# The Effects of Deleting Medical Debt from Consumer Credit Reports*

Victor Duarte
University of Illinois

Julia Fonseca
University of Illinois

Divij Kohli
University of Illinois

Julian Reif
University of Illinois and NBER

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**Abstract**

One in seven Americans carry medical debt, with $88 billion reported on consumer credit reports. In April 2023, the three major credit bureaus stopped reporting medical debts below $500. We study the effects of this information deletion on consumer credit scores, credit limits and utilization, repayment behavior, and payday borrowing. Using a machine learning model, we show that small medical debts are not meaningfully predictive of defaults, suggesting their deletion should have minimal effect on lending decisions. We test this prediction using two complementary research designs. First, a regression discontinuity analysis comparing individuals above and below the $500 threshold finds no direct benefits from the information deletion, ruling out small changes in credit access. Second, to assess indirect effects, we classify consumers based on whether their predicted default probability increases or decreases when debts are deleted. A difference-in-differences analysis comparing these groups before and after the 2023 policy change reveals no evidence of negative spillover effects. Finally, we show that larger medical debts ($\geq$ $500) are also not meaningfully predictive of default, suggesting that eliminating medical debts entirely from credit reports, as planned under a January 2025 decision by the Consumer Financial Protection Bureau, is unlikely to affect credit outcomes.

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# 1 Introduction

One in seven Americans carry medical debt (U.S. Census Bureau, 2022). Unpaid medical bills are often sent to collection agencies and subsequently reported to credit bureaus, resulting in $88 billion in medical debt appearing on consumer credit reports as of 2021 (Consumer Financial Protection Bureau, 2022). Policymakers have raised growing concerns about these reporting practices, arguing that making medical debt visible to lenders could impair access to credit following unexpected medical shocks. In response, the three major U.S. credit bureaus announced in April 2023 that they were no longer including medical debt collections below $500 in credit reports.

Building on this measure, the Consumer Financial Protection Bureau (CFPB) issued a final rule in January 2025 to eliminate all remaining medical debt collections from credit reports, arguing that this change would enhance credit access and improve loan terms for consumers burdened with medical debt.[1] To address concerns that deleting this information could inadvertently harm consumers without medical debt, the CFPB cited evidence that medical debt collections are poor predictors of default and thus unlikely to negatively affect lending decisions (Consumer Financial Protection Bureau, 2024). However, prior work finds that information deletion can reduce borrowing opportunities for individuals whose credit risk is pooled with consumers the policy aims to help (Liberman et al., 2019). Moreover, if medical debt truly lacks predictive power, eliminating it from credit reports may not improve credit access for those it is meant to help.

Against this backdrop, this paper studies the effects of deleting information about medical debt collections from credit reports on credit access and financial health, using 2019–2024 data from the Gies Consumer and Small Business Credit Panel (GCCP). Specifically, we investigate whether consumers whose medical debt information was deleted experienced any direct benefits, and whether this deletion produced negative spillovers by causing other consumers to be reclassified as higher risk. Using machine learning techniques, we build credit scoring models to evaluate the predictive value of medical debt collections for default

[1] This rule was set to go into effect 60 days after publication in the Federal Register but implementation was delayed until June 15, 2025 by the U.S. District Court for the Eastern District of Texas. For the announcement of the rule, see https://www.consumerfinance.gov/about-us/newsroom/cfpb-finalizes-rule-to-remove-medical-bills-from-credit-reports/.

risk prior to 2023. We compare two models: one trained on borrower credit histories that include medical debts below \$500, and another trained on histories excluding these small medical debts. We find that excluding small medical debts has no meaningful effect on default prediction, underscoring their limited value for lending decisions. Furthermore, we show that larger medical debts ($\geq$ \$500) also have little predictive value, suggesting that eliminating all medical debts from credit reports is similarly unlikely to influence credit access or financial health.

We test this prediction using two distinct research designs. First, we employ a regression discontinuity (RD) approach to estimate the direct effects of the 2023 deletion of small medical debts from credit reports. Comparing individuals just above and below the \$500 threshold, we find no evidence that deleting this information affected credit scores, credit limits and utilization, repayment behavior, payday borrowing, or other related outcomes. Our null estimates are precise: the 95% confidence intervals rule out increases in credit scores greater than 6.03 points (0.97%) and decreases in the balance-to-limit ratio of revolving credit exceeding 1.54 percentage points (4.80%).

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

Overall, we conclude that the 2023 decision to delete small medical debt collections from

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

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

We make several contributions to the literature. First, we investigate the effects of information deletion in a novel context: medical debt. Liberman et al. (2019) study the deletion of credit default information in Chile and, like us, use credit scoring models to assess how changes in predicted probabilities affect credit access. They find that deletion increases borrowing for consumers whose predicted default risk declines, but reduces borrowing for those reclassified as higher-risk. Similarly, Jansen et al. (2024) find that removing bankruptcy flags lowers interest rates for affected consumers while raising them for those with no history of bankruptcy, resulting in a small decline in social surplus.[3] Beyond credit markets, Agan and Starr (2017) find that removing criminal history information from job applications reduces callbacks for Black applicants, and Bartik and Nelson (2024) show that bans on employers' use of credit reports lower job-finding rates and increase involuntary separations for Black workers. Unlike these studies, we show that the deleted information in our setting—small medical debts—has minimal predictive value. As a result, we find neither direct benefits for affected consumers nor indirect harms to others. A unique feature of our setting is the presence of a cutoff value for information deletion, which allows us to estimate direct effects using a rigorous RD design.

Second, we contribute to the literature on medical debt forgiveness, a policy often discussed alongside information deletion. Kluender et al. (2024) conduct two large-scale randomized experiments and find that forgiveness modestly improves credit access for consumers whose medical debts were reported to credit bureaus, but has no effect on other consumers. Their results suggest that whether a debt appears on a credit report plays a key role in determining the impact of debt relief. However, our analysis—which focuses specifically on medical debts that were reported—fails to detect any meaningful effects on credit access. Taken together, these findings suggest that neither deleting medical debt information from

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

credit reports nor forgiving the debt itself alleviates financial distress. These results contrast with evidence from other debt relief contexts, which generally find positive results (Dobbie and Song, 2015; Di Maggio et al., 2020; Cespedes et al., 2025).

Third, we advance the literature on machine learning in credit markets. We are the first to demonstrate that medical debt collections are poor predictors of default risk.[4] However, we also show that even unreliable information like medical debt can still influence credit scores, particularly for consumers with thin credit files—a phenomenon previously documented by Blattner and Nelson (2022). Prior studies have used machine learning to study information deletion (Liberman et al., 2019) and to develop credit scoring models (e.g. Khandani et al., 2010; Frost et al., 2020; Sadhwani et al., 2020; Fuster et al., 2022; Meursault et al., 2022; Agarwal et al., 2023; Blattner et al., 2024; Chioda et al., 2024). Building on this body of work, we construct a credit scoring model using XGBoost, a state-of-the-art prediction algorithm, and achieve substantially better performance than prior studies across multiple metrics.

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

The remainder of this paper is structured as follows. Section 2 describes the data used in our analysis. Section 3 investigates whether medical debt is predictive of default. Section 4 presents RD estimates of the direct effects of deleting medical debt collections. Section 5 estimates the indirect effects on consumers reclassified as higher risk using a differences-in-

[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.

differences analysis. Section 6 concludes.

# 2 Data

Our study uses the Gies Consumer and Small Business Credit Panel (GCCP), a panel dataset of anonymized credit record data for consumers and small businesses, obtained from a major credit bureau. The GCCP features a one-percent random sample of individuals with a credit report, linked to alternative credit records and business credit records for individuals who own a business.[5] The dataset covers the years 2004–2024, with annual snapshots of credit records taken at the end of the first quarter of each year. Consumers are randomly sampled based on the last two digits of their Social Security numbers. This sampling method accounts for natural flows into the panel as new Social Security numbers are issued, as well as outflows due to death or prolonged inactivity, ensuring that the sample remains representative of the broader population over time.

The GCCP provides detailed debt information at the credit account ("tradeline") level, including outstanding balances and payment histories for mortgages, student loans, and credit cards. It also includes individuals' VantageScore credit scores, public records such as bankruptcies and judgments, and demographic variables such as age, gender, and 5-digit zip code. We classify a collection as medical debt if the associated creditor is labeled as Medical/Health Care or if the furnisher is identified as a business operating in the medical or health-related sector.[6] Table A.2 compares the share of people with medical debt collections under our classification to two external benchmarks. All three sources yield similar estimates: approximately 17 percent of the population had medical debt collections in 2018, declining to about 13 percent by 2022.

We restrict the sample to the years 2019–2024 and to consumers aged 18 or older. We

[5] 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.

[6] 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.

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

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

### 2.1 Regression Discontinuity Sample

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

## 3 Do Medical Debt Collections Predict Default?

### 3.1 Background

Medical debt arises when patients are unable to pay the out-of-pocket portions of their medical bills. Typically, healthcare providers first attempt to recover unpaid amounts directly from patients. If these efforts fail, they may enlist third-party collection agencies, which use various strategies to secure payment. These strategies include initiating lawsuits to obtain court judgments for repayment and reporting unpaid debts to credit bureaus.[7] In some cases, medical debts are sold to debt buyers who continue recovery efforts. To protect consumers, the Fair Debt Collection Practices Act prohibits abusive or deceptive practices by third-party debt collectors. Importantly, as of April 2023, debt collectors can no longer report medical debts under $500 to credit bureaus, thereby reducing their leverage in such cases.

The consequences of medical debt are complex and challenging to quantify, in part because payment rates are exceedingly low—medical debt can be purchased for pennies on the dollar (Kluender et al., 2024). This contrasts sharply with other forms of unsecured debt, such as student loans and credit card debt. Unlike medical debt, student loans are not easily dischargeable in bankruptcy; eliminating them typically requires proving "undue hardship," a demanding legal standard. Credit card debt also has much higher repayment rates, as issuers can threaten to restrict future access to credit for delinquent borrowers. Additionally, many states provide consumer protections specific to medical debt, including limits on wage garnishment and prohibitions on home foreclosure (Robertson et al., 2022).

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

The effect of deleting medical debt collections hinges on their predictive power for future default. If medical debt accurately predicts default risk, lenders who incorporate these data into their proprietary credit scoring models might adjust lending decisions following its removal, potentially limiting access to credit for some consumers. Conversely, if medical debt offers limited predictive value, its removal should not affect credit underwriting, even

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

for consumers whose information is deleted.

Not all lenders use proprietary credit scoring models. Some rely exclusively on scores provided by major credit bureaus, such as VantageScore and FICO. For these lenders, the impact of deleting medical collections on their lending decisions depends on whether those scores are affected. However, VantageScore stopped including medical collections below $500 in its model in January 2023, and FICO followed suit a few months later.[8] As a result, the deletion of small medical collections is unlikely to affect the decisions of lenders relying solely on these bureau-provided credit scores.

For lenders developing their own models, the decision to include medical debt collections depends on whether these data help predict defaults. To examine this, we simulate the effects of the April 2023 deletion of medical collections below $500 by training two credit scoring models: one that includes data on medical collections below $500 and another that excludes it. While our models do not exactly replicate any specific lender's approach, they rely on similar data and algorithms, and—as we shall show—they outperform existing models in the literature. Our approach assumes that a well-designed credit scoring model such as ours should be able to detect the predictive power of medical debt collections, if any exists.

As we demonstrate below, we find that medical debt collections below $500 provide no meaningful predictive value beyond other standard credit variables. This finding implies that the April 2023 intervention should have no direct or indirect effects on credit access or financial health—predictions which we test in Sections 4 and 5. Finally, we show that medical debts above $500 also fail to predict default, suggesting that the CFPB's 2025 final rule to delete all remaining medical debt collections from credit reports is also unlikely to affect credit access or financial health.

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

### 3.2 Credit scoring with and without medical collections

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

$$Y = f(X_1, X_2, ...X_n) + e \tag{1}$$

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

Traditional credit scoring models, such as FICO and VantageScore, typically use logit models estimated using person-level data (Federal Reserve Board, 2007). These models generally aim to predict "default," commonly 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 (Federal Reserve Board, 2007).

Following this approach, we construct a model using $n = 46$ predictors that capture a broad set of credit-related information: accounts and balances past due, the number of medical and non-medical collections, the number of bankruptcies and other public records, balances and accounts of different credit types, average account age, age of oldest account, and the number of new credit inquiries and accounts.[9] Consistent with prior work, our model excludes variables prohibited by the Equal Credit Opportunity Act—such as sex, marital status, and age—as well as variables that may serve as proxies for these characteristics, such as geographic identifiers (Federal Reserve Board, 2007; Blattner and Nelson, 2022). Unlike traditional models, we use XGBoost, a state-of-the-art machine learning algorithm well-suited for classification problems. This flexible, tree-based ensemble method is designed to capture complex, nonlinear interactions between predictors and typically outperforms standard parametric models in predictive accuracy.

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

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

We report model performance in Table 3. The first column shows results for the model including medical collections below \$500; the second column presents results for the model excluding them. Because default is a relatively rare event, the accuracy score—the share of correct predictions—provides limited insight. For example, a model that predicts no consumers will default achieves an accuracy score of 86.69%, reflecting the share of consumers in the sample who did not default. Similarly, the area under the Receiver Operating Characteristic curve (AUC), which measures the probability that the model assigns a higher default probability to a true defaulter than to a non-defaulter, is less informative in imbalanced classification settings. Instead, we focus on precision and recall, which better capture a model's ability to predict rare events (Davis and Goadrich, 2006).

Precision and recall are defined as:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \tag{2}$$

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \tag{3}$$

Precision measures the proportion of predicted defaulters who actually defaulted, while recall measures the proportion of actual defaulters who were correctly identified. Both metrics are important in our setting: high precision minimizes the misclassification of creditworthy

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

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

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

Table 3 shows that our algorithm performs well in predicting default, achieving an F1 Score of 0.557. To assess this result, we focus on its components, precision and recall, which are more commonly reported in other papers. Our recall of 0.448 ranks among the highest, with prior studies typically reporting values between 0.35 and 0.41 (e.g., Butaru et al. (2016), Agarwal et al. (2023)). Two exceptions are Khandani et al. (2010) and Chioda et al. (2024), who achieve recalls of 0.654 and 0.749, respectively, but over shorter prediction horizons of 3 and 6 months.[11] Shorter prediction windows generally yield higher precision and recall, helping explain the stronger performance in these studies. Moreover, Chioda et al. (2024) use a 20% threshold—substantially lower than our 50% threshold—which further boosts recall but reduces precision.

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

Comparing the first two columns in Table 3 shows that removing information on medical collections below $500 has no measurable impact on model performance. All metrics remain unchanged up to the third decimal, except for accuracy, which slightly *increases* by 0.001 when small medical collections are removed. This result provides strong evidence that medical collections below $500 contribute no meaningful predictive value. The third column

[11] 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.

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

To further examine the role of medical collections, Figure 1 reports variable importance measures based on average SHAP values, ranking variables in order of predictive importance.[12] Small medical collections rank near the bottom, with an average SHAP value of 0.0011, compared to an average value of 0.278 for the 10 most important features. Figure A.1 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.[13]

Although Figure A.1 suggests that small medical debt collections might improve predictive performance for a subset of individuals represented in the tails of that distribution, these effects are more likely driven by noise than by meaningful differences in default risk. To investigate this further, we categorize consumers into three groups based on the changes in their predicted default probabilities across the two models:

**Negatively treated**: Consumers in the top 5 percent of the distribution, whose predicted probability of default increases by approximately 2 percentage points or more when small medical debts are removed from the model.

**Positively treated**: Consumers in the bottom 5 percent of the distribution, whose predicted probability of default decreases by approximately 2 percentage points or more when small medical debts are removed from the model.

**Unaffected**: Consumers between the 25th and 75th percentiles, who experience a change in predicted default probabilities of no more than 0.002 percentage points.

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

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

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

However, we do not observe this pattern. Table 4 shows summary statistics for all three groups. While both the positively and negatively treated groups differ significantly from the unaffected group, they are remarkably similar to each other. Figure 2 illustrates these results using balancing regressions. All variables are standardized and each dot represents the regression coefficient of the variable labeled on the y-axis, regressed on either the positive (blue) or negatively treated (red) group indicator. If small medical debts were strongly predictive of default, we would expect a pronounced sorting effect along relevant characteristics—particularly the number of medical debts. However, Figure 2 reveals no such pattern: positively and negatively treated consumers appear statistically indistinguishable across a wide range of characteristics, including the presence of medical debts.

