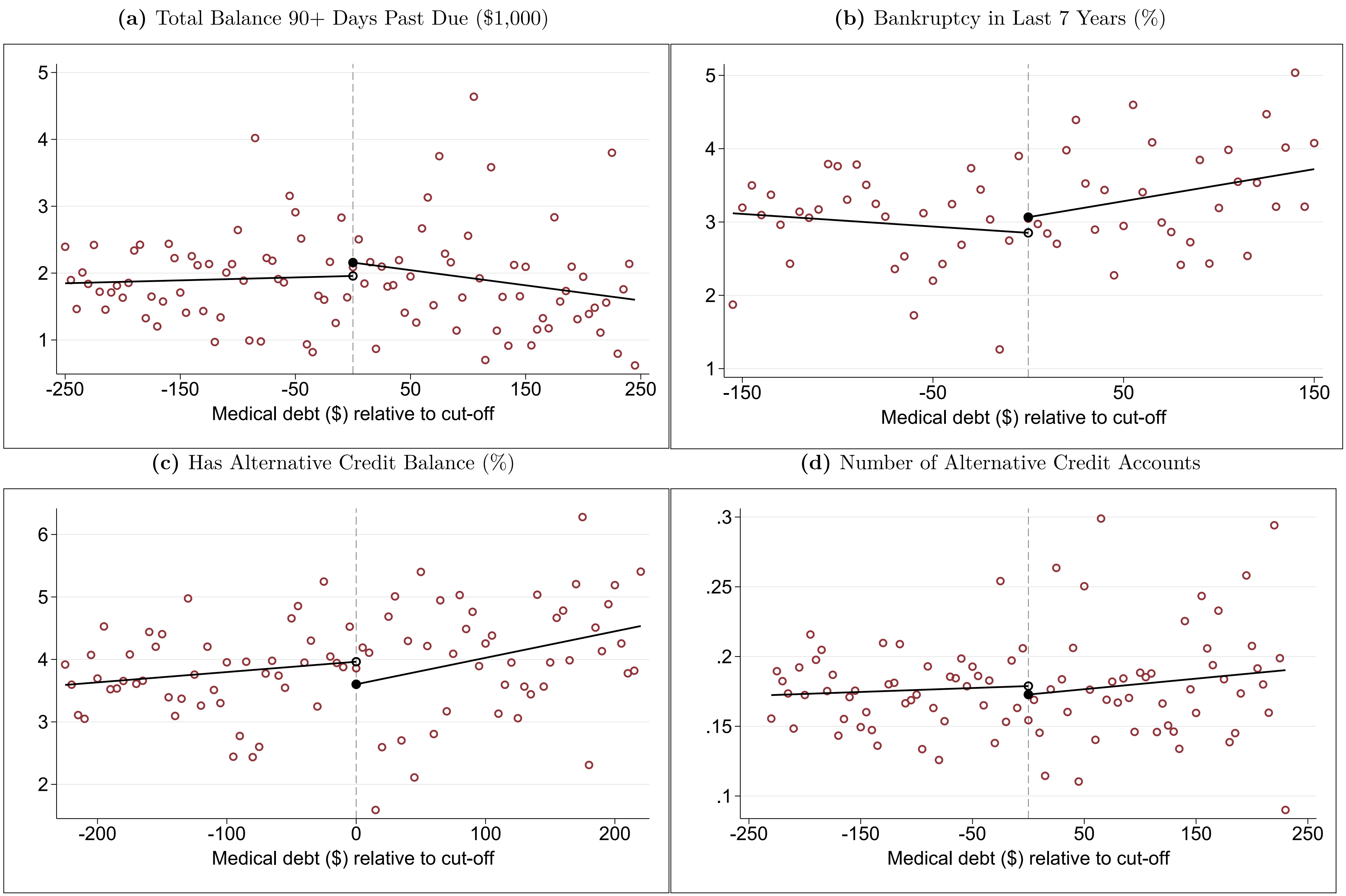
(b) Total Balance ($1,000)

(c) Number of Accounts Opened in Last 6 Months

(d) Revolving Utilization (%)

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 debt 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 ($1,000)

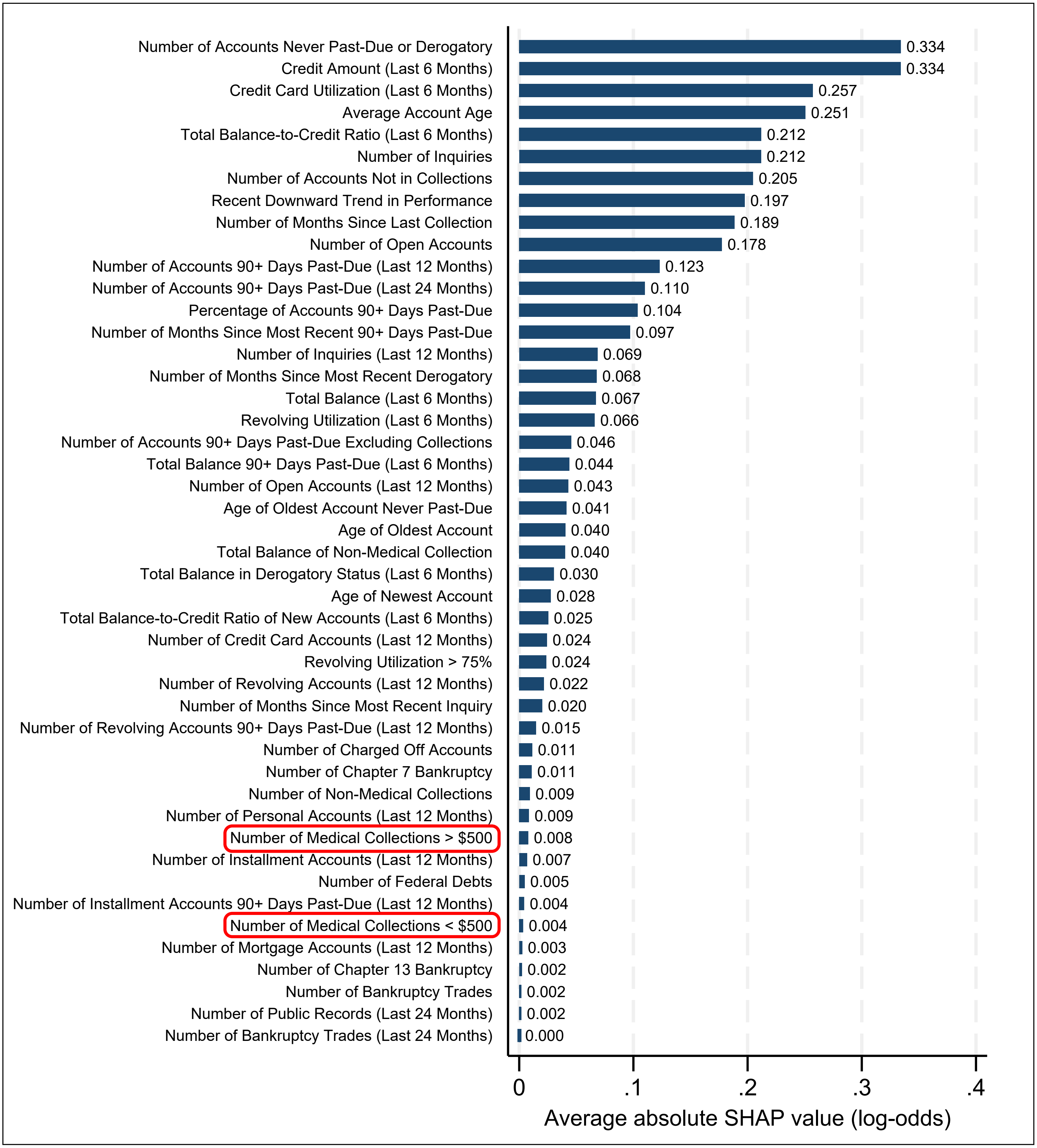
(b) Bankruptcy in Last 7 Years (%)

(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 debt collections accounts, measured relative to the $500 threshold. The corresponding RD estimates from Equation (2) are reported in Table 3.

Figure 5: Importance of Credit-Report Variables for Predicting Default



Notes: This figure reports the relative importance of credit-report variables in the credit scoring framework described in Section 5, measured by average absolute SHAP values (in log-odds units). The XGBoost specification is estimated using 2019 data to predict defaults in 2020–2021. Variables are ordered by their average contribution to predicted default risk.

Figure 6: Covariate Balance by Changes in Predicted Default Probabilities

Notes: This figure shows estimates from balancing regressions for selected outcomes. If medical debt collections contained meaningful predictive information, we would expect observable differences between higher and lower risk consumers along these dimensions; if instead they primarily introduce noise, these groups should appear similar. Each balancing regression compares higher or lower risk consumers to unaffected consumers in 2022. Higher risk consumers are those in the top 5%, whose predicted probability of default increases by approximately 2 percentage points or more when small medical collections are removed from the credit scoring model described in Section 5. Lower risk consumers are those in the bottom 5%, whose predicted default probability decreases by at least two percentage points. Unaffected consumers are those between the 25th and 75th percentiles, who experience changes of less than approximately 0.2 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 lower (blue) or higher risk (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
Total Medical Debts Below $500 ($1,000)	0.03	0.13	0.00	0.26	0.32	0.14
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 Debt 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 (%)	47.93	39.18	44.00
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
Total Medical Debts Below $500 ($1,000)	0.27	0.30	0.17
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 Effect of Medical Debt Collections 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^{2022}	–0.23**	–0.30**	0.68	–2.2	0.039	–0.59	–0.093	–0.37	0.38	0.011
	[–0.32, –0.14]	[–0.32, –0.27]	[–3.6, 6.0]	[–8.6, 2.6]	[–0.00079, 0.090]	[–2.8, 1.2]	[–0.80, 0.51]	[–1.2, 0.54]	[–0.29, 1.3]	[–0.015, 0.045]
Control Mean	1.5	0.49	618	50	0.50	53	2.0	3.2	3.9	0.18
% of Mean	–15	–61	0.11	–4.5	7.7	–1.1	–4.6	–11	9.8	6.1
Optimal Bandwidth	± 146.17	± 280.79	± 121.64	± 104.10	± 166.94	± 243.87	± 246.05	± 152.35	± 223.17	± 230.45
Observations										
Total	271,305	271,305	271,305	271,305	271,305	168,853	271,305	271,305	271,305	271,305
In-Bandwidth	38,303	83,847	31,390	26,884	44,126	42,690	70,196	40,178	62,110	64,776

Notes: This table presents the estimated coefficient ($-\beta$) and 95% confidence intervals from Equation (2). Outcome variables are defined in Table A.4. The running variable for medical debt corresponds to the highest debt amount across the consumer's medical debt collections accounts. We report MSE-optimal estimates with robust, bias-corrected 95% confidence intervals in brackets. Control Mean reports the mean of the dependent variable for consumers whose maximum medical debt in collections in 2022 falls between $500 and $600. The reported optimal bandwidth corresponds to the symmetric half-width (in dollars) around the $500 cutoff used to estimate each specification. "In-Bandwidth" observations report the number of observations falling within this window, while "Total" observations report the full estimation sample. A */** denotes statistical significance at the 5% and 1% levels respectively, using robust inference.

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

	(1)	(2)	(3)
	All Predictors	Exclude Medical Debts < \$500	Exclude All Medical Debts
Accuracy	0.906	0.906	0.905
AUC	0.902	0.902	0.902
F1 Score	0.560	0.560	0.559
Precision	0.736	0.738	0.737
Recall (1 − False Negative Rate)	0.452	0.451	0.450
False Positive Rate	0.0248	0.0246	0.0247

Notes: This table reports performance metrics for a credit scoring model predicting defaults occurring between 2020 and 2021, using 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 sample consists of 2,473,281 observations, with 90% used for model training and the remaining 10% reserved for out-of-sample performance evaluation. For reference, a naive model that predicts no defaults achieves an accuracy of 0.867, equal to one minus the average default rate (0.133). Definitions of the performance metrics are provided in Appendix C.4.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Unaffected			Lower Risk			Higher Risk		
	Mean	St. Dev.	Median	Mean	St. Dev.	Median	Mean	St. Dev.	Median
A. Demographics									
Income ($1,000)	59.79	36.06	50.00	44.66	23.45	38.00	44.75	23.72	38.00
Age (years)	56.79	19.51	58.00	45.96	15.07	44.00	45.81	14.99	44.00
Female (%)	49.87	50.00	0.00	53.88	49.85	100.00	53.98	49.84	100.00
B. Access to Credit									
Credit Score	751.28	84.64	788.00	611.40	80.95	609.00	610.79	81.35	608.00
Total Balance ($1,000)	87.71	153.46	7.69	67.56	117.54	18.63	67.37	117.80	18.57
Revolving Limit ($1,000)	31.64	38.61	19.14	6.35	16.33	0.46	6.55	16.97	0.46
Revolving Utilization (%)	15.77	22.74	6.00	54.72	38.79	56.00	54.78	38.55	56.00
Average Account Age (months)	135.78	83.83	122.00	78.19	46.99	69.00	78.23	47.09	69.00
Number of Accounts Opened in Last 6 Months	0.28	0.63	0.00	0.71	1.20	0.00	0.71	1.21	0.00
Number of Inquiries in Last 6 Months	0.26	0.56	0.00	0.77	0.99	0.00	0.78	1.00	0.00
Number of New Mortgages in Last 6 Months	0.03	0.17	0.00	0.02	0.14	0.00	0.02	0.13	0.00
C. Access to Alternative Credit									
Has Alternative Credit Record (%)	6.66	24.93	0.00	53.43	49.88	100.00	53.88	49.85	100.00
Has Alternative Credit Balance (%)	0.20	4.48	0.00	3.91	19.37	0.00	3.90	19.36	0.00
Number of Alternative Credit Accounts	0.01	0.19	0.00	0.19	0.87	0.00	0.19	0.86	0.00
Alternative Credit Balance ($1,000)	0.01	0.34	0.00	0.22	1.59	0.00	0.22	1.58	0.00
D. Financial Distress									
Number of Accounts 90+ Days Past Due	0.04	0.42	0.00	0.65	1.70	0.00	0.66	1.71	0.00
Total Balance 90+ Days Past Due ($1,000)	0.20	6.01	0.00	2.78	23.20	0.00	2.91	23.30	0.00
Bankruptcy in Last 7 Years (%)	0.89	9.39	0.00	9.21	28.92	0.00	9.55	29.39	0.00
E. Debt in Collections									
Total Debts ($1,000)	0.16	1.60	0.00	1.74	4.90	0.12	1.80	11.27	0.12
Total Medical Debts ($1,000)	0.05	0.68	0.00	0.43	1.71	0.00	0.45	10.37	0.00
Total Medical Debts Below $500 ($1,000)	0.01	0.07	0.00	0.08	0.21	0.00	0.07	0.21	0.00
Number of Debts	0.18	0.99	0.00	1.81	3.09	1.00	1.83	3.16	1.00
Number of Medical Debts	0.08	0.56	0.00	0.71	1.66	0.00	0.70	1.67	0.00
Number of Medical Debts Below $500	0.05	0.37	0.00	0.42	1.09	0.00	0.42	1.09	0.00
Observations	6,914,162			691,413			691,411		

Notes: This table reports descriptive statistics from 2019 to 2024 for unaffected consumers (columns 1–3), consumers reclassified as lower risk (columns 4–6), and consumers reclassified as higher risk (columns 7–9). Groups are defined based on changes in predicted default probability when medical collections below $500 are removed from the baseline credit scoring model described in Section 5. Higher Risk consumers are those above the 95th percentile of the distribution of probability changes, whose predicted probability of default increases by approximately 2 percentage points or more. Lower Risk consumers are those below the 5th percentile, whose predicted probability of default decreases by approximately 2 percentage points or more. Unaffected consumers are those between the 25th and 75th percentiles of the distribution. All variables are drawn from the Gies Consumer and Small Business Credit Panel. If medical debt collections primarily introduce noise rather than predictive signal, these groups should exhibit similar observable characteristics.

