Healthcare Costs and Households' Access to Credit

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ABSTRACT

Credit bureaus encounter significant frictions when collecting data on consumer medical debt and related collections. Policymakers argued that the erroneous medical liabilities data adversely affect consumers' credit scores and access to credit. This paper sheds light on this policy debate by examining whether healthcare costs—the core driver of often-unobservable consumer medical liabilities—affect the ability of credit scores and debt-to-income ratios (DTIs) to predict consumer defaults. Leveraging a novel measure of healthcare costs based on Medicare spending, we document that, conditional on credit scores (DTIs), consumers in high-healthcare-cost CBSAs are 16.4% more likely to default than those in low-healthcare-cost CBSAs. These effects are particularly pronounced among consumers with low credit scores or high DTIs. Lenders are aware of these limitations and impose higher rejection rates on mortgage applicants in high-healthcare-cost CBSAs, disproportionately affecting riskier borrowers. These effects are amplified after Q1 2022, when credit bureaus ceased factoring small medical debt collection accounts into credit scores and DTI calculations—confirming the role of the information collection frictions. Our findings suggest that restricting medical debt information flows biases credit scores (DTIs) estimates upwards (downwards), distorts the quality of the information provided by credit bureaus, and hinders efficient credit allocation.

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I. Introduction

With healthcare expenditures reaching 17.6% of U.S. GDP, medical debt has become a pervasive financial burden among American consumers (Kluender, Mahoney, Wong, and Yin, 2021). The Kaiser Family Foundation (KFF) estimates that as of December 2021, approximately 15% of U.S. households held medical debt, amounting to $250 billion in unpaid medical expenses (KFF, 2024). Despite its widespread prevalence, medical debt is not systematically recorded in consumer credit files.[1] The incomplete and, at times, erroneous medical liabilities data reported to credit bureaus has spurred an intense (and as of the date of this draft ongoing) policy debate.

The policymakers argue that incorporating flawed medical debt data into credit reports unfairly penalizes consumers, lowering their credit scores and restricting their access to credit as (uninformed) lenders base their decision on (downward biased) credit scores and debt-to-income estimates.[2] Conversely, the lending industry contends that even imperfect medical debt data enhances credit bureaus' ability to predict consumer financial distress. Removing such information from consideration has the potential to inflate credit scores and debt-to-income ratios (DTIs), impairing lenders' ability to efficiently allocate credit to consumers (Dobbie, Goldsmith-Pinkham, Mahoney, and Song, 2020).

Whether medical debt information frictions affect consumers' credit files and access to credit negatively (policymakers' view) or positively (industry view), the information collection frictions should be felt more acutely in high healthcare costs markets. Higher healthcare costs

[1] As of September 2021, one of the major credit bureaus featured about $55 billion of medical debt and related collection balances in contrast to $250 billion estimated by KFF. There is a wide set of reasons for the medical debt to be subject to the information flow frictions. See Section 2.1 for a detailed discussion.

[2] In announcing the CFPB rule pertaining the exclusion of medical debt and collections from consumer credit files, Kamala Harris said that the rule would be "lifechanging" for millions of families as "No one should be denied economic opportunity because they got sick or experienced a medical emergency" (Washington Post, January 7, 2025, "Biden administration bans unpaid medical bills from appearing on credit reports").

contribute to higher *potentially unaccounted* medical liabilities, which in turn should make credit scores and DTIs less informative in predicting consumer defaults and, by extension, affect consumer access to credit.

This paper sheds light on this policy debate by exploring whether healthcare costs affect the default predictive accuracy of credit scores (DTIs) and consumers' access to credit. Using novel Medicare-spending-based measures, we document that healthcare costs affect the quality of the traditional creditworthiness indicators: Conditional on credit scores (DTIs), consumers in high-healthcare-cost CBSAs are 14% more likely to default than those in low-healthcare-cost CBSAs (Figure 1). These effects are larger for low credit scores or high DTIs consumers. Lenders appear cognizant of the limitations posed by the medical debt information collection frictions. They are more likely to reject mortgage applications in high-healthcare-cost CBSAs, particularly for riskier borrowers (Figure 2). These effects intensify after Q1 2022, when credit bureaus ceased incorporating small medical debt collection accounts into credit scores and DTI calculations, which exacerbated the information collection frictions, but did not affect consumer financial obligations. Collectively, our findings suggest that imperfect flow of medical liabilities information compromises the accuracy of credit bureau data and hampers the efficiency of consumer credit allocation.

Our empirical design relies on novel healthcare cost measures that are plausibly exogenous to local consumers' financial conditions and credit demand. In our analysis, we rely on the Medicare Spending Per Beneficiary (MSPB) data.[3] MSPB provides average Medicare expenditures per hospitalization across U.S. hospitals, covering payments before, during, and 30 days post-discharge. These data are used by health economists to evaluate hospital (in)efficiencies

[3] https://data.cms.gov/provider-data/dataset/rrqw-56er

(Norton, Li, Das, and Chen, 2018; Currie, Karpova, and Zeltzer 2023). Although MSPB data does not fully capture the heterogeneity in healthcare costs across CBSAs, it offers several advantages. Amounting to about 21% of total U.S. healthcare spending, Medicare shapes local healthcare costs. MSPB data captures hospitalization related expenses during the period when hospital care costs grew three times faster than the physician care costs (Cooper et al., 2019). Medicare policies serve as a benchmark for private insurer pricing (Clemens and Gottlieb, 2017) and standards of care (Moses et al., 2013).

More importantly, MSPB data captures the drivers of the local healthcare costs that are arguably unrelated to local consumer financial conditions and credit demand. Based on national reimbursement policies (Skinner, 2011) Medicare spending is not impacted by the service provider's ability to adjust prices in response to local economic conditions. It also focuses on services provided to the homogenous 65+ population that is least likely to borrow to cover medical expenses (Batty, Gibbs, and Ippolito, 2018). Finally, MSPB measures costs per patient per incident, avoiding the effects of endogenous healthcare utilization rates (Anderson, Dobkin, and Gross, 2012; Finkelstein, Gentzkow, and Williams, 2016). The core variation in the MSPB estimates stems from the quality of care and over/under provision of medical services per patient by U.S. hospitals.[4]

Using MSPB data we construct three measures that capture healthcare costs heterogeneity across CBSAs (Figure 3). First, we utilize the average hospital-level MSPB costs normalized each year by the national average and aggregated to CBSA market. Second, we focus on the post-hospital-discharge costs that are known to drive the differences in MSBP costs across hospitals

[4] Hospital have a discretion over the amount and intensity of the services they provide (see e.g., Clemens and Gottlieb 2014; Dranove, Garthwaite, and Ody 2017; Adelino, Lewellen, and McCartney 2022)

(Das et al., 2016). While Medicare mandates eligible in-hospital procedures, post-discharge services are driven by the quality of in-hospital care (e.g., post-surgical infection rates) and over/under provision of services by hospitals (Norton et al. 2018; Currie, Karpova, and Zeltzer 2023). Third, we use the post-discharge MSPB costs normalized by pre- and in-hospital MSPB costs. This measure accounts for the heterogeneity in the complexity of the medical care local *patients need* and *hospitals can provide*. We validate all three healthcare cost measures using the available consumer medical liabilities data. Specifically, we document that consumers in higher healthcare costs CBSAs are more likely to have medical debt and medical debt collection accounts and accumulate larger medical liability balances (Figure 4).[5]

Armed with the validated healthcare costs measures, we assess the impact of the healthcare costs on the ability of credit scores and DTIs to predict consumer defaults. Here, we rely on a 5% random sample of US individuals with a credit bureau record (about 13 million people) from 2017-2023. We aggregate data to a representative ZIP-code-level consumer and focus on consumer default rates defined as the share of ZIP-code consumers that are in a derogatory event on more than 5% of their total outstanding debt balances within the next six (twelve) months.

Using these data, we first document that a representative ZIP-code level consumer default rate is about 16.4% higher in high healthcare costs markets relative to low healthcare cost markets. Panels A and B of Figure 1 illustrate that lowest credit score decile consumers experience 9.95% default rate in low healthcare costs quartile markets and 11.58% in high healthcare costs quartile markets (1.6% default differential). The effect monotonically declines across credit score deciles, reaching 0.19% default rate differential for top credit score decile consumers. We confirm this

[5] The validation tests rely on the assumption that while the medical data is incomplete and not always up to date, it is not randomly distributed across U.S. geographies and is driven by local healthcare costs.

effect in a regression setting (outlined in Figure 5) where we control for a vast array of local economic fundamentals, consumer financial condition and demographic characteristics, time and CBSA fixed effects.

Similar effects are observable for DTIs (Panels C and D of Figure 1). Consumers in the top healthcare costs quartile CBSAs are, on average, 1.8% more likely to default than consumers with the same DTI levels residing in the bottom healthcare cost quartile CBSAs. The default rate differential is 0.7% for the lowest DTI decile but increases to 2.77% for the highest DTI decile. These findings support the lending industry's argument that credit scores and DTIs—constructed without fully accounting for medical liabilities— likely underestimate the default risk.

A natural concern is that local healthcare costs might influence consumer defaults through channels other than information frictions. Consumers residing in high-healthcare-cost markets may face lower wages (Arnold and Whaley, 2020) or face greater future medical expenses. Either factor could reduce consumers' ability to service existing debt, increasing the likelihood of derogatory events.

To isolate the role of the information collection frictions, we exploit the 2022 shift in how medical liabilities are accounted for in consumer credit files. In early 2022, under pressure from the CFPB and other policymakers, the three major credit bureaus announced that as of July 2022, they would exclude medical debts less than one year old and remove medical debt collection balances below $500 from credit scores and DTI calculations. This decision did not eliminate underlying medical liabilities—it simply prevented these debts from being recorded in credit files (Figure 5).[6] This policy shift presents a natural experiment that allows us to isolate the information

[6] These numbers represent the implied aggregate medical debt liabilities amounts based on 5% random sample of consumers covered by the credit bureau data available to us.

frictions channel. We find that the 2022 shift increased the adverse effect of healthcare costs on the predictive power of credit scores and DTIs. The findings suggest that restricting medical debt information inflates credit scores (and deflates DTIs), further distorting credit risk assessments and weakening the quality of information available to lenders.

The natural next question is whether lenders recognize the healthcare costs related distortions in consumer creditworthiness assessments and adjust their lending accordingly. In the second half of this paper, we examine whether and how healthcare costs influence consumer access to mortgage credit using 2018–2023 HMDA data. To isolate the supply of capital effect, we focus on mortgage acceptance rates. Loan amounts and consumer leverage are likely to be affected by the demand effects, as consumers facing high healthcare costs are likely to *demand* more debt to cover the medical bills (KFF, 2024) or delay existing debt repayment. Mortgage acceptance rates allow us to isolate the credit supply effects as we can capture within lender-year-loan type decisions across different healthcare cost markets conditional on requested loan amount and DTI.

The results show that lenders are about 2.5% more likely to reject mortgage applications in the top quartile healthcare cost markets compared to the bottom quartile healthcare cost markets (Figure 2). The effect is larger for riskier borrowers: mortgage rejection rates increase by 3.47% for the bottom credit score decile applicants, compared to 1.96% for the top credit score decile applicants. Similarly, the effects are larger for the top DTI decile consumers (2.40%), and lower for the bottom DTI decile consumers (1.54%). Regression analysis confirms these patterns. These effects nearly double following the 2022 policy shift, further supporting the information collection frictions channel.

Our findings challenge the prevailing policy narrative that lenders are unaware of the hidden risks associated with medical debt. Instead, our results suggest that lenders—confronted

with growing uncertainty regarding borrowers' true financial health—respond by broadly restricting access to credit in high-healthcare-cost markets, irrespective of individual borrower characteristics. This indiscriminate tightening of credit supply reduces the efficiency of credit allocation.

Our paper contributes to several strands of academic inquiry. First, we add to the literature exploring the impact of rising healthcare costs on consumer financial health. Several papers have documented that medical liabilities are significant contributors to consumer bankruptcy (e.g., Himmelstein et al., 2009; and Dobkin et al. 2018). Access to health insurance, Medicare, and Medicaid alleviate these adverse effects of healthcare on consumer financial well-being (Batty, Gibbs, and Ippolito, 2022; Caswell and Goddeeris, 2020; Engelhardt and Gruber, 2011; Goldsmith-Pinkham, Pinkovskiy, and Wallace, 2023; Gross and Notowidigdo 2011; and Kluender et al., 2021). Medical debt forgiveness is effective in improving consumers' credit scores (Kluender et al, 2024). We add to this literature by documenting the systematic effects of the healthcare costs on credit scoring and consumers' access to credit.

Second, we add to the rapidly growing empirical literature exploring the effects of healthcare costs on a variety of economic outcomes by offering a novel healthcare cost proxy that is reasonably exogenous to local economic conditions. To date, the literature relied on private insurance claims data (e.g., Brot-Goldberg et al. 2024) or employer-sponsored health insurance plan premiums (Aghamolla, Jain, and Thakor, 2023; Gao et al., 2022). Similar to ours, these proxies do not capture full variation in local healthcare costs, but in contrast to our measures these proxies are undoubtedly endogenous to local economic conditions and require complex instrumentation (e.g., accounting for hospital mergers, private equity entry, or insurance company financial conditions).

Third, we add to the literature exploring how economic agents' behavior affects the accuracy of statistical models used to predict defaults. The literature scrutinized the failure of credit agencies' models to estimate the quality of CDO tranches (see, e.g., Griffin and Tang, 2012) as well as the ability of FICO scores to predict defaults among sub-prime borrowers (Mayer 2010; Pagano and Volpin, 2010). Rajan, Seru, and Vig (2015) documents how unique information flows of the RMBS market eroded the ability of interest rates to predict defaults. Dobbie et al. (2020) demonstrate that changes in the reporting of bankruptcy on consumer credit files impact consumers' access to credit. We add to this literature by documenting the effects of restricting usage of the medical liabilities data on consumer credit scoring and access to credit.

Finally, we contributed to the policy debate that has profound implications on lenders and consumers alike. More recently, in January 2025, the CFPB announced a new rule that calls "to remove an estimated $49 billion in medical bills and collection from consumer credit reports of about 15 million Americans" (CFPB, 2025) without eliminating the associated medical liabilities from the consumers' balance sheets. Our results suggest that this policy is likely to undermine credit bureaus' ability to provide quality creditworthiness assessment to lenders and by extension to adversely affect consumers' access to credit.

II. Medical Liabilities in Consumer Credit Files

II.1 Institutional Details

As of December 2021, Americans owed approximately $250 billion in medical debt (KFF, 2024). The KFF survey estimated that around 21 million U.S. adults carried medical liabilities, with 52% of them owing more than $2,000 to healthcare providers. However, consumer medical liabilities are not systematically incorporated into credit reporting agencies' (CRAs) files. As of

September 2021, credit files of a major credit bureau recorded only $55 billion in medical debt and related collection balances—substantially below the $250 billion estimated by KFF.