The similarity between these two groups, despite their substantial divergence from the unaffected group, suggests that the changes in predicted risk are driven by estimation noise. As shown in Blattner and Nelson (2022), default probabilities are estimated with considerable noise for low-income consumers with thin credit files (Blattner and Nelson, 2022). In such settings, even uninformative predictors like small medical debts can receive non-zero weights during model training.[14] As a result, excluding an uninformative feature may shift predictions for noisy cases, creating two groups with large changes in predicted risk but no meaningful underlying differences. This process effectively assigns consumers randomly to the positively or negatively treated groups, while separating them from the more stable, unaffected group. To validate this interpretation, Section 3.3 introduces a randomly generated variable into the model and shows that excluding it produces a nearly identical pattern to the one observed when excluding small medical collections debts.

[14] 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.

## 3.3 Placebo test: credit scoring with and without random noise

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

Table A.3 presents the performance metrics. Columns (1)–(2) replicate the estimates from the first two columns of Table 3, confirming that removing small medical collections has no discernible impact on model performance. Comparing Column (3) to Column (1) shows a nearly identical pattern when a random variable is included and then removed.[15] Figure A.2 reinforces this result by overlaying the distribution of probability changes from Figure A.1 with the corresponding distribution obtained after removing the noise variable. The two distributions are nearly indistinguishable.

Figure A.3 further supports this interpretation by showing that removing the random variable sorts consumers into our three groups—unaffected, positively treated, and negatively treated—in the same way as removing medical collections under $500. Panel A reproduces the balance plot from Figure 2, where each dot represents the coefficient from a regression of the standardized variable labeled (y-axis) on either the positively treated (blue) or negatively treated (red) group indicator. Panel B presents the same analysis using the random variable instead of medical collections. In both panels, "treated" consumers have, on average, lower credit scores, lower income, and lower balances, reinforcing the conclusion that default probability estimates are substantially noisier for these consumers (Blattner and Nelson, 2022).

One potential concern with this placebo test is that removing any variable—regardless of its predictive power—might fail to generate systematic differences between the positively and negatively treated groups. To address this concern, Figure A.4 examines the impact of removing a clearly informative piece of information: credit history length, as measured by average account age, the age of the oldest account, and the age of the oldest account that

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

was never delinquent or derogatory. Credit history length is widely used in credit scoring models as a predictor of default (Federal Reserve Board, 2007) and average account age is one of the most important features in our model as measured by SHAP values (Figure 1). When we exclude these variables, we observe clear sorting patterns: the positively treated group is younger and has a shorter credit history, as measured by average account age, than the negatively treated group. In contrast to the removal of small medical collections or a random variable, excluding a truly predictive predictor produces meaningful differences between the groups. This contrast underscores that our placebo test is meaningful: removing uninformative variables leads to random sorting, while removing valuable predictors results in systematic differences across groups.

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

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

To test whether medical debt predicts default in the absence of stronger predictors, we train a restricted version of our baseline XGBoost model using only four predictors. These predictors include the number of medical debts below and above $500, and two of the least important predictors in our model (as measured by the SHAP values shown in Figure 1): bankruptcy trades and bankruptcy trades in the past 24 months. Thus, this restricted model relies solely on medical debt and variables with even less predictive power.

Table A.4 presents the performance metrics for the restricted model. As expected, Column (1) shows that this model performs very poorly. Its accuracy is 0.8669—identical to that of a naive model that predicts no defaults. The recall score is just 0.0008, meaning that it correctly identifies only 0.08 percent of true defaulters. Among borrowers classified as defaulters, only 34.62 percent are correctly classified, and the model achieves an F1 Score of just 0.0016, far below our baseline of 0.557.

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

# 4 Direct Effect: Regression Discontinuity

## 4.1 Empirical strategy

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

$$Y_{ij}^{2024} = \alpha_1 \text{DEBT}_{ij}^{2022} + \beta_1 \text{ABOVE}_{ij}^{2022} + \gamma_1 (\text{ABOVE}_{ij}^{2022} \times \text{DEBT}_{ij}^{2022}) + \epsilon_{ij} \tag{5}$$

The dependent variable, $Y_{ij}^{2024}$, represents an outcome in 2024 for account $j$ belonging to consumer $i$. The running variable, $\text{DEBT}_{ij}^{2022}$, 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 $\text{ABOVE}_{ij}^{2022}$ is equal to one if $\text{DEBT}_{ij}^{2022} \geq 0$. Our model employs a local linear approximation to the unknown regression functions underlying the average causal effect at the threshold. We allow the slope of our linear approximation to vary on either side of the cutoff.

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

$$Y_{i}^{2024} = \alpha \text{MAXDEBT}_{i}^{2022} + \beta \text{ABOVE}_{i}^{2022} + \gamma (\text{ABOVE}_{i}^{2022} \times \text{MAXDEBT}_{i}^{2022}) + \epsilon_{i} \tag{6}$$

The running variable, $\text{MAXDEBT}_{i}^{2022}$, is defined as the largest medical debt for consumer

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

Our main identifying assumption is that assignment around the \$500 threshold is effectively random. This assumption is plausible because medical debt balances are typically determined by fixed and often opaque pricing, leaving consumers with limited ability to manipulate their placement relative to the threshold. Additionally, our data come from administrative records, which minimizes concerns about measurement error or sample selection bias.

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

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

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

## 4.2 Results

We begin by estimating the first-stage effect of the 2023 deletion on medical collections accounts. Panel A of Figure 3 shows that by 2024, nearly all accounts with balances below \$500 in 2022 had been removed from credit reports, whereas more than 10 percent of accounts with balances above \$500 remained. Panel B demonstrates that this effect also appears at the consumer level. After aggregating the running variable by taking the maximum debt amount across all accounts, the intervention is shown to have reduced the number of medical debt collections per person in 2024 by 0.29 (107%).[16]

Figure 4 shows the direct effect of the 2023 deletion on credit access and utilization. We find no evidence of significant discontinuities around the \$500 threshold. Table 5 presents formal estimates, with 95% confidence intervals ruling out improvements in credit scores greater than 6.03 points (0.97%), increases in balances greater than \$2,602 (5.05%), new credit accounts by 0.09 (17.65%), and decreases in revolving utilization by 1.54 (4.80%).[17] Figure 5 shows the direct effect of the 2023 deletion on delinquency, bankruptcy, and alternative credit use. Again, the 95% confidence intervals can rule out that deletion improved delinquency balance by \$802 (42.36%), the probability of bankruptcy by 1.19 percentage points (37.42%), the probability of having alternative credit balance by –0.29 percentage points (7.51%), and an increase in the number of alternative credit accounts by 0.04 (22.60%).

Figure A.6 shows results for additional credit 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. We again detect no significant effects. Our null estimates remain precise, with 95% confidence intervals ruling out meaningful changes across all outcomes.

In Table A.9, we focus on the subsample of consumers whose debts in collections consist solely of medical debts—a group for which Kluender et al. (2024) found modest positive effects of debt relief, including a 13.8 point (2.3%) increase in average credit scores. However,

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

[17] Medical collections have not been used in the VantageScore model since January 2023; there is therefore no mechanical relationship between these two variables in this analysis.

we find no such benefits, ruling out a credit score increase of 9.91 points (1.52%) at the 95% confidence level. One possible reason for this discrepancy is that the two major credit scoring models—VantageScore and FICO—stopped using medical debt as a predictor in 2023, after the study period in Kluender et al. (2024) but before our post-period outcome measurements. Thus, while removing medical debt from credit reports may have affected credit scores in the earlier period, it no longer has a direct effect on them in our setting.[18]

Under the assumptions of our RD design, outcomes unrelated to medical debt should remain unchanged at the threshold. Figure A.5 confirms this prediction, showing no discontinuities in key demographic variables such as income, age, and gender.

We also conduct a series of falsification and placebo tests. Our falsification tests, shown in Figures A.7 and A.8, replicate our RD specification (6) but use 2022 outcomes instead of 2024 outcomes. We find no effects, as expected. Similarly, our placebo tests, presented in Figures A.10 and A.11, replicate our RD analysis using the 2020–2022 period instead of 2022–2024. Once again, we find no significant effects, reinforcing the validity of our design.

# 5 Indirect Effect: Difference-in-differences

## 5.1 Empirical strategy

We use a differences-in-differences research design to study the indirect effects (negative spillovers) of deleting small medical debt collections from credit reports. To isolate consumers most exposed to these negative spillovers, we define the treatment group as consumers whose predicted probability of default increases by about two percentage points or more when small medical debts are excluded from our credit scoring model (the "negatively treated" group described in Section 3). Because this classification is based on 2019 characteristics, we restrict our analysis to 2020–2024.

A natural control group would be consumers whose predicted default risk remains un-

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

changed ("unaffected" consumers).[19] However, as shown in Table 4, these consumers differ significantly from the "negatively treated" group across observables. Instead, we use the "positively treated" group—consumers whose predicted probability of default decreases when small medical debts are removed—as the control group. These individuals are more comparable in terms of observables, and because small medical debts have minimal predictive power, the assignment to the "negatively" and "positively" treated groups is effectively random (see Section 3). This randomness lends credibility to our key identifying assumption: in the absence of the information deletion, outcomes for the two groups would have followed similar trends.[20]

We estimate the following regression model at the individual level:

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

where $Y_{ict}$ is an outcome for consumer $i$, residing in county $c$, in year $t$; $\text{TREATED}_i$ is an indicator equal to one if the consumer belongs to the "negatively treated" group and zero if they belong to the "positively treated" group; $\text{POST}_t$ is an indicator equal to one beginning in 2023, the year of information deletion; and $\lambda_i$ and $\delta_{ct}$ denote consumer and county-year fixed effects, respectively.

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

Our coefficient of interest, $\beta$, captures the average effect of deleting medical debt collections for the treatment group—consumers whose predicted default probability increases when medical debts are removed—relative to the control group. To assess the validity of the

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

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

parallel trends assumption, we also estimate an event-study version of Equation (7):

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

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

## 5.2 Results

Figure 6 presents event-study estimates of the indirect effect of information deletion (Equation (8)) on credit-access outcomes: credit scores (panel A), total balance across all credit products (panel B), number of accounts opened in the last 6 months (panel C), and revolving utilization (panel D). Outcome trends are similar between the treatment and control groups prior to 2023, with no statistically significant differences. We observe no significant trend changes after 2023, consistent with the absence of any indirect effects.

Figure 7 shows similar results for measures of payment history and subprime borrowing, including the total balance 90+ days past due (panel A), whether a consumer had a bankruptcy in the last 7 years (panel B), whether a consumer has an alternative credit balance (panel C), and the number of alternative credit records (panel D). We again find no evidence of pre-trends or of any significant effects.[21]

Table 6 presents estimates from Equation (7), which assumes a constant treatment effect over time and aggregates years to increase statistical power. Across all 8 outcomes, estimated effects are small and generally insignificant. The only significant estimate—a 0.721-point increase in credit scores—is economically small, representing just 0.12% of the sample mean (617.13). Overall, our estimates are precise and consistently point to null effects,, allowing us to rule out even small negative spillovers from the deletion of small medical debts.

[21] We show additional outcomes in Appendix Figure A.16.

# 6 Conclusion

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

Our analysis focuses on small medical debts under $500, which were removed from credit reports by all three major credit bureaus in 2023. We begin by showing that this information has little predictive value for default, based on a comparison of two credit scoring models: one that includes small medical debts and one that excludes them.

We then test an implication of this finding: if small medical debts are not relevant for risk pricing, their removal should not affect credit access or loan terms. Using a regression discontinuity design, we find no evidence that consumers benefit from the removal of this information in terms of credit access, repayment behavior, or payday borrowing, ruling out even small effects. Next, we analyze potential spillover effects using a differences-in-differences framework. We compare consumers whose predicted default probability rises when small medical debts are removed to observably similar consumers whose predicted default probability declines. We find no evidence of negative spillover effects, again ruling out small effects.

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

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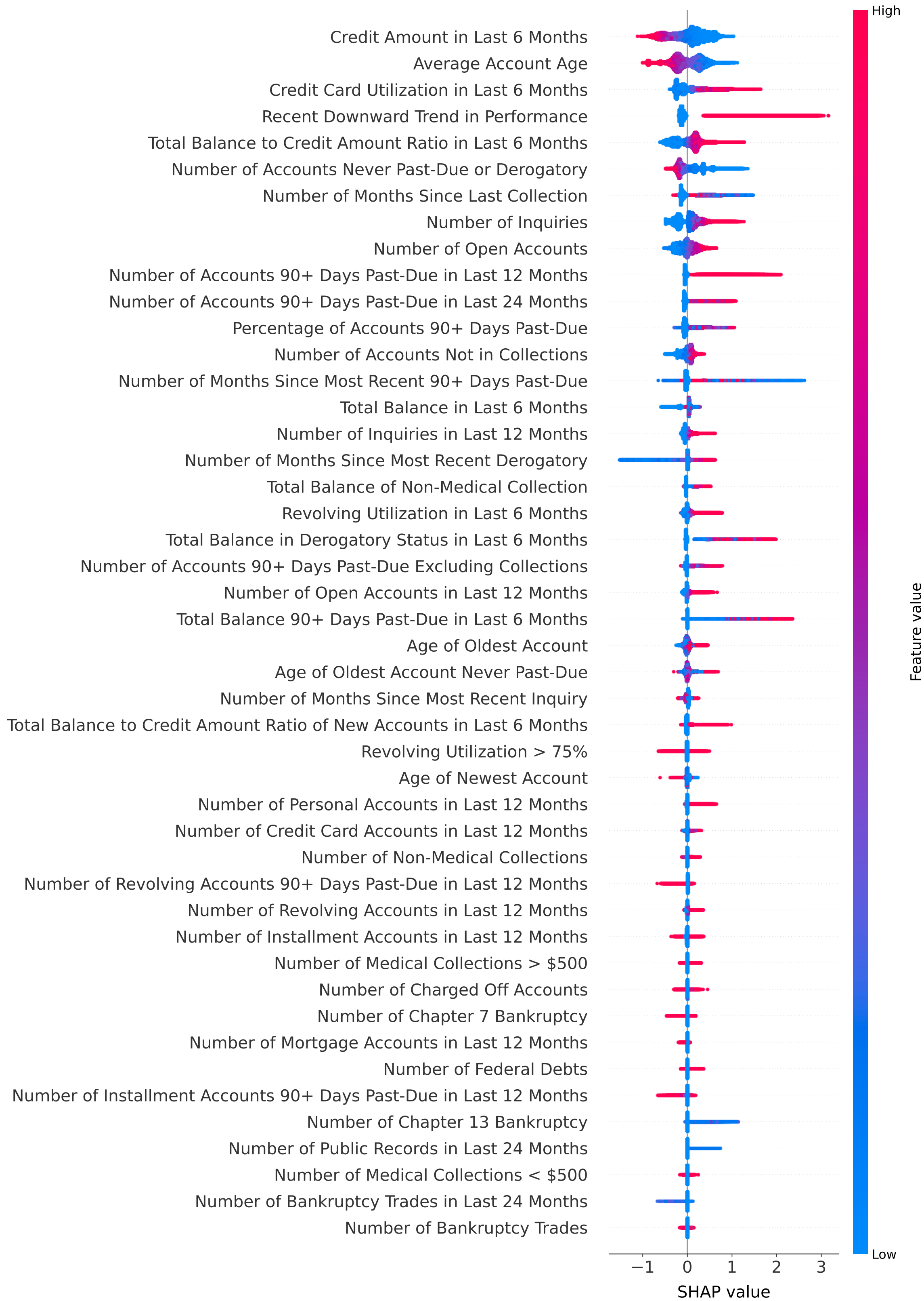
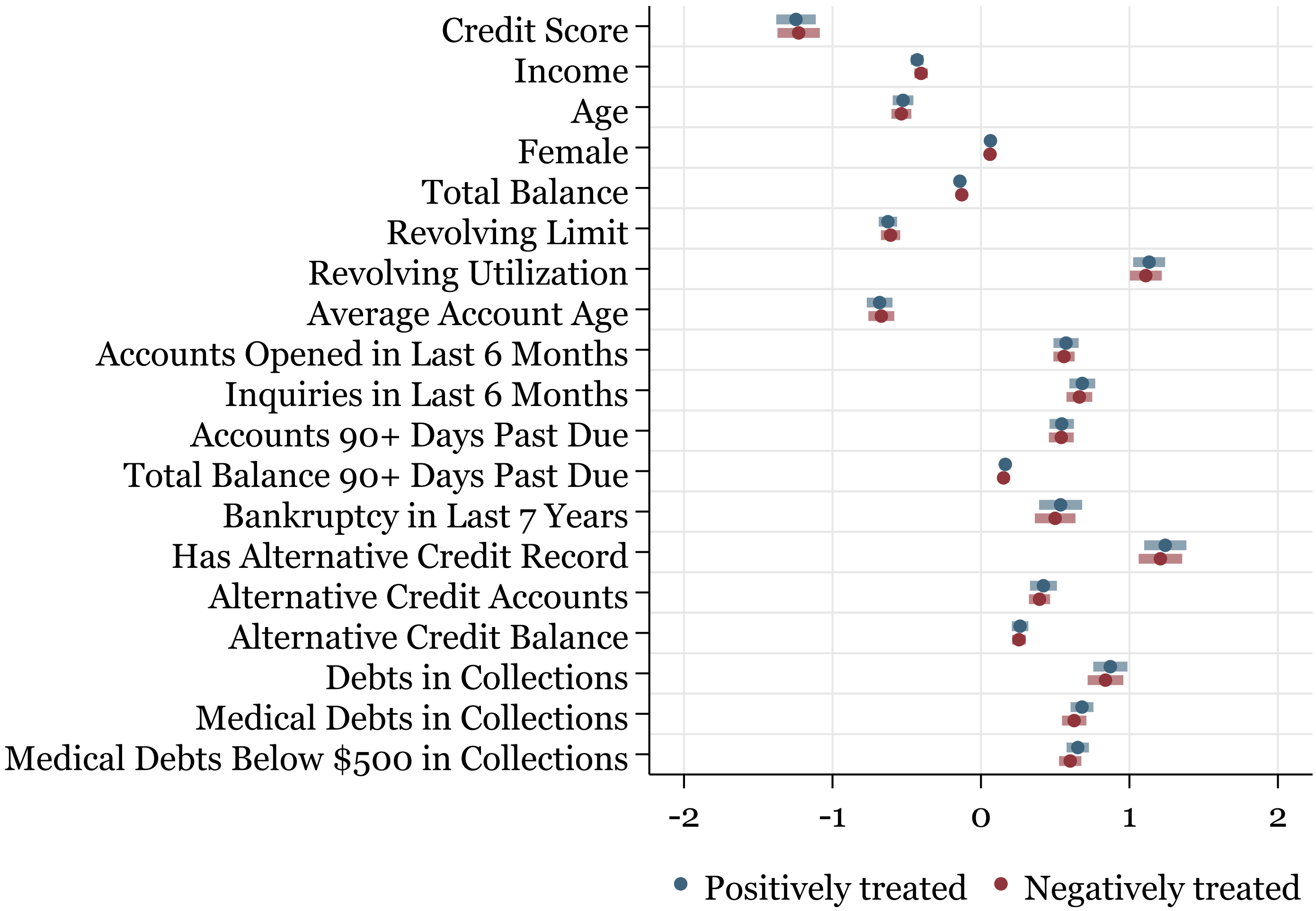
**Figure 1:** Variable Importance in the Credit Scoring Model