Online Appendix

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

Victor Duarte, Julia Fonseca, Divij Kohli, Julian Reif

A GCCP Data Appendix

A.1 Comparing Medical Debt Collection Data to External Sources

To identify consumers with medical debt 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 if the furnisher is identified as a business in the medical or health-related sector.[1]

To assess whether the GCCP accurately captures the prevalence and magnitude of medical debt collections, we conduct a benchmarking exercise comparing our data to estimates from external sources.

Table A.1 compares the share of consumers with at least one medical debt collection in the GCCP to estimates from other sources. Column (1) reports the annual share of consumers with at least one medical debt collection in the GCCP from 2018 to 2023, showing a decline from 16.8% in 2018 to 7.1% in 2023. This decline coincides with a series of policy changes affecting medical debt reporting, 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.

Similar trends appear in columns (2) and (3), which report estimates from the Urban institute (Blavin et al., 2023) and the CFPB (Sandler and Nathe, 2022), 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 likely reflect differences in measurement timing: the GCCP data are measured in March, the Urban Institute data in August, and the CFPB data in January. Overall, the GCCP closely tracks both the levels and trends observed in these external benchmarks.

Table A.2 presents a similar benchmarking exercise for medical debt balances. Column (1) reports total medical debt collections balances by year in the GCCP, while column (2)

[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.

reports balances for accounts with amounts below \$500. Column (3) reports corresponding estimates of total medical debt balances from the CFPB (CFPB, 2022). The total balances in the GCCP closely match those reported by the CFPB in years where both are available, further supporting the representativeness of the GCCP medical debt data.

B Alternative RD Specifications

B.1 Alternative Definitions of the Running Variable

The RD specification in the main text (Equation (2)) defines the running variable as the maximum medical debt collection balance across all of a consumer's accounts. Under this person-level (max) specification, the underlying policy treatment is the deletion of all medical collection accounts, which occurs only if all of an individual's medical collection accounts fall below the \$500 reporting threshold. The regression is parameterized using an indicator for the complementary event—having at least one account at or above \$500—so that the coefficient β captures the intent-to-treat effect of having at least one account remain on the credit report. Equivalently, $-\beta$ can be interpreted as the effect of having all accounts deleted.

Alternative constructions of the running variable correspond to different treatment definitions and estimands. To assess the robustness of our results, we consider three such definitions:

1. **Person level (max)**: Treatment occurs only if all of an individual's accounts are deleted (baseline specification).

2. **Person level (min)**: Treatment occurs if any (i.e., at least one) account is deleted.

3. **Account level**: Treatment intensity scales with the proportion of deleted accounts.

The person-level (max) specification is estimated using Equation (2) and is reported in the main text. The person-level (min) specification is estimated analogously, replacing the maximum medical debt collection balance with the minimum balance. Specifically, we define $\text{MINDEBT}_i^{2022} = \min_j \text{DEBT}_{ij}^{2022}$ as the consumer's smallest medical collection balance relative to the \$500 cutoff and estimate:

$$Y_i^{2024} = \alpha\text{MINDEBT}_i^{2022} + \beta\text{ABOVE}_i^{2022} + \gamma(\text{ABOVE}_i^{2022} \times \text{MINDEBT}_i^{2022}) + \epsilon_i \qquad (4)$$

The account-level specification allows treatment intensity to vary with the share of accounts deleted and can be estimated using Equation (1). Account-level estimates for this specification are reported in Panel A of Figure 2. In this appendix, we extend this account-level framework to examine additional outcomes that are naturally defined at the consumer level. Because outcomes such as credit scores do not vary across accounts, standard errors are clustered at the individual level.

Table A.3 reports estimates for all three treatment definitions. Panel A replicates the main text estimates from Table 3—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 show that our main estimates are robust to alternative definitions of the running variable and corresponding treatment effects.

B.2 Robustness to the Credit Score Restriction

Our main sample includes only consumers with non-missing credit scores. This restriction could bias our results if the deletion of small medical debts altered the probability that a consumer is scorable. To assess this possibility, we drop the credit-score restriction and test for discontinuities in the likelihood of having a credit score around the $500 cutoff.

Because there is a pre-existing discontinuity at the threshold in the share of scorable consumers, we estimate a pooled difference-in-discontinuities model using data from 2022 and 2024 to test whether this discontinuity changed following the April 2023 deletion. Let $D_t^{2024} = \mathbf{1}\{t = 2024\}$. Following Grembi et al. (2016), our difference-in-discontinuities specification is:

$$\begin{aligned} Y_i^t = &\alpha \text{MAXDEBT}_i^{2022} + \beta \text{ABOVE}_i^{2022} + \gamma(\text{ABOVE}_i^{2022} \times \text{MAXDEBT}_i^{2022}) \\ &+ \delta D_t^{2024} + \alpha_1(\text{MAXDEBT}_i^{2022} \times D_t^{2024}) + \theta(\text{ABOVE}_i^{2022} \times D_t^{2024}) \\ &+ \gamma_1(\text{ABOVE}_i^{2022} \times \text{MAXDEBT}_i^{2022} \times D_t^{2024}) + \epsilon_{it} \end{aligned} \tag{5}$$

Our parameter of interest is θ, which captures the change in the discontinuity at the cutoff after the deletion and thus serves as the difference-in-discontinuities estimate of the deletion's effect on scorable status.

Table A.11 reports the results. In Column (3), the coefficient for *Has Credit Score* is small and statistically insignificant, indicating that the deletion of small medical debts did not meaningfully affect the probability of having a credit score. This result indicates that restricting the main analysis to consumers with non-missing credit scores is unlikely to have introduced bias.

For completeness, we also report difference-in-discontinuities estimates for our other main outcomes. The results closely resemble the RD estimates obtained in the main sample (Table 3), providing evidence that our null findings are not driven by pre-existing discontinuities at the cutoff.

C Gradient-Boosted Tree Model

C.1 Model

In Section 5, we estimate a supervised machine-learning model based on gradient-boosted decision trees (XGBoost). Let $y_i \in \{0, 1\}$ denote the binary outcome for observation i and let X_i denote the corresponding feature vector. XGBoost represents the latent score as an additive ensemble of regression trees:

$$f(X_i) = \sum_{m=1}^{M} g_m(X_i), \tag{6}$$

where each $g_m(\cdot)$ is a decision tree and M is the number of boosting rounds. For binary classification, we obtain predicted probabilities via the logistic link:

$$\hat{p}_i \equiv \Pr(y_i = 1 \mid X_i) = \frac{1}{1 + \exp(-f(X_i))}. \tag{7}$$

XGBoost fits trees sequentially to reduce the logistic (cross-entropy) loss, with regularization to control model complexity. In our implementation, we tune L1 and L2 regularization on leaf weights (`alpha` and `lambda`) as well as standard depth, shrinkage, and subsampling parameters.

C.2 Train/validation/test Split

We use a three-way split to separate hyperparameter tuning, final model training, and out-of-sample evaluation. Starting from the full sample, we first create a holdout test set containing 10% of observations. We then further split the remaining 90% of the data into a training set and a validation set, where the validation set is 10% of the remaining 90% (i.e., 9% of the full sample). Both splits are stratified on the target variable to preserve the same proportions of the positive (default) and negative (non-default) classes as in the full sample.

C.3 Hyperparameter Tuning

We tune hyperparameters to maximize predictive performance on the validation set. We use the F1 score as the tuning criterion to balance precision and recall in a setting with class imbalance, while reporting AUC as a threshold-free measure of predictive performance. Using the `hyperopt` package in Python, we search over a pre-specified hyperparameter space with a Tree-structured Parzen Estimator (TPE) algorithm (`tpe.suggest`), running 200 evaluations. Let $\mathcal{L}(\theta)$ denote the validation loss associated with hyperparameter vector θ. TPE is a form of Bayesian optimization that models the distribution of hyperparameters conditional on performance: after each batch of trials, it partitions observed configurations into "good" and "bad" sets based on a loss quantile and fits separate density estimators. Let $p(\theta)$ denote a density over the hyperparameter space, and let $\ell(\theta)$ and $g(\theta)$ denote the densities conditional on low- and high-loss realizations, respectively:

$$\ell(\theta) = p(\theta \mid \mathcal{L}(\theta) \leq \gamma)$$
$$g(\theta) = p(\theta \mid \mathcal{L}(\theta) > \gamma)$$

New candidates are then proposed by sampling values that are relatively more probable under $\ell(\theta)$ than under $g(\theta)$, allowing the search to concentrate on promising regions of the hyperparameter space while maintaining exploration. For each candidate parameter vector, we fit an `XGBClassifier` on the training sample and compute the F1 score on the validation sample. The tuning objective is the negative F1 score (so that `hyperopt` minimizes loss):

$$\mathcal{L}(\theta) = -\mathrm{F1}(\theta)$$

The search space is:

- `max_depth` $\in \{2, 3, \ldots, 9\}$,
- `learning_rate` drawn from a log-uniform distribution on $[\exp(-5), \exp(-2)]$,
- `subsample` drawn uniformly on $[0.5, 1]$,
- `max_delta_step` $\in \{0, 1, 10\}$,
- `lambda` (L2 regularization; `reg_lambda` in XGBoost) drawn from a log-uniform distribution on $[\exp(-10), \exp(0)]$,
- `alpha` (L1 regularization; `reg_alpha` in XGBoost) drawn from a log-uniform distribution on $[\exp(-10), \exp(0)]$.

Candidate models are trained on a CPU with settings `tree_method=hist` and `objective=binary:logistic`. The following table reports the optimal hyperparameters:

Optimal XGBoost hyperparameters

Hyperparameter	Value
`max_depth`	9
`learning_rate`	0.125467
`subsample`	0.943974
`max_delta_step`	1
`lambda`	0.049165
`alpha`	0.000149

C.4 Final Model Fitting and Evaluation

After selecting hyperparameters, we refit the model using the combined training and validation data (the full 90% non-test sample) and then evaluate predictive performance on the untouched 10% holdout test sample.

The following performance metrics are reported in our tables:

Accuracy measures the share of observations that are correctly classified:

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{True Positives} + \text{True Negatives} + \text{False Positives} + \text{False Negatives}}$$

Precision measures the share of predicted defaulters who actually defaulted:

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

Recall (1 − False Negative Rate) measures the share of actual defaulters who were correctly identified:

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

F1 score is the harmonic mean of Precision and Recall:

$$\text{F1} = 2 \cdot \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Area Under the Receiver Operating Characteristic Curve (AUC) measures the probability that the model assigns a higher predicted default probability to a randomly chosen defaulter than to a randomly chosen non-defaulter:

$$\text{AUC} = \Pr\left(\hat{p}_i^D > \hat{p}_j^{ND}\right)$$

where $\hat{p}_i^D$ denotes the predicted default probability for a randomly selected defaulter and $\hat{p}_j^{ND}$ denotes the predicted default probability for a randomly selected non-defaulter.

