Hidden Medical Debt and Consumer Access to Credit

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ABSTRACT

Credit bureaus face significant frictions in collecting consumer medical debt liabilities data, which spurred an intense ongoing policy debate. Leveraging novel healthcare costs proxies based on Medicare spending data, we evaluate the impact of hidden medical liabilities on consumer credit scoring and access to credit. We document that the traditional creditworthiness measures underestimate the ex-post default for consumers residing in higher healthcare costs markets. Consumers in high-healthcare-cost CBSAs are 36.2% more likely to default than those in low-healthcare-cost CBSAs. These effects are more pronounced among higher risk consumers, those with low credit scores and high DTIs. Lenders internalize these biases and impose higher mortgage rejection rates in high-healthcare-cost CBSAs, particularly for riskier applicants. These effects intensify following a policy shift that partially removed medical liabilities from credit reports without affecting consumer balance sheets. Our findings suggest that limiting the flow of medical liabilities data undermines the predictive accuracy of standard credit metrics, impairs the information value of credit bureau outputs, and leads to less efficient credit allocation.

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I. Introduction

By 2021, healthcare expenditures reached 17.6% of the U.S. GDP, and medical debt became a pervasive financial burden among American consumers (Kluender, Mahoney, Wong, and Yin, 2021). As of December 2021, 15% of U.S. households held about $250 billion in medical debt (KFF, 2024). Yet credit bureaus observe only a fraction of these liabilities due to numerous information collection frictions.[1] These incomplete medical liabilities data affect consumer creditworthiness assessment and, by extension, access to credit.

Improving the information flows to better account for medical liabilities should be uncontroversial, given that other forms of debt are already accounted for. Yet consumer advocates, including CFBP, argue that credit bureaus should ignore even the available medical liabilities information. They justify their arguments by arguing that medical debt is unique. It is prone to errors, disputes, insurance adjustments, and a slow rate of decision-making (see discussion in Section II). Using such data, thus, "disproportionately harms low-income Americans" – lowers their credit scores, and restricts their access to credit.[2] Regulators went as far as pressuring credit bureaus in Q1 of 2022 to dramatically restrict medical liabilities data used in credit scoring without any change to the underlying consumers' financial obligations.

This paper sheds light on how imperfect medical liabilities data affects consumer creditworthiness assessment and access to credit. The core challenge we face is the lack of reasonably complete and importantly unbiased medical liabilities data. We address this by exploiting a novel healthcare costs (HCC) proxy. We argue that consumers residing in high

[1] CFPB (2022) estimates that only $88 billion of the medical liabilities were accounted for in consumer credit files. The credit bureau data utilized in this paper suggests that in 2021, consumers carried about $69 billion in medical liabilities, or 27.6% of the amounts reported by KFF (2024)..

[2] "Biden proposes to ban medical debt from credit reports, loan decisions" The Washington Post, June 11th, 2024

healthcare cost markets are more susceptible to the accumulation of medical liabilities. While our HCC measure is not comprehensive, it has two crucial characteristics: it is plausibly exogenous to local consumers' financial health and contributes to the accumulation of medical liabilities.

Our results suggest that hidden medical liabilities data adversely affect the informativeness of the traditional creditworthiness indicators and distort consumer access to credit. Conditional on credit scores and DTIs, consumers in high-healthcare-cost CBSAs are 36.2% relatively more likely to default than those in low-healthcare-cost CBSAs (Figure 1). These effects are larger for riskier consumers – those with low credit scores and high DTI. Lenders appear cognizant of this upward bias in the traditional creditworthiness assessment measures and reject more mortgage applications in higher healthcare cost CBSAs, particularly for riskier borrowers (Figure 2). Both effects intensify after Q1 2022, which partially removed medical liabilities from credit reports, confirming the role of hidden medical liabilities. Collectively, our findings suggest that the imperfect flow of medical liabilities data compromises the accuracy of credit bureau data and restricts consumers' access to credit.