There is a wide set of reasons for the medical liabilities to be subject to the information collection frictions (CFPB, 2014). First, medical debt is typically processed in-house by the healthcare providers as "*hospitals become frequent collection agents*" (Richman et al., 2023). Non-transparent pricing of the services, medical billing errors, wrongfully denied claims, frequent insurance adjustments, and billing disputes require healthcare provider expertise and make the medical debt formation and collection cycles lengthy, complicated, and very dynamic. Beyond initial billing, providers frequently engage in debt renegotiations and restructuring to enhance recovery rates (NPR, 2023). However, healthcare providers seldom have direct reporting relationships with CRAs (Consumer Reports, 2018), as their primary obligation is to provide care irrespective of patients' financial situations.

Second, the major contributors to the medical liabilities information in credit bureau files are collections agencies (CFPB, 2014). These economic agents take over the debt once consumers default on their medical bills but not earlier than 1809 days after medical bills were incurred (Kluender et al., 2021). Collectors are more likely to report the medical liabilities data to credit bureaus. As of September 2021, $42 billion out of $55 billion of medical liabilities cited above are medical debt *collection* balances. This implies that for each dollar of medical debt, credit bureaus recorded $3.2 in medical debt collections. By contrast, in other consumer debt segments (excluding mortgages and auto loans), credit bureaus recorded only $0.03 in collection balances per dollar of debt.

Information provided by collection agencies is also subject to distortions. The medical debt collection industry is highly fragmented, with approximately 1,400 different agents (CFPB,

2014).[7] Collectors do not always have systematic relationships with CRAs leading to inconsistent reporting. Moreover, medical debt collectors are incentivized to underreport repayment and even report fraudulent debt amounts to "use the credit reporting system to coerce people into paying medical bills they do not owe" (CFPB Director Rohit Chopra, CFPB, 2025). Furthermore, selling medical debt to collection agencies is at the discretion of the healthcare provider. There are no objective or enforceable standards determining when a debt should be classified as in collections (CFPB, 2014). Large hospital systems implement collections in-house. Other healthcare providers push patients' debt into collections well before all insurance adjustments are completed and disputes are settled.

These factors contribute to significant medical liabilities information collection frictions, leading to inaccurate medical liabilities data in consumer credit files. When available, this information significantly affects consumers' creditworthiness assessment (Kluender et al., 2024; Brevoort, Grodzicki, and Hackmann, 2020) and access to credit. FICO Corporation estimates that "if a consumer had an otherwise spotless credit report and eliminated medical bills – paid or unpaid – it could boost FICO score by more than 25 points" (NYT, 2022b).

II.2 Policy Debate

The combination of imperfect data and its role in consumers' access to credit has become a focal point in protracted policy debate. Policymakers and federal regulators (e.g., CFPB) argue that medical debt information is unreliable and *should not* be factored in consumer creditworthiness assessment due to inaccuracies and outdated reporting. CFPB, and more recently, the Biden Administration contend that credit scores incorporating medical debt

[7] According to Congressional Research Service Report (2024) it accounts for 24.7% of the consumer debt collection industry

systematically underestimate borrower quality, leading to unjustified credit rationing. Excluding medical liabilities data from consideration would enhance financial inclusion without materially increasing credit risk (Washington Post 2024a).

On the other side of the debate, including CRAs, medical debt collectors, and lenders argue that excluding unpaid medical liabilities from credit reports would have several adverse effects on consumers.[8] For one, excluding this, admittedly imperfect, information would further undermine the informativeness of CRAs' data, lead to increased upward (downward) bias in credit scores (DTIs), and weaken lenders' ability to properly assess consumer default risk. Unable to properly differentiate between high- and low-risk consumers, uninformed lenders might oversupply credit. Additionally, removing such data could eliminate consumer incentives to pay medical debt and lead debt collectors to rely on more costly litigation. Both factors would adversely affect healthcare providers' revenue and impose additional costs on patients (Washington Post 2024b).

This debate led to numerous policy shifts. In March 2022, under pressure from CFPB and the Biden Administration, the three major credit bureaus announced that they would dramatically curtail medical liabilities data used in credit assessment. Specifically, starting July 1st, 2022, the CRAs stopped considering (a) repaid medical tradelines, and (b) unpaid debt transferred to collectors within the prior 12 months. By 2023, they also stopped considering (c) unpaid medical collections below $500. The move was expected to eliminate 70% of medical liabilities from credit files without changing consumers' financial obligations to healthcare providers and collectors. Our data shows that this policy shift had a dramatic impact on the medical liabilities

[8] The lending industry arguments are well outlined and supported by quotes in the October 18th, 2024 Washington Post article titled "The big business that opposes wiping medical debt from credit reports."

in consumer credit files (Figure 6). Total unpaid medical debt collections dropped from $42 billion in September 2021 to $30.7 billion in September 2022. (Blavin, Braga, and Karpman 2023) estimate that the 2022 move improved VantageScores of sub-prime consumers by about 30 points while leaving the credit scores of prime consumers unaffected. We exploit this information frictions shock in our empirical analysis.

More recently, in January 2025, the outgoing Administration announced a new CFPB Rule that mandated CRAs to fully exclude medical liabilities from consumer credit files. The rule is expected to remove an estimated $49 billion in medical bills and collection from consumer credit reports of about 15 million Americans" (CFPB, 2025). Vice President Kamala Harris announcing the rule stated that this rule would be "life-changing" for millions of families as "no one should be denied economic opportunity because they got sick or experienced a medical emergency."

III. Data and Sample Selection

III.1 Healthcare Costs Proxies

To support their core arguments, CFPB conducted a study that compared the unconditional frequency of derogatory events among consumers with and without medical liabilities recorded in consumer credit files (CFPB, 2014). This empirical approach presents two key issues. First, it implicitly assumes that medical liabilities data—described by the CFPB itself as "incomplete and frequently erroneous"—can reliably isolate the affected consumer group. Second, it overlooks the endogeneity of medical liability accumulation, which is influenced by consumer financial conditions, healthcare provider incentives and capabilities, and local economic factors.

In this study, we propose an alternative approach. Instead of relying on flawed medical liabilities data, we focus on healthcare costs. We argue that higher healthcare costs contribute to greater (unobserved) medical liabilities, which in turn should reduce the informativeness of credit

scores and debt-to-income (DTI) ratios in predicting consumer defaults. In other words, whether medical debt imperfections negatively (as policymakers argue) or positively (as the industry suggests) affect consumer credit files and access to credit, the impact of these reporting frictions should be more pronounced in high healthcare cost markets. The core challenge we face is to isolate (drivers of) healthcare costs that are arguably exogenous to local consumer financial health, demographic characteristics, and local economic conditions.

Medicare Spending per Beneficiary (MSPB) Data

We advance three novel measures that capture such heterogeneity in healthcare costs. These measures rely on 2017-2023 annual Medicare Spending per Beneficiary (MSPB) data from the Center for Medicare and Medicaid Services (CMS). MSPB provides average Medicare expenditures per hospitalization across U.S. hospitals, covering payments from three days before, to during, to 30 days post-discharge. The data includes expenditures on inpatient stays, outpatient visits, skilled nursing facilities, home health, etc. (Table A1). Health economists use the data to evaluate hospital (in)efficiencies (Norton et al., 2018; Currie et al., 2023).

Although MSPB data does not fully capture the heterogeneity in healthcare costs across CBSAs, it offers several advantages for our empirical approach. First, by construction, MSPB data captures the drivers of healthcare costs that are arguably exogenous to consumer balance sheets. Medicare reimbursement rates are set by national policies (Skinner, 2011) and remain relatively insulated from local economic conditions and providers' ability to adjust prices in response to market conditions. Medicare primarily serves a relatively homogenous population of individuals aged 65 and older, who are unlikely to finance medical expenses through borrowing (Goldsmith-Pinkham, Pinkovskiy, and Wallace, 2023).

Second, the MSPB data formation process was designed to enable comparisons of hospital efficiency for Medicare patients. To ensure fairness, MSPB data relies on standardized pricing that is adjusted to geographic and policy-related payment variations. The data is also risk-adjusted to account for differences in patient age and health conditions, enhancing its reliability in comparing healthcare costs across providers.[9] MSPB measures also capture costs per patient per incident, mitigating potential biases arising from geographical variations in healthcare utilization. Ultimately, the core variation in MSPB cost estimates reflects structural differences in care quality and the extent of medical service provision across hospitals in the United States.

Finally, MSPB data captures one of the most important drivers of local healthcare costs. Amounting to about 21% of total U.S. healthcare spending, Medicare shapes local healthcare markets. Medicare reimbursement rates serve as a benchmark for private insurer pricing (Clemens & Gottlieb, 2017). It also shapes local standards of care (Moses et al, 2013). One can be concerned that MSPB data covers only hospitalization-related payments. Yet Cooper et al. (2019) show that during the 2000-2017 period, hospital care costs grew three times faster than physician care costs.

Our Healthcare Costs Measures

Using the MSPB we construct three healthcare cost measures. First, we utilize the average within CBSA *MSPB Costs* – the average annual Medicare Spending per Beneficiary per hospital aggregated to CBSA level and scaled by the national average provided by MSPB data:

$$MSPB\ Costs_{CBSA,t} = \sum_{Hospital} \frac{Average\ MSPB\ Costs_{Hospital,t}}{National\ Average_t} \qquad (1a)$$

[9] Detailed description of how MSPB is constructed can be found here:
https://www.qualityreportingcenter.com/globalassets/migrated-pdf/sg_hvbp_mspb-presentation-6-3-15_slides_20150526_v-final-508-1s.pdf.

Healthcare economics literature documents that post-discharge Medicare spending drives the core heterogeneity in Medicare costs as it captures hospital inefficiencies (e.g., see Das et al., 2016). These costs (e.g., post-acute care, hospice, skilled nursing facility) represent 41.9% of the average MSPB reimbursement amounts in comparison to in-hospital costs that constitute 54.3%, on average. Consistently in our second measure we focus on the *Post-discharge MSPB Costs*:

$$Post\text{-}Discharge\ MSPB\ Costs_{CBSA,t} = \frac{Average\ Post\text{-}Discharge\ MSPB_{CBSA,t}}{National\ Average_t}. \qquad (1b)$$

One can argue that while MSPB data might be affected by local patient medical care needs and local hospitals' ability to provide complex medical services, even though, by construction, the data aims to account for patient risk factors (e.g., age, severity of illness, and comorbidity interactions). To further account for heterogeneity in local health demographic factors and hospital capabilities, we advance a third measure of healthcare costs heterogeneity where we normalize the post-discharge MSPB costs by the pre-discharge MSPB Costs:

$$\begin{matrix} Post\text{-}to\ Pre\text{-}Discharge \\ MSPB\ Costs_{CBSA,t} \end{matrix} = \frac{Post\text{-}Discharge\ MSPB_{CBSA,t}}{Pre\text{-}Discharge\ MSPB_{CBSA,t}} / NationalAverage_t. \qquad (1c)$$

The denominator captures the complexity of in-hospital care demanded by the local population and provided by the local hospitals. As a result, our third measure is driven by quality of in-hospital care (e.g., post-surgical infection rates) and care inefficiencies (e.g., overprovision of services).

Panels A and B of Figure 3 illustrate the geographic distribution of *Post-discharge MSPB Costs* from Equation (1b) at the start and the end of our sample period, 2017 and 2023 respectively. The heatmaps illustrate that MSPB costs exhibit significant healthcare cost heterogeneity across U.S. CBSAs, as well as notable time-series variations over our sample period.

Panel A of Table 1 further reports the summary statistics for our measures. The sample average Medicare Spending per Beneficiary is $20,337, with post-discharge spending averaging $8,527—accounting for 41.9% of total MSPB costs. Normalized $MSPB\ Costs_{CBSA,t}$ has an average of 0.94. The average is below 1 since hospitals are unevenly distributed across CBSAs, with some areas having significantly more hospitals than others. This further emphasizes the importance of conducting the robustness tests using our second and third measures.

III.2 Consumer Financials Data and Sample Selection

Consumer Credit Panel

To capture consumer financial characteristics we rely on data from one of the major U.S. credit bureaus. We utilize data about a 5% representative sample of U.S. consumers observed at the end of March and September each year from 2017 to 2023. These data offer detailed information about consumer debt, including delinquent and derogatory events and balances, credit scores, income level, leverage relative to income, a proxy for consumer age, and borrower demographics. Moreover, the data offers, arguably imperfect, information on consumer medical debt and medical collection balances and allows us to capture both the extensive and intensive margin of medical liabilities.

Using this data, we construct a panel of representative ZIP-code-level consumers' financial characteristics (e.g., incomes, credit scores, debt-to-income ratios, etc.) and non-financial characteristics (e.g., consumer age). Our baseline sample consists of approximately 27,246 ZIP-codes. Panels B, C, and D of Table 1 report summary statistics of the core variables of interest provided by these data. These panels report statistics on consumer medical debt and collections, ex-post default rates, and ex-ante financial characteristics, respectively.

Consumer Credit Flows Data (HMDA)

In addition to consumer financial health data, we rely on the Home Mortgage Disclosure Act (HMDA) data to capture consumers' access to credit. This comprehensive dataset includes 98% of the residential mortgage applications in the United States and provides detailed information about property location, loan type, loan purpose, loan amount, applicant income, race, ethnicity, and numerous other characteristics. We restrict our sample to conventional home purchase loans for single-family residential properties (excluding manufactured housing). HMDA data offers the loan application decisions. Throughout our analysis, we use the HMDA data to construct a panel of representative mortgage applicants at the ZIP-code-lender-year-loan type level. The loan type is defined by two characteristics: (a) the conforming loan indicator (conforming vs non-conforming, i.e., jumbo) and (b) loan purpose (new loan vs. refinancing) leading to four loan types considered.

Other Data

We complement the credit bureau and HMDA data using multiple other data sources. We use the BLS's Quarterly Census of Employment and Wages (QCEW) data to capture the local economic conditions including wage levels and employment growth. QCEW also provides local industry composition captured by the local employment shares of two-digit NAICS industries. The latter allows to control for local industry growth option. We further collect the proportion of businesses that have less than 50 employees from the County Business Pattern data provided by the U.S. Census Bureau to capture the consumers' exposure to employment-related insurances. This data allow us to control for potential distortions in health insurance coverage across regions as businesses with less than 50 employees do not have to provide employee health insurance.