False positive rate is the share of non-defaulters incorrectly classified as defaulters:

$$\text{False Positive Rate} = \frac{\text{False Positives}}{\text{False Positives} + \text{True Negatives}}$$

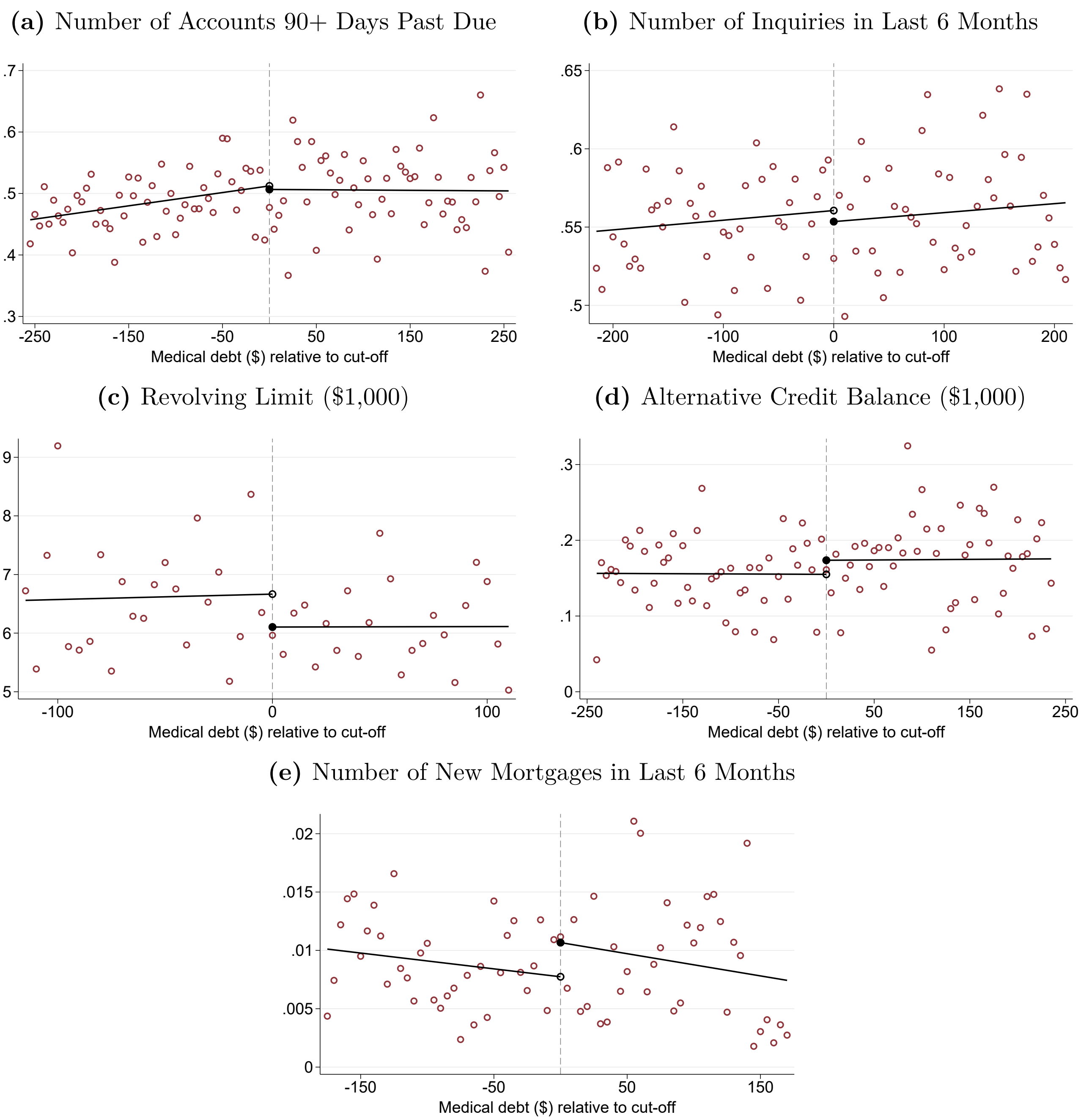
Equivalently, using Precision, Recall, and the average default rate π, the false positive rate can be written as:

$$\text{False Positive Rate} = \frac{\pi\,\text{Recall}\,(1 - \text{Precision})}{(1 - \pi)\,\text{Precision}}$$

where π denotes the average default rate in the evaluation sample.

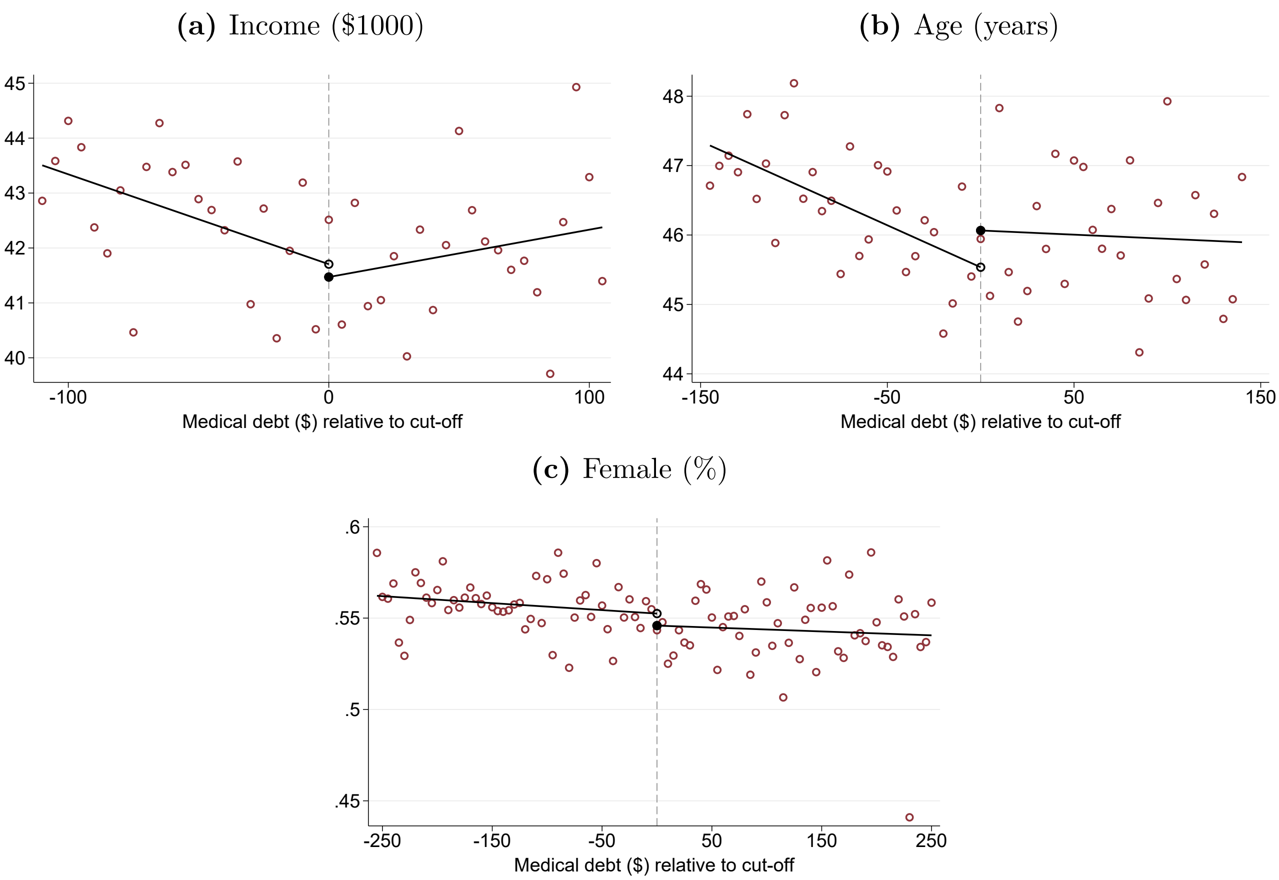
D Additional Figures and Tables

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



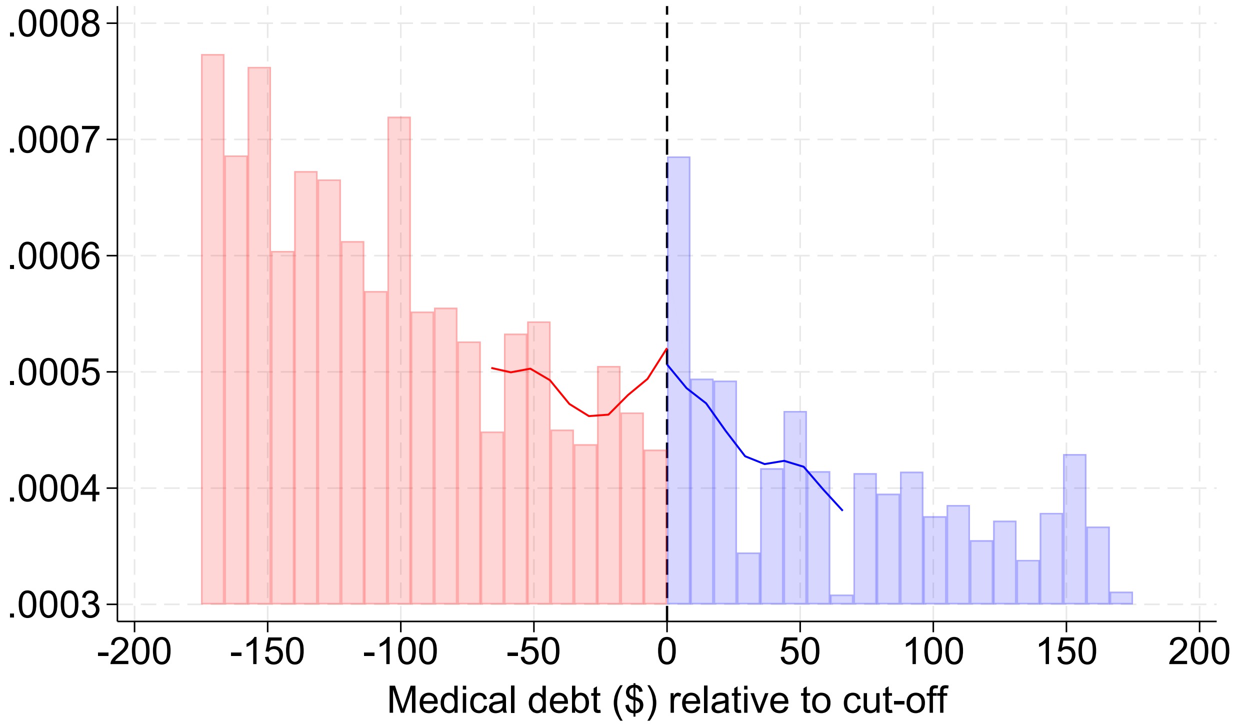
Notes: This figure shows the relationship between 2022 medical debt and five supplementary credit outcomes in 2024. Medical debt is defined as the maximum value of the consumer's 2022 medical debt collections accounts, measured relative to the $500 threshold. RD estimates from Equation (2) are reported in Table A.6.

Figure A.2: Covariate Smoothness Test: Demographics



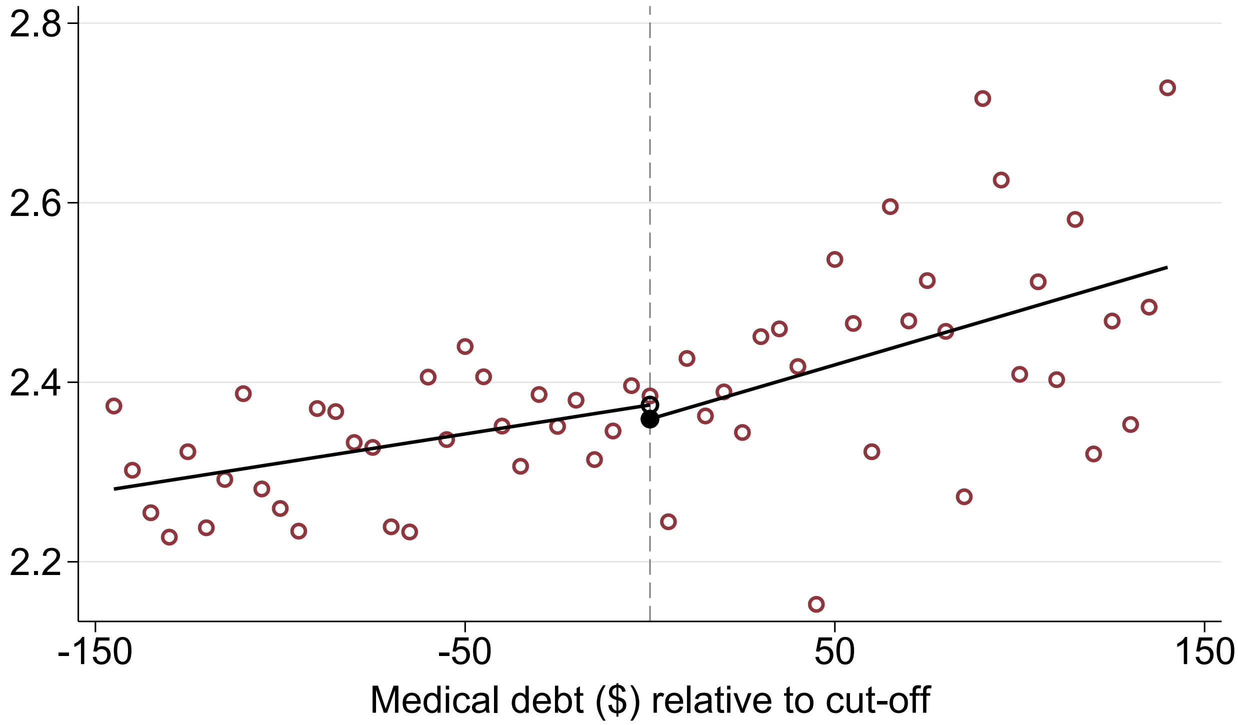
Notes: This figure shows the relationship between 2022 medical debt and three demographic variables in 2024. Medical debt is defined as the maximum value of the consumer's 2022 medical debt collections accounts, measured relative to the $500 threshold. RD estimates from Equation (2) are reported in Table A.5.

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 debt 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.