Our empirical design is built on novel HCC proxies based on the Medicare Spending Per Beneficiary (MSPB) data.[3] These data provide average Medicare expenditures *per patient per hospitalization incident* across all U.S. hospitals. These expenditures are adjusted for the severity of the patients' medical conditions and avoid the effects of endogenous healthcare utilization by consumers (Anderson, Dobkin, and Gross, 2012; Finkelstein, Gentzkow, and Williams, 2016). Health economists utilize MSPB data to compare hospital (in)efficiencies stemming from care quality and (over-) provision of services (Norton, Li, Das, and Chen, 2018; Currie, Karpova, and

[3] The MSPB data are made publicly available by the Center for Medicare and Medicaid Services (CMS): https://data.cms.gov/provider-data/dataset/rrqw-56er

Zeltzer, 2023). Using available medical liabilities data for 5% random sample of a major credit bureau's files (about 13 million people) from 2017-2023, we confirm that our MSPB-based proxies are positively associated with consumer medical liabilities accumulation (Figure 4).

Although our MSPB-based HCC proxies do not fully capture the heterogeneity in healthcare costs across CBSAs, they capture the driver of healthcare costs that is arguably unrelated to local consumers' financial conditions and credit demand (see detailed discussion in Section III.1). MSPB data covers a homogeneous 65+ population that is least likely to borrow for medical expenses (Batty, Gibbs, and Ippolito, 2018). Medicare follows national reimbursement policies (Skinner, 2011) insulated from the provider's price adjustments in response to local economic conditions. These policies form a foundation for private insurers' reimbursement rates (Clemens and Gottlieb, 2017).

In the first part of the paper, we use the MSPB-based HCC measures to assess whether hidden medical liabilities data affect the informativeness of the traditional creditworthiness indicators in predicting consumer defaults. We find that a representative ZIP-code level consumers experience a 1.53% higher 6-month default rate if they reside in the top quartile HCC market than if they reside in the bottom quartile HCC market (Figure 1). This constitutes 36.2% of the average default rate in our sample (4.23%). This default-rate differential monotonically declines (increases) across credit score (DTI) deciles. The HCC-related default rate differential is 1.63% for the lowest credit score decile consumers and declines to 0.19% for the highest credit score decile consumers. Similarly, the default rate differential is 2.77% for the highest DTI decile and 0.7% for the lowest DTI decile consumers. We confirm these effects in a regression setting where we control for an array of local economic fundamentals, consumer financial condition, demographic characteristics,

time, and CBSA fixed effects. Furthermore, these effects persist even when we focus solely on consumers with available medical liability accounts in the credit bureau data.

One can argue that local healthcare costs might influence consumer defaults through channels other than information friction, such as the cash flow channel. Consumers residing in high-healthcare-cost markets are likely to face greater future expected medical expenses and are known to receive lower wages (Arnold and Whaley, 2020). These factors should reduce consumers' ability to service existing debt and increase the likelihood of derogatory events.

To isolate the role of the information frictions from the cash flow channel, we exploit the 2022 policy shift that further restricted credit bureaus' access to medical liabilities data. We find that this shift amplified the adverse effect of healthcare costs on the informativeness of credit scores and DTIs in predicting defaults.[4] These results reinforce the notion that hidden medical liabilities create an upward bias in the traditional creditworthiness measures. They suggest that restricting credit bureaus' access to medical liabilities data weakens the quality of information available to lenders.

In the second part of the paper, we explore whether lenders are aware of the HCC-induced distortions in consumer creditworthiness assessments and adjust their lending accordingly. To isolate the credit supply effect, we focus on mortgage acceptance rates using 2018–2023 HMDA data. ZIP-code level mortgage acceptance rates capture lenders' credit allocation decisions across different HCC markets, conditional on loan and borrower characteristics and lender-year-loan type fixed effects.

[4] Duarte, Kohli, Fonseca, and Reif (2025) study a similar regulatory change in medical liability reporting and find no impact on default. Unlike their machine learning based credit scoring models, we use healthcare cost proxies and explore heterogeneous effects by credit score and DTI.