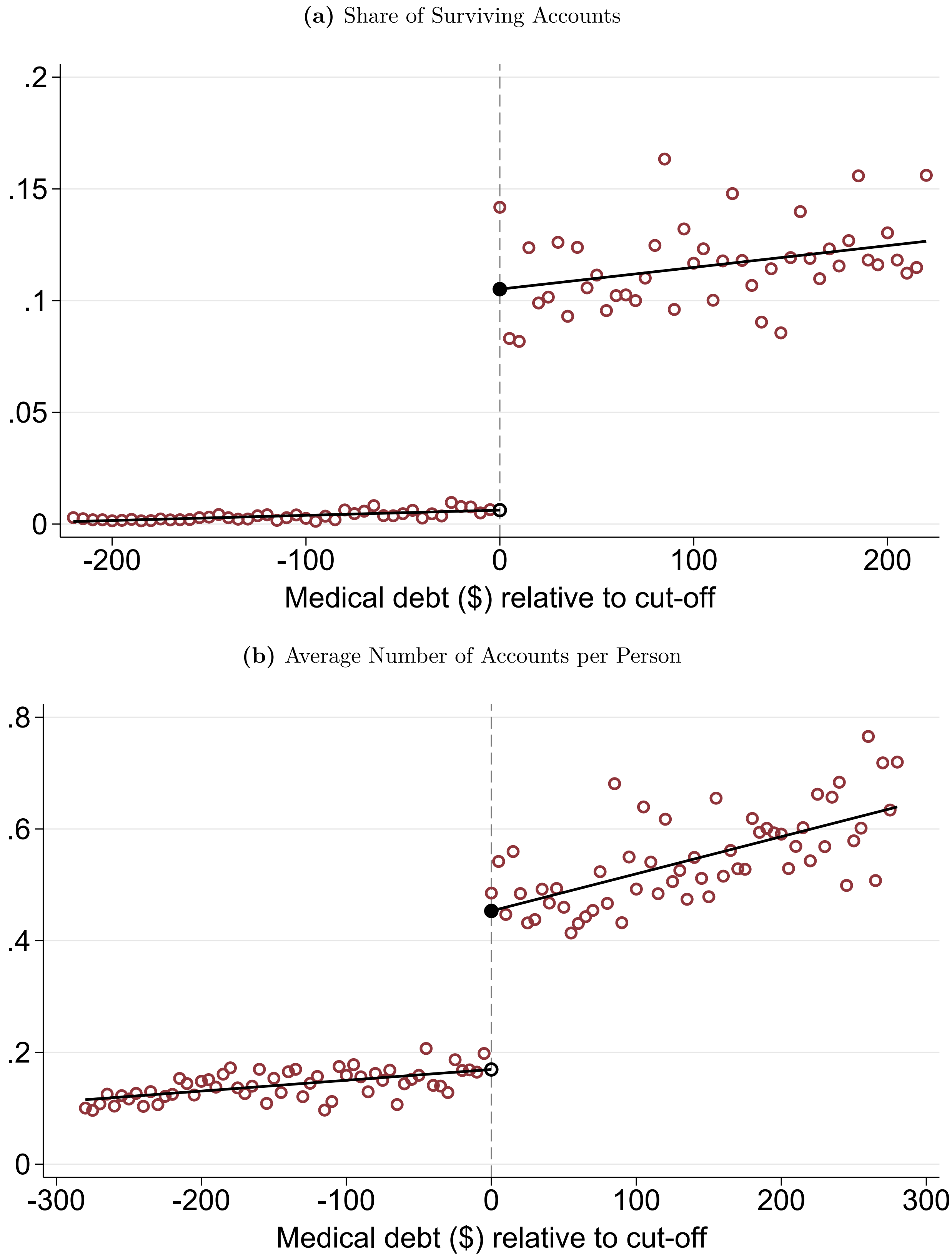

Notes: This figure displays variable importance measures, expressed as average SHAP values, for the credit scoring model presented in Section 3. The model, trained on 2019 data, predicts defaults occurring in 2020–2021 and is estimated using XGBoost. It incorporates 46 predictors, including medical collections under $500. Predictors ("features") are listed from top to bottom based on their average contribution to the model's predictions (average absolute SHAP value). Each row shows the distribution of SHAP values for individual observations, with the predictor's value ($X_i$) color-coded according to the heat map on the right. Narrow horizontal lines centered around 0 indicate that the predictor has little effect on predictions.

**Figure 2:** Covariate Balance by Changes in Default Probabilities



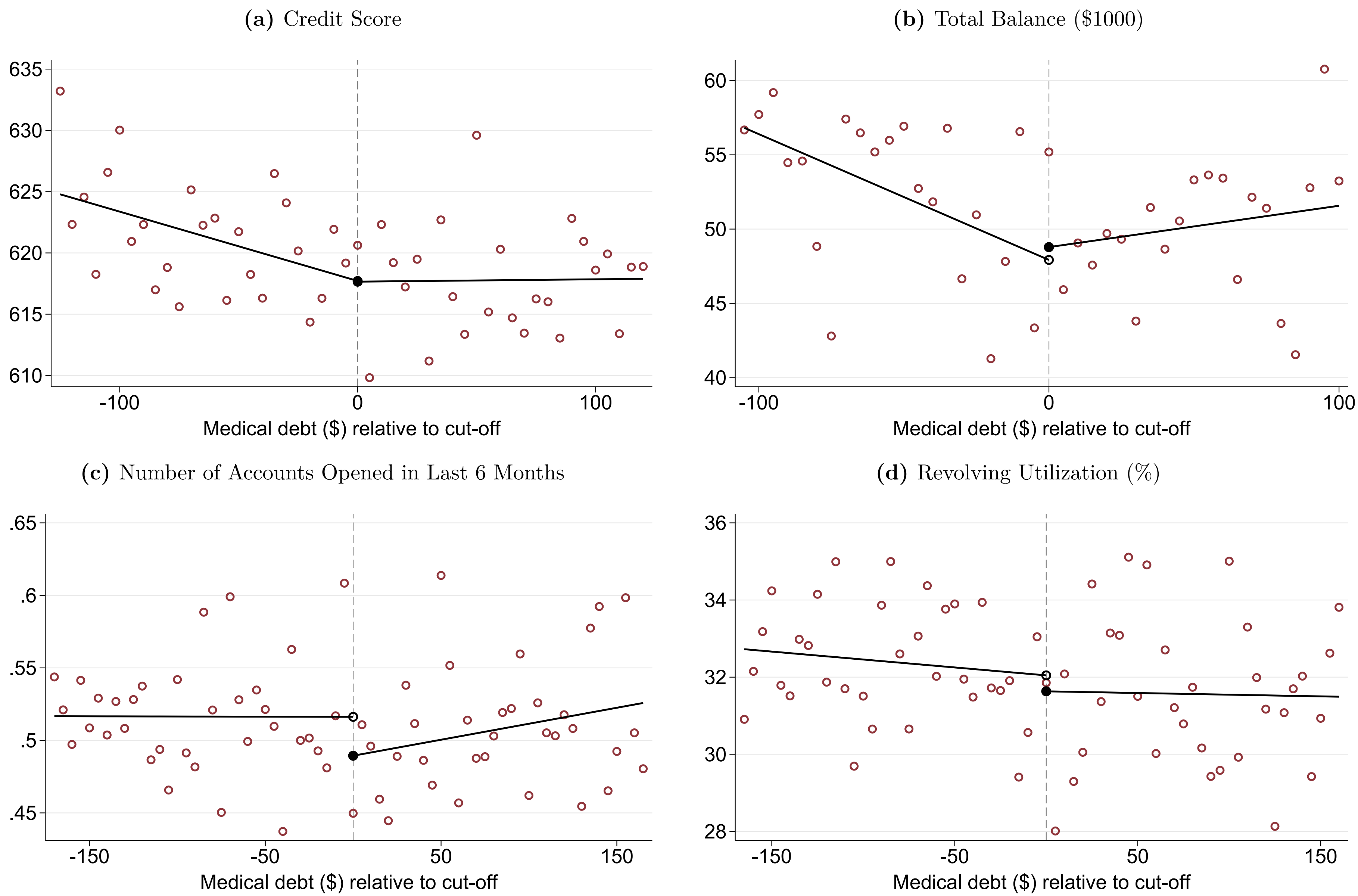

Notes: This figure shows estimates from balancing regressions for selected outcomes. Each balancing regression compares positively or negatively treated consumers to unaffected consumers. Negatively treated consumers are those whose predicted probability of default increases by 2 percentage points or more when small medical collections are removed from the credit scoring model described in Section 3. Positively treated consumers are those whose predicted default probability decreases by at least two percentage points. Unaffected consumers experience changes of less than 0.002 percentage points. All variables are standardized, and each dot represents the regression coefficient of the variable labeled on the y-axis, regressed on either the positive (blue) or negatively treated (red) group indicator. We divide consumers into 100 equal-sized bins based on changes in predicted default probability and cluster standard errors at the bin level.

**Figure 3:** Two-Year Evolution of 2022 Medical Collections Accounts



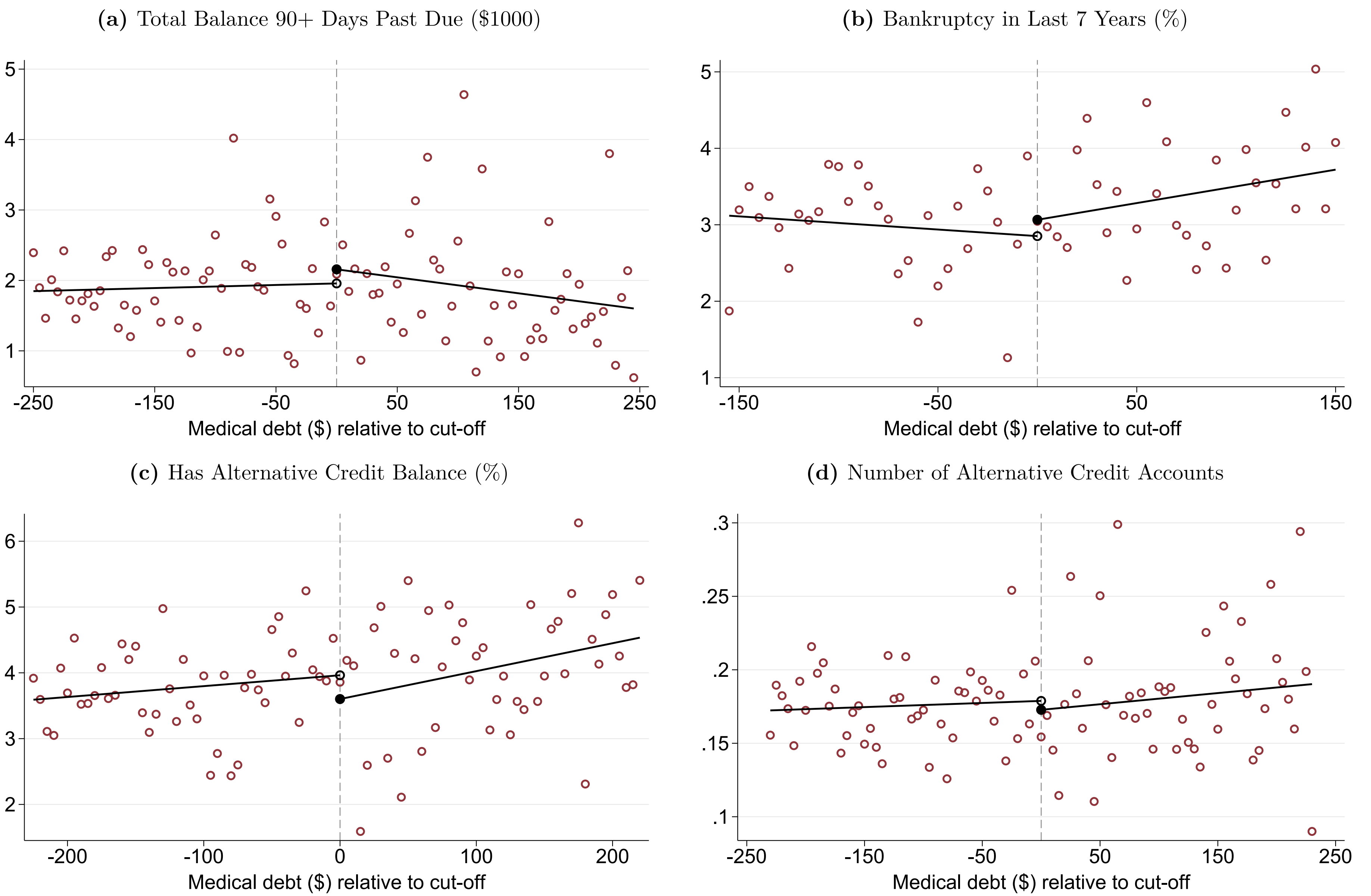

Notes: Panel (a) shows the proportion of 2022 medical debt collection accounts that remain on credit reports in 2024 by account amount, where the amount is measured as distance from the $500 threshold. Panel (b) shows the average number of medical debt collections accounts per person in 2024, where the running variable is the maximum value of the consumer's 2022 medical collections accounts. The fitted lines are estimated using Equation (5) for Panel (a) and Equation (6) for Panel (b). The RD estimate for Panel (a) is reported in Column (11) of Table A.1, and the estimate for Panel (b) appears in Column (2) of Table 5.

**Figure 4:** Access to Credit, 2024




Notes: This figure shows the relationship between medical debt in 2022 and four different measures of credit access in 2024. Medical debt is defined as the maximum value of the consumer's 2022 medical collections accounts, measured relative to the $500 threshold. The corresponding RD estimates from Equation (6) are reported in Table 5.