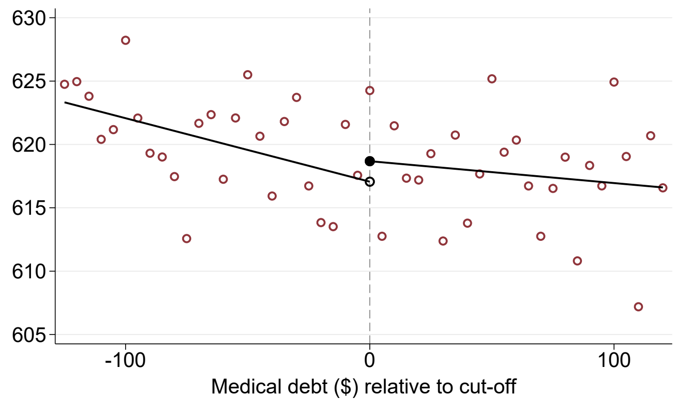
Figure A.4: Falsification test: Average Number of Accounts per Person, 2022



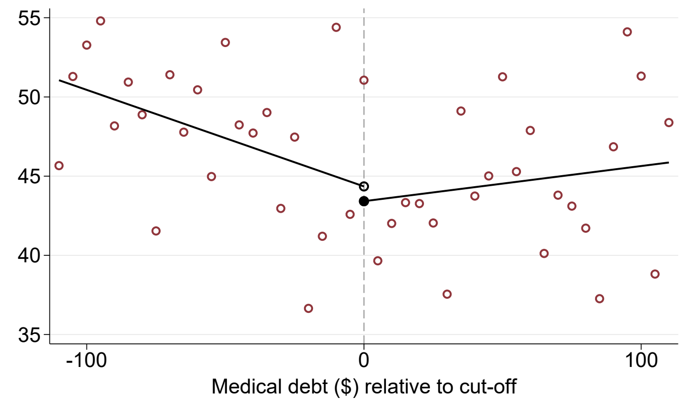
Notes: This figure shows the relationship between the medical debt running variable and the average number of medical debt collections accounts per person in 2022. The medical debt running variable is defined as the maximum value of the consumer's 2022 medical debt collections accounts, measured relative to the $500 threshold. RD estimates from Equation (2) are reported in Table A.7.

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

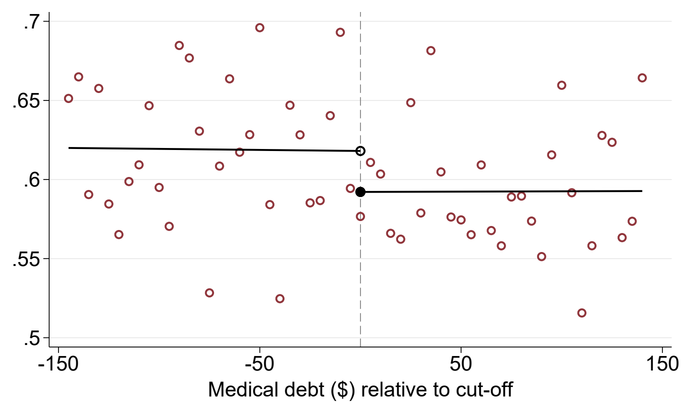
(a) Credit Score



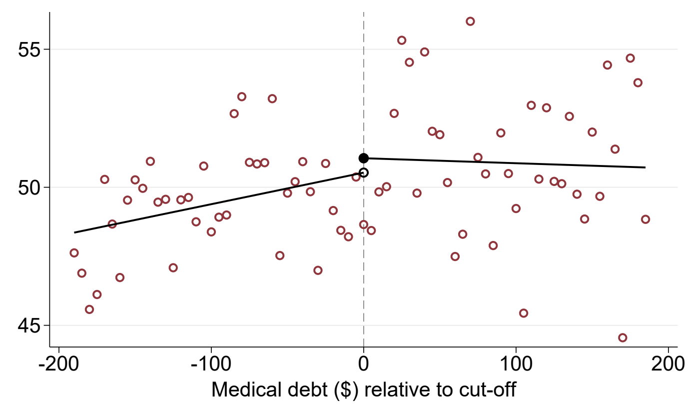
(b) Total Balance ($1,000)



(c) Number of Accounts Opened in Last 6 Months

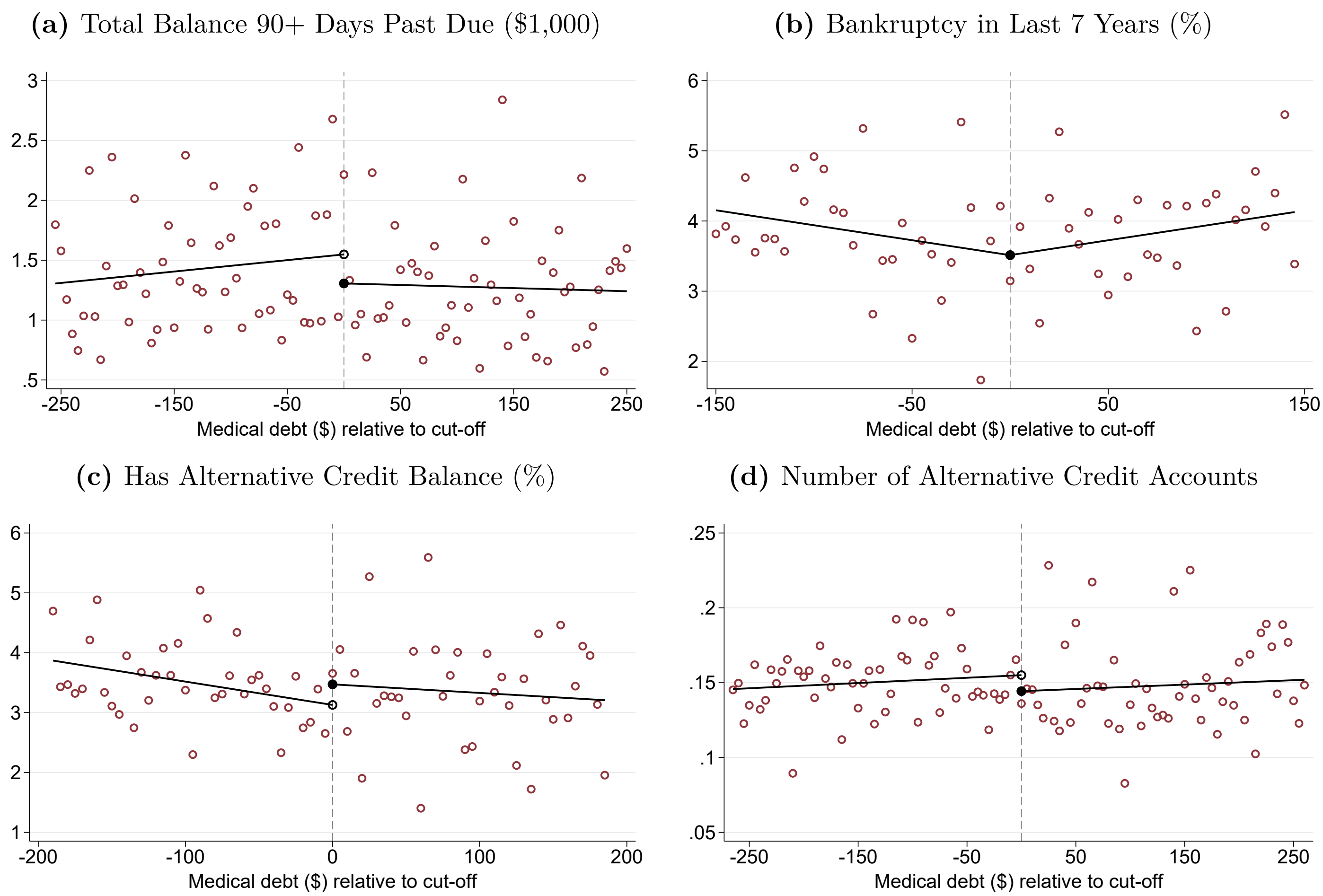


(d) Revolving Utilization (%)



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 debt collections accounts, measured relative to the $500 threshold. RD estimates from Equation (2) are reported in Table A.7.

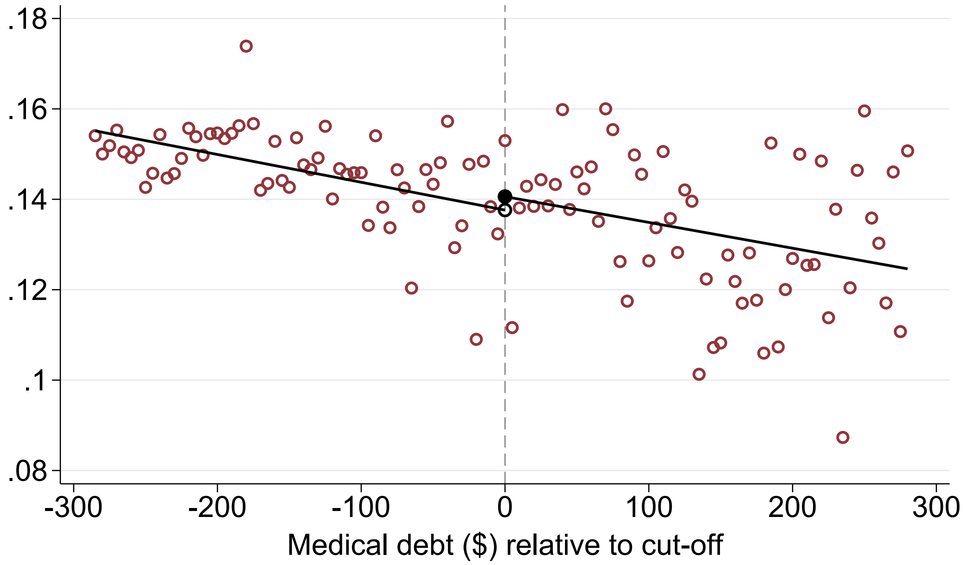
Figure A.6: Falsification Test: Financial Distress and Access to Alternative Credit, 2022



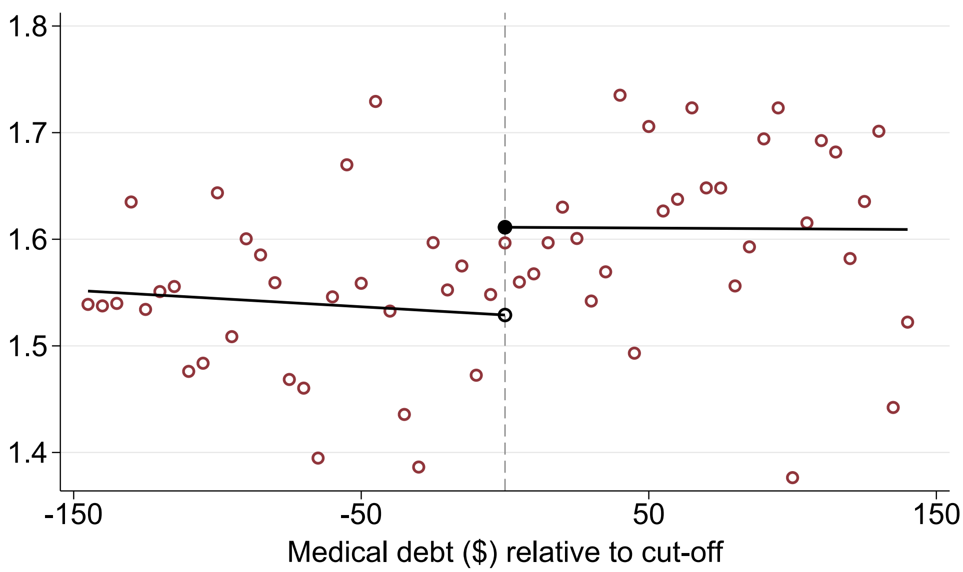
Notes: This figure shows the relationship between medical debt in 2022 and measures of financial distress and access to alternative credit in 2022. Medical debt is defined as the maximum value of the consumer's 2022 medical debt collections accounts, measured relative to the $500 threshold. RD estimates from Equation (2) are reported in Table A.7.