The results show that lenders are about 2.97% more likely to reject mortgage applications in the top quartile HCC markets compared to the bottom quartile HCC markets (Figure 2). This is economically significant relative to the 18.7% average rejection rate in our sample. The effect is larger for riskier borrowers: those with lower credit scores and higher DTIs. The mortgage rejection rate differential is 3.47% for the bottom credit score decile applicants, compared to 1.96% for the top credit score decile applicants. Similarly, the differentials are larger for the top DTI decile consumers (2.40%) and lower for the bottom DTI decile consumers (1.54%). These effects nearly double following the 2022 policy shift, further supporting the information collection frictions channel.

These results challenge the prevailing narrative that lenders are unaware of the hidden risks associated with medical debt. Instead, the 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 borrowers' exposure to medical liabilities. This indiscriminate tightening of credit supply potentially 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 medical liabilities on consumer financial health. Several papers have documented that medical liabilities are significant contributors to consumer bankruptcy (e.g., Himmelstein et al., 2009; Dobkin et al., 2018). Access to health insurance, Medicare, and Medicaid alleviates 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).[5] 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 literature exploring the effects of healthcare costs on a variety of economic outcomes by offering a novel healthcare cost proxy that is plausibly exogenous to local consumers' economic conditions. To date, the literature has 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 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 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 subprime 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 imperfect medical liabilities data on consumer credit scoring and access to credit, particularly for riskier consumers.

[5] Kluender et al. (2024) document that medical debt forgiveness leads to, on average, 20 points increase in the consumer credit scores. Our contract with a credit bureau limits our ability to conduct commensurate analysis of the effects of omitted medical liabilities data on consumer credit scores.

Finally, we contributed to the policy debate with profound implications for lenders and consumers alike. On January 7th, 2025, the CFPB called to remove $49 billion in medical debt from the credit reports of 15 million Americans (CFPB, 2025), without eliminating the underlying debt. On July 15th, 2025, the U.S. Eastern District Court of Texas effectively voided this ruling. Our results indicate that limiting credit bureaus' access to medical liabilities data weakens the quality of information available to lenders and potentially restricts 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 bureaus' (CBs) files. As of September 2021, credit files of a major credit bureau used in this study recorded only $69 billion in medical debt and related collection balances, substantially below the $250 billion estimated by KFF.[6]

There is a wide set of reasons for the medical liabilities to be incomplete and at times inaccurate (CFPB, 2014). First, non-transparent pricing of services, medical billing errors, wrongful denials of 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). Healthcare providers typically process medical debt in-house. "… *hospitals become frequent collection agents*"

[6] A survey by the CFPB (2022) estimates a similar figure of $88 billion as of December 2021.

(Richman et al., 2023). However, healthcare providers seldom have direct reporting relationships with CBs (Consumer Reports, 2018).

Second, major contributors of the medical liabilities information in credit bureau files are collections agencies (CFPB, 2014). These economic agents take over debt once consumers default on their medical bills, but not earlier than 180 days after medical bills are incurred (Kluender et al., 2021). As of September 2021, $42 billion out of $69 billion of medical liabilities cited above are medical debt *collection* balances. This implies that for each dollar of medical debt, credit bureaus recorded $1.55 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.

Third, even data provided by collection agencies is 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 CBs, leading to inconsistent reporting. Moreover, medical debt collectors might be 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).

Finally, 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 collection" (CFPB, 2014). Some healthcare providers push patients' debt into collections well before all insurance adjustments are completed and disputes are settled.

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

These factors contribute to significant frictions in collecting medical liabilities information, leading to incomplete and at times 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 available medical liabilities data is unreliable and *should not* be factored into consumer creditworthiness assessment due to inaccuracies and outdated reporting. CFPB contends that credit scores incorporating medical debt 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, CBs, medical debt collectors, and lenders argue that excluding medical liabilities from credit reports would undermine the informativeness of CBs' data, lead to upward (downward) bias in credit scores (DTIs), and weaken lenders' ability to properly assess consumer creditworthiness. Unable to properly differentiate between high- and low-risk consumers, lenders might oversupply credit. Additionally, removing such data could eliminate consumer incentives to pay medical debt and lead debt collectors to rely on costly litigation. Both factors would adversely affect healthcare providers' revenue and impose additional costs on patients (Washington Post 2024b).