III.3 Healthcare Measures Validation Tests and Results

We first and foremost use these data to confirm that the proposed healthcare cost measures do contribute to consumer accumulation of medical liabilities using the available medical liabilities data recorded in credit files of one of the major credit bureaus. We acknowledge that this analysis relies on the assumption that, while the medical liabilities data does not correctly capture medical liabilities for individual consumers, it is not randomly distributed across U.S. geographies – ZIP-codes in our case. CFPB (2014) argues that small dollar medical liabilities balances recorded in credit files are most prone to error. Panel B of Table 1 shows that only 0.07% of consumers have medical debt, while 13% of consumers have medical collections. This data once again highlights the extent to which medical debt is hidden from credit agencies.

Using the resulting sample we focus on four variables of interest: (a) total medical debt balances accumulated by ZIP-code consumers; (b) average medical debt balances accumulated by ZIP-code consumers; (c) total medical collection balances accumulated by ZIP-code consumers; and (d) average medical collection balances accumulated by ZIP-code consumers. Panel B of Table 1 offers summary statistics for these variables.

Figure 4 reports the bin-scatter plots the natural logarithm of these four measures against our second measure of healthcare costs heterogeneity – $Post\text{-}Discharge\ MSPB\ Costs_{CBSA,t}$.[10] Panel A suggests that a one percentage point increase in relative MSPB Costs corresponds to a 4.41 percentage points increase in local medical debt. Panel B illustrates that a one percentage point increase in relative MSPB Costs leads to a 2.63 percentage points increase in local medical collection balances. Panels C and D confirm that the effect works through both intensive and

[10] Bin-scatter plots that utilize other healthcare costs measures look qualitatively similar and are available upon request.

extensive margins as the increase in average medical liabilities balances does not fully explain the effect.

Table 2 formally confirms these conclusions using the following regression specification:

$$Medical\ Liabilities_{ZIP,t} = \beta_1 HCC_{CBSA,t} + Controls + \gamma_t + \varepsilon_{ZIP,t}. \quad (2)$$

We explore the relationship between one of three healthcare costs measures (Panels A through C) on six medical liability measures that capture intensive and extensive margins alongside the medical debt and medical debt collection dimensions. Note that in Column (1) which explores the effects on the share of ZIP-code consumers with medical debt, we multiply the dependent variable by 100 for coefficient tractability. As we discussed in the previous section, medical debt information is rarely reported to credit bureaus.

The analysis reported in Table 2 incorporates a wide set of control variables that account for ZIP-code representative borrowers' financial characteristics and CBSA-level local economic conditions. At the ZIP-code level, borrower financial controls encompass the average debt-to-income ratio, the natural logarithm of consumer income, the natural logarithm of consumer age (proxied by the oldest credit account), the proportion of consumers with a collection account (either medical or non-medical), and the ratio of total collections to total debt balance. At the CBSA level, local economic controls include average local wage, employment levels, wage growth, employment growth, the local industry composition across two-digit NAICS industries, and the share of local businesses with less than 50 employees.

Table 2 uniformly shows that all the proposed measures of healthcare costs heterogeneity are strongly positively correlated with medical liabilities indicators even after we control for a host of macro- and micro-economic factors potentially affecting both consumer financial health and local healthcare costs. Columns (4) through (6) indicate that one percentage point increase in

$MSPB\ Costs_{CBSA,t}$ is associated with 2.4% increase in the share of consumers with medical collection accounts, 1.08% increase in average medical collection balances, and 1.155% increase in ZIP-code level total medical collections. Overall, these results validate our novel healthcare cost measures. Table 2 confirms that the proposed measures capture heterogeneity that contributes to consumer medical liabilities formation.

IV. Empirical Tests and Results

IV.1 Healthcare Costs and Consumer Defaults

The first part of our analysis explores whether exposure to high healthcare costs affects the ability of creditworthiness measures to predict consumer default. To shed light on this question, we implement the following regression analysis:

$$Default_{ZIP,t+1} = \boldsymbol{\beta_1} HCC_{CBSA,t} + \boldsymbol{\beta_2}\, Creditworthiness_{ZIP,t} \times HCC_{CBSA,t} + \boldsymbol{\beta_0} Creditworthiness_{ZIP,t} + Controls + \gamma_t + \mu_{CBSA} + \varepsilon_{ZIP,t+1}. \quad (3)$$

where $Default_{ZIP,t+1}$ is the share of individuals in a given ZIP-code that have delinquent or derogatory accounts exceeding 5% of their outstanding debt balances in the subsequent six (or twelve) months. $HCC_{CBSA,t}$ represents one of three healthcare cost measures advanced in this study.

We do not include observed medical debt or related collections in our set of regressors for three reasons. First, the information is already accounted for in the credit scores and the debt-to-income ratios. Second, the medical liabilities information recorded in credit bureau files is likely to be inaccurate and incomplete. Third, medical debt and collection are endogenous to consumer financial conditions and are likely to undermine the quality of our inferences.

Figure 5 summarizes our empirical predictions graphically. Panel A (B) illustrates these predictions when credit scores (DTIs) are used as the primary measure of creditworthiness. Policymakers argue that imperfect medical liabilities data recorded in credit files creates a downward bias in consumer creditworthiness assessment, i.e., unfairly deflates credit scores and inflates DTI. This view suggests that consumers exposed to high healthcare costs should default less than their credit score estimates would suggest. These effects would be felt more acutely by riskier borrowers who are more likely to borrow to cover their medical care expenses. Combined, the policymakers' view is consistent with $\beta_1 < 0$ and $\beta_2 > 0$ in the case of credit scores (and $\beta_1 > 0$ and $\beta_2 < 0$ in case of DTIs).

The lending industry agents, on the other hand, argue that imperfect information has the opposite effect. It leads to credit scores and DTIs overestimating creditworthiness and underestimating future consumer default rates, particularly for riskier borrowers. In this case, we would expect $\beta_1 > 0$ and $\beta_2 < 0$ in the case of credit scores (and $\beta_1 < 0$ and $\beta_2 > 0$ in case of DTIs).

Figure 1 illustrates our results graphically by plotting the unconditional consumer default rates by credit score deciles, DTI deciles, and healthcare cost quartiles captured by $Post\text{-}Discharge\ MSPB\ Costs_{CBSA,t}$ measure. Panels A and B plot the default rates, while Panels C and D offer the difference in default rates across consumers residing in top quartile healthcare cost CBSAs and bottom quartile healthcare cost CBSAs conditional on their credit score (DTI) decile.

Panels A and B of Figure 1 show that a representative ZIP-code level consumer is 16.4% more likely to default if they reside in high versus low healthcare costs CBSAs. Lowest credit score decile consumers experience a 9.95% default rate in bottom HCC quartile CBSAs and

11.58% in top HCC quartile CBSAs resulting in a 1.6% default differential. The effect monotonically declines with credit scores reaching 0.19% default rate differential for top credit score decile consumers. Similar effects are observable for DTIs (Panels C and D of Figure 1). The default rate differential across the top and bottom HCC quartile CBSAs is 0.7% for the bottom DTI decile but increases to 2.77% for the top DTI decile. These findings support the lending industry's argument that credit scores and DTIs—constructed based on imperfect medical liabilities data—underestimate the default risk, on average.

Default Regression Analysis

We confirm these findings using the regression analysis following equation (3). Regression setting allows to eliminate various alternative explanations for our results via a wide set of control variables. First, we control for a wide set of ZIP-code representative consumer financial characteristics that capture access to credit markets and default likelihood. The set of controls includes the credit score, debt-to-income ratio, the natural logarithm of income, the natural logarithm of the age of the oldest credit account (a proxy for consumer's age), the proportion of consumers with collections, and the ratio of total collections to total debt balance. These variables are aggregated across all individuals assigned to a given ZIP-code.

Second, we include an extensive set of control variables that capture local economic conditions. To account for differences across localities due to wage and employment differences, rely on the (natural logarithm) of total local employment and average wage. To account for potential differences in the local economic growth option, we include employment and wage growth, as well as control for the local industry composition via digit NAICS industry labor shares. Further, to account for the exposure of consumers to workplace-provided health insurance, we

include the proportion of employment in businesses with less than 50 employees, which are least likely to provide health insurance to their workers.

Finally, time fixed effects (γ_t) control for macroeconomic conditions such as overall consumer credit conditions, business cycles, and shifts in Medicare policies and reimbursement rates. To ensure that some unobserved CBSA-specific heterogeneity drives our results, in a subset of tests we include CBSA fixed effects (μ_{CBSA}).

Table 3 presents the results based on the credit scores as a measure of consumer creditworthiness. Panels A, B, and C rely on each of the healthcare costs measures we advance in this paper. The results show that consumers residing in high healthcare costs markets are more likely to default ($\beta_1 > 0$) and this effect is more pronounced for riskier consumers, those with lower credit scores ($\beta_2 < 0$). The effect is economically meaningful. An interquartile increase in healthcare costs is associated with a 0.29% higher default rate for 25th credit score percentile consumers and a 0.069% higher default rate for 75th credit score percentile consumers. For comparison, the sample average default rate is 5.03% (Panel C of Table 1). The slope of the consumer default curve relative to credit scores becomes 3.2% steeper (than an average HCC area) as the local healthcare costs increase.

The economic magnitudes of these effects increase once we expand the potential default window to 12 months (columns (5) to (8) of Table 2). Here the dependent variable is the proportion of ZIP-code consumers with delinquent or derogatory accounts exceeding 5% of their outstanding balance in the next twelve months.

Our findings remain robust when substituting *MSPB Costs* with *Post-Discharge MSPB Costs* (Panel B) or *Post- to Pre-Discharge MSPB Costs* (Panel C). The magnitudes of the

coefficients also do not significantly change once we saturate the model with CBSA fixed effects, indicating that our findings are robust to controlling for unobserved CBSA-specific factors.

Table 4 presents similar results based on DTIs. As in Table 3, each panel focuses on one of the three healthcare cost variables, columns (1) through (4) exploring the 6-month default rates, and columns (5) through (8) exploring the 12-month default rates.

The results presented in Table 4 uniformly illustrate that high DTI consumers residing in high healthcare costs markets are more likely to default than similar consumers residing in low healthcare costs markets ($\beta_2 > 0$). The effects are economically significant. An interquartile increase in healthcare costs is associated with a 0.21% higher default rate for 75th DTI percentile consumers and a 0.14% higher default rate for 25th DTI percentile consumers. For comparison, the sample average default rate is 5.03% (Panel C of Table 1).

The results documented in Tables 3 and 4 are consistent with the notion that as healthcare costs rise, the credit scores (DTIs) that rely on imperfect medical information become, on average, more upward (downward) biased, underestimating consumer defaults and overestimating their creditworthiness.

2022 Medical Liabilities Reporting Policy Shift

While the core regression results are largely consistent with the argument that information frictions undermine the accuracy of the traditional creditworthiness measures to overestimate borrowers' creditworthiness, they might be subject to alternative interpretations. High healthcare costs might affect consumer default rates, conditional on available credit file information, via the cash flow channel rather than the information friction channel. Consumers residing on high healthcare costs markets are more likely to incur future higher medical bills, which should lead

them to borrow more and/or hamper their ability to repay existing debt in the future, thus making current creditworthiness measures less accurate in predicting future defaults.

To further isolate the information frictions channel, we employ the 2022 policy shift that eliminated about 70% of the medical debt and medical collection accounts from consumer credit files. This quasi-natural experiment offers a great setting to confirm the role of the information frictions as the shift led to credit bureaus ignoring part of the medical liabilities in the creditworthiness assessment, but it did not eliminate these liabilities from consumer balance sheets. Figure 6 illustrates that the policy shift is well captured in our data. The plot shows the total amount of medical collections in our sample dropping precipitously starting from the first half of 2022, providing a clear indication of the reform's impact.

To confirm the information friction channel, we modify our regression equation (3) to:

$$Default_{ZIP,t+1} = +\beta_0 Credit\ Score_{ZIP,t} + \boldsymbol{\beta_1} HCC_{CBSA,t} + \boldsymbol{\beta_{1,Post'22}} HCC_{CBSA,t} \times D_{Post\ 2022}$$
$$+\boldsymbol{\beta_2}\ Credit\ Score_{ZIP,t} \times HCC_{CBSA,t} + \boldsymbol{+\beta_{2,Post'22}} Credit\ Score_{ZIP,t} \times HCC_{CBSA,t} \times D_{Post\ 2022}$$
$$+Controls + \gamma_t + \mu_{CBSA} + \varepsilon_{ZIP,t+1}. \quad (4)$$

Equation (4) introduces two additional interaction terms: $HCC_{CBSA,t} \times D_{Post\ 2022}$ and $Credit\ Score_{ZIP,t} \times HCC_{CBSA,t} \times D_{Post\ 2022}$. These interaction terms allow us to detect whether the change in treatment of medical liabilities information has any impact on the reliability of credit scores (or DTI) in predicting consumer default. In this analysis, we focus on the subsample spanning 2021 and 2023 and exclude observations for March 2021 to remove potential anticipation effects that might confound our analysis.

Table 5 reports the results based on credit scores. Panels A, B, and C report findings using *MSPB Costs*, *Post-Discharge MSPB Costs*, and *Post- to Pre-Discharge MSPB Costs*, respectively. Across all panels, we observe that the policy shock amplified the upward bias of the

credit scores leading them to underestimate the default rates, particularly so for higher risk borrowers. The reform amplified the economic magnitudes of the main coefficients of interest. In Panel A, the baseline estimates of 0.279 for β_1 and -0.038 for β_2, closely align with those reported in Table 3 (Column (2) of Panel A). After the reform, the magnitudes increase to 0.392 (0.308 + 0.084) for β_1 and -0.049 (-0.038 - 0.011) for β_2, reflecting a 27.3% to 28.9% rise in magnitude correspondingly. Our findings are robust to the inclusion of CBSA fixed effects.

Table 6 presents similar results based on DTIs. Once again, we find that the core coefficients of interest are amplified post 2022 shift. For instance, in Panel A, the baseline estimates are 0.209 for β_2, closely aligning with those in Table 3 (in Column (2) of Panel A). After the reform, the effects increase to 0.269 (0.209 + 0.060) for β_2, reflecting a 28.7% increase in magnitude. Our findings are robust to the inclusion of the CBSA fixed effects.

These results presented in Tables 5 and 6 are consistent with the notion that the medical debt information frictions affect the ability of the traditional creditworthiness indicators to predict consumer defaults.

IV.2 Healthcare Costs and Access to Credit

A natural question that emerges from our analysis is whether lenders recognize these healthcare costs-related distortions in creditworthiness assessments and adjust their lending decisions accordingly. The lending industry advocates argue that lenders armed with potentially upward biased credit scores (and downward biased DTIs) oversupply credit. However, if lenders are aware of these distortions in credit assessment, they are likely to restrict consumers' access to credit indiscriminately, i.e., irrespective of perceived medical liabilities.