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

(a) Share of Surviving Accounts

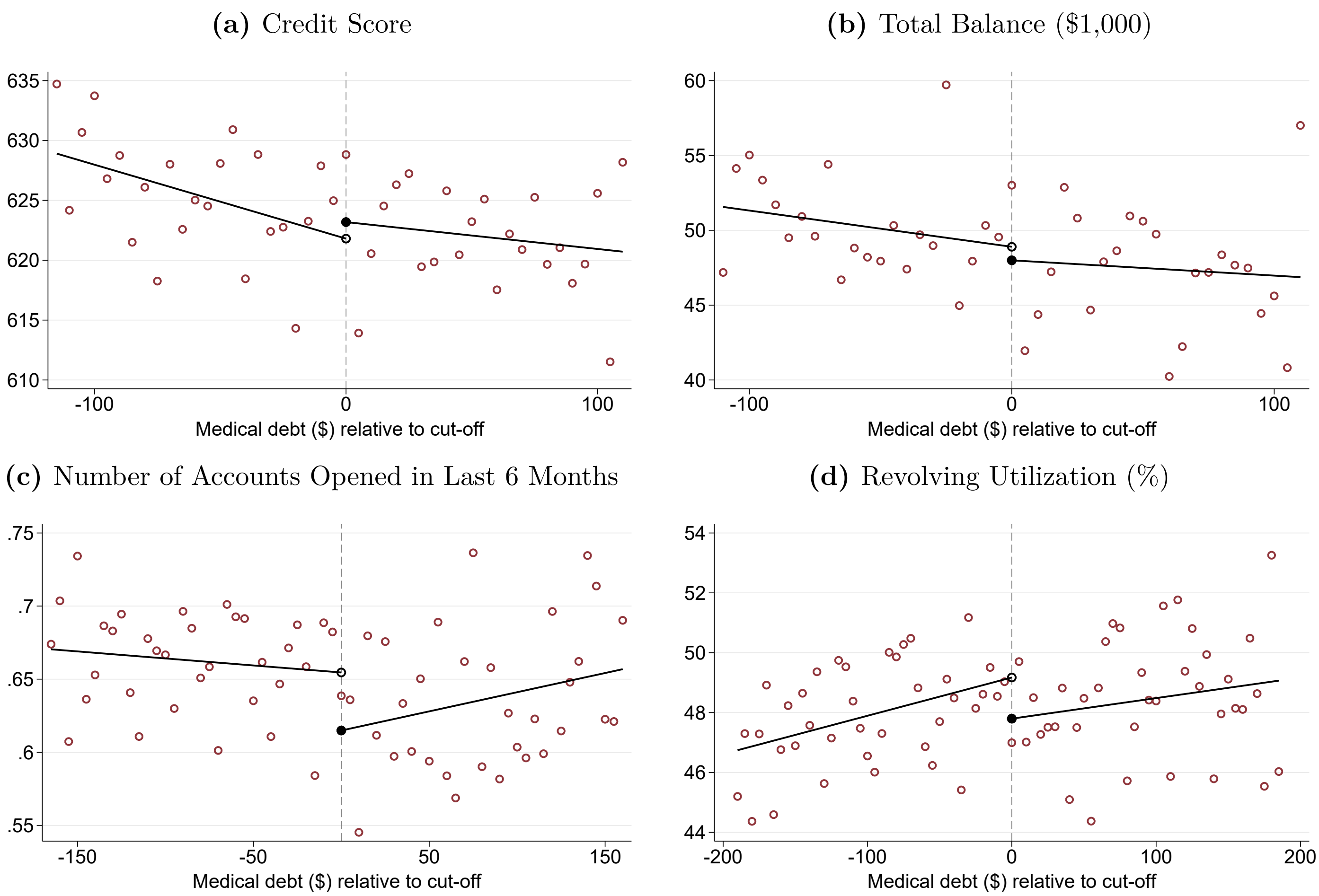


(b) Average Number of Accounts per Person



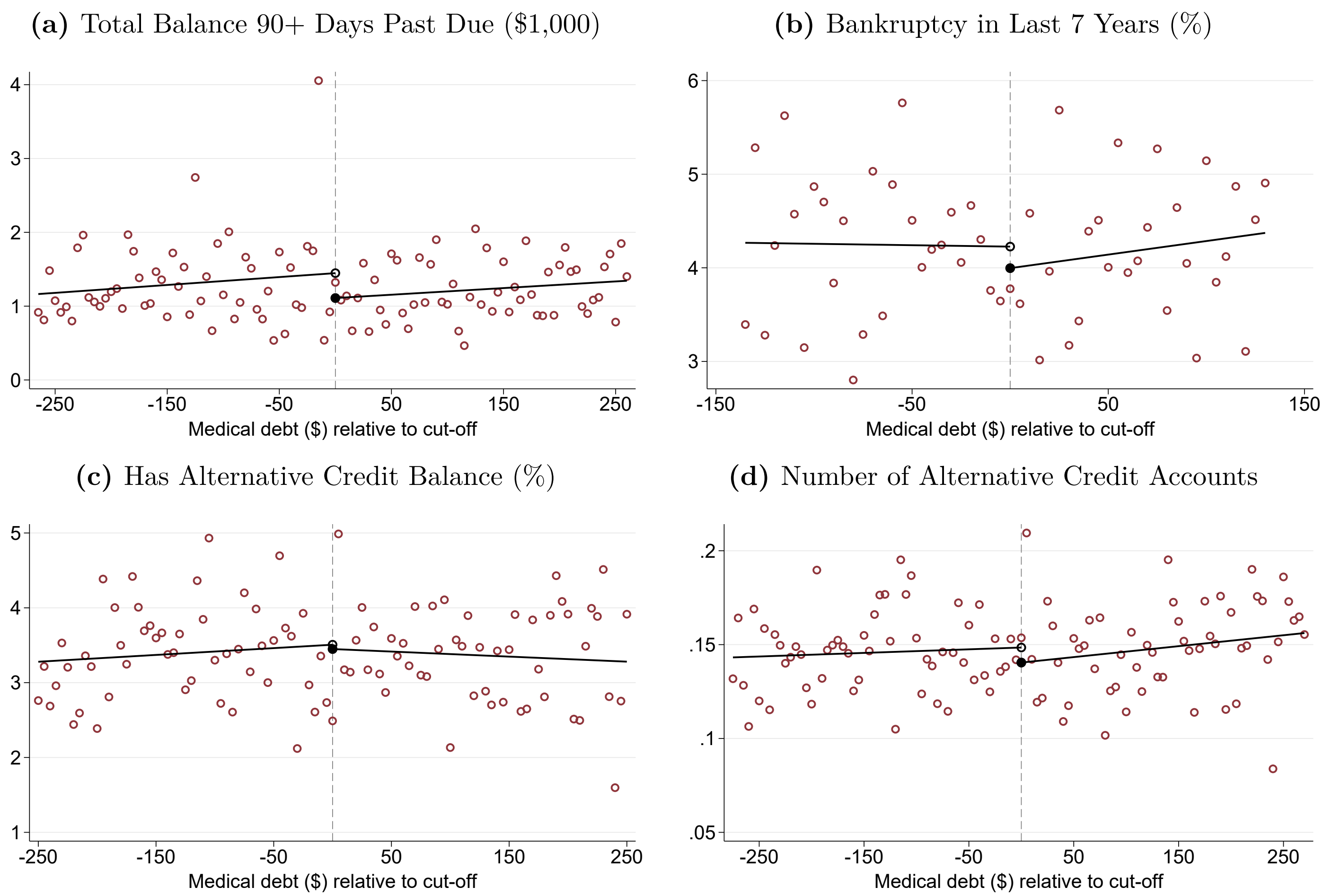
Notes: Panel (a) shows the proportion of 2020 medical debt collection accounts which remain present on 2022 credit reports by account amount, where the amount is measured as distance from the $500 threshold. Panel (b) shows the average number of accounts per person. In panel (b), the running variable is equal to the maximum value of the consumer's medical debt collections accounts. RD estimates from Equation (2) are reported in Table A.8.

Figure A.8: Placebo Test: Access to Credit



Notes: This figure shows the relationship between 2020 medical debt and four supplementary credit outcomes in 2022. Medical debt is defined as the maximum value of the consumer's 2020 medical debt collections accounts, measured relative to the $500 threshold. RD estimates from Equation (2) are reported in Table A.8.

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



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

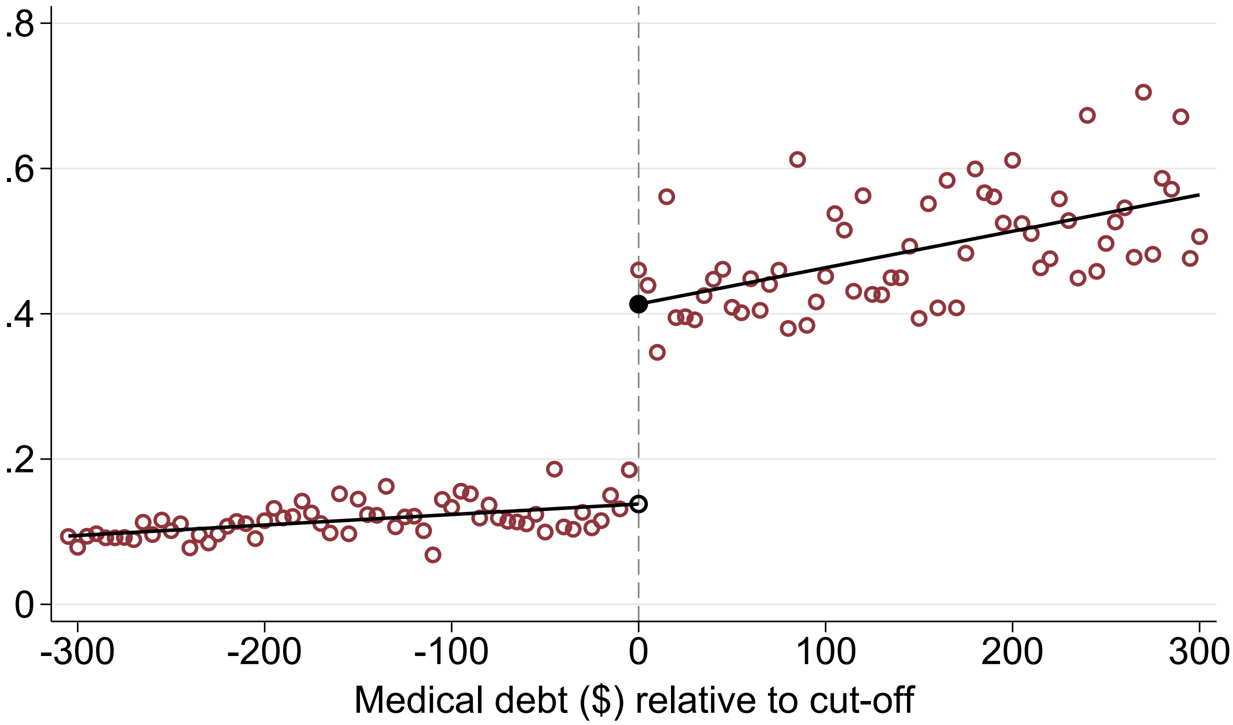
(b) Bankruptcy in Last 7 Years (%)

(c) Has Alternative Credit Balance (%)

(d) Number of Alternative Credit Accounts

Notes: This figure shows the relationship between medical debt in 2020 and measures of financial distress and access to alternative credit in 2022. Medical debt is defined as the maximum value of the consumer's 2020 medical debt collections accounts, measured relative to the $500 threshold. RD estimates from Equation (2) are reported in Table A.8.

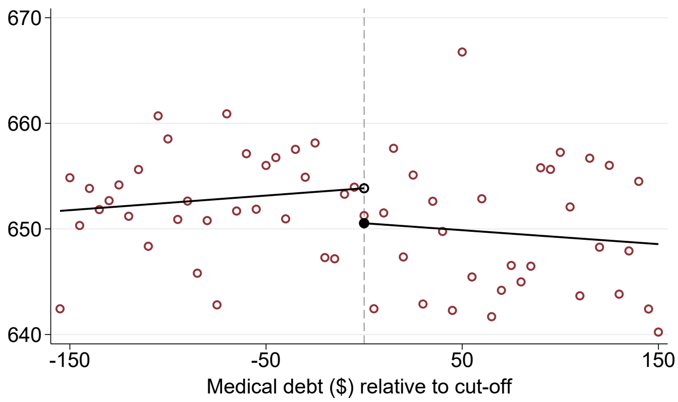
Figure A.10: Medical Debt Collections Sub-Sample: Average Number of Accounts per Person, 2022



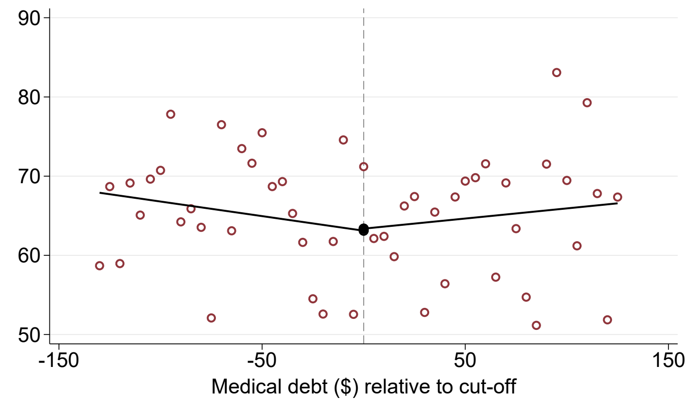
Notes: This figure shows the average number of medical debt collection accounts per person in 2024, where the running variable is the maximum value of the consumer's 2022 medical debt collection accounts, measured relative to the $500 threshold. The medical debt collections sub-sample restricts the RD sample to consumers for whom the total number of accounts in collection is same as the total number of medical debt collections accounts. RD estimates from Equation (2) are reported in Table A.9.

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

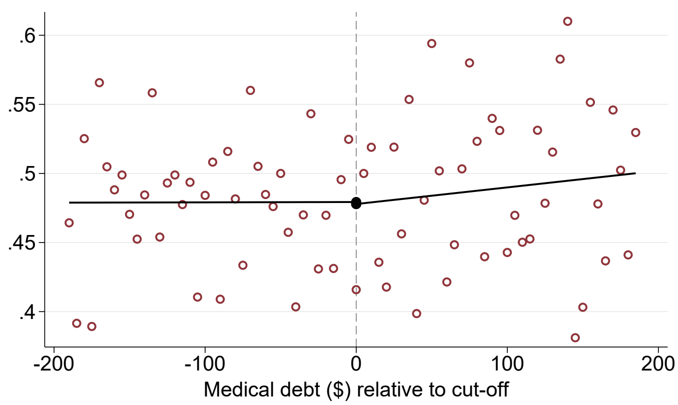
(a) Credit Score



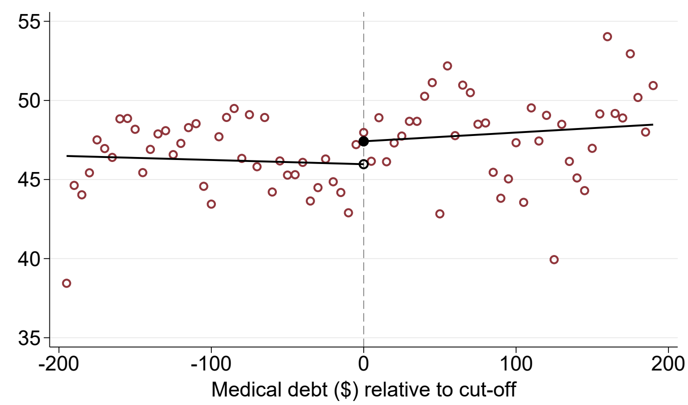
(b) Total Balance ($1,000)