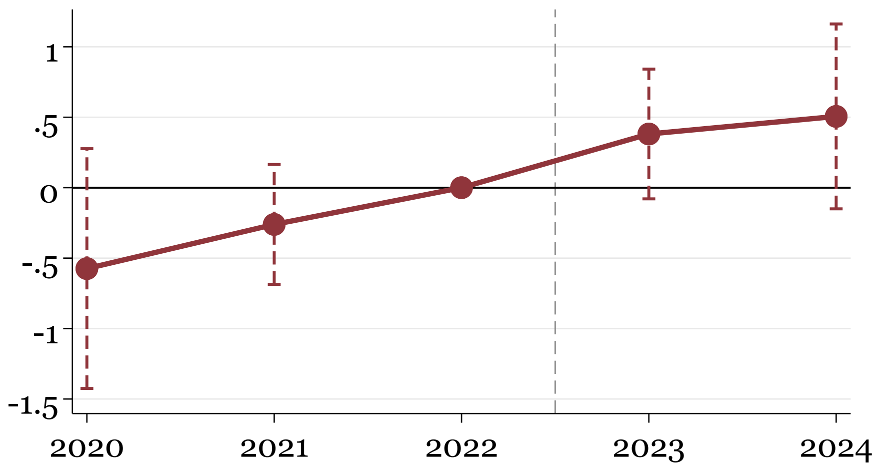
**Figure 5:** Financial Distress and Access to Alternative Credit, 2024



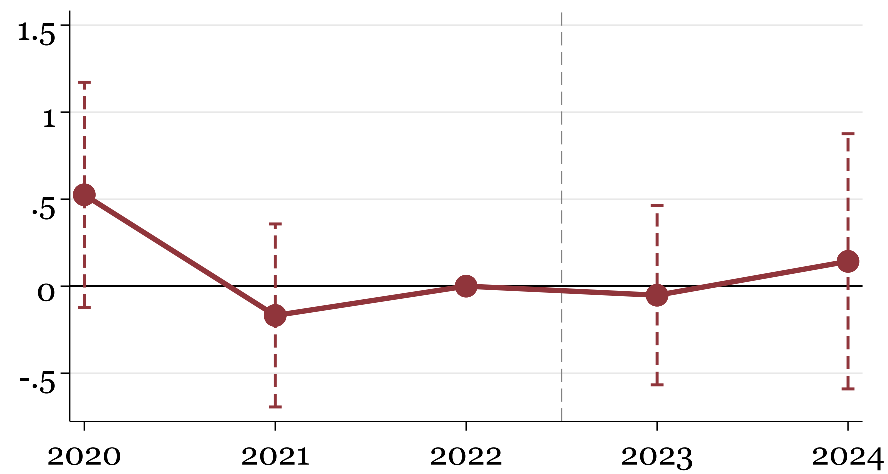

Notes: This figure shows the relationship between medical debt in 2022 and measures of financial distress and access to alternative credit in 2024. Medical debt is defined as the maximum value of the consumer's 2022 medical collections accounts, measured relative to the $500 threshold. The corresponding RD estimates from Equation (6) are reported in Table 5.

**Figure 6:** Effect of Removing Medical Debts on Credit Access for Consumers Reclassified as Higher Risk

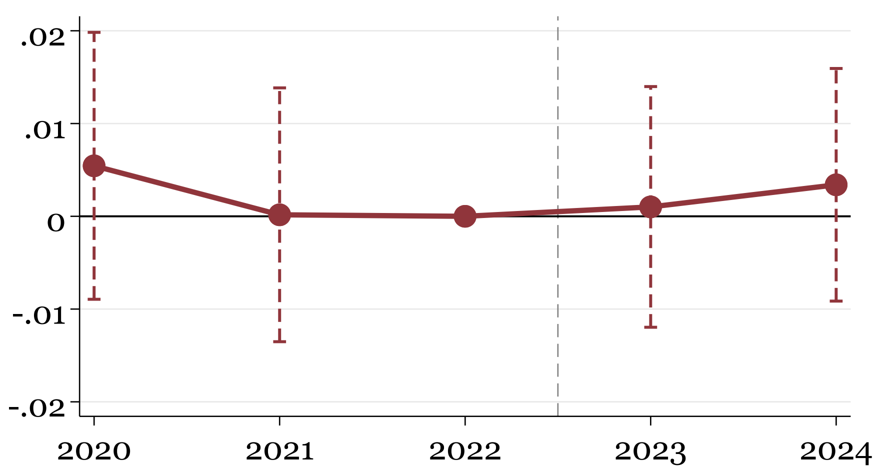
**(a)** Credit Score




**(b)** Total Balance ($1,000)




**(c)** Number of Accounts Opened in Last 6 Months




**(d)** Revolving Utilization (%)

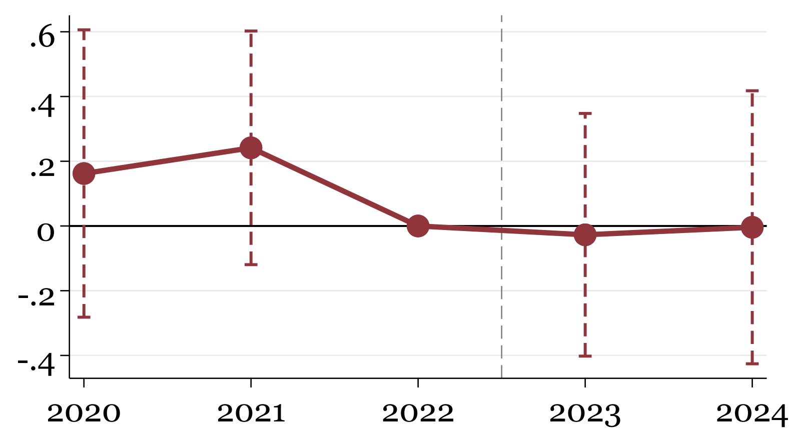
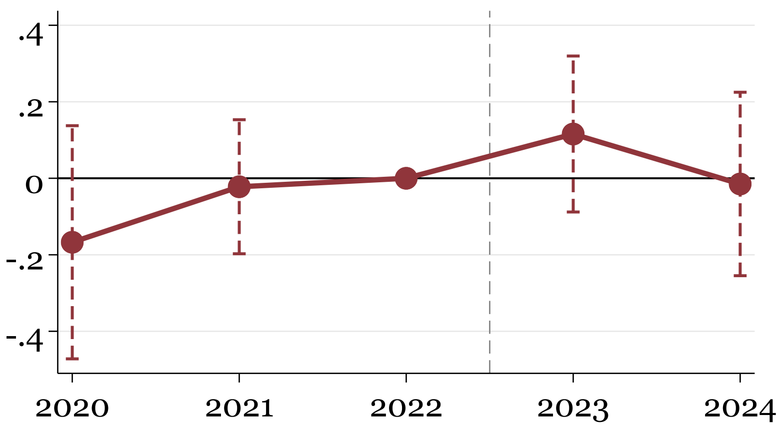
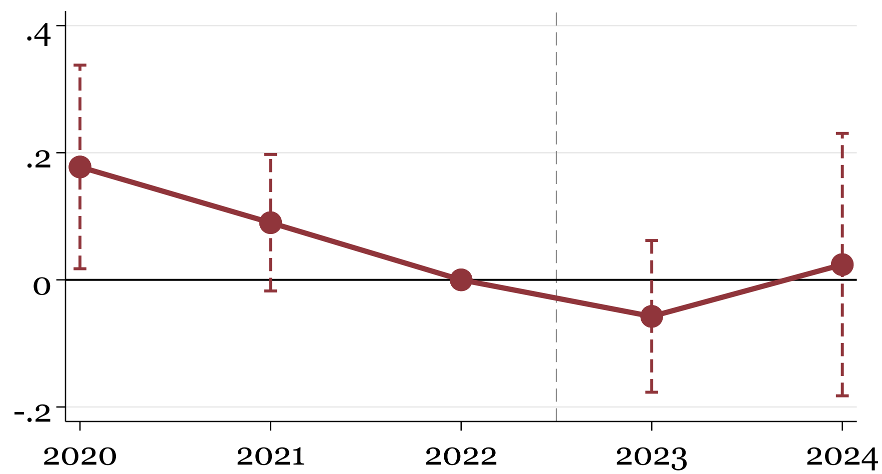


**Figure 7:** Effect of Removing Medical Debts on Financial Distress and Alternative Credit Access for Consumers Reclassified as Higher Risk

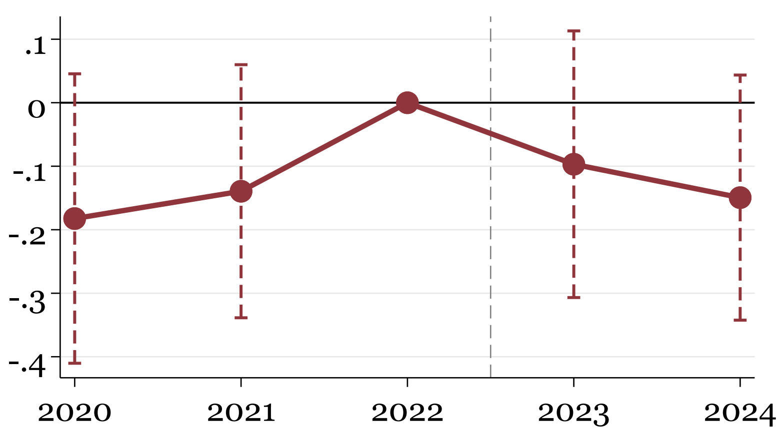
**(a)** Total Balance 90+ Days Past Due ($1,000)




**(b)** Bankruptcy in Last 7 Years (%)




**(c)** Has Alternative Credit Balance (%)




**(d)** Number of Alternative Credit Accounts

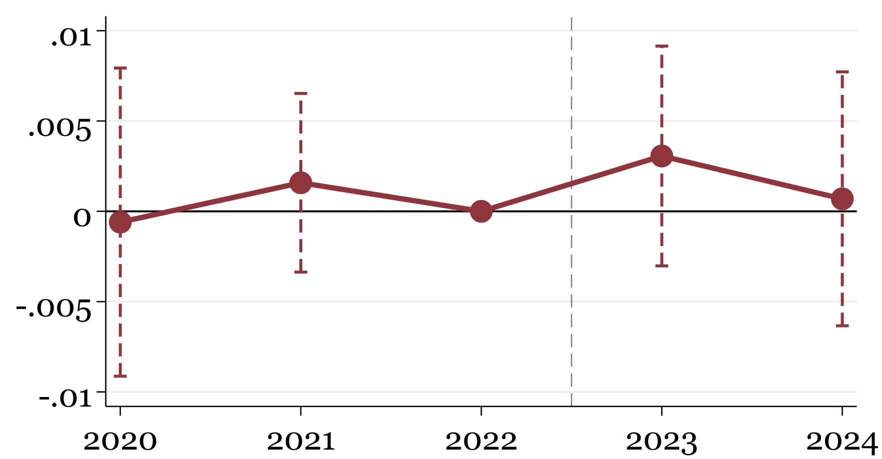


**Table 1:** Summary Statistics, 2019–2024

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

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

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

| | (1) | (2) | (3) |
|---|---|---|---|
| | Mean | St. Dev. | Median |
| **A. Demographics** | | | |
| Income ($1,000) | 40.70 | 20.53 | 35.00 |
| Age (years) | 45.11 | 15.19 | 43.00 |
| Female (%) | 55.28 | 49.72 | 100.00 |
| **B. Access to Credit** | | | |
| Credit Score | 625.38 | 87.95 | 618.00 |
| Total Balance ($1,000) | 48.89 | 94.40 | 10.66 |
| Revolving Limit ($1,000) | 6.03 | 15.79 | 0.23 |
| Revolving Utilization (%) | 29.51 | 38.58 | 6.00 |
| Average Account Age (months) | 73.74 | 49.08 | 66.00 |
| Number of Accounts Opened in Last 6 Months | 0.60 | 1.09 | 0.00 |
| Number of Inquiries in Last 6 Months | 0.67 | 0.93 | 0.00 |
| Number of New Mortgages in Last 6 Months | 0.02 | 0.13 | 0.00 |
| **C. Access to Alternative Credit** | | | |
| Has Alternative Credit Record (%) | 51.72 | 49.97 | 100.00 |
| Has Alternative Credit Balance (%) | 3.20 | 17.59 | 0.00 |
| Number of Alternative Credit Accounts | 0.14 | 0.67 | 0.00 |
| Alternative Credit Balance ($1,000) | 0.18 | 1.45 | 0.00 |
| **D. Financial Distress** | | | |
| Number of Accounts 90+ Days Past Due | 0.31 | 0.91 | 0.00 |
| Total Balance 90+ Days Past Due ($1,000) | 1.31 | 13.17 | 0.00 |
| Bankruptcy in Last 7 Years (%) | 4.11 | 19.86 | 0.00 |
| **E. Debt in Collections** | | | |
| Number of Debts | 3.53 | 3.77 | 2.00 |
| Total Debts ($1,000) | 2.69 | 6.51 | 1.09 |
| 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:** Performance Metrics for Credit Scoring Models With and Without Medical Collections

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

Notes: This table reports performance metrics for a credit scoring model predicting defaults occurring between 2020 and 2021, based on borrower characteristics from 2019. Column (1) presents metrics for the baseline model, which includes 48 predictors and is estimated using XGBoost. Column (2) reports metrics when small (under $500) medical collections are excluded from the predictors. Column (3) shows metrics when all medical collections are excluded. The accuracy score represents the share of correct predictions. For comparison, a naive model predicting no defaults achieves an accuracy of 0.867. Precision is the proportion of predicted defaults that were correctly classified. Recall is the proportion of actual defaults correctly classified. F1 score is the harmonic mean of Precision and Recall. The AUC (Area Under the Receiver Operating Characteristic Curve) indicates the probability that the model assigns a higher default probability to a true defaulter than to a non-defaulter.

**Table 4:** Summary Statistics by Treatment Groups Based on Changes in Default Probabilities

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

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

**Table 5:** RD Estimates of the Direct Effect of Medical Debt Deletion

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

Notes: This table presents the estimated coefficient ($-\beta$) and 95% confidence intervals from Equation (6). The running variable for medical debt corresponds to the highest debt amount across the consumer's medical collections accounts. We report MSE-optimal estimates with robust, bias-corrected 95% confidence intervals in brackets. Sample Mean reports the mean of the dependent variable in 2024. A ***, **, and * indicate significance at the 1%, 5%, and 10% level respectively, using conventional inference.

**Table 6:** Difference-in-Differences estimates of the Indirect Effect of Medical Debt Deletion

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

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

# Online Appendix

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

Victor Duarte, Julia Fonseca, Divij Kohli, Julian Reif

# A Alternative RD specifications

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

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

The account-level specification can be estimated using Equation (5). First-stage estimates for this case are reported in Panel A of Figure 3. In this appendix, we extend this specification to estimate second-stage outcomes. Since outcomes such as an individual's credit score do not vary across accounts, we cluster standard errors at the individual level.

The person-level (max) specification, where treatment occurs only if all medical debts are deleted, is estimated using Equation (6), as reported in the main text. The person-level (min) specification, where treatment occurs if any medical collection is deleted, can be estimated using a variant of this approach, with the running variable $\text{MINDEBT}_i^{2022}$ defined as the balance of the consumer's smallest medical debt relative to the \$500 cutoff:

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

We present estimates for these three treatment definitions in Table A.1. Panel A replicates the main text estimates from Table 5, which correspond to the person-level (max) specification. Panel B reports estimates for the person-level (min) specification. The first-stage estimates in Columns (1) and (2) are slightly larger in magnitude, likely due to sample composition differences near the threshold. However, as in Panel A, all second-stage estimates in Columns (3)–(10) remain statistically insignificant. Panel C presents results for the account-level specification, showing a similar pattern. Overall, these findings suggest that our main estimates are robust to alternative RD specifications.

**Table A.1:** Direct Effect: Alternative RD Specifications

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

Notes: This table shows the coefficient ($-\beta$) estimates and 95% confidence intervals of Equation (6). The running variable in Panel A corresponds to the highest debt amount across the consumer's medical collections accounts. The running variable in Panel B corresponds to the smallest debt amount across the consumer's medical collections accounts. Whereas, the running variable in Panel C corresponds to the debt amount in the consumer's medical collections account. "Share of Surviving Accounts" varies across accounts and is not reported for the person-level specifications presented in Panels A and B. We report MSE-optimal estimates with robust, bias-corrected 95% confidence intervals in brackets. Sample Mean reports the mean of the dependent variable in 2024. A ***, **, and * indicate significance at the 1%, 5%, and 10% level respectively, using conventional inference.