In this section, we analyze the impact of healthcare costs on consumer access to mortgage credit using HMDA data from 2018 to 2023.[11] To capture the credit supply decision we focus on mortgage acceptance rates rather than consumer leverage or loan amounts. Consumers facing high healthcare costs may seek additional debt to cover medical expenses (KFF, 2024) or postpone repayment of existing obligations. By examining mortgage acceptance rates, we can isolate the credit supply effects by comparing lender-year-loan type decisions across markets with varying healthcare costs, while controlling for requested loan amounts and other consumer financial characteristics.

We aggregate HMDA data to ZIP-code-lender-loan type-year level observations that allow us to capture lenders credit supply decision at a granular level. We map this loan applicant data to available measures of CBSA healthcare costs, CBSA economic conditions, and ZIP-code consumer financial characteristics.

Mortgage Acceptance Rate Regression Analysis

First we evaluate whether healthcare costs affect lenders willingness to supply credit using the following regression specification:

$$Approval\ Rate_{ZIP,lender,loan\ type,t} = \\ = \boldsymbol{\beta_1} HCC_{CBSA,t} + \boldsymbol{\beta_2} HCC_{CBSA,t} \times Creditworthiness_{ZIP,t} + \\ + Controls + \gamma_{lender \times loan\ type \times t} + \mu_{CBSA} + \varepsilon_{ZIP,lender,loan\ type,t}. \quad (5)$$

The dependent variable, $Approval\ Rate_{ZIP,lender,loan\ type,t}$, is the average acceptance rate of a mortgage application in a given ZIP-code by a specific lender within different loan types.

[11] We exclude 2017 because HMDA provides the debt-to-income ratio (DTI) of mortgage applicants starting from 2018.

The loan type is defined by two characteristics: (a) the conforming loan indicator (conforming vs non-conforming, i.e., jumbo) and (b) loan purpose (new loan vs. refinancing) leading to four loan types considered. $\gamma_{lender \times loan\ type \times t}$ fixe effects allow us to capture and rely on the variation in mortgage approval rates across U.S. ZIP-code but within the same lender, year and loan type. The set of control includes CBSA-level economic characteristics, ZIP-code consumer financials from the credit bureau data, as well as mortgage application characteristics supplied by HMDA: the natural logarithm of: the average loan amount, maturity, log applicant income, the share of minority applicants, average DTI, and loan-to-value ratio.

Ideally, we would like to utilize in our analysis both traditional measures of mortgage applicants' creditworthiness – credit scores and DTIs. Yet HMDA data only provides us with the mortgage applicants' DTIs but not their credit scores. Consistently we supplement HMDA data with average ZIP-code-year-level average credit scores supplied by the credit bureau data.

Figure 2 illustrates our results graphically. It plots the unconditional mortgage approval rates differential across applicants residing in top health-care cost quartile CBSAs and those residing in bottom healthcare costs quartile CBSAs. Panel A (B) plots these differentials by credit score (DTI) deciles. Healthcare cost heterogeneity is captured by $Post\text{-}Discharge\ MSPB\ Costs_{CBSA,t}$ though the graphs look qualitatively and quantitatively similar if we utilize other available healthcare costs measures.

Panel A of Figure 2 shows that lenders are about 3.47% more likely to reject mortgage applications from bottom credit score decile ZIP codes if they reside in the top healthcare cost quartile CBSAs compared to the bottom healthcare costs quartile CBSAs. Thes approval rate differential increases in magnitude to 1.96% higher rejection rates for applicants in the top credit score decile. Panel B shows similar result based on DTI deciles. The rejection rate differential

between the highest healthcare costs CBSAs and the lowest healthcare costs CBSAs is 2.40% in the top DTI decile, and declines monotonically to 1.54% for the bottom DTI deciles. For comparison, the average rejection rate in our sample is 18.77%. These graphs suggest that lenders are aware of the healthcare costs related distortions in the creditworthiness measures.

We confirm these results us the regression analysis where we control for a wide array of local economic fundamentals. Table 7 reports the results for the average ZIP-code credit score supplied by the credit bureau data, while Table 8 reports the results based on mortgage applicants' DTIs supplied by HMDA. [12] Column (8) of Table 7 suggests that a one percentage point increase in healthcare costs is associated with 0.35 percentage points increase in the mortgage rejection rates. This effect is stronger for riskier borrowers – for every 100 points decline in credit scores and rejection rate increases by 5.1 basis points. One can look at the results differently and state that healthcare costs amplify the association between mortgage approval rates and credit scores (coefficient of 0.051). The results are robust to the inclusion of lender-year-loan type fixed effects and CBSA fixed effects, indicating that they are not driven by unobserved heterogeneity across lenders, loan types, or geographic areas.

Table 8 offers similar findings but now around the DTIs. We find that the negative relationship between DTIs and the mortgage acceptance rates is more pronounced in high healthcare costs areas. Fully saturated specification reported in column (8) suggests that for mortgage applicants at the 75th percentile of the DTI distribution face 0.67 percentage point higher rejection rate if they reside in the top quartile healthcare cost CBSAs as compared to those residing in the bottom healthcare cost quartile CBSAs. This approval rate differential becomes

[12] We report the results for the Post- to Pre-Discharge MSPB Costs measure, though the results are qualitatively and quantitatively similar if we employ other measures.

economically negligible for applicants with DTI at or below 25th percentile. Overall, our findings are consistent with the notion that lenders are aware of the healthcare cost related distortions in creditworthiness indicators.

2022 Medical Liabilities Reporting Policy Shift

Again, one can argue that the loam approval results might be due to the cash flow channel rather than the information collection frictions channel. To isolate the role of the information frictions. we extend our investigation and evaluate the role of the 2022 medical collection reporting reform (Section 5.2) on mortgage approval rates. If lenders' differential treatment across areas with varying healthcare costs is primarily driven by information frictions, then the higher degree of medical debt-related information opacity introduced by the reporting reform should intensify lenders' reactions documented in Tables 7 and 8. To test this, we introduce two interaction terms to Equation (5):

$$Approval\ Rate_{ZIP,lender,loan\ type,t} = \boldsymbol{\beta_1} HCC_{CBSA,t} + \boldsymbol{\beta_{1,Post'22}}\ Credit\ Score_{ZIP,t} \times D_{Post\ 2022}$$
$$+\boldsymbol{\beta_2}\ Credit\ Score_{ZIP,t} \times HCC_{CBSA,t} + \boldsymbol{\beta_{2,Post'22}} Credit\ Score_{ZIP,t} \times HCC_{CBSA,t} \times D_{Post\ 2022}$$
$$+ Controls + \gamma_t + \mu_{CBSA} + \varepsilon_{ZIP,lender,loan\ type,t}. \quad (6)$$

The results of this analysis are presented in Table 9. We find that the effect of the healthcare costs on the mortgage approval decisions are amplified post 2022 when an individual applicant's healthcare cost information is less likely to be captured by the credit bureau files. Panel A reports the results for credit scores. The core coefficients of interest increase in magnitude post 2022 shock. The baseline estimate of β_1 (-0.225) increases to 0.398 (-0.225 - 0.173) or 75.9% increase in magnitude. The baseline estimate of β_2 (0.029)increases to 0.051 (0.029 + 0.022) or 76.9% increases in magnitude. Panel B of Table 9 reports the results for DTIs. Like in case of the credit

scores, we find that the effect of healthcare costs on lenders mortgage approval decision intensifies after the reporting reform. The core coefficients of interest increase in magnitudes by about 60%.

Overall, the results presented in this section suggests that lenders are aware about the medical liabilities information collection frictions. Knowing that the medical liabilities data in credit bureau files is incomplete or even erroneous, lenders are restricting consumers' access to (mortgage) credit by rejecting more local applications (all else equal) in higher healthcare cost markets. Notably, without direct access to medical liabilities data, lenders are likely to limit credit supply indiscriminately to both consumers with and without medical liabilities. As such the medical liabilities information collection frictions are likely to contribute to less efficient allocation of consumer credit.

V. Conclusion

This paper underscores the significant impact of healthcare costs on the reliability of traditional creditworthiness indicators and consumer access to credit. We document that consumers in high-healthcare-cost markets are more likely to default than their counterparts in low-cost markets, even when controlling for credit scores and debt-to-income ratios. This suggests that unaccounted medical liabilities weaken the predictive power of these key credit metrics, leading to distortions in credit risk assessments.

The 2022 policy shift, which removed certain medical debt records from credit files, exacerbated these distortions. This policy change increased information asymmetries in credit markets by inflating credit scores and deflating DTIs without addressing underlying medical liabilities. Our analysis shows that lenders responded by tightening credit access, particularly in high-healthcare-cost areas, disproportionately affecting riskier borrowers. This suggests that, rather than being unaware of medical debt risks, lenders actively adjust their credit allocation

strategies to account for missing information, potentially leading to inefficient credit supply constraints.

Our findings contribute to ongoing policy debates regarding the role of medical debt in credit reporting. While removing medical debt from credit files was intended to protect consumers, it appears to have had unintended consequences, reducing credit access for borrowers in high-cost healthcare markets. Our results highlight the trade-offs involved in such policy decisions and suggest that improving the accuracy and completeness of medical debt reporting—rather than eliminating it entirely—may better balance consumer protection with credit market efficiency.

More broadly, our study contributes to the literature on the intersection of healthcare costs and consumer finance. While prior research has documented the role of medical debt in financial distress, we provide new evidence that healthcare cost heterogeneity systematically distorts credit risk assessments and lending decisions. These insights have important implications for policymakers, credit bureaus, and lenders, underscoring the need for a more nuanced approach to integrating medical debt information into credit evaluations. Future research should explore alternative mechanisms for incorporating healthcare-related financial risks into credit models without unduly penalizing consumers or distorting credit allocation.

References

Adelino, Manuel, Katharina Lewellen, and W. Ben McCartney, "Hospital Financial Health and Clinical Choices: Evidence from the Financial Crisis," *Management Science*, 68 (2022), 2098–2119.

Aghamolla, Cyrus, Jash Jain, and Richard T. Thakor, "When Private Equity Comes to Town: The Local Economic Consequences of Rising Healthcare Costs," *SSRN Electronic Journal*, (2023).

Anderson, Michael, Carlos Dobkin, and Tal Gross, "The Effect of Health Insurance Coverage on the Use of Medical Services," *American Economic Journal: Economic Policy*, 4 (2012), 1–27.

Arnold, Daniel, and Christopher Whaley, "Who Pays for Health Care Costs? The Effects of Health Care Prices on Wages," SSRN Scholarly Paper, 2020 (Rochester, NY, Social Science Research Network).

Batty, Michael, Christa Gibbs, and Benedic Ippolito, "Unlike Medical Spending, Medical Bills In Collections Decrease With Patients' Age," *Health Affairs*, 37 (2018), 1257–1264.

——, "Health insurance, medical debt, and financial well-being," *Health Economics*, 31 (2022), 689–728.

Blavin, Fredric, Breno Braga, and Michael Karpman, "Medical Debt Was Erased from Credit Records for Most Consumers, Potentially Improving Many Americans' Lives," *Urban Institute*, (2023).

Brevoort, Kenneth, Daniel Grodzicki, and Martin B. Hackmann, "The credit consequences of unpaid medical bills," *Journal of Public Economics*, 187 (2020) (Elsevier).

Brot-Goldberg, Zarek, Zack Cooper, Stuart V Craig, Lev R Klarnet, Ithai Lurie, and Corbin L Miller, "WHO PAYS FOR RISING HEALTH CARE PRICES? EVIDENCE FROM HOSPITAL MERGERS," *NBER Working Paper*, (2024).

Caswell, Kyle J., and John H. Goddeeris, "Does Medicare Reduce Medical Debt?," *American Journal of Health Economics*, 6 (2020).

CFPB, "Consumer credit reports: A study of medical and non-medical collections," *Consumer Financial Protection Bureau*, (2014).

——, "CFPB Finalizes Rule to Remove Medical Bills from Credit Reports," *Consumer Financial Protection Bureau*, (2025).

Clemens, Jeffrey, and Joshua D. Gottlieb, "Do Physicians' Financial Incentives Affect Medical Treatment and Patient Health?," *American Economic Review*, 104 (2014), 1320–1349.

——, "In the Shadow of a Giant: Medicare's Influence on Private Physician Payments," *Journal of Political Economy*, 125 (2017), 1–39 (The University of Chicago Press).

Cooper, Zack, Stuart Craig, Martin Gaynor, Nir J. Harish, Harlan M. Krumholz, and John Van Reenen, "Hospital Prices Grew Substantially Faster Than Physician Prices For Hospital-Based Care In 2007–14," *Health Affairs*, 38 (2019), 184–189 (Health Affairs).

CR, "What Medical Debt Does to Your Credit Score," 2018 (Consumer Reports).

Currie, Janet, Anastasia Karpova, and Dan Zeltzer, "Do urgent care centers reduce Medicare spending?," *Journal of Health Economics*, 89 (2023), 102753.

Das, Anup, Edward C. Norton, David C. Miller, and Lena M. Chen, "Association of Postdischarge Spending and Performance on New Episode-Based Spending Measure," *JAMA Internal Medicine*, 176 (2016), 117.

Dobbie, Will, Paul Goldsmith-Pinkham, Neale Mahoney, and Jae Song, "Bad Credit, No Problem? Credit and Labor Market Consequences of Bad Credit Reports," *The Journal of Finance*, 75 (2020), 2377–2419.

Dobkin, Carlos, Amy Finkelstein, Raymond Kluender, and Matthew J. Notowidigdo, "The Economic Consequences of Hospital Admissions," *American Economic Review*, 108 (2018), 308–352.

Dranove, David, Craig Garthwaite, and Christopher Ody, "How do nonprofits respond to negative wealth shocks? The impact of the 2008 stock market collapse on hospitals," *The RAND Journal of Economics*, 48 (2017), 485–525.

Engelhardt, Gary V, and Jonathan Gruber, "Medicare Part D and the Financial Protection of the Elderly," *American Economic Journal: Economic Policy*, 3 (2011), 77–102.

Finkelstein, Amy, Matthew Gentzkow, and Heidi Williams, "Sources of Geographic Variation in Health Care: Evidence From PatientMigration*," *The Quarterly Journal of Economics*, 131 (2016), 1681–1726.

Gao, Janet, Shan Ge, Lawrence D W Schmidt, and Cristina Tello-Trillo, "How Do Health Insurance Costs Affect Low- and High-Income Workers?," *Available at SSRN*, (2022).

Goldsmith-Pinkham, Paul, Maxim Pinkovskiy, and Jacob Wallace, "THE GREAT EQUALIZER: MEDICARE AND THE GEOGRAPHY OF CONSUMER FINANCIAL STRAIN," *NBER Working Paper*, (2023).