In March 2022, under pressure from CFPB and the Biden Administration, three major credit bureaus announced that they would dramatically curtail the use of medical liabilities data in credit assessment. Specifically, starting July 1st, 2022, CBs 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 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 the VantageScores of subprime consumers by about 30 points while leaving the credit scores of prime consumers unaffected. We exploit this information friction shock in our empirical design.

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 was 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

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 imperfect medical liabilities data, we focus on healthcare costs – the core driver of (unobserved) medical liabilities. We argue that irrespective of whether medical debt information collection frictions affect consumers' access to credit negatively (as policymakers argue) or positively (as the lending industry advocate suggests), the impact of these frictions should be more pronounced in high healthcare cost markets.

III.1 Healthcare Costs Proxies

The core challenge we face is to isolate the driver(s) of healthcare costs that are arguably exogenous to local consumer financial health and credit demand. 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 incident per beneficiary* for all participating U.S. hospitals, covering payments from three days before, to during, to 30 days after hospital stay. The data includes expenditures on inpatient stays, outpatient visits, skilled nursing facilities, home health, etc. (Table A1).

The MSPB data was designed to enable comparisons of hospitals' cost efficiency (Norton et al., 2018; Currie et al., 2023). To ensure comparability, MSPB data relies on (internal) standardization procedure that accounts for geographic and policy-related payment variation; and

differences in patient age and health conditions.[8] This enhances the reliability of the MSPB data in comparing healthcare costs across providers.[9] MSPB data is also free of potential biases stemming from geographical variations in healthcare utilization by patients, as it reports costs *per hospitalization incident* (Skinner, 2011). Ultimately, the core variation in MSPB cost data captures the heterogeneity in care price/quality ratio and the extent of medical service (over-) provision across U.S. hospitals.

Although MSPB data does not fully capture the heterogeneity in healthcare costs across CBSAs, it 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 and 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 during the 2000-2017 period, hospital care costs grew three times faster than physician care costs (Cooper et al., 2019).

More importantly, MSPB costs capture the drivers of healthcare costs that are arguably exogenous to local consumer financial conditions. Medicare reimbursement rates are set by national policies (Skinner, 2011) and remain relatively insulated from providers' ability to adjust prices in response to market conditions. Medicare 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).

[8] Detailed description of MSPB data 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.

[9] We independently verify this using the case complexity index provided by the American Hospital Association data.

Healthcare Costs Proxies

Using MSPB data, we construct three healthcare cost measures. First, we utilize the average within CBSA *MSPB Costs* – the average annual Medicare Spending per Beneficiary per hospitalization aggregated to the CBSA level and scaled by the national average provided by MSPB data:[10]

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

Second, we look into post-hospital-discharge Medicare spending. These costs (e.g., post-acute care, hospice, skilled nursing facilities) represent 41.9% of the average MSPB reimbursement amounts per hospitalization incident, while in-hospital costs constitute 54.3% of the reimbursement. Healthcare economists document that post-hospital-discharge costs are major contributors to the heterogeneity in Medicare spending across hospitals and best capture hospital cost inefficiencies (Das et al., 2016).. Medicare standardizes coverage for in-hospital procedures, but post-discharge services vary based on the quality of the inpatient care (e.g., post-surgical infection rates) and the degree of post-hospitalization service provision by hospitals (Norton et al. 2018; Currie, Karpova, and Zeltzer 2023). 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 even though MSPB data aims to account for patient health risks (e.g., age, severity of illness, and comorbidity interactions), it still might be affected by local patients' health and local hospitals' ability to provide complex medical services. To further account for

[10] We have conducted an array of robustness tests defining a healthcare market for a given ZIP-code using 15-, 25-, and 50-mile distance to the local hospitals. We find the results to be robust to those reported in this paper.

heterogeneity in local health demographic factors and hospital capabilities, we advance a *third* HCC measure where we normalize the post-discharge MSPB costs by the pre-discharge MSPB costs:

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

Normalization aims to capture any residual complexity of in-hospital care demanded by the local population and provided by the local hospitals. We argue that our third measure captures cost differences stemming from the quality of in-hospital care (e.g., post-surgical infection rates) and over- or under-provision of services after hospitalization.[11]

Panel A of Table 1 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. 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.[12] These heatmaps show that MSPB costs exhibit significant healthcare cost heterogeneity across U.S. CBSAs, as well as notable time-series variations over our sample period.