(c) Number of Accounts Opened in Last 6 Months

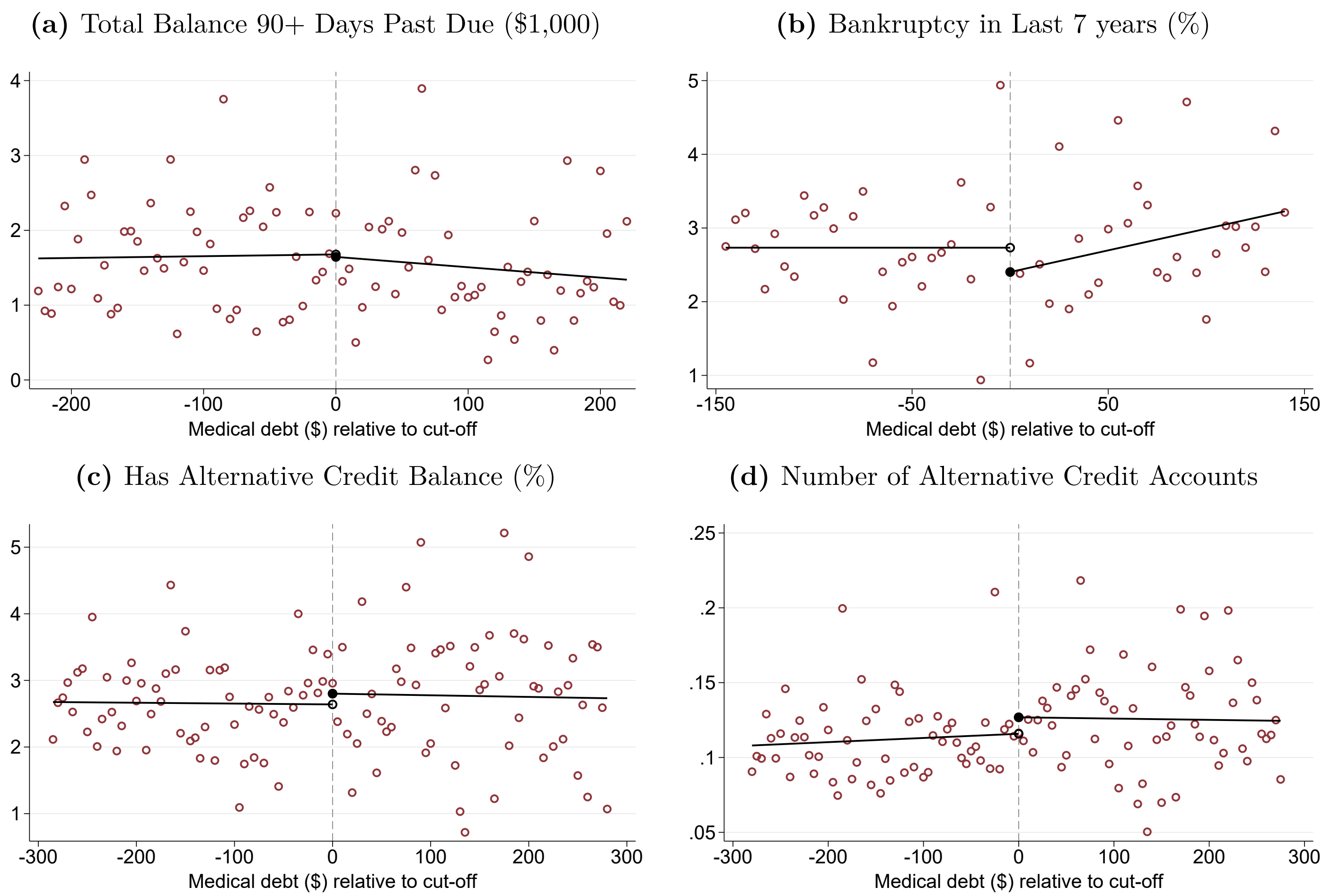


(d) Revolving Utilization (%)



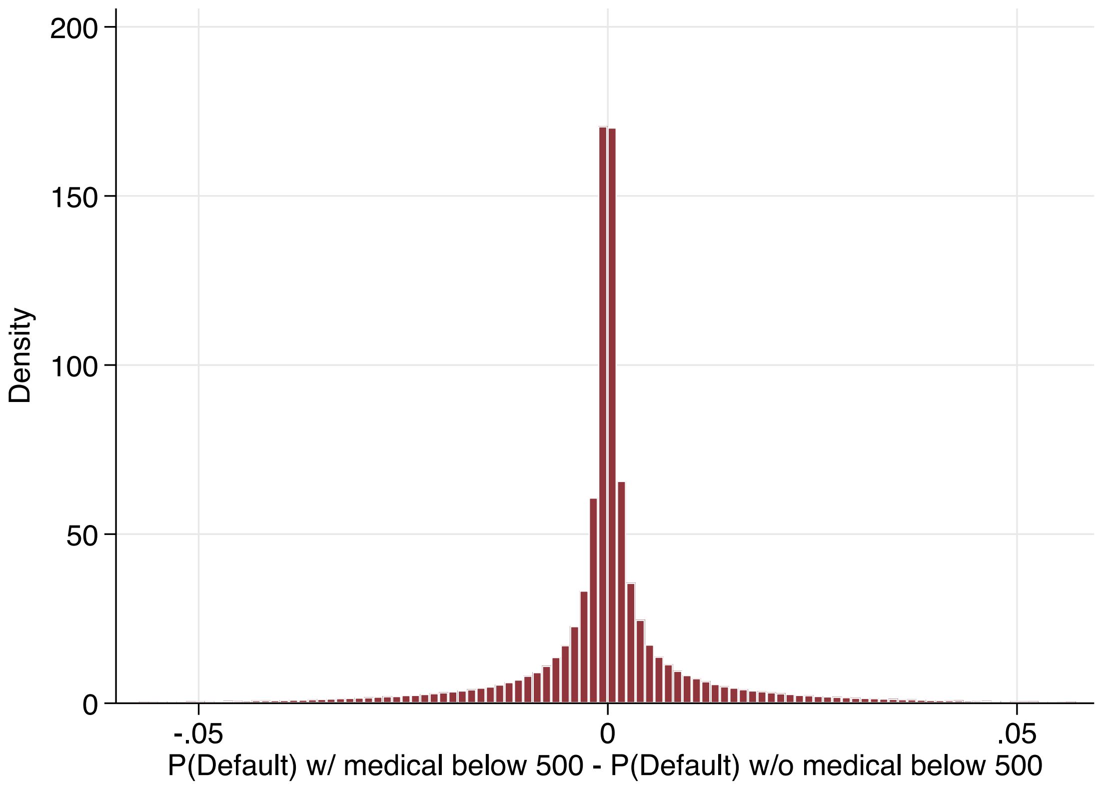
Notes: This figure shows the relationship between medical debt collections in 2022 and four different measures of credit access in 2024. The medical debt collections sub-sample restricts the RD sample to consumers for whom the total number of accounts in collections is the same as the total number of medical debt collection accounts. Medical debt is defined as the maximum value of the consumer's 2022 medical debt collections accounts, measured relative to the $500 threshold. RD estimates from Equation (2) are reported in Table A.9.

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



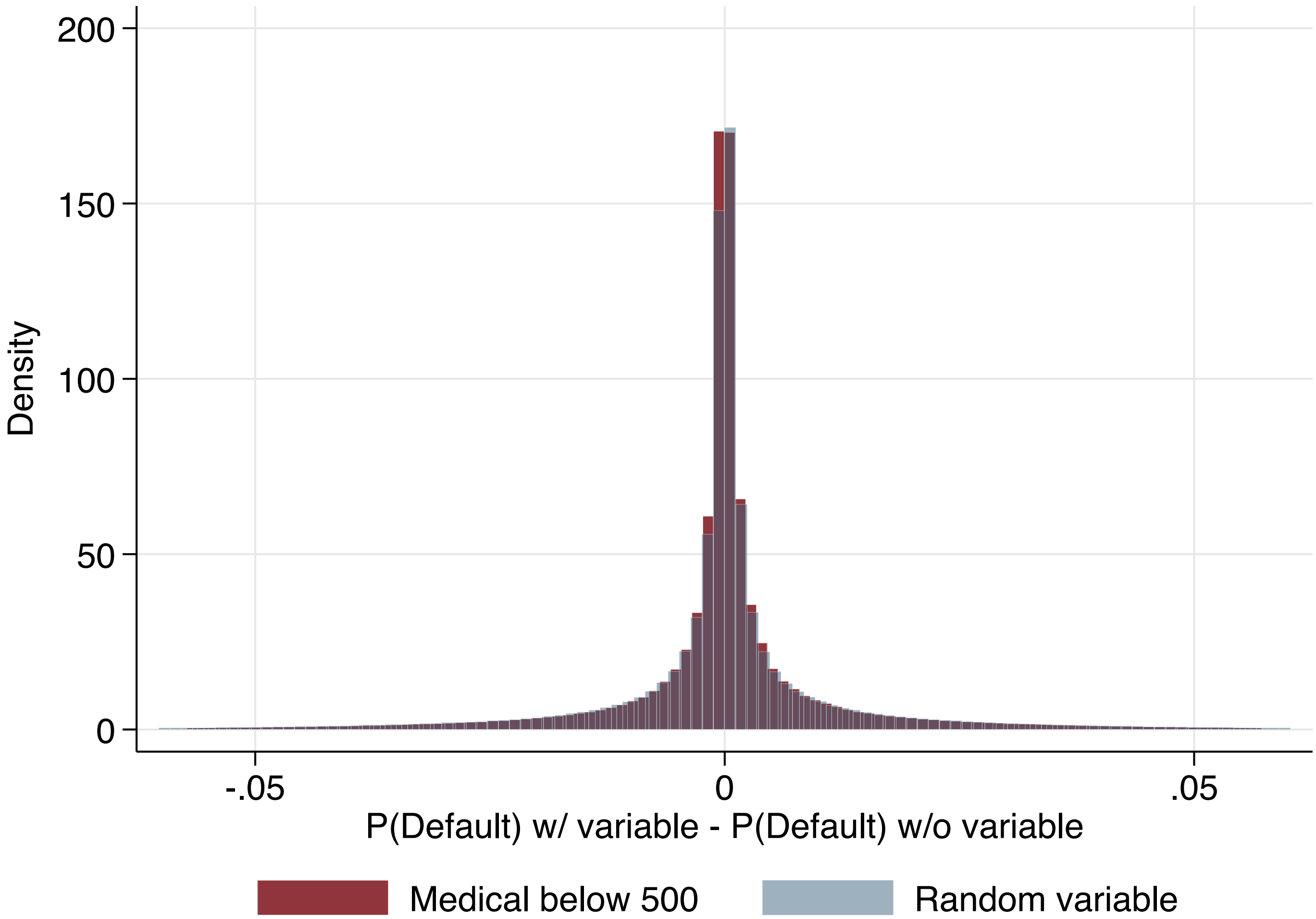
Notes: This figure shows the relationship between medical debt collections in 2022 and measures of financial distress and access to alternative credit in 2024. The medical debt collections sub-sample restricts the RD sample to consumers for whom the total number of accounts in collections is the same as the total number of medical debt collection accounts. Medical debt is defined as the maximum value of the consumer's 2022 medical debt collections accounts, measured relative to the $500 threshold. RD estimates from Equation (2) are reported in Table A.9.

Figure A.13: Effect of Removing Small Medical Debt 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 debt collections for 2.4 million consumers in the GCCP. Predictions, generated using the credit scoring model described in Section 5, are based on 2019 data.

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

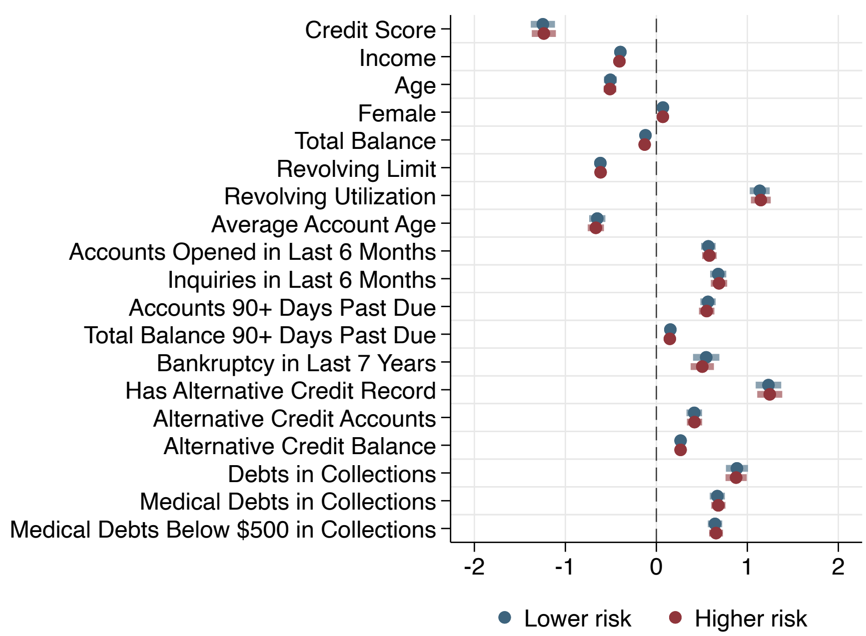


Notes: This figure shows the change in the predicted probability of default over 24 months following the removal of a variable from the credit scoring model described in Section 5. The red histogram reproduces the plot from Figure A.13, showing the effect of removing small (< $500) medical debt collections. 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 Debt Collections vs. Noise

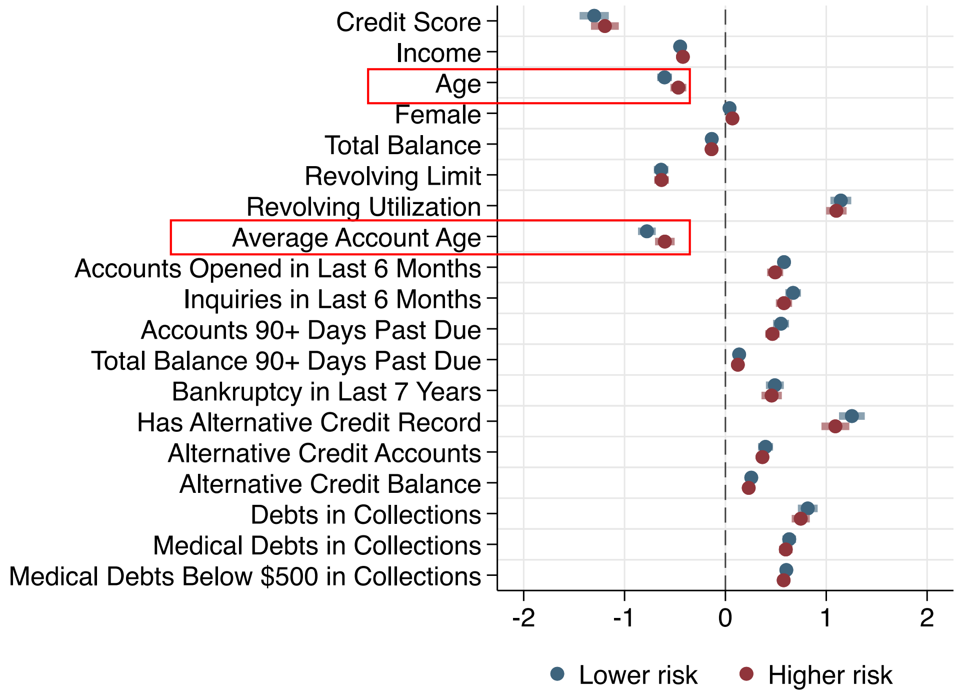
(a) Small (< $500) Medical Collections

(b) Random Variable



Notes: This figure shows estimates from balancing regressions for selected outcomes. Each balancing regression compares higher or lower risk consumers to unaffected consumers in 2022. Higher risk consumers are those in the top 5%, whose predicted probability of default increases by approximately 2 percentage points or more when small medical debt collections (Panel a) or a randomly generated predictor (Panel b) are removed from the credit scoring model described in Section 5. Lower risk consumers are those in the bottom 5%, whose predicted default probability decreases by at least two percentage points. Unaffected consumers are those between the 25th and 75th percentiles, who experience changes of less than approximately 0.2 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 lower (blue) or higher risk (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 higher or lower risk consumers to unaffected consumers in 2022. Higher risk refers to consumers in the top 5% of the distribution of probability differences according to credit scoring models with and without information on credit history length. Lower risk refers to consumers in the bottom 5% of 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 lower (blue) or higher risk (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 A.1: Share of Consumers with Medical Debt Collections: GCCP vs. External Sources

	(1)	(2)	(3)
Year	GCCP	Urban Institute	CFPB
2018	16.8%	16%	17.6%
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 debt collections in the GCCP to estimates from other sources. Column (1) reports the share of consumers with at least one account in medical debt 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.