Griffin, John M., and Dragon Yongjun Tang, "Did Subjectivity Play a Role in CDO Credit Ratings?," *The Journal of Finance*, 67 (2012), 1293–1328.

Gross, Tal, and Matthew J. Notowidigdo, "Health insurance and the consumer bankruptcy decision: Evidence from expansions of Medicaid," *Journal of Public Economics*, 95 (2011), 767–778.

Himmelstein, David U., Deborah Thorne, Elizabeth Warren, and Steffie Woolhandler, "Medical Bankruptcy in the United States, 2007: Results of a National Study," *The American Journal of Medicine*, 122 (2009), 741–746.

KFF, "The burden of medical debt in the United States," *Peterson-KFF Health System Tracker*, (2024).

Kluender, Raymond, Neale Mahoney, Francis Wong, and Wesley Yin, "Medical Debt in the US, 2009-2020," *JAMA*, 326 (2021), 250.

——, "THE EFFECTS OF MEDICAL DEBT RELIEF: EVIDENCE FROM TWO RANDOMIZED EXPERIMENTS," *The Quarterly Journal of Economics*, (2024).

Mayer, Christopher, "Housing, subprime mortgages, and securitization: how did we go wrong and what can we learn so this doesn't happen again?," 2010 (Testimony before Financial Crisis Inquiry Commission).

Moses, Hamilton, David H. M. Matheson, E. Ray Dorsey, Benjamin P. George, David Sadoff, and Satoshi Yoshimura, "The Anatomy of Health Care in the United States," *JAMA*, 310 (2013), 1947.

Norton, Edward C., Jun Li, Anup Das, and Lena M. Chen, "Moneyball in Medicare," *Journal of Health Economics*, 61 (2018), 259–273.

NPR, "Medical bills can cause a financial crisis. Here's how to negotiate them," 2023 (National Public Radio).

NYT, "Credit Companies Will Remove Stains From Repaid Medical Debts - The New York Times," *The New York Times*, (2022).

Pagano, Marco, and Paolo Volpin, "Credit ratings failures and policy options," *Economic Policy*, (2010).

Rajan, Uday, Amit Seru, and Vikrant Vig, "The failure of models that predict failure: Distance, incentives, and defaults," *Journal of Financial Economics*, 115 (2015), 237–260.

Richman, Barak, Sara Sternberg Greene, Sean Chen, and Julie Havlak, "Hospitals Suing Patients: How Hospitals Use North Carolina Courts to Collect Medical Debt," *Duke Law School Public Law & Legal Theory Series*, 2023–49 (2023).

Skinner, Jonathan, "Causes and Consequences of Regional Variations in Health Care," in *Handbook of Health Economics* (Elsevier, 2011).

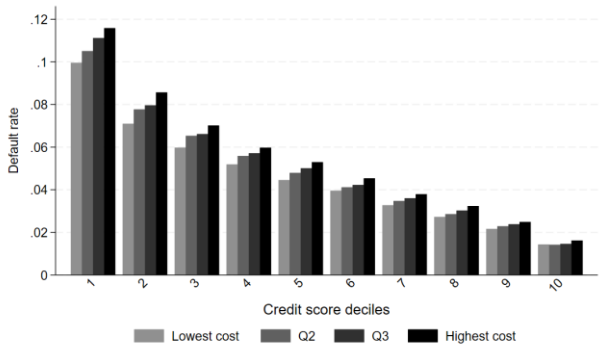
Washington Post, "Biden proposes to ban medical debt from credit reports, loan decisions," *The Washington Post*, (2024a).

——, "The Big Business That Opposes Wiping Medical Debt From Credit Reports," *Washington Post*, (2024b).

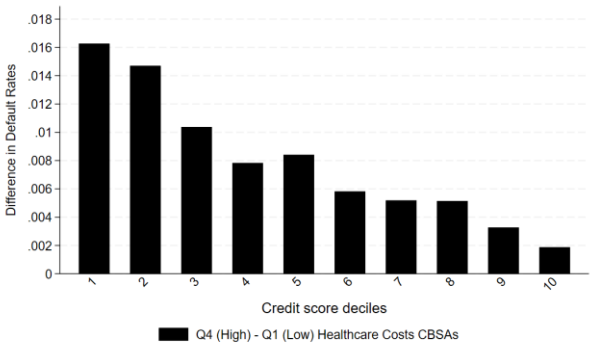
Figure 1
Consumer Default Rates and Healthcare Costs

Panels A and B plot the average consumer default rates across credit score deciles and healthcare cost quartiles. Healthcare costs are measured as the average post-discharge Medicare Spending Per Beneficiary (MSPB), scaled by the national average from Equation (1b). Default rates represent the share of consumers with more than 5% of their outstanding debt balances classified as delinquent or in a derogatory condition. Panel A (C) plots the average consumer default rates by credit score (DTI) deciles and healthcare costs quartiles. Panel B (D) shows the difference in default rates between the highest and lowest healthcare cost quartiles for each credit score (DTI) decile. The analysis utilizes the 2017 – 2023 5% consumer credit panel from one of the top credit bureaus.

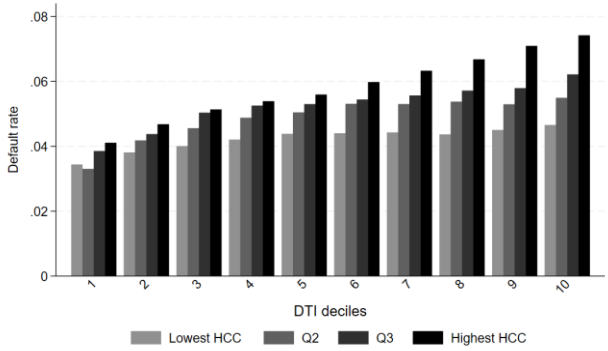
Panel A: Default Rates across Credit Score Deciles



Panel B: Differences in Default Rates across Credit Score Deciles



Panel C: Default Rates across DTI Deciles



Panel D: Differences in Default Rates across DTI Deciles

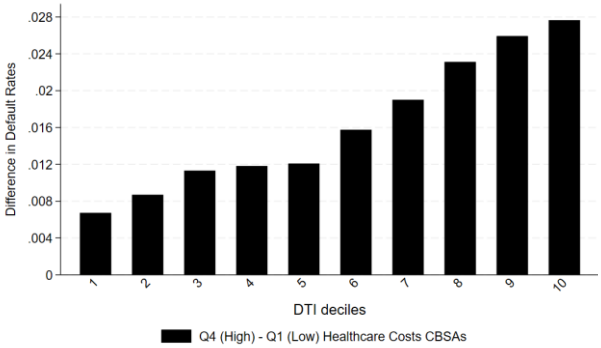
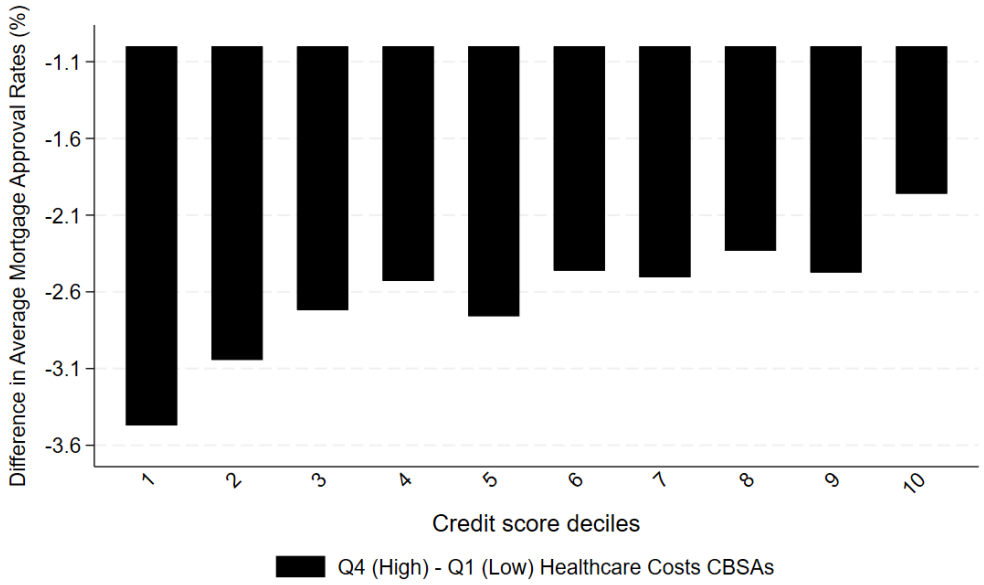


Figure 2
Mortgage Approval Rate Differences by Healthcare Costs

Panels A and B show the differences in mortgage approval rates of new loans between the highest and lowest healthcare cost quartiles across credit scores and debt-to-income (DTI) ratios. Healthcare costs are measured as the average post-discharge Medicare Spending Per Beneficiary (MSPB), scaled by the national average from Equation (1b). Panel A presents the approval rate differences by credit score, while Panel B reports the differences by DTI ratio. The analysis utilizes the 2018 – 2023 Home Mortgage Disclosure Act (HMDA) data and 5% consumer credit panel from one of the top credit bureaus.

Panel A: By Credit Score Deciles



Panel B: By Debt-to-Income Ratio Deciles

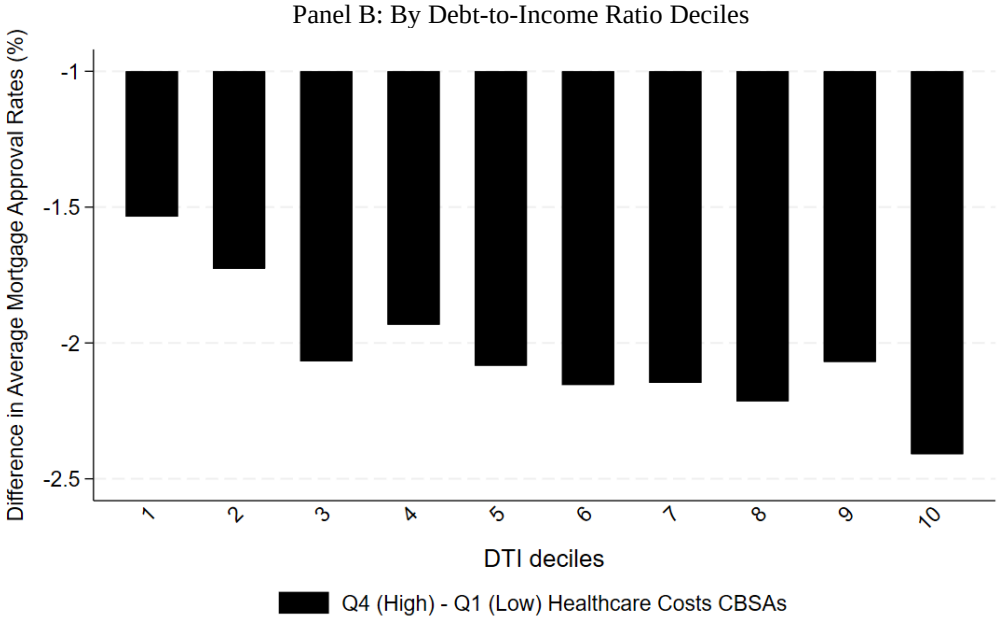
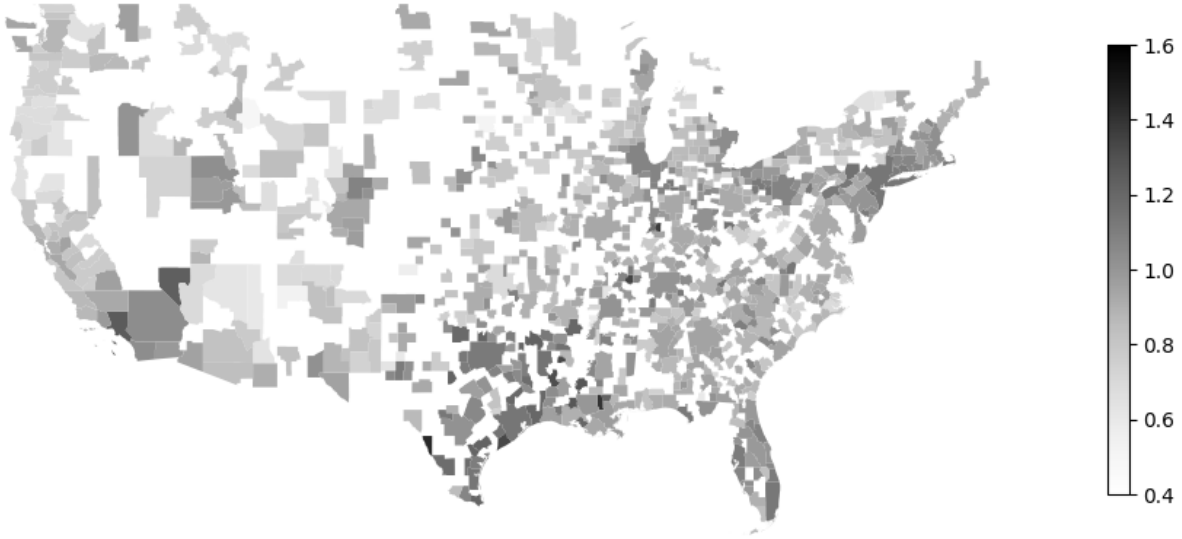


Figure 3
Heatmaps: Medicare Spending Per Beneficiary

Panels A and B show the geographic variation in healthcare costs across CBSAs. Healthcare costs are measured as the average post-discharge Medicare Spending Per Beneficiary (MSPB), scaled by the national average from Equation (1b). Panel A presents the variation for 2017, while Panel B shows the variation for 2023.