# B Comparing GCCP Medical Collection Data to External Sources

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

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

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

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

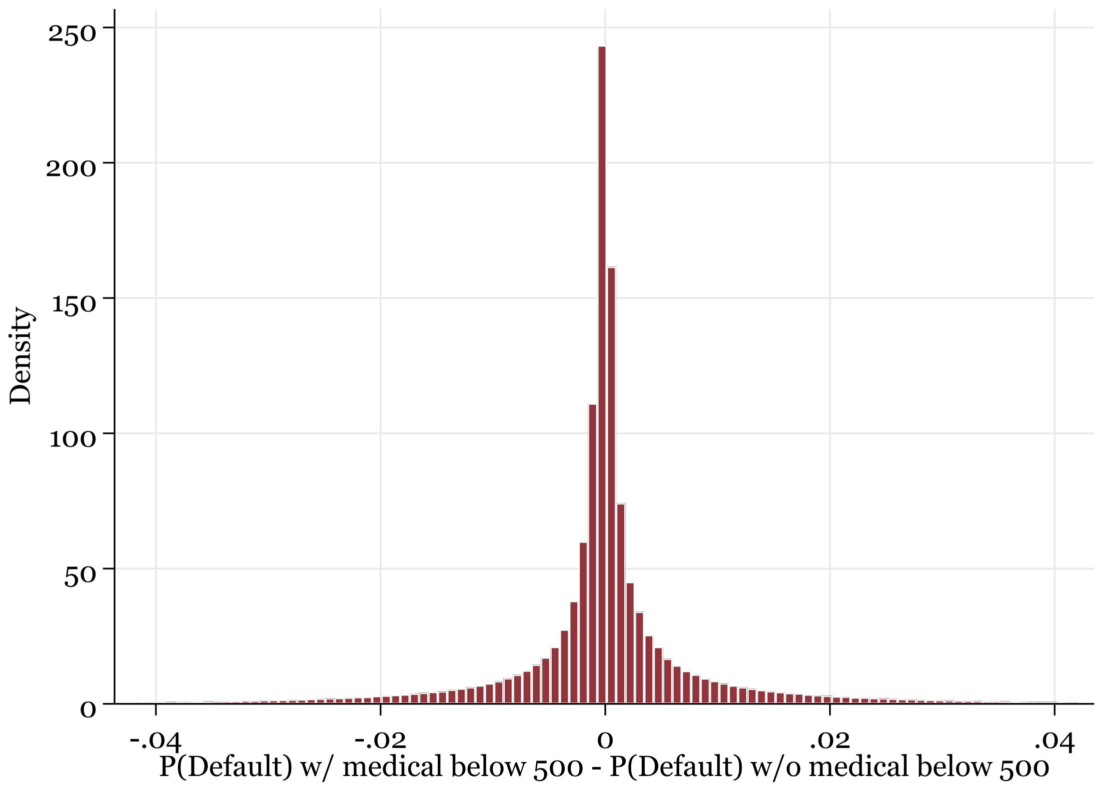
**Table A.2:** Comparing GCCP Medical Collection Data to External Sources

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

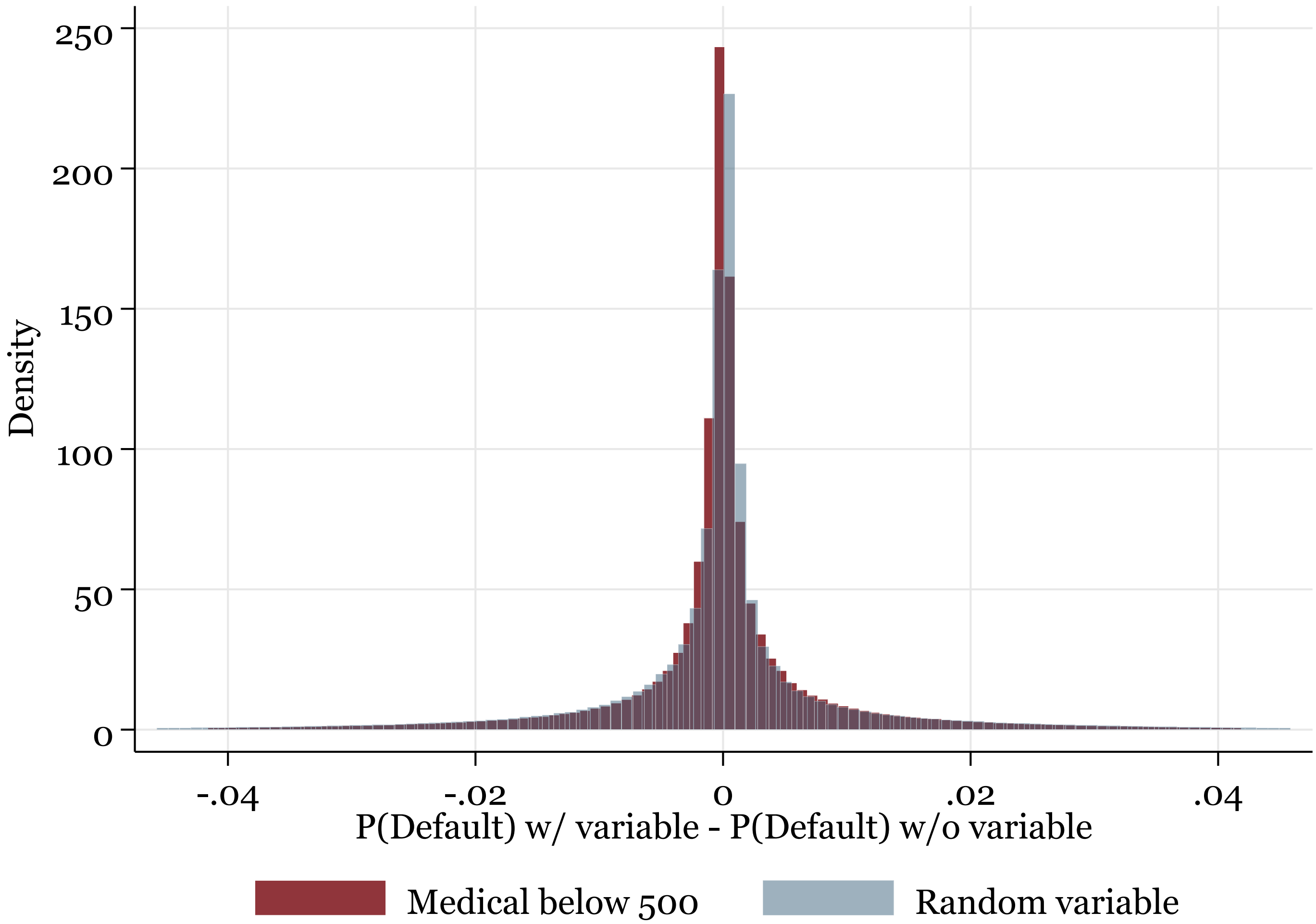
# C Additional Figures and Tables

**Figure A.1:** Effect of Removing Small Medical Collections on Predicted Default Probabilities




Notes: This figure shows the change in the predicted probability of default over 24 months following the removal of small (< $500) medical collections for 2.8 million consumers in the GCCP. Predictions, generated using the credit scoring model described in Section 3, are based on 2019 data.

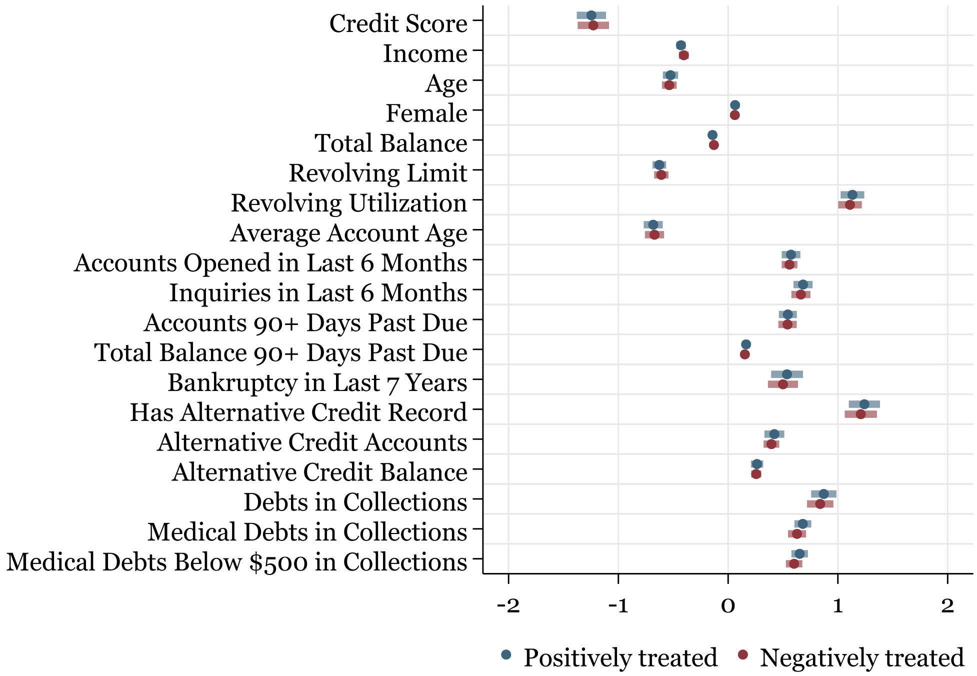
**Figure A.2:** Effect of Removing Small Medical Collections vs. Removing Noise



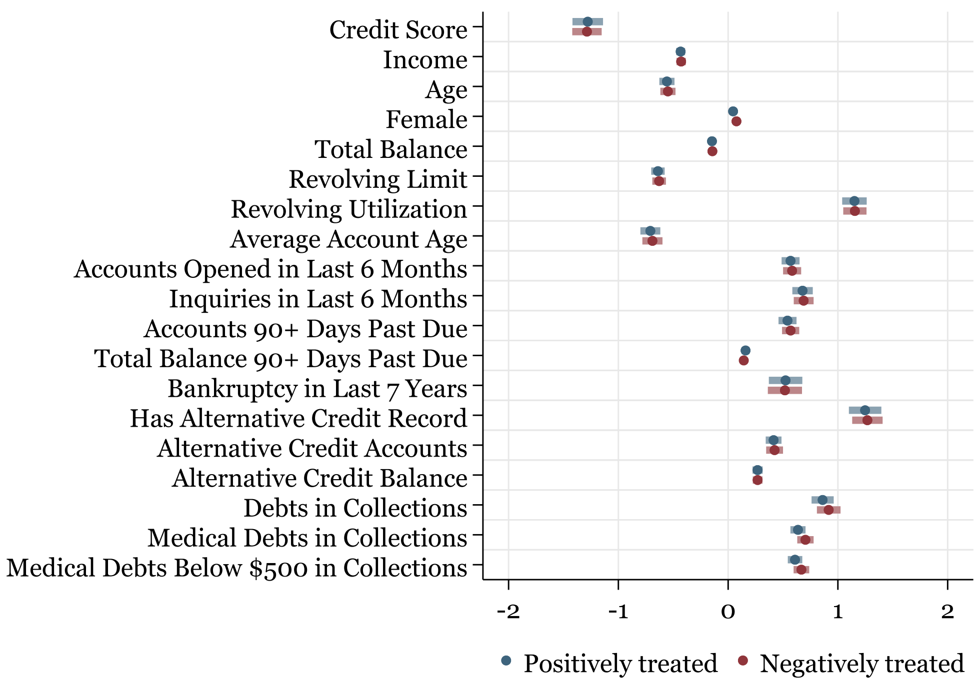

Notes: This figure shows the change in the predicted probability of default over 24 months following the removal of a variable from the credit scoring model described in Section 3. The red histogram reproduces the plot from Figure A.1, showing the effect of removing small (< $500) medical collections. The blue histogram shows the effect of removing a random noise predictor that was drawn randomly from a uniform distribution.

**Figure A.3:** Covariate Balance by Changes in Default Probabilities: Small Medical Collections vs. Noise

**(a)** Small (< $500) Medical Collections

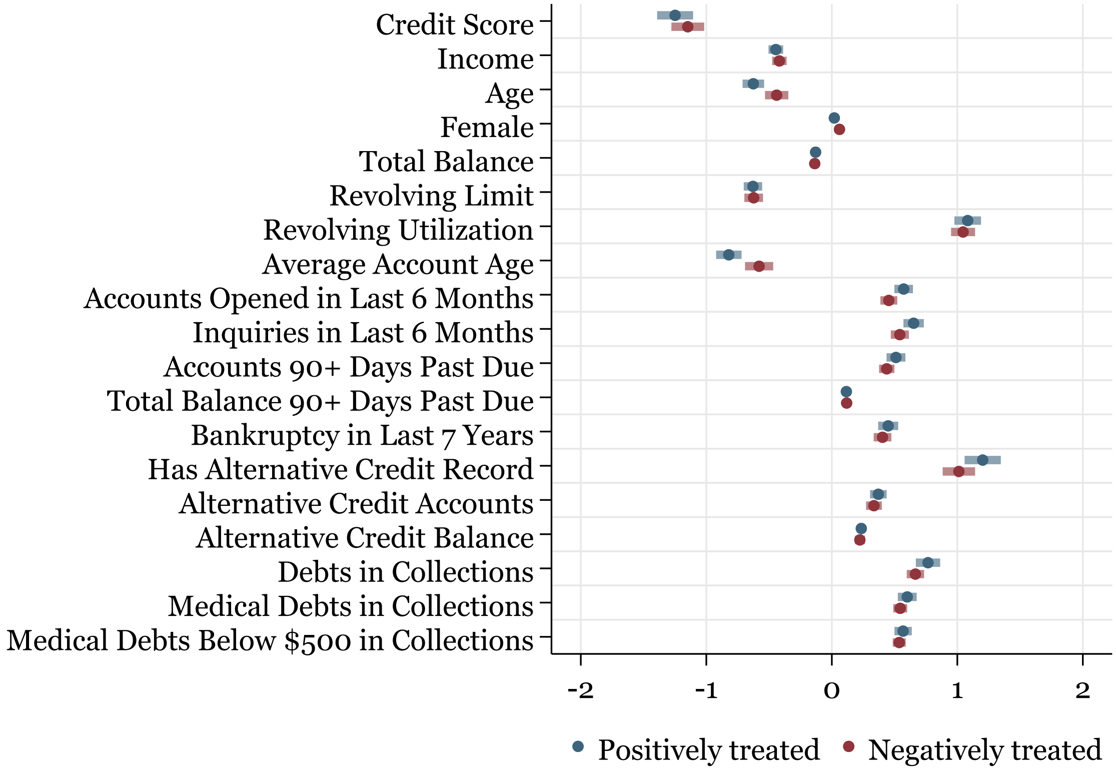



**(b)** Random Variable




Notes: This figure shows estimates from balancing regressions for selected outcomes. Each balancing regression compares positively or negatively treated consumers to unaffected consumers. Negatively treated consumers are those whose predicted probability of default increases by 2 percentage points or more when small medical collections (Panel a) or a randomly generated predictor (Panel b) are removed from the credit scoring model described in Section 3. Positively treated consumers are those whose predicted default probability decreases by at least two percentage points. Unaffected consumers experience changes of less than 0.002. All variables are standardized, and each dot represents the regression coefficient of the variable labeled on the y-axis, regressed on either the positive (blue) or negatively treated (red) group indicator. We divide consumers into 100 equal-sized bins based on changes in predicted default probability and cluster standard errors at the bin level.