Table A.2: Medical Debt Collection Balances ($bn): GCCP vs. CFPB

	(1)	(2)	(3)
Year	All Medical Debt Balance	Balance for Accounts <$500	CFPB
2018	95.92	17.29	96.78
2019	95.79	16.18	96.50
2020	94.91	15.78	95.79
2021	89.35	13.99	89.29
2022	68.93	11.63	-
2023	52.12	2.91	-
2024	39.07	0.06	-

Notes: This table compares aggregate medical debt collection balances in the GCCP to external estimates from the CFPB. Column (1) reports the total medical debt collections balance. Column (2) reports the total medical debt collections balance for accounts with balances below $500. Column (3) presents corresponding aggregate balance estimates reported by the CFPB (CFPB, 2022). Both the GCCP and CFPB balances are measured in March of the indicated year.

Table A.3: 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^{2022}	–0.23**	–0.30**	0.68	–2.2	0.039	–0.59	–0.093	–0.37	0.38	0.011	N/A
	[–0.32, –0.14]	[–0.32, –0.27]	[–3.6, 6.0]	[–8.6, 2.6]	[–0.00079, 0.090]	[–2.8, 1.2]	[–0.80, 0.51]	[–1.2, 0.54]	[–0.29, 1.3]	[–0.015, 0.045]	
Control Mean	1.5	0.49	618	50	0.50	53	2.0	3.2	3.9	0.18	
% of Mean	–15	–61	0.11	–4.5	7.7	–1.1	–4.6	–11	9.8	6.1	
Optimal Bandwidth	± 146.17	± 280.79	± 121.64	± 104.10	± 166.94	± 243.87	± 246.05	± 152.35	± 223.17	± 230.45	
Observations											
Total	271,305	271,305	271,305	271,305	271,305	168,853	271,305	271,305	271,305	271,305	
In-Bandwidth	38,303	83,847	31,390	26,884	44,126	42,690	70,196	40,178	62,110	64,776	
B. Running Variable is Minimum Debt											
ABOVE^{2022}	–0.41**	–0.43**	0.41	–2.6	0.0081	–0.42	0.16	0.14	0.015	–0.0069	N/A
	[–0.56, –0.29]	[–0.53, –0.37]	[–5.3, 6.1]	[–9.6, 2.7]	[–0.038, 0.060]	[–3.1, 2.4]	[–0.53, 0.75]	[–0.68, 1.1]	[–0.71, 0.98]	[–0.040, 0.031]	
Control Mean	1.7	0.72	614	46	0.47	52	2.0	2.5	3.8	0.17	
% of Mean	–24	–60	0.067	–5.6	1.7	–0.81	8.1	5.5	0.39	–4.0	
Optimal Bandwidth	± 120.96	± 120.60	± 123.20	± 103.75	± 191.65	± 203.35	± 247.91	± 162.46	± 260.92	± 282.70	
Observations											
Total	271,305	271,305	271,305	271,305	271,305	168,853	271,305	271,305	271,305	271,305	
In-Bandwidth	22,814	22,814	23,385	19,495	38,630	24,460	54,144	31,698	59,233	66,524	
C. Running Variable is Amount of Debt in Medical Account											
ABOVE^{2022}	–0.436**	–0.438**	2.85	0.160	0.014	0.81	0.078	0.038	0.284	0.009	-0.101**
	[–0.642, –0.286]	[–0.628, –0.295]	[–0.149, 6.78]	[–3.61, 3.23]	[–0.014, 0.051]	[–2.928, 0.931]	[–0.342, 0.434]	[–0.535, 0.638]	[–0.288, 0.912]	[– 0.011,0.032]	[–0.104, 0.096]
Control Mean	1.75	0.74	613.7	45.9	0.49	52.63	1.91	2.85	3.89	0.177	0.113
% of Mean	-24.88	-59.5	0.46	0.35	2.82	1.53	4.10	1.32	7.31	5.1	-90.13
Optimal Bandwidth	± 93	± 90	± 103	± 100	± 175	± 178	± 232	± 151	± 249	± 243	±221
Observations											
Total	723,088	723,088	723,088	723,088	723,088	407,570	723,088	723,088	723,088	723,088	723,088
In-Bandwidth	59,101	56,571	66,119	64,284	118,082	64,041	168,314	99,417	185,582	178,873	247,653

Notes: This table presents the estimated coefficient ($-\beta$) and 95% confidence intervals from Equation (2). Outcome variables are defined in Table A.4. The running variable in Panel A corresponds to the highest debt amount across the consumer's medical debt collections accounts. The running variable in Panel B corresponds to the smallest debt amount across the consumer's medical debt collections accounts. The running variable in Panel C, an account-level specification, corresponds to the debt amount in the consumer's medical debt 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. Control Mean reports the mean of the dependent variable for consumers whose maximum medical debt in collections in 2022 falls between $500 and $600. The reported optimal bandwidth corresponds to the symmetric half-width (in dollars) around the $500 cutoff used to estimate each specification. "In-Bandwidth" observations report the number of observations falling within this window, while "Total" observations report the full estimation sample. A */** denotes statistical significance at the 5% and 1% levels respectively, using robust inference.

Table A.4: Definitions of Main RD Outcomes

Outcome	Definition	Notes
Number of Debts	Total number of debt collection accounts	
Number of Medical Debts	Total number of medical debt collection accounts	
Credit Score	Consumer credit score (VantageScore)	
Total Balance ($1,000)	Total balance across all open credit accounts	
Number of Accounts Opened in Last 6 Months	Total number of newly opened credit accounts	
Revolving Utilization (%)	Balance-to-limit ratio on open revolving credit accounts	Equal to missing if limit equals 0
Total Balance 90+ Days Past Due ($1,000)	Total balance across all accounts 90 or more days past due	
Bankruptcy in Last 7 Years (%)	Indicator for any bankruptcy filing (Chapter 7 or Chapter 13) in past 7 years	
Has Alternative Credit Balance (%)	Indicator for positive alternative (non-traditional) credit balance, including payday loans and title loans	
Number of Alternative Credit Accounts	Total number of alternative credit accounts	

Notes: Outcome names match those reported in the main text tables and figures. All outcomes are measured at the consumer level using GCCP data.

Table A.5: Covariate Smoothness: RD Estimates of the Effect of Medical Debt Collections Deletion

	(1)	(2)	(3)
	Income ($1,000)	Age (years)	Female (%)
ABOVE^{2022}	–0.066	–0.51	0.0097
	[–1.4, 1.0]	[–1.2, 0.31]	[–0.0099, 0.030]
Control Mean	42	46	0.54
% of Mean	–0.16	–1.1	1.8
Optimal Bandwidth	± 109.17	± 141.32	± 253.64
Observations			
Total	271,305	271,305	263,895
In-Bandwidth	28,210	36,833	71,606

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 debt collections accounts. We report MSE-optimal estimates with robust, bias-corrected 95% confidence intervals in brackets. Control Mean reports the mean of the dependent variable for consumers whose maximum medical debt in collections in 2022 falls between $500 and $600. The reported optimal bandwidth corresponds to the symmetric half-width (in dollars) around the $500 cutoff used to estimate each specification. "In-Bandwidth" observations report the number of observations falling within this window, while "Total" observations report the full estimation sample. A */** denotes statistical significance at the 5% and 1% levels respectively, using robust inference.

Table A.6: Additional Credit Outcomes: RD Estimates of the Effect of Medical Debt Collections 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^{2022}	0.015	0.017	0.64	–0.0067	–0.00073
	[–0.033, 0.070]	[–0.020, 0.052]	[–0.20, 1.7]	[–0.049, 0.050]	[–0.0051, 0.0046]
Control Mean	0.50	0.56	6.1	0.18	0.0095
% of Mean	2.9	3.0	10	–3.8	–7.7
Optimal Bandwidth	± 255.46	± 212.23	± 114.49	± 236.31	± 174.48
Observations					
Total	271,305	271,305	271,305	271,305	271,305
In-Bandwidth	74,519	58,615	29,535	66,862	46,333

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 debt collections accounts. We report MSE-optimal estimates with robust, bias-corrected 95% confidence intervals in brackets. Control Mean reports the mean of the dependent variable for consumers whose maximum medical debt in collections in 2022 falls between $500 and $600. The reported optimal bandwidth corresponds to the symmetric half-width (in dollars) around the $500 cutoff used to estimate each specification. "In-Bandwidth" observations report the number of observations falling within this window, while "Total" observations report the full estimation sample. A */** denotes statistical significance at the 5% and 1% levels respectively, using robust inference.

Table A.7: Falsification Test: RD Estimates of the Effect of Medical Debt Collections 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^{2022}	0.087	0.031	–2.0	–0.43	0.026	–0.99	0.14	–0.091	–0.46	0.0052
	[–0.064, 0.19]	[–0.067, 0.13]	[–6.7, 2.9]	[–6.2, 4.0]	[–0.029, 0.084]	[–3.5, 1.2]	[–0.49, 0.68]	[–1.1, 0.81]	[–1.4, 0.17]	[–0.024, 0.030]
Control Mean	3.5	2.4	618	44	0.59	51	1.3	3.7	3.5	0.15
% of Mean	2.5	1.3	–0.32	–0.96	4.3	–1.9	11	–2.5	–13	3.5
Optimal Bandwidth	± 192.93	± 143.02	± 124.10	± 110.93	± 144.15	± 188.29	± 251.35	± 149.92	± 188.23	± 263.55
Observations										
Total	271,305	271,305	271,305	271,305	271,305	167,039	271,305	271,305	271,305	271,305
In-Bandwidth	52,022	37,355	32,103	28,514	37,595	30,776	73,095	39,040	50,698	77,407

Notes: This table presents the estimated coefficient ($-\beta$) and 95% confidence intervals from Equation (2). Outcome variables are defined in A.4. The running variable for medical debt corresponds to the highest debt amount across the consumer's medical debt collections accounts. We report MSE-optimal estimates with robust, bias-corrected 95% confidence intervals in brackets. Control Mean reports the mean of the dependent variable for consumers whose maximum medical debt in collections in 2022 falls between $500 and $600. The reported optimal bandwidth corresponds to the symmetric half-width (in dollars) around the $500 cutoff used to estimate each specification. "In-Bandwidth" observations report the number of observations falling within this window, while "Total" observations report the full estimation sample. A */** denotes statistical significance at the 5% and 1% levels respectively, using robust inference.

Table A.8: Placebo Test: RD Estimates of the Effect of Medical Debt Collections 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^{2022}	–0.029	–0.063	–1.2	0.43	0.033	1.4	0.32	0.26	–0.093	0.00099
	[–0.18, 0.077]	[–0.17, 0.0040]	[–5.1, 3.8]	[–4.1, 5.9]	[–0.023, 0.078]	[–0.49, 3.5]	[–0.17, 0.85]	[–0.57, 1.3]	[–0.80, 0.44]	[–0.027, 0.024]
Control Mean	2.7	1.6	622	48	0.63	48	1.2	4.2	3.4	0.14
% of Mean	–1.1	–3.9	–0.19	0.91	5.3	2.9	27	6.2	–2.7	0.69
Optimal Bandwidth	± 154.48	± 144.59	± 111.47	± 110.33	± 163.50	± 189.25	± 263.92	± 134.48	± 250.18	± 273.71
Observations										
Total	322,756	322,756	322,756	322,756	322,756	197,618	322,756	322,756	322,756	322,756
In-Bandwidth	50,689	46,639	35,610	35,335	53,821	38,818	94,167	43,152	88,917	98,316

Notes: This table presents the estimated coefficient ($-\beta$) and 95% confidence intervals from Equation (2). Outcome variables are defined in A.4. The running variable for medical debt corresponds to the highest debt amount across the consumer's medical debt collections accounts. We report MSE-optimal estimates with robust, bias-corrected 95% confidence intervals in brackets. Control Mean reports the mean of the dependent variable for consumers whose maximum medical debt in collections in 2020 falls between $500 and $600. The reported optimal bandwidth corresponds to the symmetric half-width (in dollars) around the $500 cutoff used to estimate each specification. "In-Bandwidth" observations report the number of observations falling within this window, while "Total" observations report the full estimation sample. A */** denotes statistical significance at the 5% and 1% levels respectively, using robust inference.