Panel A: MSPB healthcare costs heatmap at the start of the sample period, 2017



Panel B: MSPB healthcare costs heatmap at the end of the sample period, 2023

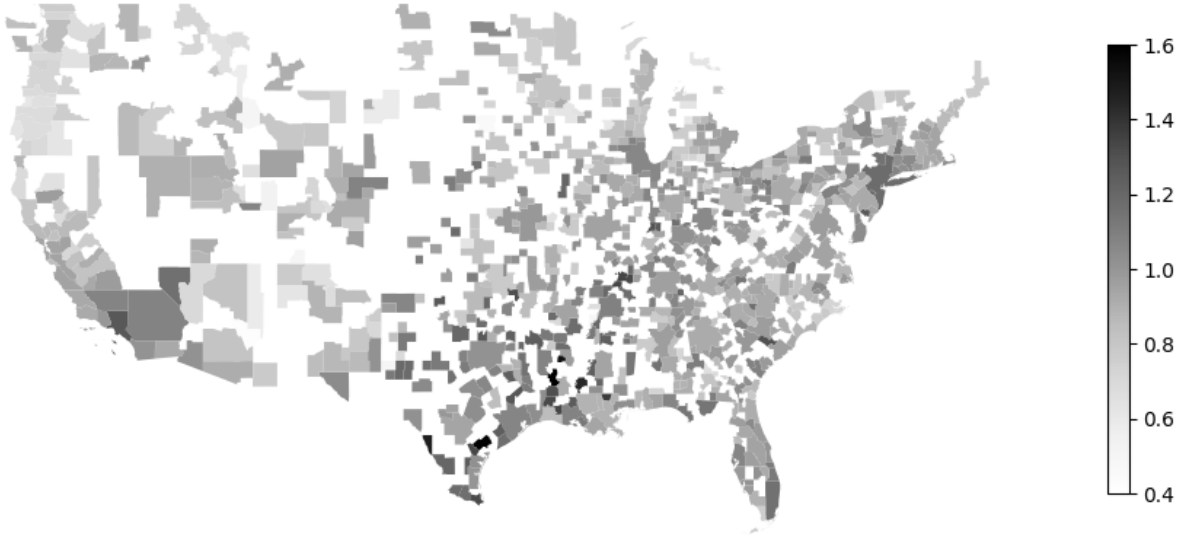
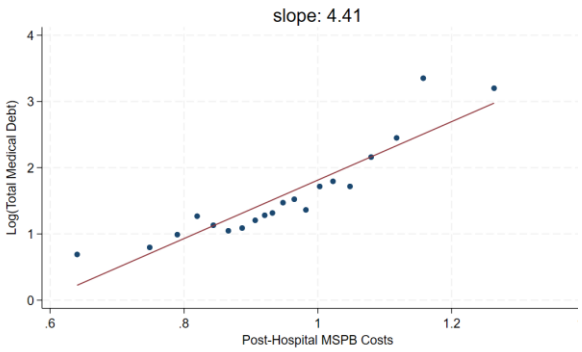


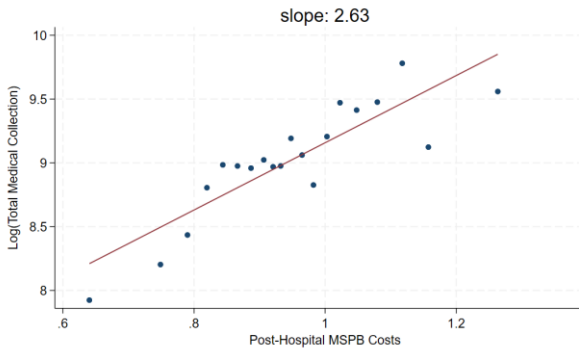
Figure 4
Validation of Medicare-Spending-per-Beneficiary Based Healthcare Costs Measures

Panels A, B, C and D present binned scatter plots examining the relationship between our healthcare cost measure and medical debt/collections. Healthcare costs are measured as the average post-discharge Medicare Spending Per Beneficiary (MSPB), scaled by the national average from Equation (1b). Panels A and B plot healthcare costs against the natural logarithm of total medical debt and the natural logarithm of total medical collection, respectively. Panels C and D plot healthcare costs against the natural logarithm of average medical debt and the natural logarithm of average medical collection, respectively.

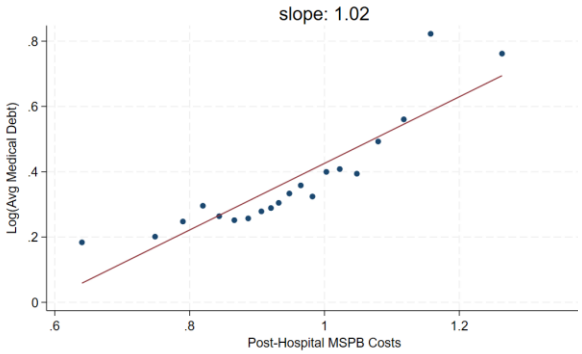
Panel A: Healthcare Costs and Total Medical Debt



Panel B: Healthcare Costs and Total Medical Collection



Panel C: Healthcare Costs and Average Medical Debt



Panel D: Healthcare Costs and Average Medical Collection

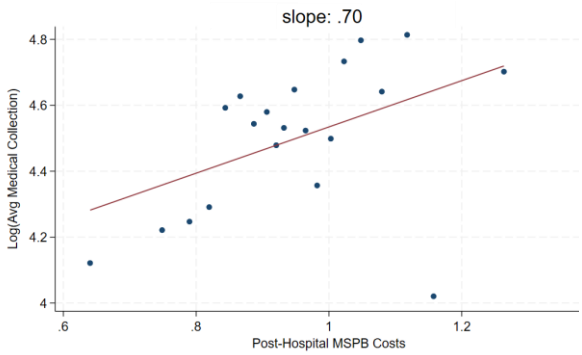
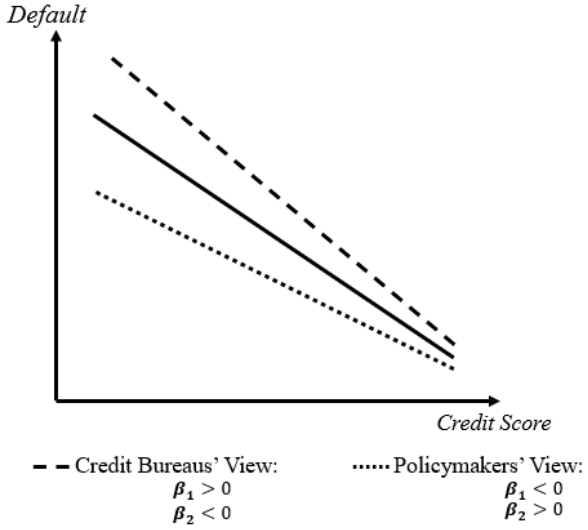


Figure 5
Empirical Design and Predictions

Panels A and B present predictions from our empirical design using the OLS regression specification below. Panel A uses credit score as the measure of creditworthiness, while Panel B uses the debt-to-income ratio. In both panels, solid lines represent the default-creditworthiness relationship under full information, while dashed and dotted lines reflect the perspectives of credit bureaus and policymakers, respectively.

$$Default_{ZIP,t+1} = \boldsymbol{\beta_1} HCC_{CBSA,t} + \boldsymbol{\beta_2}\, Creditworthiness_{ZIP,t} \times HCC_{CBSA,t} + \boldsymbol{\beta_0}\, Creditworthiness_{ZIP,t} + CONTROLS + \gamma_t + \mu_{CBSA} + \varepsilon_{ZIP,t+1}$$

Panel A. Credit Score



Panel B. Debt-to-Income Ratio

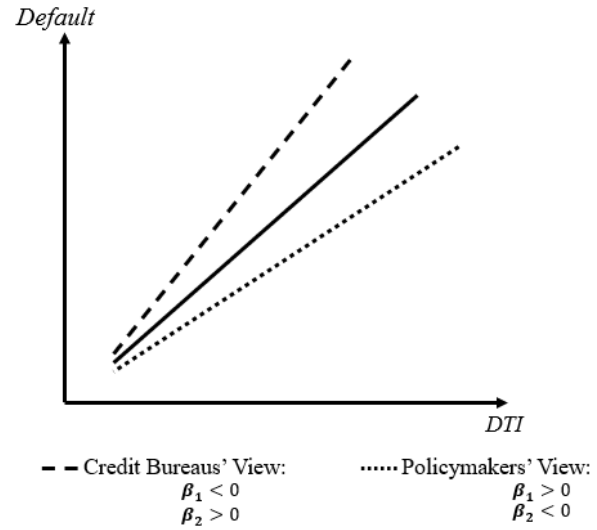


Figure 6
Total Medical Debt Collection Balances

This figure plots total medical debt collection balances (in billions of dollars) for a 5% random sample from one of the major credit bureaus consumer credit files, recorded in March and September of each year from 2017 to 2023.

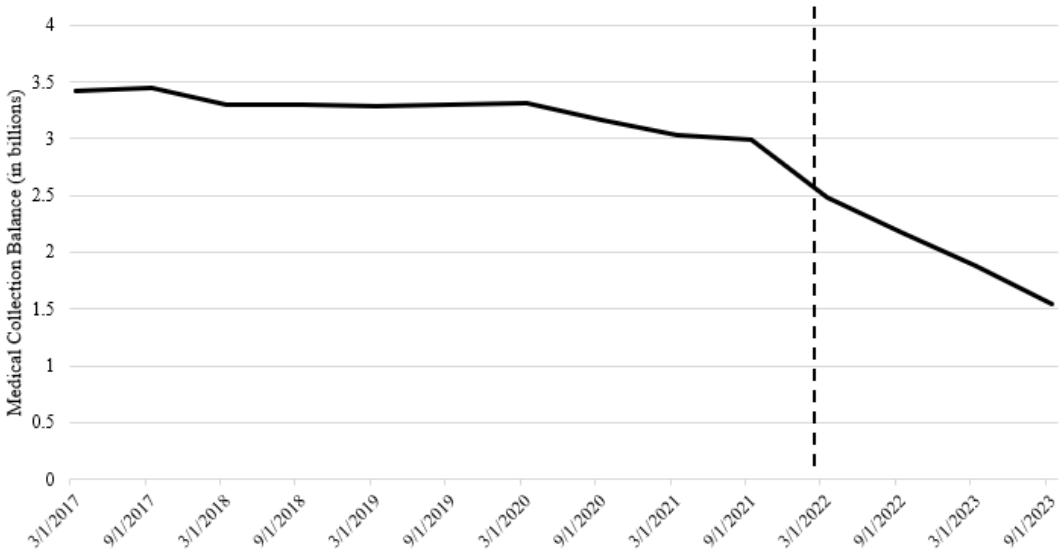


Table 1
Summary Statistics

The table presents summary statistics for our baseline sample. All shares and ratios are in decimals unless specified in parentheses. Panel A reports statistics on healthcare cost measures. Panel B covers medical debt and collections. Panel C summarizes consumer financial health variables. Panel D details consumer financial characteristics. Panel E presents local economic fundamentals.

	# Observ.	Mean	St.Dev	P25	P50	P75
Panel A: Healthcare Costs Measures (avg per beneficiary per episode at CBSA-year-level)						
Medicare Spending ($)	345,696	20,337	2,262	19,029	20,335	21,789
MSPB Costs	345,696	0.94	0.09	0.89	0.95	1.00
Post-Hospital Medicare Spending ($)	345,696	8,527	1,360	7,676	8,471	9,357
Post-Hospital MSPB Costs	345,696	0.95	0.14	0.86	0.94	1.03
Post- to Pre-Discharge MSPB Costs	345,696	1.03	0.20	0.90	1.02	1.16
Panel B: Medical Debt and Related Collections (ZIP-code-semiannual level)						
Share of consumers with medical debt (%)	345,696	0.07	0.51	0	0	0
Average(medical debt) ($)	345,696	2.53	23.04	0	0	0
Average(medical debt / total debt) (%)	345,696	0.01%	0.27%	0.00%	0.00%	0.00%
Share of consumers with medical collection accounts	345,696	0.13	0.11	0.05	0.11	0.18
Average(medical collections) ($)	345,696	275	613	42	144	337
Average(medical collections / total debt)	345,696	0.01	0.03	0.001	0.002	0.007
Average(medical collections / total collections)	345,696	0.39	0.27	0.17	0.37	0.57
Panel C: Consumer Default Rates (ZIP-code-semiannual level)						
% Delinquency or default in the next 6 month	345,696	5.03%	5.59%	1.58%	3.99%	6.98%
% Delinquency or default in the next 12 month	293,364	7.54%	6.74%	3.23%	6.38%	10.39%
Panel D: Consumer Financial Characteristics (ZIP-code-semiannual level)						
Avg. Credit Score	345,696	702.5	40.1	677.9	705.7	730.9
Avg. Debt-to-Income Ratio	345,696	0.12	0.03	0.10	0.12	0.13
ln (Avg. Income)	345,696	4.46	0.30	4.27	4.44	4.63
Avg.oldest account age (years)	345,696	17.85	4.00	15.57	17.90	20.11
ln (Avg. total debt balance)	345,696	10.84	0.89	10.50	10.93	11.36
ln (Avg. nonmedical collections balance)	345,696	4.99	1.78	4.72	5.47	6.02
Share of consumers with accounts in nonmedical collections	345,696	0.14	0.11	0.07	0.13	0.20
Panel E: Local Economic Fundamentals (CBSA-semiannual level)						
ln(Total local employment)	345,696	14.09	2.46	12.75	14.40	16.04
ln(Average local wages)	345,696	6.33	0.49	5.94	6.44	6.73
Δ ln (Total local employment)	345,696	0.38	4.30	-1.76	0.52	2.65
Δ ln (Average local wages)	345,696	2.75	7.77	-2.03	2.27	7.28

Table 2
Healthcare Cost Measures: Validation

The table presents validation tests on the relationship between healthcare cost variables and medical debt and related collections. Panels A, B, and C present results using *MSPB Costs*, *Post-Discharge MSPB Costs*, and *Post- to Pre-Discharge MSPB Costs* as measures of healthcare costs, respectively. Column (1) uses the percentage of consumers with medical debt as the dependent variable. Columns (2) and (3) use the natural logarithm of average and total medical debt (plus one), respectively. Column (4) uses the percentage of consumers with medical collections. Columns (5) and (6) use the natural logarithm of average and total medical collections (plus one), respectively. Other borrower financial information (at the ZIP-code level) includes the average debt-to-income ratio, natural logarithm of average income, natural logarithm of the oldest account, proportion of consumers with collections, and the ratio of total collections to total debt balance. Local economy controls (at the CBSA-level) include wage, employment, wage growth, employment growth, and the fraction of employment in the set of two-digit NAICS industries. Standard errors are clustered at the CBSA level. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable (zip,t)	% consumers with medical debt **x 100** *(1)*	Log (avg med debt +1) *(2)*	Log (total med debt + 1) *(3)*	% consumers with med collections *(4)*	Log (avg med collections + 1) *(5)*	Log (total med collections + 1) *(6)*
Panel A: Normalized avg Medicare spending						
MSPB Costs$_{(CBSA,\ t)}$	0.084***	0.430***	1.755***	0.061***	1.085***	1.155**
	(2.66)	(3.69)	(3.91)	(2.94)	(2.96)	(2.21)
Other borrower financials $_{(ZIP,\ t)}$	Y	Y	Y	Y	Y	Y
Local economy controls $_{(CBSA,\ t)}$	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Observations	345,279	345,279	345,279	345,279	345,279	345,279
R-squared	0.01	0.08	0.12	0.42	0.23	0.15
Panel B: Norm. post-Discharge Medicare spending						
Post-Discharge MSPB Costs$_{(CBSA,\ t)}$	0.110***	0.544***	2.108***	0.039***	0.787***	1.410***
	(5.05)	(7.03)	(7.38)	(3.29)	(3.52)	(4.64)
Other borrower financials $_{(ZIP,\ t)}$	Y	Y	Y	Y	Y	Y
Local economy controls $_{(CBSA,\ t)}$	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Observations	345,279	345,279	345,279	345,279	345,279	345,279
R-squared	0.01	0.09	0.12	0.43	0.23	0.15
Panel C: Norm. ratio of post- to pre-Discharge Medicare spending						
Post- to Pre-Discharge MSPB Costs$_{(CBSA,\ t)}$	0.070***	0.351***	1.334***	0.018**	0.380**	0.889***
	(4.62)	(6.50)	(6.72)	(2.24)	(2.35)	(4.02)
Other borrower financials $_{(ZIP,\ t)}$	Y	Y	Y	Y	Y	Y
Local economy controls $_{(CBSA,\ t)}$	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Observations	345,279	345,279	345,279	345,279	345,279	345,279
R-squared	0.01	0.08	0.12	0.42	0.23	0.15