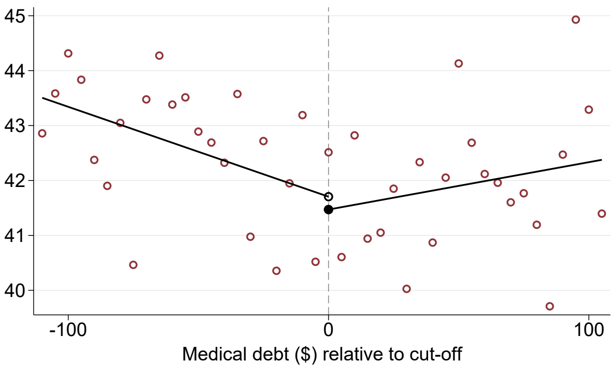
**Figure A.4:** Covariate Balance by Changes in Default Probabilities: Length of Credit History



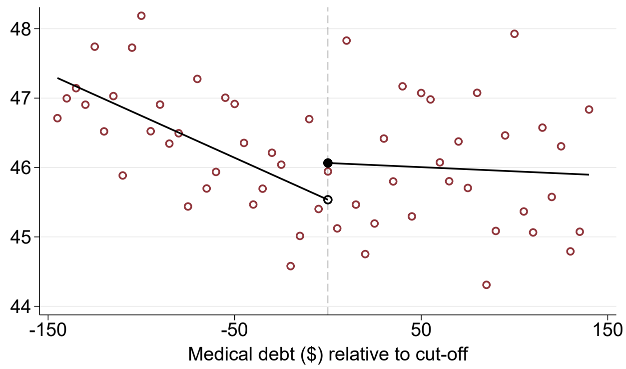

Notes: This figure shows estimates from balancing regressions for selected outcomes. Each balancing regression compares positively or negatively treated consumers to unaffected consumers. Negatively treated refers to consumers above the 95th percentile in the distribution of probability differences according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

**Figure A.5:** Covariate Smoothness Test: Demographics

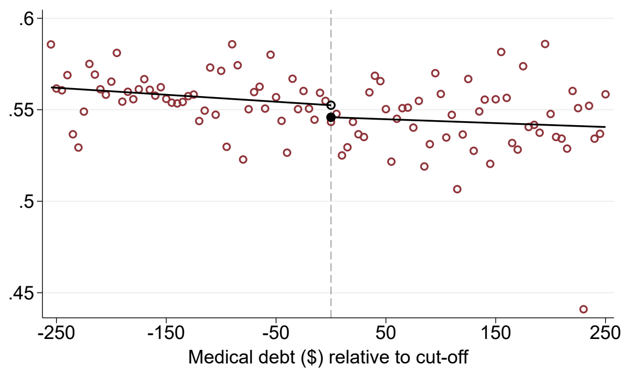
**(a)** Income ($1000)




**(b)** Age (years)



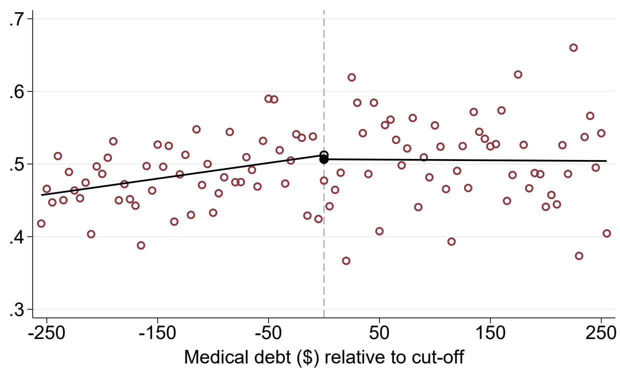

**(c)** Female (%)



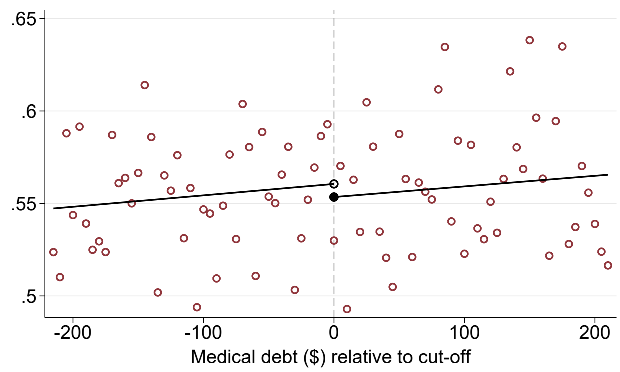

Notes: This figure shows the relationship between 2022 medical debt and three demographic variables in 2024. Medical debt is defined as the maximum value of the consumer's 2022 medical collections accounts, measured relative to the $500 threshold. RD estimates from Equation (6) are reported in Table A.5.

**Figure A.6:** Additional Credit Outcomes for RD Analysis, 2024

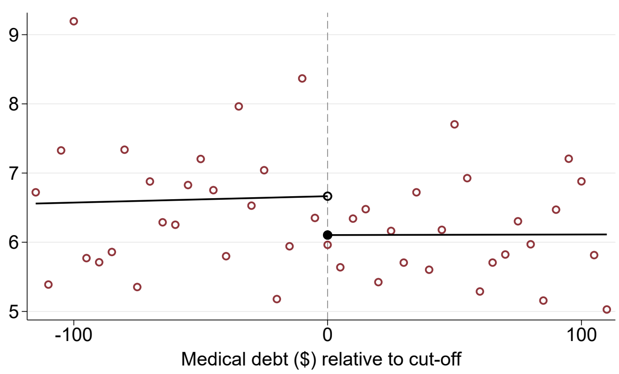
**(a)** Number of Accounts 90+ Days Past Due



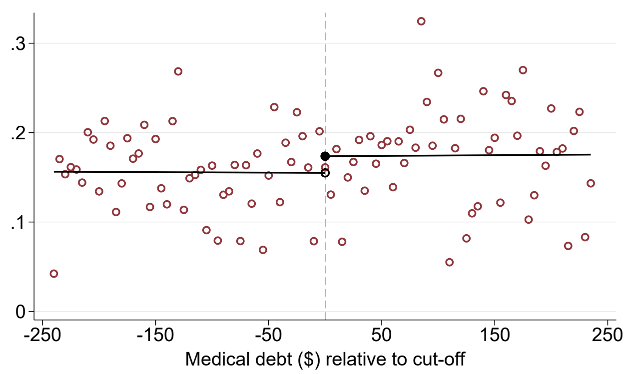

**(b)** Number of Inquiries in Last 6 Months



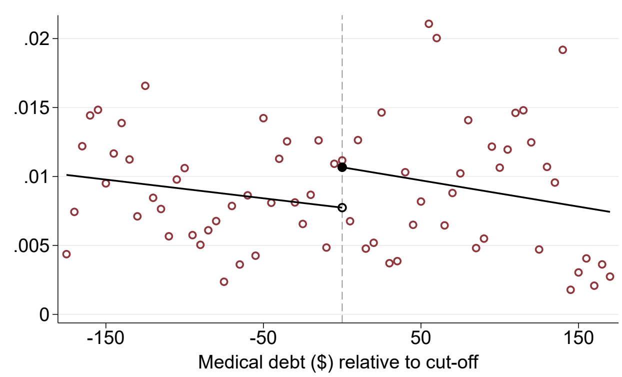

**(c)** Revolving Limit ($1,000)




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

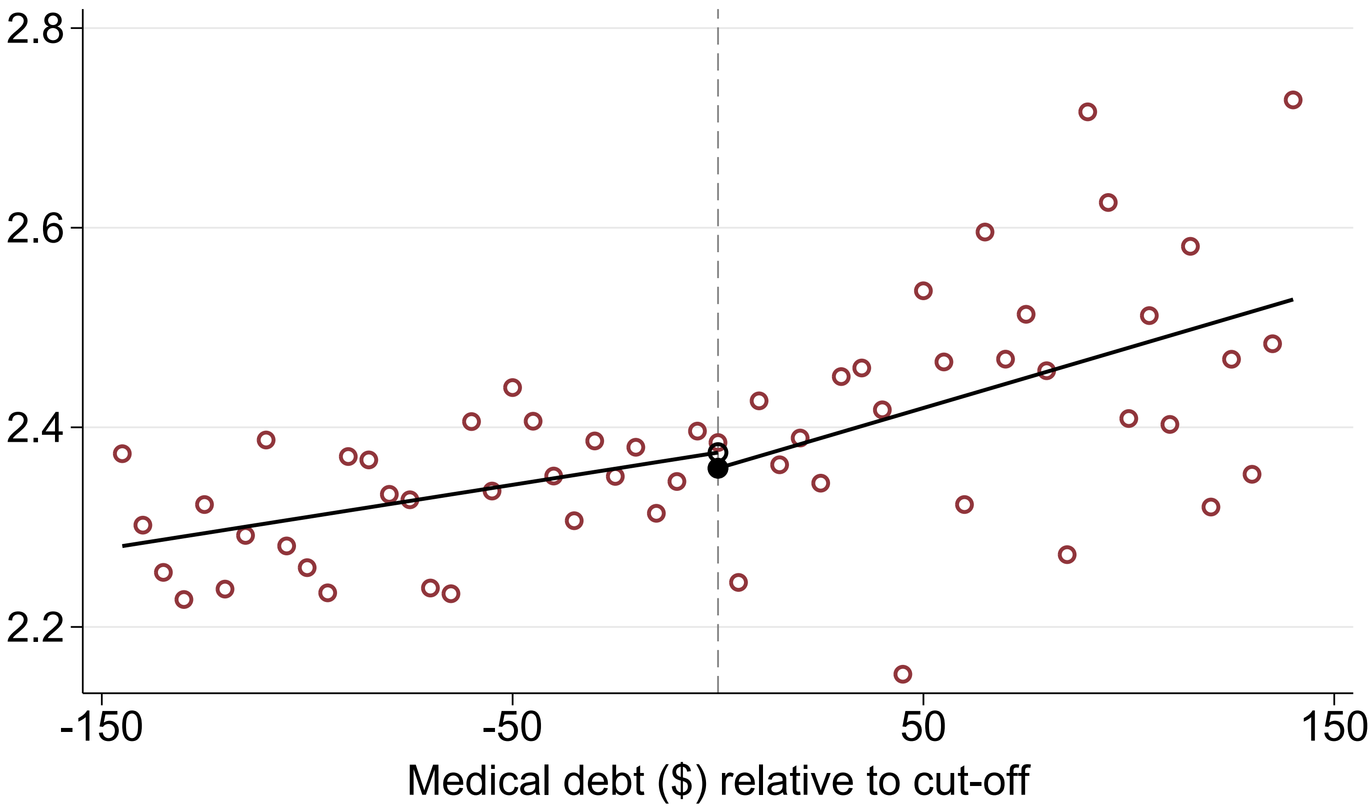



**(e)** Number of New Mortgages in Last 6 Months



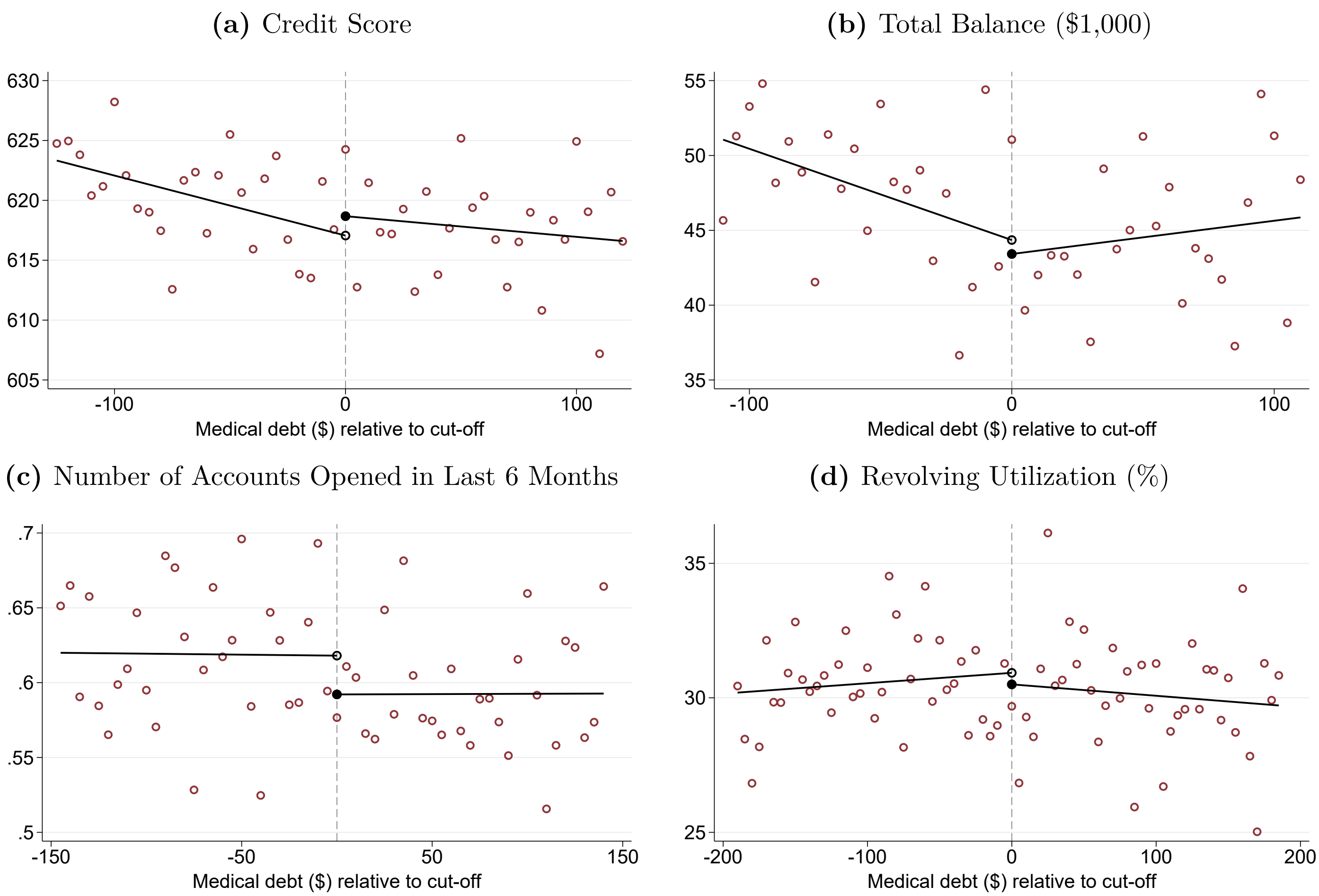

Notes: This figure shows the relationship between 2022 medical debt and five supplementary credit outcomes in 2024. Medical debt is defined as the maximum value of the consumer's 2022 medical collections accounts, measured relative to the $500 threshold. RD estimates from Equation (6) are reported in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

**Figure A.7:** Falsification test: Average Number of Accounts per Person, 2022



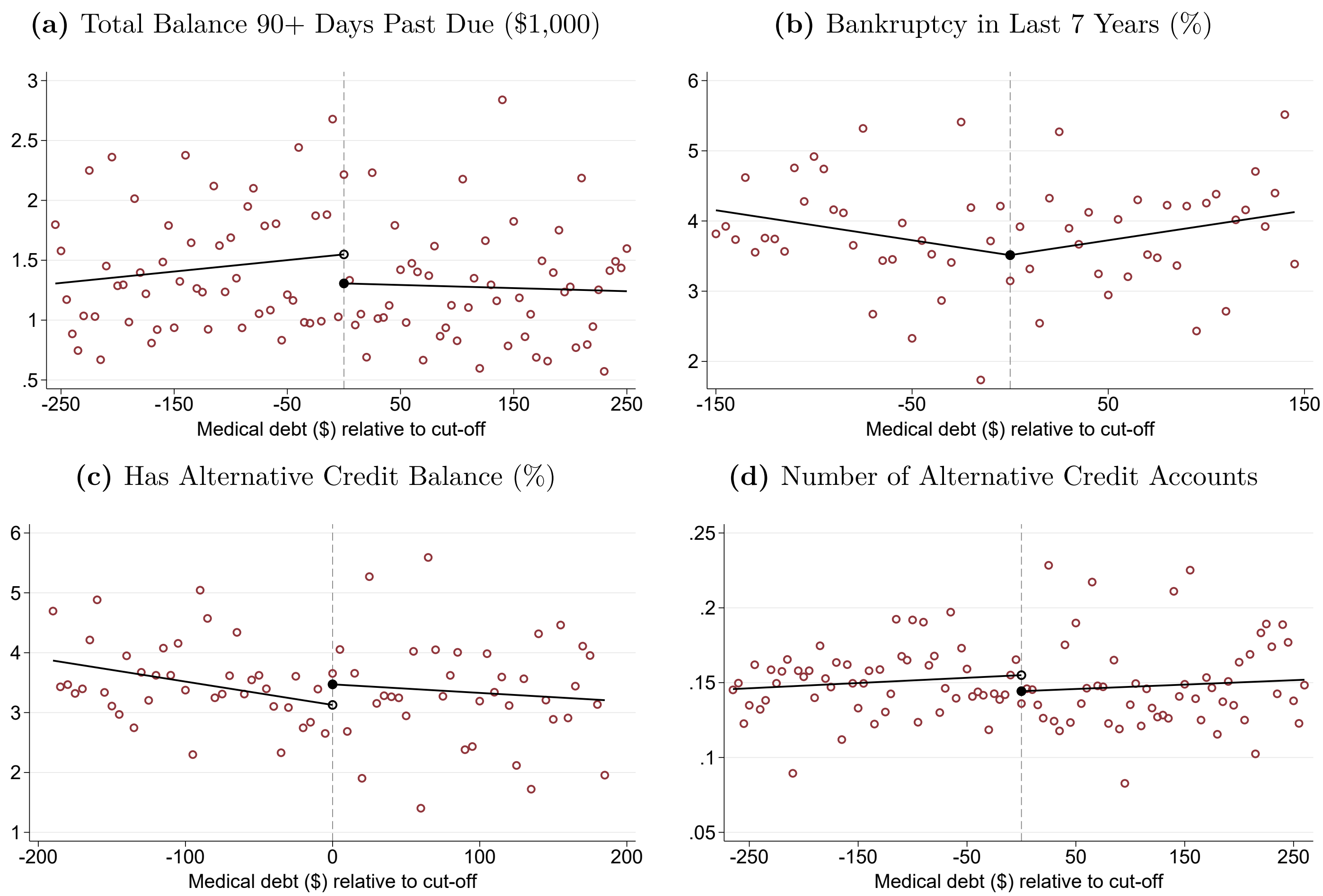

Notes: This figure shows the relationship between the medical debt running variable and the average number of medical collections accounts per person in 2022. The medical debt running variable is defined as the maximum value of the consumer's 2022 medical collections accounts, measured relative to the $500 threshold. RD estimates from Equation (6) are reported in Table 5.