Table A.9: Medical Collections Sub-Sample: RD Estimates of the Effect of Medical Debt Collections 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^{2022}	–0.26**	–0.28**	2.9	–3.3	0.0062	–3.0**	–0.17	0.58	0.029	–0.0098
	[–0.32, –0.20]	[–0.31, –0.25]	[–2.1, 9.9]	[–13, 4.1]	[–0.046, 0.066]	[–6.1, –0.90]	[–1.1, 0.49]	[–0.39, 1.9]	[–0.80, 0.90]	[–0.042, 0.023]
Control Mean	0.76	0.44	650	65	0.49	48	1.7	2.7	2.8	0.13
% of Mean	–34	–65	0.45	–5.2	1.3	–6.3	–10	21	1.0	–7.6
Optimal Bandwidth	± 241.09	± 303.47	± 151.86	± 127.90	± 189.20	± 192.44	± 224.00	± 144.09	± 283.40	± 278.18
Observations										
Total	149,596	149,596	149,596	149,596	149,596	108,009	149,596	149,596	149,596	149,596
In-Bandwidth	36,667	50,793	21,017	17,219	27,017	19,538	33,096	19,766	45,753	44,676

Notes: This table presents the estimated coefficient ($-\beta$) and 95% confidence intervals from Equation (2). Outcome variables are defined in A.4. 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 debt collection accounts. The running variable for medical debt corresponds to the highest debt amount across the consumer's medical debt collections accounts. We report MSE-optimal estimates with robust, bias-corrected 95% confidence intervals in brackets. Control Mean reports the mean of the dependent variable for consumers whose maximum medical debt in collections in 2022 falls between $500 and $600. The reported optimal bandwidth corresponds to the symmetric half-width (in dollars) around the $500 cutoff used to estimate each specification. "In-Bandwidth" observations report the number of observations falling within this window, while "Total" observations report the full estimation sample. A */** denotes statistical significance at the 5% and 1% levels respectively, using robust inference.

Table A.10: Longer-run (Two-Year) RD Estimates of the Effect of Medical Debt Collections 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^{2022}	–0.11*	–0.16**	0.63	–0.60	0.023	0.82	0.26	–0.51	–0.033	0.0087
	[–0.22, –0.025]	[–0.19, –0.14]	[–3.9, 5.8]	[–6.8, 4.7]	[–0.018, 0.075]	[–1.3, 2.6]	[–0.52, 1.0]	[–1.3, 0.34]	[–0.75, 0.75]	[–0.023, 0.046]
Control Mean	1.4	0.31	619	50	0.53	51	3.6	3.1	4.2	0.21
% of Mean	–8.1	–50	0.10	–1.2	4.4	1.6	7.4	–16	–0.79	4.2
Optimal Bandwidth	± 155.27	± 282.15	± 130.23	± 112.89	± 175.95	± 278.96	± 260.76	± 152.40	± 279.86	± 253.92
Observations										
Total	264,753	264,753	264,753	264,753	264,753	166,189	264,753	264,753	264,753	264,753
In-Bandwidth	40,136	82,561	33,088	28,430	45,729	50,477	74,589	39,256	81,390	72,016

Notes: This table presents the estimated coefficient ($-\beta$) and 95% confidence intervals from Equation (2) using outcomes measured in 2025. Outcome variables are defined in A.4. The running variable for medical debt corresponds to the highest debt amount across the consumer's medical debt collections accounts. We report MSE-optimal estimates with robust, bias-corrected 95% confidence intervals in brackets. Control Mean reports the mean of the dependent variable for consumers whose maximum medical debt in collections in 2022 falls between $500 and $600. The reported optimal bandwidth corresponds to the symmetric half-width (in dollars) around the $500 cutoff used to estimate each specification. "In-Bandwidth" observations report the number of observations falling within this window, while "Total" observations report the full estimation sample. A */** denotes statistical significance at the 5% and 1% levels respectively, using robust inference.

Table A.11: Difference-in-Discontinuities Estimates of the Effect of Medical Debt Collections Deletion

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Number of Debts	Number of Medical Debts	Has Credit Score (%)	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
$\text{ABOVE}^{2022} \times \text{D}^{2024}$	–0.37** [–0.48, –0.25]	–0.47** [–0.52, –0.43]	0.0031 [–0.0019, 0.0082]	2.5 [–0.68, 5.6]	–0.77 [–3.3, 1.8]	–0.0017 [–0.043, 0.040]	0.16 [–1.8, 2.1]	–0.15 [–0.69, 0.38]	–0.34 [–0.86, 0.18]	0.050 [–0.53, 0.63]	–0.0021 [–0.021, 0.016]
Control Mean	1.4	0.54	0.93	617	45	0.46	53	1.9	2.9	3.6	0.16
% of Mean	–26	–87	0.34	0.40	–1.7	–0.36	0.31	–8.0	–12	1.4	–1.3
Optimal Bandwidth	± 176.53	± 414.08	± 389.41	± 119.31	± 123.86	± 231.03	± 246.21	± 323.58	± 189.08	± 397.47	± 383.30
Observations	295,092	295,092	295,092	280,339	295,092	295,092	171,761	295,092	295,092	295,092	295,092

Notes: This table presents the estimated coefficient ($-\theta$) and 95% confidence intervals from Equation (5). Outcome variables are defined in A.4. The running variable for medical debt corresponds to the highest debt amount across the consumer's medical debt collections accounts. We report MSE-optimal estimates with 95% confidence intervals in brackets, standard errors are clustered at the consumer level. Control Mean reports the mean of the dependent variable for consumers whose maximum medical debt in collections in 2022 falls between $500 and $600. The reported optimal bandwidth corresponds to the symmetric half-width (in dollars) around the $500 cutoff used to estimate each specification. A */** denotes statistical significance at the 5% and 1% levels respectively, using conventional inference.

Table A.12: RD Estimates of the Effect of Medical Debt Collections Deletion: Excluding New York and Colorado

	(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^{2022}	–0.25**	–0.31**	1.8	–2.2	0.034	–0.80	–0.093	–0.45	0.36	0.0079
	[–0.36, –0.17]	[–0.34, –0.28]	[–2.6, 7.3]	[–8.8, 2.7]	[–0.0067, 0.086]	[–3.2, 1.1]	[–0.84, 0.51]	[–1.3, 0.45]	[–0.34, 1.3]	[–0.020, 0.043]
Control Mean	1.5	0.51	618	50	0.51	53	1.9	3.2	4.0	0.18
% of Mean	–17	–62	0.29	–4.5	6.7	–1.5	–4.8	–14	9.0	4.4
Optimal Bandwidth	± 143.26	± 293.15	± 119.47	± 102.14	± 170.20	± 235.52	± 233.20	± 155.00	± 225.68	± 236.99
Observations										
Total	259,521	259,521	259,521	259,521	259,521	161,101	259,521	259,521	259,521	259,521
In-Bandwidth	35,719	84,804	29,406	25,162	43,393	39,187	62,727	39,282	60,195	63,850

Notes: This table presents the estimated coefficient ($-\beta$) and 95% confidence intervals from Equation (2). Outcome variables are defined in A.4. This subsample restricts the RD analysis to consumers residing outside Colorado and New York. The running variable for medical debt corresponds to the highest debt amount across the consumer's medical debt collections accounts. We report MSE-optimal estimates with robust, bias-corrected 95% confidence intervals in brackets. Control Mean reports the mean of the dependent variable for consumers whose maximum medical debt in collections in 2022 falls between $500 and $600. The reported optimal bandwidth corresponds to the symmetric half-width (in dollars) around the $500 cutoff used to estimate each specification. "In-Bandwidth" observations report the number of observations falling within this window, while "Total" observations report the full estimation sample. A */** denotes statistical significance at the 5% and 1% levels respectively, using robust inference.

Table A.13: Association Between Number of Medical Debts and Two-Year Default Rates

	(1)	(2)	(3)	(4)	(5)
Number of medical debts < \$500					
1	0.147**	0.110**	0.091**	0.028**	0.013**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
2	0.160**	0.122**	0.101**	0.035**	0.015**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
3+	0.148**	0.111**	0.092**	0.031**	0.010**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Number of medical debts ≥ \$500					
1	0.126**	0.101**	0.076**	0.036**	0.021**
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
2	0.116**	0.096**	0.067**	0.041**	0.026**
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
3+	0.095**	0.084**	0.048**	0.041**	0.033**
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Control Variables Included					
Num Accounts 90+ Days Past-Due (24 Months)		X	X	X	X
Percent Accounts 90+ Days Past-Due			X	X	X
All Credit-Report Controls				X	X
Flexible Controls (Polynomial Terms)					X
In-Sample Performance Metrics					
Accuracy	0.867	0.871	0.871	0.889	0.897
AUC	0.605	0.752	0.778	0.878	0.886
F1 Score	-	0.161	0.180	0.385	0.486
Precision	-	0.610	0.579	0.727	0.730
Recall (1 − False Negative Rate)	0	0.093	0.106	0.262	0.364
False Positive Rate	0	0.009	0.012	0.015	0.021
R-squared	0.038	0.130	0.148	0.291	0.337
Mean outcome	0.133	0.133	0.133	0.133	0.133
Observations	2,473,281	2,473,281	2,473,281	2,473,281	2,473,281

Notes: This table reports estimates from a linear probability model relating the number of medical debt collections in 2019 to default occurring between 2020 and 2021. Medical debt collections are separated into balances below \$500 and balances at or above \$500; for each group, the omitted category is zero collections. Column (1) includes no control variables. Column (2) controls for the number of accounts 90+ days past due in the last 24 months. Column (3) additionally controls for the percentage of accounts 90+ days past due. Column (4) includes the complete set of credit-report controls listed in Figure 5. Column (5) augments this specification with a fifth-order polynomial in credit-report variables. For the purpose of computing classification metrics, observations are classified as predicted defaults if the fitted value from the linear probability model is at least 0.5. A */** denotes statistical significance at the 5% and 1% levels, respectively. Standard errors are robust to heteroskedasticity. Definitions of the performance metrics are provided in Appendix C.4.

Table A.14: Association Between Medical Debt Amounts and Two-Year Default Rates

	(1)	(2)	(3)	(4)	(5)
Medical debt $< \$250$	0.184**	0.141**	0.117**	0.045**	0.024**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Medical debt $\$250 - \$500$	0.203**	0.156**	0.126**	0.051**	0.029**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Medical debt $\$500 - \$1,000$	0.214**	0.169**	0.132**	0.059**	0.036**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Medical debt $\geq \$1,000$	0.209**	0.165**	0.125**	0.059**	0.035**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Control Variables Included					
Num Accounts 90+ Days Past-Due (24 Months)		X	X	X	X
Percent Accounts 90+ Days Past-Due			X	X	X
All Credit-Report Controls				X	X
Flexible Controls (Polynomial Terms)					X
In-Sample Performance Metrics					
Accuracy	0.867	0.871	0.871	0.889	0.897
AUC	0.602	0.750	0.777	0.878	0.886
F1 Score	-	0.152	0.177	0.386	0.486
Precision	-	0.611	0.592	0.726	0.730
Recall (1 − False Negative Rate)	0	0.087	0.104	0.263	0.364
False Positive Rate	0	0.008	0.011	0.015	0.021
R-squared	0.041	0.132	0.149	0.291	0.337
Mean outcome	0.133	0.133	0.133	0.133	0.133
Observations	2,473,281	2,473,281	2,473,281	2,473,281	2,473,281

Notes: This table reports estimates from a linear probability model relating medical debt collections in 2019 to default occurring between 2020 and 2021. Medical debt collections are defined as the maximum medical debt collection balance across a consumer's accounts in 2019. The omitted category consists of individuals with no medical debt collections. Column (1) includes no control variables. Column (2) controls for the number of accounts 90+ days past due in the last 24 months. Column (3) additionally controls for the percentage of accounts 90+ days past due. Column (4) includes the complete set of credit-report controls listed in Figure 5. Column (5) augments this specification with a fifth-order polynomial in credit-report variables. For the purpose of computing classification metrics, observations are classified as predicted defaults if the fitted value from the linear probability model is at least 0.5. A */** denotes statistical significance at the 5% and 1% levels, respectively. Standard errors are robust to heteroskedasticity. Definitions of the performance metrics are provided in Appendix C.4.

Table A.15: Performance Metrics for Credit Scoring Models With and Without Medical Debt Collections Versus a Random Variable

	(1)	(2)	(3)
	All Predictors + Noise	Exclude Noise (Baseline)	Exclude Medical Debts < $500
Accuracy	0.905	0.906	0.906
AUC	0.902	0.902	0.902
F1 Score	0.560	0.560	0.560
Precision	0.737	0.736	0.738
Recall	0.452	0.452	0.451
False Positive Rate	0.0248	0.0248	0.0246

Notes: This table reports out-of-sample performance metrics for a credit scoring model predicting defaults occurring between 2020 and 2021, using borrower characteristics from 2019. Column (1) reports metrics for a model that adds a random variable to the baseline set of 46 predictors, estimated using XGBoost. Column (2) presents metrics for the baseline model, with 46 predictors. Column (3) reports metrics when small (under $500) medical collections are excluded from the baseline set of predictors. The sample consists of 2,473,281 observations, with 90% used for model training and the remaining 10% reserved for out-of-sample performance evaluation. For reference, a naive model that predicts no defaults achieves an accuracy of 0.867, equal to one minus the average default rate (0.133). Definitions of the performance metrics are provided in Appendix C.4.

Table A.16: Performance Metrics for Credit Scoring Models With and Without Medical Debt Collections: Logit Model

	(1)	(2)	(3)
	All Predictors	Exclude Medical Debts < $500	Exclude All Medical Debts
Accuracy	0.897	0.897	0.897
AUC	0.890	0.890	0.890
F1 Score	0.495	0.495	0.494
Precision	0.726	0.726	0.726
Recall	0.375	0.376	0.374
False Positive Rate	0.0217	0.0218	0.0217

Notes: This table reports out-of-sample performance metrics for a credit scoring model predicting defaults occurring between 2020 and 2021, using 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 all medical collections are excluded. The sample consists of 2,473,281 observations, with 90% used for model training and the remaining 10% reserved for out-of-sample performance evaluation. For reference, a naive model that predicts no defaults achieves an accuracy of 0.867, equal to one minus the average default rate (0.133). Definitions of the performance metrics are provided in Appendix C.4.