Table 3
Healthcare Costs and Distortions in the Credit Score Reliability

The table presents results on healthcare cost and distortion in the credit score reliability. Panels A, B, and C present results using *MSPB Costs*, *Post-Discharge MSPB Costs*, and *Post- to Pre-Discharge MSPB Costs* as measures of healthcare costs, respectively. Columns (1) to (4) use the proportion of consumers in an area who are delinquent or in default on more than 5% of their total outstanding debt within the next six months as the dependent variable. Columns (5) to (8) use the same measure over the next twelve months. Other borrower financial information (at the ZIP-code level) includes the average debt-to-income ratio, natural logarithm of average income, natural logarithm of the oldest account, proportion of consumers with collections, and the ratio of total collections to total debt balance. Local economy controls (at the CBSA-level) include wage, employment, wage growth, employment growth, and the fraction of employment in the set of two-digit NAICS industries. Standard errors are clustered at the CBSA level. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable (zip,t+1)	*% Delinquency or default in the next 6 month*				*% Delinquency or default in the next 12 month*			
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Panel A: MSPB Costs								
MSPB Costs$_{(CBSA, t)}$	-	0.284***	-	0.291***	-	0.225***	-	0.272***
		(5.05)		(4.11)		(3.00)		(2.94)
Credit Score/100 $_{(ZIP, t)}$ ×	-	-0.038***	-	-0.042***	-	-0.029***	-	-0.039***
MSPB Costs$_{(CBSA, t)}$		(4.92)		(4.16)		(2.78)		(2.96)
Credit Score/100 $_{(ZIP, t)}$	-0.061***	-0.025***	-0.058***	-0.019**	-0.077***	-0.051***	-0.071***	-0.035***
	(32.91)	(3.54)	(30.29)	(2.08)	(33.71)	(5.21)	(31.20)	(2.84)
Other borrower financials $_{(ZIP, t)}$	Y	Y	Y	Y	Y	Y	Y	Y
Local economy controls $_{(CBSA, t)}$	Y	Y	Y	Y	Y	Y	Y	Y
CBSA FEs	-	-	Y	Y	-	-	Y	Y
Time FEs	Y	Y	Y	Y	Y	Y	Y	Y
Observations	345,279	345,279	345,279	345,279	293,364	293,364	293,364	293,364
R-squared	0.29	0.29	0.30	0.30	0.38	0.38	0.4	0.4

Table 3 (Continued)

Panel B: Post-Discharge MSPB Costs								
Post-Discharge MSPB Costs$_{(CBSA,\ t)}$	-	0.255***	-	0.222***	-	0.276***	-	0.257***
		(5.13)		(3.91)		(4.35)		(3.61)
Credit Score/100 $_{(ZIP,\ t)}$ ×	-	-0.034***	-	-0.032***	-	-0.036***	-	-0.036***
Post-Discharge MSPB Costs$_{(CBSA,\ t)}$		(5.04)		(3.91)		(4.12)		(3.56)
Credit Score/100 $_{(ZIP,\ t)}$	-0.061***	-0.029***	-0.058***	-0.029***	-0.077***	-0.044***	-0.071***	-0.038***
	(32.91)	(4.74)	(30.29)	(3.91)	(33.71)	(5.72)	(31.20)	(4.12)
Other borrower financials $_{(ZIP,\ t)}$	Y	Y	Y	Y	Y	Y	Y	Y
Local economy controls $_{(CBSA,\ t)}$	Y	Y	Y	Y	Y	Y	Y	Y
Time FEs	Y	Y	Y	Y	Y	Y	Y	Y
Observations	345,279	345,279	345,279	345,279	293,364	293,364	293,364	293,364
R-squared	0.28	0.28	0.30	0.30	0.37	0.37	0.39	0.39
Panel C: Post- to Pre-Discharge MSPB Costs								
Post- to Pre-Discharge MSPB Costs$_{(CBSA,\ t)}$	-	0.123***		0.101***		0.168***		0.142***
		(4.08)		(2.89)		(4.30)		(3.24)
Credit Score/100 $_{(ZIP,\ t)}$ ×	-	-0.016***		-0.014***		-0.022***		-0.020***
Post- to Pre-Discharge MSPB Costs$_{(CBSA,\ t)}$		(3.94)		(2.86)		(4.04)		(3.13)
Credit Score/100 $_{(ZIP,\ t)}$	-0.061***	-0.044***	-0.058***	-0.044***	-0.077***	-0.054***	-0.071***	-0.051***
	(32.91)	(9.76)	(30.29)	(8.29)	(33.71)	(10.03)	(31.20)	(8.13)
Other borrower financials $_{(ZIP,\ t)}$	Y	Y	Y	Y	Y	Y	Y	Y
Local economy controls $_{(CBSA,\ t)}$	Y	Y	Y	Y	Y	Y	Y	Y
Time FEs	Y	Y	Y	Y	Y	Y	Y	Y
Observations	345,279	345,279	345,279	345,279	293,364	293,364	293,364	293,364
R-squared	0.28	0.28	0.30	0.30	0.37	0.37	0.39	0.39

Table 4
Healthcare Costs and Distortions in the Debt-to-Income Ratio Reliability

The table presents results on healthcare cost and distortion in the debt-to-income ratio reliability. Panels A, B, and C present results using *MSPB Costs*, *Post-Discharge MSPB Costs*, and *Post- to Pre-Discharge MSPB Costs* as measures of healthcare costs, respectively. Columns (1) to (4) use the proportion of consumers in an area who are delinquent or in default on more than 5% of their total outstanding debt within the next six months as the dependent variable. Columns (5) to (8) use the same measure over the next twelve months. Other borrower financial information (at the ZIP-code level) includes the average debt-to-income ratio, natural logarithm of average income, natural logarithm of the oldest account, proportion of consumers with collections, and the ratio of total collections to total debt balance. Local economy controls (at the CBSA-level) include wage, employment, wage growth, employment growth, and the fraction of employment in the set of two-digit NAICS industries. Standard errors are clustered at the CBSA level. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable (zip,t+1)	*% Delinquency or default in next 6 month*				*% Delinquency or default in next 12 month*			
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Panel A: MSPB Costs								
MSPB Costs$_{(CBSA, t)}$	-	-0.006	-	-0.012	-	0.002	-	-0.007
		(0.70)		(1.43)		(0.18)		(0.55)
DTI $_{(ZIP, t)}$ × MSPB Costs$_{(CBSA, t)}$	-	0.191***	-	0.089	-	0.183*	-	0.057
		(2.97)		(1.33)		(1.74)		(0.52)
DTI $_{(ZIP, t)}$	0.039***	-0.140**	0.036***	-0.048	0.061***	-0.111	0.061***	0.008
	(5.56)	(2.32)	(5.04)	(0.76)	(6.66)	(1.11)	(6.57)	(0.08)
Credit Score/100 $_{(ZIP, t)}$	-0.061***	-0.061***	-0.058***	-0.058***	-0.077***	-0.077***	-0.071***	-0.071***
	(32.91)	(33.03)	(30.29)	(30.22)	(33.71)	(33.84)	(31.20)	(31.16)
Other borrower financials $_{(ZIP, t)}$	Y	Y	Y	Y	Y	Y	Y	Y
Local economy controls $_{(CBSA, t)}$	Y	Y	Y	Y	Y	Y	Y	Y
CBSA FEs	-	-	Y	Y	-	-	Y	Y
Time FEs	Y	Y	Y	Y	Y	Y	Y	Y
Observations	345,279	345,279	345,279	345,279	293,364	293,364	293,364	293,364
R-squared	0.28	0.28	0.30	0.30	0.37	0.37	0.39	0.39

Table 4 (Continued)

Panel B: Post-Discharge MSPB Costs								
Post-Discharge MSPB Costs$_{(CBSA, t)}$	-	-0.010*	-	-0.013**	-	-0.001	-	-0.007
		(1.84)		(2.28)		(0.18)		(0.91)
DTI $_{(ZIP, t)}$ ×	-	0.214***	-	0.119***	-	0.234***	-	0.104
Post-Discharge MSPB Costs$_{(CBSA, t)}$		(5.30)		(2.63)		(3.94)		(1.58)
DTI $_{(ZIP, t)}$	0.039***	-0.161***	0.036***	-0.077*	0.061***	-0.155***	0.061***	-0.036
	(5.56)	(4.20)	(5.04)	(1.79)	(6.66)	(2.72)	(6.57)	(0.58)
Credit Score/100 $_{(ZIP, t)}$	-0.061***	-0.060***	-0.058***	-0.058***	-0.077***	-0.076***	-0.071***	-0.071***
	(32.91)	(33.08)	(30.29)	(30.30)	(33.71)	(33.47)	(31.20)	(31.20)
Other borrower financials $_{(ZIP, t)}$	Y	Y	Y	Y	Y	Y	Y	Y
Local economy controls $_{(CBSA, t)}$	Y	Y	Y	Y	Y	Y	Y	Y
CBSA FEs	-	-	Y	Y	-	-	Y	Y
Time FEs	Y	Y	Y	Y	Y	Y	Y	Y
Observations	345,279	345,279	345,279	345,279	293,364	293,364	293,364	293,364
R-squared	0.28	0.28	0.30	0.30	0.37	0.37	0.39	0.39
Panel C: Post- to Pre-Discharge MSPB Costs								
Post- to Pre-Discharge MSPB Costs$_{(CBSA, t)}$	-	-0.004	-	-0.007*	-	0.002	-	-0.002
		(1.09)		(1.70)		(0.34)		(0.29)
DTI $_{(ZIP, t)}$ ×	-	0.115***	-	0.074**	-	0.124***	-	0.066
Post- to Pre-Discharge MSPB Costs$_{(CBSA,}$		(3.76)		(2.32)		(2.99)		(1.51)
DTI $_{(ZIP, t)}$	0.039***	-0.077**	0.036***	-0.039	0.061***	-0.062	0.061***	-0.005
	(5.56)	(2.43)	(5.04)	(1.19)	(6.66)	(1.43)	(6.57)	(0.12)
Credit Score/100 $_{(ZIP, t)}$	-0.061***	-0.060***	-0.058***	-0.058***	-0.077***	-0.076***	-0.071***	-0.071***
	(32.91)	(32.92)	(30.29)	(30.32)	(33.71)	(33.28)	(31.20)	(31.17)
Other borrower financials $_{(ZIP, t)}$	Y	Y	Y	Y	Y	Y	Y	Y
Local economy controls $_{(CBSA, t)}$	Y	Y	Y	Y	Y	Y	Y	Y
CBSA FEs	-	-	Y	Y	-	-	Y	Y
Time FEs	Y	Y	Y	Y	Y	Y	Y	Y
Observations	345,279	345,279	345,279	345,279	293,364	293,364	293,364	293,364
R-squared	0.28	0.28	0.30	0.30	0.37	0.37	0.39	0.39

Table 5
The 2022 Medical Collection Reporting Reform: Credit Score Distortion

The table examines the distortion in the credit score reliability around the 2022 Medical Collection Reporting Reform. Panels A, B, and C present results using *MSPB Costs*, *Post-Discharge MSPB Costs*, and *Post- to Pre-Discharge MSPB Costs* as measures of healthcare costs, respectively. The dependent variable is the proportion of consumers in an area who are delinquent or in default on more than 5% of their total outstanding debt within the next six months. Other borrower financial information (at the ZIP-code level) includes the average debt-to-income ratio, natural logarithm of average income, natural logarithm of the oldest account, proportion of consumers with collections, and the ratio of total collections to total debt balance. Local economy controls (at the CBSA-level) include wage, employment, wage growth, employment growth, and the fraction of employment in the set of two-digit NAICS industries. Standard errors are clustered at the CBSA level. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable (zip,t+1)	*% Delinquency or default within next 6 months*			
Subsample between 2021 Q1 and 2023 Q3	*Main effect*	*Incremental effect post 2022*	*Main effect*	*Incremental effect post 2022*
Panel A: MSPB Costs				
MSPB Costs$_{(CBSA, t)}$	0.279***	0.084***	0.356***	0.082***
	(3.44)	(5.17)	(3.45)	(4.89)
Credit Score/100 $_{(ZIP, t)}$ × MSPB Costs$_{(CBSA, t)}$	-0.038***	-0.011***	-0.051***	-0.011***
	(3.46)	(4.87)	(3.52)	(4.76)
Credit Score/100 $_{(ZIP, t)}$		-0.021**		-0.006
		(2.16)		(0.48)
Other borrower financials $_{(ZIP, t)}$		Y		Y
Local economy controls $_{(CBSA, t)}$		Y		Y
CBSA FEs		-		Y
Time FEs		Y		Y
Observations		105,186		105,186
R-squared		0.26		0.28
Panel B: Post-Discharge MSPB Costs				
Post-Discharge MSPB Costs$_{(CBSA, t)}$	0.257***	0.069***	0.241***	0.071***
	(4.01)	(4.38)	(3.13)	(4.47)
Credit Score/100 $_{(ZIP, t)}$ × Post-Discharge MSPB Costs$_{(CBSA, t)}$	-0.034***	-0.010***	-0.034***	-0.011***
	(4.02)	(4.81)	(3.14)	(4.81)
Credit Score/100 $_{(ZIP, t)}$		-0.024***		-0.022**
		(3.03)		(2.18)
Other borrower financials $_{(ZIP, t)}$		Y		Y
Local economy controls $_{(CBSA, t)}$		Y		Y
CBSA FEs		-		Y
Time FEs		Y		Y
Observations		105,186		105,186
R-squared		0.26		0.28

Table 5 (Continued)