**Figure A.8:** Falsification Test: Access to Credit, 2022




Notes: This figure shows the relationship between 2022 medical debt and four credit measures in 2022. Medical debt is defined as the maximum value of the consumer's 2022 medical collections accounts, measured relative to the $500 threshold. RD estimates from Equation (6) are reported in Table A.7.

**Figure A.9:** Falsification Test: Financial Distress and Access to Alternative Credit, 2022




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

**(b)** Bankruptcy in Last 7 Years (%)

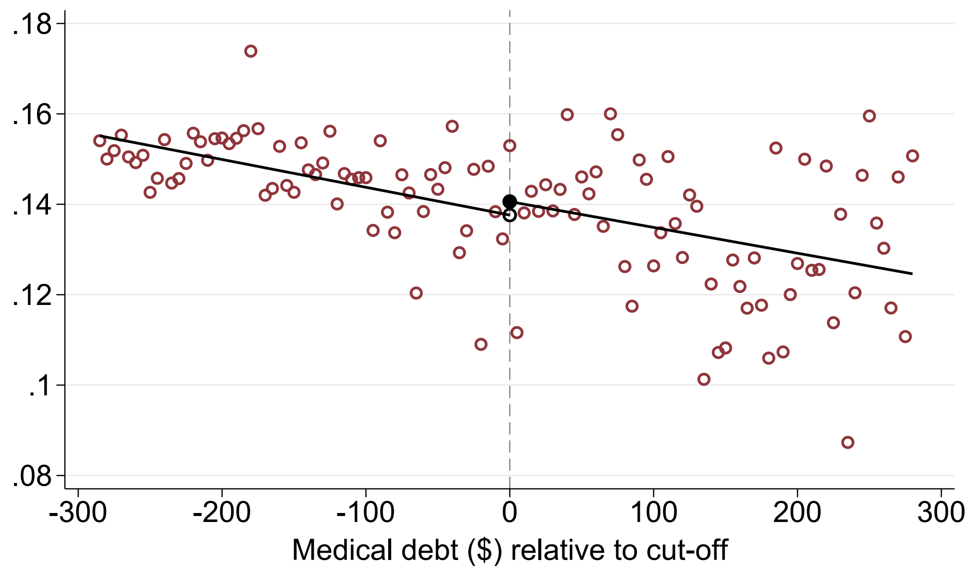
**(c)** Has Alternative Credit Balance (%)

**(d)** Number of Alternative Credit Accounts

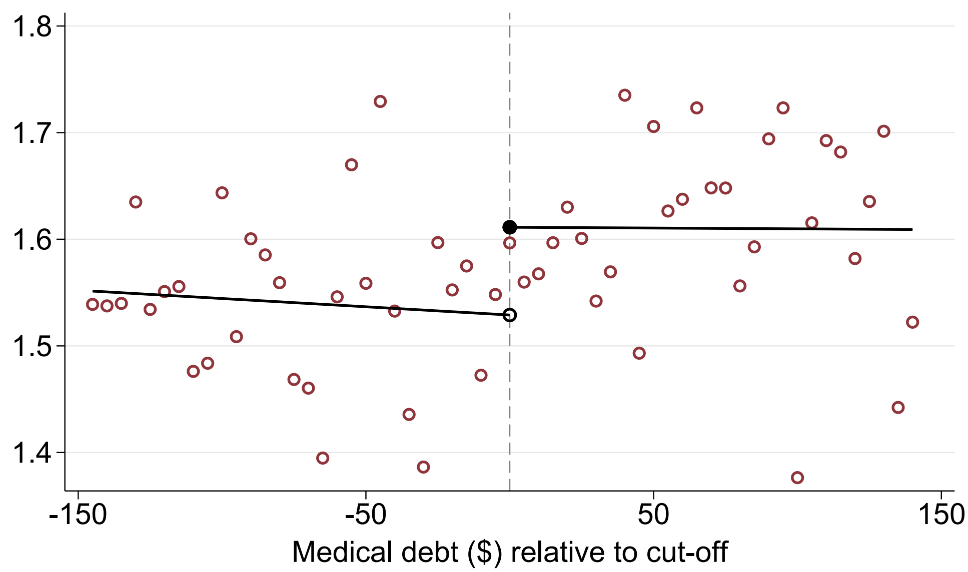
Notes: This figure shows the relationship between medical debt in 2022 and measures of financial distress and access to alternative credit in 2022. Medical debt is defined as the maximum value of the consumer's 2022 medical collections accounts, measured relative to the $500 threshold. RD estimates from Equation (6) are reported in Table A.7.

**Figure A.10:** Placebo Test: Two-Year Evolution of 2020 Medical Collections Accounts

**(a)** Share of Surviving Accounts

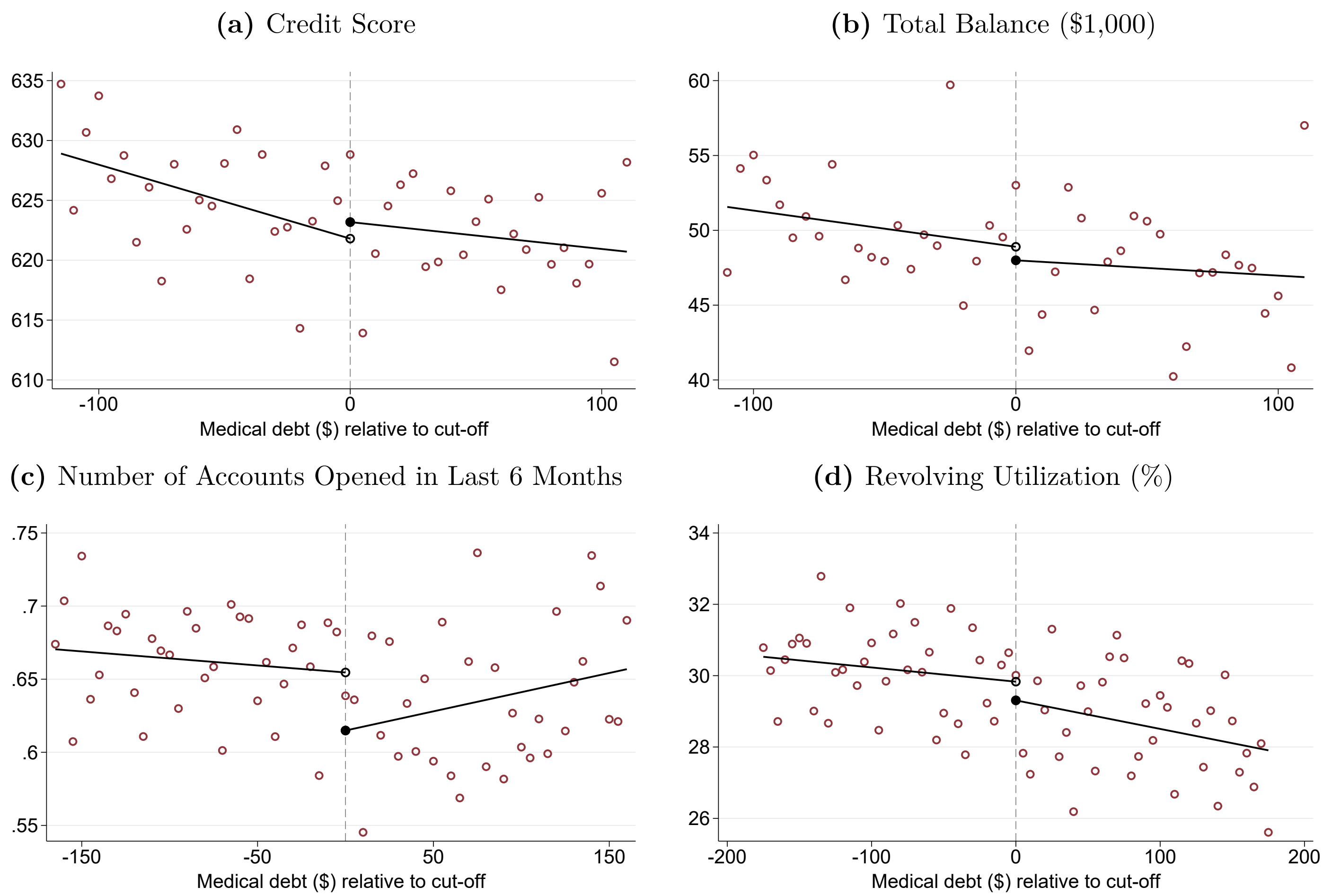



**(b)** Average Number of Accounts per Person




Notes: Panel (a) shows the proportion of 2020 medical collection accounts which remain present on 2022 credit reports by account amount, where the amount is measured as distance from the $500 threshold. Panel (b) shows the average number accounts per person. In panel (b), the running variable is equal to the maximum value of the consumer's medical collections accounts. RD estimates from Equation (6) are reported in Table A.8.

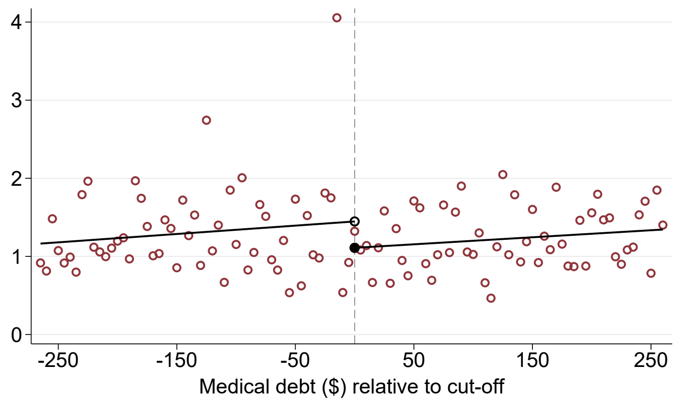
**Figure A.11:** Placebo Test: Access to Credit



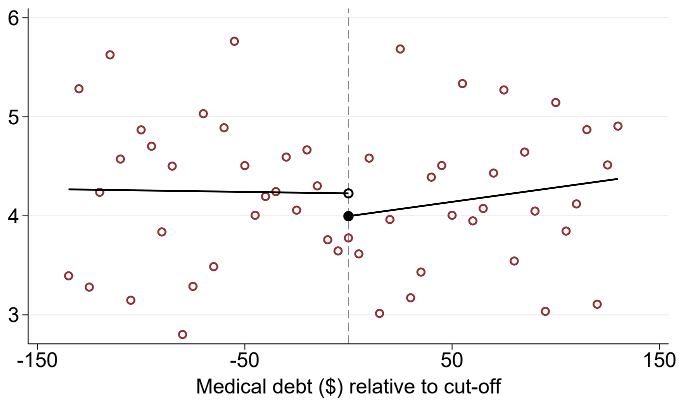

Notes: This figure shows the relationship between 2022 medical debt and five supplementary credit outcomes in 2022. Medical debt is defined as the maximum value of the consumer's 2022 medical collections accounts, measured relative to the $500 threshold. RD estimates from Equation (6) are reported in Table A.8.

**Figure A.12:** Placebo Test: Financial Distress and Access to Alternative Credit

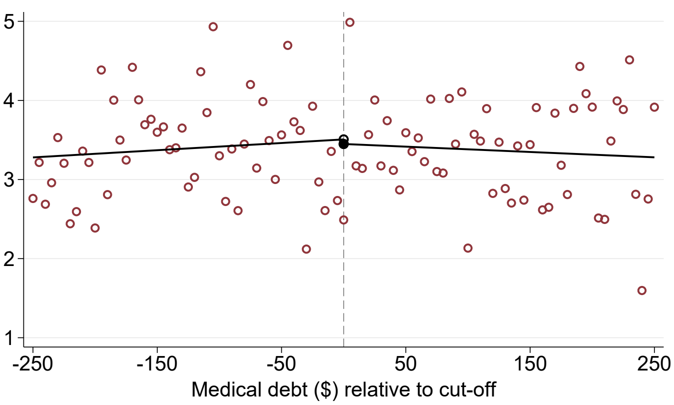
**(a)** Total Balance 90+ Days Past Due ($1,000)