Panel C: Post- to Pre-Discharge MSPB Costs				
Post- to Pre-Discharge MSPB Costs$_{(CBSA, t)}$	0.115***	0.067***	0.084*	0.068***
	(3.17)	(4.91)	(1.93)	(4.90)
Credit Score/100$_{(ZIP, t)}$ ×	-0.015***	-0.010***	-0.011*	-0.010***
Post- to Pre-Discharge MSPB Costs$_{(CBSA, t)}$	(3.01)	(5.35)	(1.84)	(5.29)
Credit Score/100 $_{(ZIP, t)}$		-0.040***		-0.042***
		(6.74)		(5.72)
Other borrower financials $_{(ZIP, t)}$		Y		Y
Local economy controls $_{(CBSA, t)}$		Y		Y
CBSA FEs		-		Y
Time FEs		Y		Y
Observations		105,186		105,186
R-squared		0.26		0.28

Table 6
The 2022 Medical Collection Reporting Reform: Debt-to-Income Ratio Distortion

The table examines the distortion in the debt-to-income ratio reliability around the 2022 Medical Collection Reporting Reform. Panels A, B, and C present results using *MSPB Costs*, *Post-Discharge MSPB Costs*, and *Post- to Pre-Discharge MSPB Costs* as measures of healthcare costs, respectively. The dependent variable is the proportion of consumers in an area who are delinquent or in default on more than 5% of their total outstanding debt within the next six months. Other borrower financial information (at the ZIP-code level) includes the average debt-to-income ratio, natural logarithm of average income, natural logarithm of the oldest account, proportion of consumers with collections, and the ratio of total collections to total debt balance. Local economy controls (at the CBSA-level) include wage, employment, wage growth, employment growth, and the fraction of employment in the set of two-digit NAICS industries. Standard errors are clustered at the CBSA level. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable (zip,t+1)	*% Delinquency or default within next 6 months*			
Subsample between 2021 Q1 and 2023 Q3	*Main effect*	*Incremental effect post 2022*	*Main effect*	*Incremental effect post 2022*
Panel A: MSPB Costs				
MSPB Costs$_{(CBSA, t)}$	-0.017	0.002	-0.021*	0.000
	(1.45)	(0.35)	(1.75)	(0.00)
DTI $_{(ZIP, t)}$ ×	0.209**	0.060***	0.133	0.064***
MSPB Costs$_{(CBSA, t)}$	(2.46)	(3.15)	(1.47)	(3.30)
DTI $_{(ZIP, t)}$		-0.184**		-0.120
		(2.34)		(1.46)
Credit Score/100 $_{(ZIP, t)}$		-0.062***		-0.059***
		(21.55)		(19.25)
Other borrower financials $_{(ZIP, t)}$		Y		Y
Local economy controls $_{(CBSA, t)}$		Y		Y
CBSA FEs		-		Y
Time FEs		Y		Y
Observations		105,186		105,186
R-squared		0.26		0.28
Panel B: Post-Discharge MSPB Costs				
Post- to Pre-Discharge MSPB Costs$_{(CBSA, t)}$	-0.011	-0.007**	-0.011	-0.007**
	(1.38)	(2.05)	(1.51)	(2.18)
DTI (ZIP, t) ×	0.200***	0.057***	0.107*	0.062***
Post- to Pre-Discharge MSPB Costs$_{(CBSA, t)}$	(3.50)	(2.99)	(1.75)	(3.24)
DTI $_{(ZIP, t)}$		-0.175***		-0.097*
		(3.33)		(1.77)
Credit Score/100 $_{(ZIP, t)}$		-0.061***		-0.059***
		(21.55)		(19.33)
Other borrower financials $_{(ZIP, t)}$		Y		Y
Local economy controls $_{(CBSA, t)}$		Y		Y
CBSA FEs		-		Y
Time FEs		Y		Y
Observations		105,186		105,186
R-squared		0.26		0.28

Table 6 (Continued)

Panel C: Post- to Pre-Discharge MSPB Costs				
Post- to Pre-Discharge MSPB Costs$_{(CBSA, t)}$	-0.001	-0.009***	-0.002	-0.009***
	(0.18)	(3.58)	(0.36)	(3.53)
DTI$_{(ZIP, t)}$ ×	0.088*	0.052***	0.042	0.055***
Post- to Pre-Discharge MSPB Costs$_{(CBSA, t)}$	(1.95)	(3.05)	(0.91)	(3.24)
DTI$_{(ZIP, t)}$		-0.075*		-0.037
		(1.65)		(0.79)
Credit Score/100$_{(ZIP, t)}$		-0.061***		-0.059***
		(21.38)		(19.27)
Other borrower financials$_{(ZIP, t)}$		Y		Y
Local economy controls$_{(CBSA, t)}$		Y		Y
CBSA FEs		-		Y
Time FEs		Y		Y
Observations		105,186		105,186
R-squared		0.26		0.28

Table 7
Healthcare Costs and Access to Credit: Credit Scores

The table examines the association between the distortion in the credit score reliability and consumers' access to credit. The dependent variable is the average mortgage approval rate in an area by lender and loan type. Other loan characteristics (at the ZIP-code level) include the natural logarithm of the average loan amount, the natural logarithm of the average loan maturity, the natural logarithm of the average income of the mortgage applicants, proportion of minorities, the average debt-to-income ratio of mortgage applicants, and the average loan-to-value ratio. Other borrower financial information (at the ZIP-code level) includes the average debt-to-income ratio, natural logarithm of average income, natural logarithm of the oldest account, proportion of consumers with collections, and the ratio of total collections to total debt balance. Local economy controls (at the CBSA-level) include wage, employment, wage growth, employment growth, and the fraction of employment in the set of two-digit NAICS industries. Standard errors are clustered at the CBSA level. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Mortgage Approval Rate (%) (ZIP, year, lender, loan type)							
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Post- to Pre-Discharge MSPB Costs$_{(CBSA, t)}$	-	-0.343***	-	-0.397***	-	-0.293***	-	-0.358***
		(-3.60)		(-3.43)		(-3.24)		(-3.16)
Credit Score/100 $_{(ZIP, t)}$ ×	-	0.046***	-	0.056***	-	0.038***	-	0.051***
Post- to Pre-Discharge MSPB Costs$_{(CBSA, t)}$		(3.48)		(3.47)		(3.10)		(3.17)
Credit Score/100$_{(ZIP, t)}$	0.050***	0.004	0.040***	-0.015	0.048***	0.008	0.037***	-0.013
	(15.07)	(0.25)	(10.28)	(-0.84)	(16.51)	(0.61)	(10.61)	(-0.74)
Other loan characteristics$_{(ZIP,t)}$	Y	Y	Y	Y	Y	Y	Y	Y
Local consumer financials $_{(ZIP, t)}$	Y	Y	Y	Y	Y	Y	Y	Y
Local economy controls $_{(CBSA, t)}$	Y	Y	Y	Y	Y	Y	Y	Y
Lender x year FEs	Y	Y	Y	Y	-	-	-	-
CBSA FEs	-	-	Y	Y	-	-	Y	Y
Lender x year x loan type FEs	-	-	-	-	Y	Y	Y	Y
Observations	4,254,094	4,254,094	4,254,094	4,254,094	4,251,896	4,251,896	4,251,896	4,251,896
R-squared	0.58	0.58	0.58	0.58	0.64	0.64	0.64	0.64

Table 8
Healthcare Costs and Access to Credit: Debt-to-Income Ratio

The table examines the association between the distortion in the debt-to-income ratio reliability and consumers' access to credit. The dependent variable is the average mortgage approval rate in an area by lender and loan type. Other loan characteristics (at the ZIP-code level) include the natural logarithm of the average loan amount, the natural logarithm of the average loan maturity, the natural logarithm of the average income of the mortgage applicants, proportion of minorities, the average debt-to-income ratio of mortgage applicants, and the average loan-to-value ratio. Other borrower financial information (at the ZIP-code level) includes the average debt-to-income ratio, natural logarithm of average income, natural logarithm of the oldest account, proportion of consumers with collections, and the ratio of total collections to total debt balance. Local economy controls (at the CBSA-level) include wage, employment, wage growth, employment growth, and the fraction of employment in the set of two-digit NAICS industries. Standard errors are clustered at the CBSA level. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable	*Mortgage Approval Rate (%) (ZIP, year, lender,loan type)*							
	(1)	*(2)*	*(3)*	*(4)*	*(3)*	*(4)*	*(7)*	*(8)*
Post- to Pre-Discharge MSPB Costs$_{(CBSA, t)}$	-	0.116***	-	0.137***	-	0.096***	-	0.113***
		(4.44)		(5.25)		(4.45)		(5.35)
DTI$_{(ZIP, t)}$ × Post- to Pre-Discharge MSPB Costs$_{(CBSA, t)}$	-	-0.364***	-	-0.378***	-	-0.324***	-	-0.316***
		(-4.83)		(-5.10)		(-4.87)		(-5.37)
DTI$_{(ZIP, t)}$	-0.989***	-0.612***	-0.986***	-0.598***	-0.851***	-0.515***	-0.841***	-0.518***
	(-43.43)	(-9.15)	(-41.01)	(-9.22)	(-47.82)	(-8.28)	(-45.95)	(-9.67)
Credit Score/100$_{(ZIP, t)}$	0.050***	0.048***	0.040***	0.040***	0.048***	0.045***	0.037***	0.037***
	(15.07)	(13.98)	(10.28)	(10.19)	(16.51)	(15.27)	(10.61)	(10.51)
Other loan characteristics$_{(ZIP,t)}$	Y	Y	Y	Y	Y	Y	Y	Y
Local consumer financials $_{(ZIP, t)}$	Y	Y	Y	Y	Y	Y	Y	Y
Local economy controls $_{(CBSA, t)}$	Y	Y	Y	Y	Y	Y	Y	Y
Lender x year FEs	Y	Y	Y	Y	-	-	-	-
Lender x year x loan type FEs	-	-	-	-	Y	Y	Y	Y
CBSA FEs	-	-	Y	Y	-	-	Y	Y
Observations	4,254,094	4,254,094	4,254,094	4,254,094	4,251,896	4,251,896	4,251,896	4,251,896
R-squared	0.58	0.58	0.58	0.58	0.64	0.64	0.64	0.64

Table 9
Healthcare Costs and Access to Credit: The 2022 Reporting Reform

The table examines the association between the distortion in the credit score (and the debt-to-income ratio) reliability and consumers' access to credit around the 2022 Medical Collection Reporting Reform. Panel A examines the distortion in the credit score reliability. Panel B examines the distortion in the debt-to-income ratio reliability. The dependent variable is the average mortgage approval rate in an area by lender and loan type. Other loan characteristics (at the ZIP-code level) include the natural logarithm of the average loan amount, the natural logarithm of the average loan maturity, the natural logarithm of the average income of the mortgage applicants, proportion of minorities, the average debt-to-income ratio of mortgage applicants, and the average loan-to-value ratio. Other borrower financial information (at the ZIP-code level) includes the average debt-to-income ratio, natural logarithm of average income, natural logarithm of the oldest account, proportion of consumers with collections, and the ratio of total collections to total debt balance. Local economy controls (at the CBSA-level) include wage, employment, wage growth, employment growth, and the fraction of employment in the set of two-digit NAICS industries. Standard errors are clustered at the CBSA level. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Mortgage Approval Rate (%) (ZIP, year, lender, loan type)			
Subsample between 2021 and 2023	*Main effect*	*Incremental effect post 2022*	*Main effect*	*Incremental effect post 2022*
Panel A: Credit score				
Post- to Pre-Discharge MSPB Costs$_{(CBSA,\ t)}$	-0.225***	-0.173***	-0.268**	-0.178***
	(-2.74)	(-11.22)	(-2.53)	(-11.38)
Credit Score/100$_{(ZIP,\ t)}$ ×	0.029***	0.022***	0.039***	0.023***
Post- to Pre-Discharge MSPB Costs$_{(CBSA,\ t)}$	(2.59)	(10.77)	(2.65)	(11.64)
Credit Score/100$_{(ZIP,\ t)}$	0.009		-0.006	
	(0.76)		(0.42)	
Other loan characteristics$_{(ZIP,t)}$	Y		Y	
Local consumer financials $_{(zip,\ t)}$	Y		Y	
Local economy controls $_{(CBSA,\ t)}$	Y		Y	
Lender x year x loan type FEs	Y		Y	
CBSA FEs	-		Y	
Observations	1,472,068		1,472,068	
R-squared	0.64		0.64	
Panel B: DTI				
Post- to Pre-Discharge MSPB Costs$_{(CBSA,\ t)}$	0.065***	0.049***	0.088***	0.049***
	(3.17)	(7.82)	(3.99)	(8.78)
DTI$_{(ZIP,\ t)}$ ×	-0.235***	-0.140***	-0.225***	-0.138***
Post- to Pre-Discharge MSPB Costs$_{(CBSA,\ t)}$	(-3.71)	(-13.43)	(-3.79)	(-13.31)
DTI $_{(ZIP,\ t)}$	-0.564***		-0.567***	
	(-9.48)		(-10.40)	
Credit Score/100$_{(ZIP,\ t)}$	0.045***		0.038***	
	(12.91)		(9.66)	
Other loan characteristics$_{(ZIP,t)}$	Y		Y	
Local consumer financials $_{(ZIP,\ t)}$	Y		Y	
Local economy controls $_{(CBSA,\ t)}$	Y		Y	
Lender x year x loan type FEs	Y		Y	
CBSA FEs	-		Y	
Observations	1,472,068		1,472,068	
R-squared	0.64		0.64	

Table A1
Healthcare Cost Measures: Validation

The table describes the share of average Medicare Spending per Beneficiary (MSPB) by periods of treatment and types of services provided by the Center for Medicare and Medicaid Services (CMS). The last column (Percentage of costs per incident) adds up to 100% reflecting the full MSPB.

Period	Type of services	Percent of costs per incident
1 to 3 days Prior to Index Hospital Admission	Home Health Agency	0.06%
	Hospice	0.00%
	Inpatient	0.03%
	Outpatient	0.73%
	Skilled Nursing Facility	0.01%
	Durable Medical Equipment	0.04%
	Carrier	2.72%
During Index Hospital Admission	Home Health Agency	0.00%
	Hospice	0.00%
	Inpatient	47.16%
	Outpatient	0.00%
	Skilled Nursing Facility	0.00%
	Durable Medical Equipment	0.09%
	Carrier	7.06%
1 through 30 days After Discharge from Index Hospital Admission	Home Health Agency	3.75%
	Hospice	0.70%
	Inpatient	13.24%
	Outpatient	4.01%
	Skilled Nursing Facility	14.50%
	Durable Medical Equipment	0.43%
	Carrier	5.47%