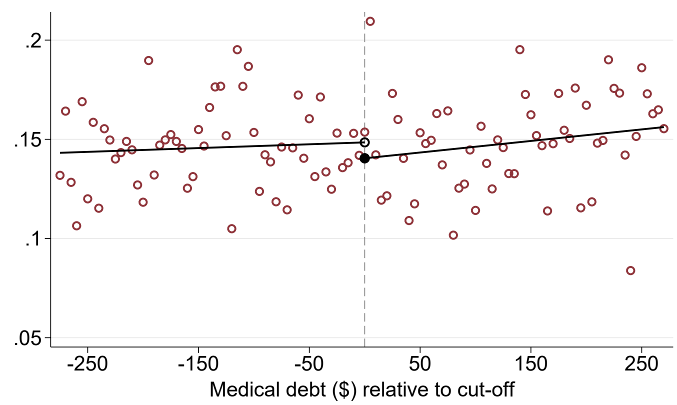

**(b)** Bankruptcy in Last 7 Years (%)




**(c)** Has Alternative Credit Balance (%)

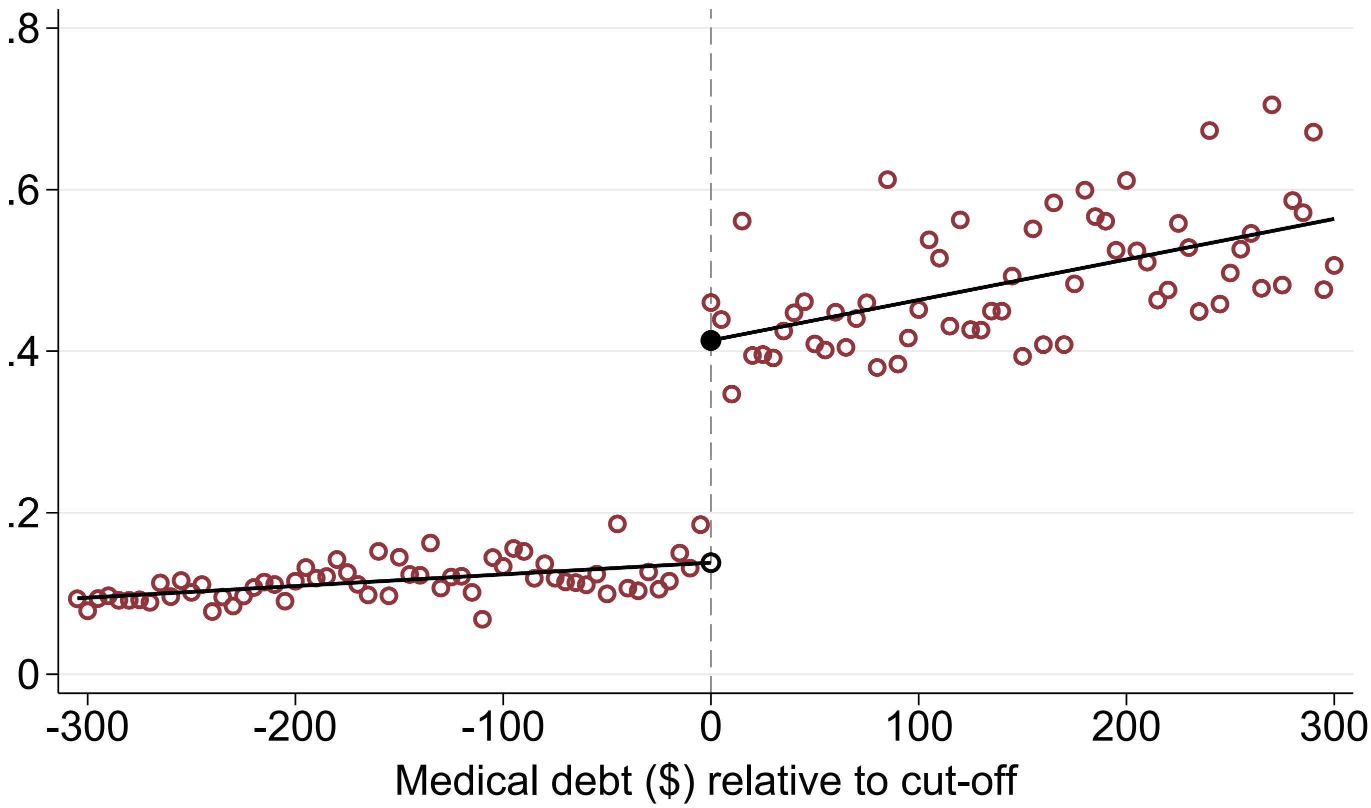



**(d)** Number of Alternative Credit Accounts



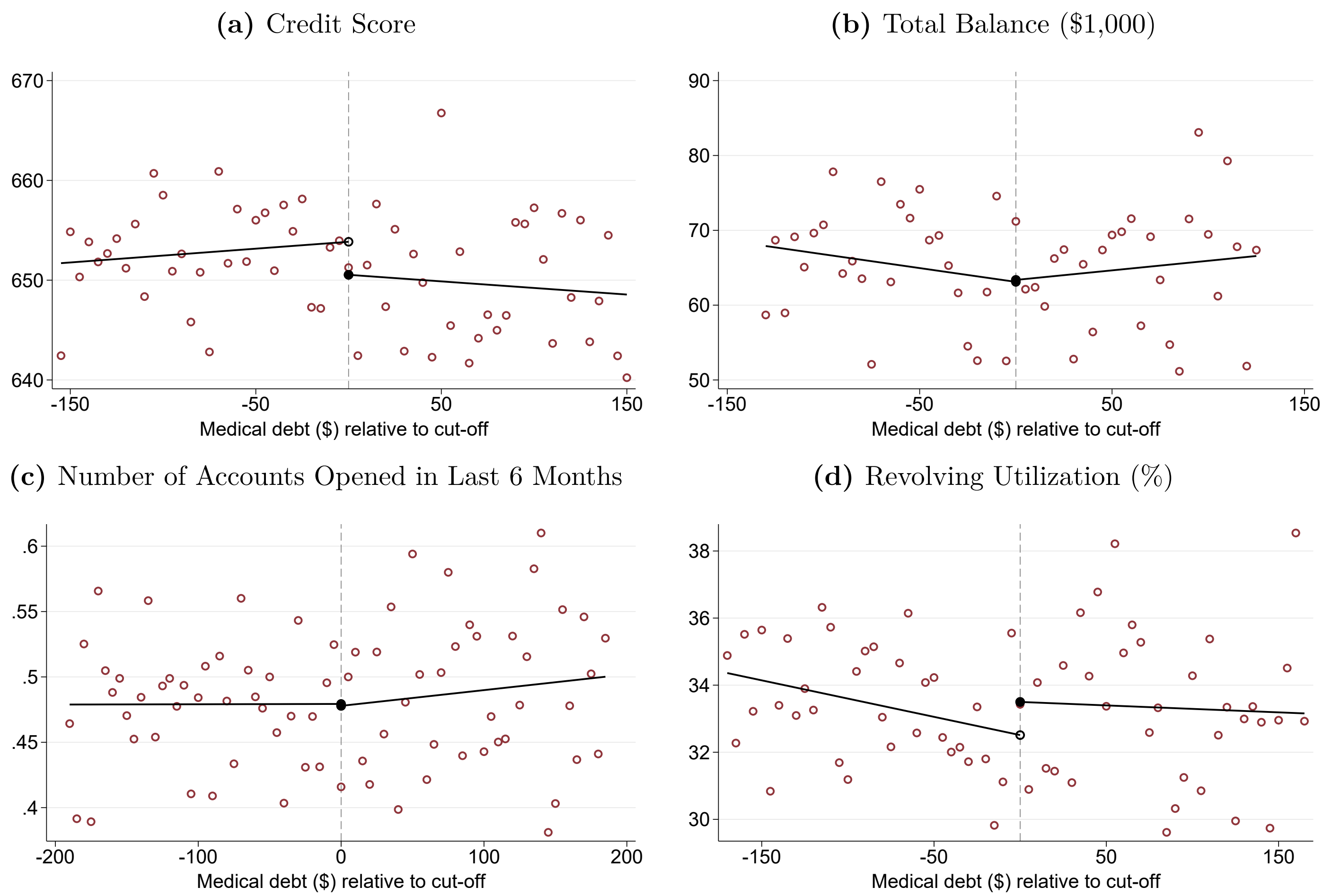

Notes: This figure shows the relationship between medical debt in 2022 and measures of financial distress and access to alternative credit in 2022. Medical debt is defined as the maximum value of the consumer's 2022 medical collections accounts, measured relative to the $500 threshold. RD estimates from Equation (6) are reported in Table A.8.

**Figure A.13:** Medical Collections Sub-Sample: Average Number of Accounts per Person, 2022




Notes: This figure shows the average number of medical collections accounts per person in 2024, where the running variable is the maximum value of the consumer's 2022 medical collections account, measured relative to the $500 threshold. The medical collections sub-sample restricts the RD sample to consumers for whom the total number of accounts in collection is same as the total number of medical collections accounts. RD estimates from Equation (6) are reported in Table A.9.

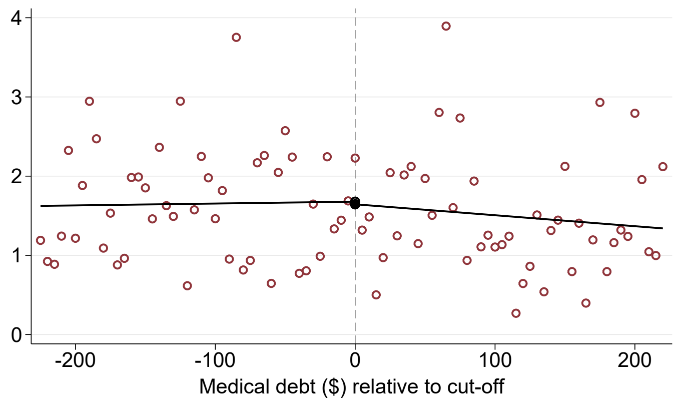
**Figure A.14:** Medical Collections Sub-Sample: Access to Credit



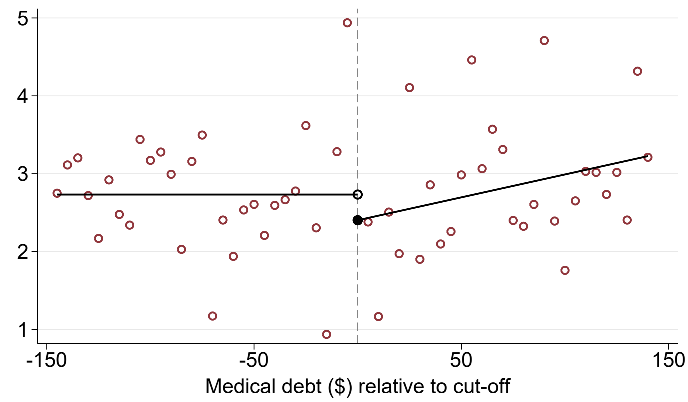

Notes: This figure shows the relationship between medical debt in 2022 and four different measures of credit access in 2024. The medical collections sub-sample restricts the RD sample to consumers for whom the total number of accounts in collections is same as the total number of medical collection accounts. Medical debt is defined as the maximum value of the consumer's 2022 medical collections accounts, measured relative to the $500 threshold. RD estimates from Equation (6) are reported in Table A.9.

**Figure A.15:** Medical Collections Sub-Sample: Financial Distress and Access to Alternative Credit

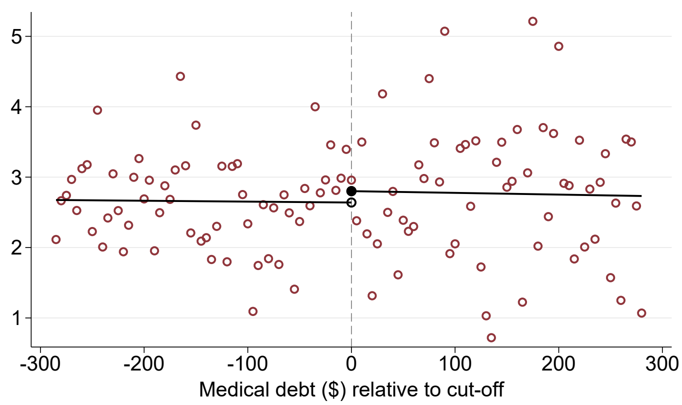
**(a)** Total Balance 90+ Days Past Due ($1,000)



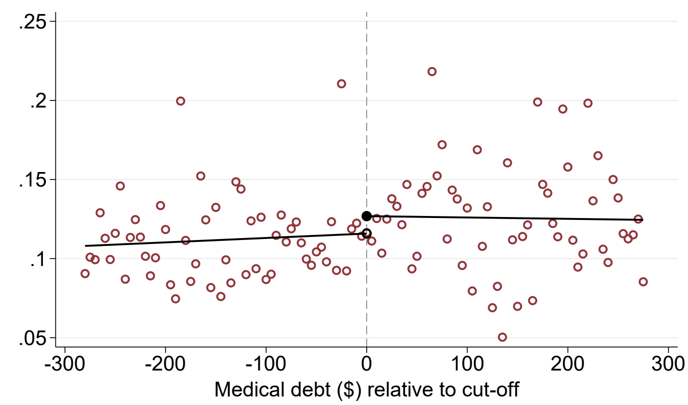

**(b)** Bankruptcy in Last 7 years (%)




**(c)** Has Alternative Credit Balance (%)



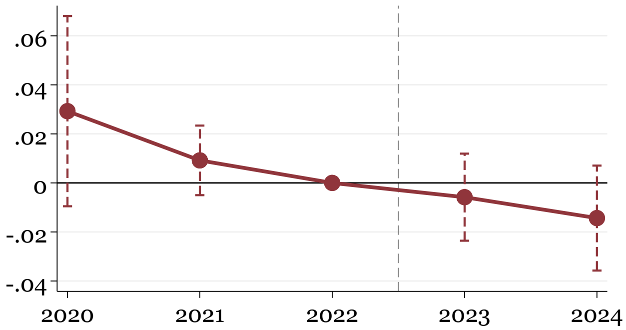

**(d)** Number of Alternative Credit Accounts



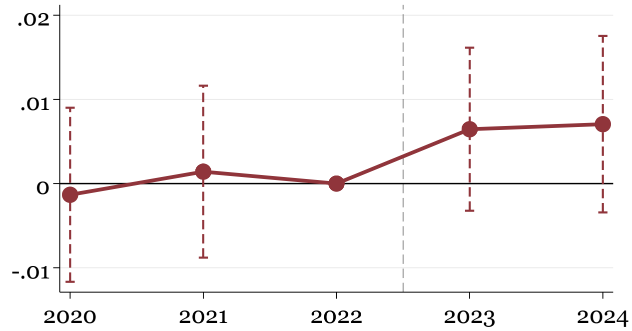

Notes: This figure shows the relationship between medical debt in 2022 and measures of financial distress and access to alternative credit in 2024. The medical collections sub-sample restricts the RD sample to consumers for whom the total number of accounts in collections is same as the total number of medical collection accounts. Medical debt is defined as the maximum value of the consumer's 2022 medical collections accounts, measured relative to the $500 threshold. RD estimates from Equation (6) are reported in Table A.9.

**Figure A.16:** Effect of Removing Small Medical Collections on Additional Outcomes

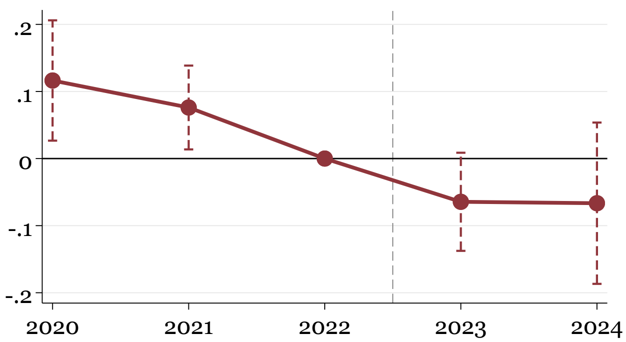
**(a)** Number of Accounts 90+ Days Past Due



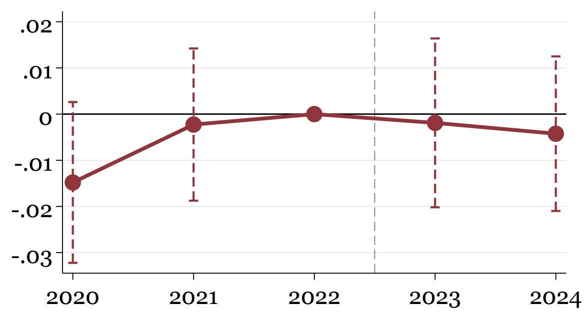

**(b)** Number of Inquiries in Last 6 Months



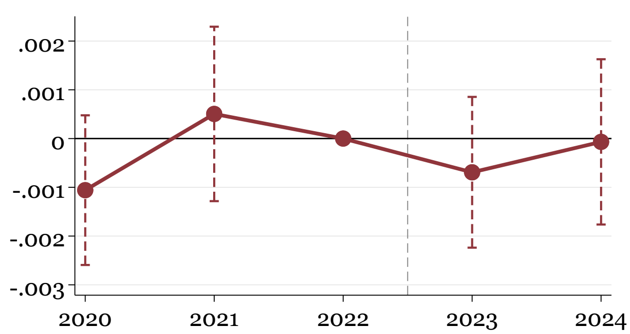

**(c)** Revolving Limit ($1,000)




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




**(e)** Number of New Mortgages in Last 6 Months




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

**Table A.3:** Performance Metrics for Credit Scoring Models With and Without Medical Collections Versus a Random Variable

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

Notes: This table reports performance metrics for a credit scoring model predicting defaults occurring between 2020 and 2021, based on borrower characteristics from 2019. Column (1) presents metrics for the baseline model, which includes 48 predictors and is estimated using XGBoost. Column (2) reports metrics when small (under $500) medical collections are excluded from the predictors. Column (3) shows metrics when a random variable is included to the set of predictors. The accuracy score represents the share of correct predictions. For comparison, a naive model predicting no defaults achieves an accuracy of 0.867. Precision is the proportion of predicted defaults that were correctly classified. Recall is the proportion of actual defaults correctly classified. F1 score is the harmonic mean of Precision and Recall. The AUC (Area Under the Receiver Operating Characteristic Curve) indicates the probability that the model assigns a higher default probability to a true defaulter than to a non-defaulter.

**Table A.4:** Performance Metrics for Credit Scoring Models With and Without Medical Collections: Restricted Model

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

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

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

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

Notes: This table presents the estimated coefficient ($-\beta$) and 95% confidence intervals from Equation (6). The running variable for medical debt corresponds to the highest debt amount across the consumer's medical collections accounts. We report MSE-optimal estimates with robust, bias-corrected 95% confidence intervals in brackets. Sample Mean reports the mean of the dependent variable in 2024. A ***, **, and * indicate significance at the 1%, 5%, and 10% level respectively, using conventional inference.

**Table A.6:** Additional Credit Outcomes: RD Estimates of the Direct Effect of Medical Debt Deletion

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

Notes: This table presents the estimated coefficient ($-\beta$) and 95% confidence intervals from Equation (6). The running variable for medical debt corresponds to the highest debt amount across the consumer's medical collections accounts. We report MSE-optimal estimates with robust, bias-corrected 95% confidence intervals in brackets. Sample Mean reports the mean of the dependent variable in 2024. A ***, **, and * indicate significance at the 1%, 5%, and 10% level respectively, using conventional inference.

**Table A.7:** Falsification Test: RD Estimates of the Direct Effect of Medical Debt Deletion

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

Notes: This table presents the estimated coefficient ($-\beta$) and 95% confidence intervals from Equation (6). The running variable for medical debt corresponds to the highest debt amount across the consumer's medical collections accounts. We report MSE-optimal estimates with robust, bias-corrected 95% confidence intervals in brackets. Sample Mean reports the mean of the dependent variable in 2024. A ***, **, and * indicate significance at the 1%, 5%, and 10% level respectively, using conventional inference.

**Table A.8:** Placebo Test: RD Estimates of the Direct Effect of Medical Debt Deletion

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

Notes: This table presents the estimated coefficient ($-\beta$) and 95% confidence intervals from Equation (6). The running variable for medical debt corresponds to the highest debt amount across the consumer's medical collections accounts. We report MSE-optimal estimates with robust, bias-corrected 95% confidence intervals in brackets. Sample Mean reports the mean of the dependent variable in 2024. A ***, **, and * indicate significance at the 1%, 5%, and 10% level respectively, using conventional inference.

**Table A.9:** Medical Collections Sub-Sample: RD Estimates of the Direct Effect of Medical Debt Deletion

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

Notes: This table presents the estimated coefficient ($-\beta$) and 95% confidence intervals from Equation (6). The medical collections sub-sample restricts the RD sample to consumers for whom the total number of accounts in collections is same as the total number of medical collection accounts. The running variable for medical debt corresponds to the highest debt amount across the consumer's medical collections accounts. We report MSE-optimal estimates with robust, bias-corrected 95% confidence intervals in brackets. Sample Mean reports the mean of the dependent variable in 2024. A ***, **, and * indicate significance at the 1%, 5%, and 10% level respectively, using conventional inference.