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

[11] 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)

[12] Appendix Figures A1 and A2 offer the geographic heatmaps in 2017 and 2023 for the remaining two healthcare costs measures.

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 consumer 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 margins 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. Panel B of Table 1 shows that only 2% of consumers have medical debt accounts, while 13% of consumers have medical collections accounts. This data once again highlights the extent to which medical debt is hidden from credit agencies.

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). 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 us to control for the local industry growth option. We further collect the proportion of businesses that have less than 50 employees from the County Business Patterns data provided by the U.S. Census Bureau to capture the consumers' exposure to employment-related insurance. This data allows us to control for potential distortions in health insurance coverage across regions, as businesses with fewer than 50 employees do not have to provide employee health insurance.

III.3 Healthcare Measures Validation Tests

We first and foremost use the credit bureau data to confirm that the proposed healthcare cost measures do contribute to the accumulation of consumer medical liabilities. In this analysis, we rely on (limited) medical liabilities data recorded in consumer credit files. We acknowledge that this analysis relies on the assumption that, while the medical liabilities data is incomplete, it is not randomly distributed across U.S. ZIP-codes.

To validate our HCC measures, we focus on four types of balances accumulated by ZIP-code representative consumers: (a) total medical debt balances; (b) average medical debt balances; (c) total medical collection balances; and (d) average medical collection balances. Panel B of Table 1 offers summary statistics for these variables.

Figure 4 reports the bin-scatter plots of the natural logarithm of these four measures against our second measure of healthcare costs heterogeneity – $Post\text{-}Discharge\ MSPB\ Costs_{CBSA,t}$.[13] Panel A suggests that a one percentage point increase in *Post-Discharge MSPB Costs* corresponds to a 2.63 percentage point increase in medical collections balances. Panel C illustrates that a one percentage point increase in *Post-Discharge MSPB Costs* leads to a 4.41 percentage point increase in local medical debt. Panels B and D confirm that the effect works through both intensive and extensive margins, as the increase in average medical liabilities balances does not fully explain the effect.

Table 2 confirms these conclusions. We explore the relationship between three HCC measures (Panels A through C) and the extent of the medical liabilities using the following regression specification:

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

The analysis incorporates a wide set of control variables that account for ZIP-code representative consumers' financial characteristics and CBSA-level local economic conditions. At the ZIP-code level, we control for 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, we control for log average local wage and 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, i.e., businesses that do not have to provide health insurance to their full-time employees.

[13] Bin-scatter plots that utilize other healthcare costs measures look qualitatively as shown in the Appendix Figures A3 and A4.

Table 2 uniformly shows that all the proposed MSPB healthcare costs measures are strongly positively correlated with the extensive and intensive margins along the medical debt and medical debt collections dimensions, even after we control for a host of macro- and micro-economic factors potentially affecting consumer financial health. Columns (4) through (6) indicate that a one percentage point increase in $MSPB\ Costs_{CBSA,t}$ is associated with a 6.1% increase in the share of consumers with medical debt collection accounts, a 1.08% increase in average medical collection balances, and a 1.155% increase in ZIP-code level total medical collections. Overall, these results validate our healthcare cost measures.

IV. Empirical Tests and Results

IV.1 Healthcare Costs and Consumer Defaults

Armed with validated measures of healthcare costs (HCC), we explore whether exposure to high healthcare costs affects the ability of the traditional creditworthiness measures to predict consumer default.

Consumer Defaults

Figure 1 illustrates our results graphically by plotting the unconditional consumer default rates by credit score (DTI) deciles and healthcare cost quartiles captured by $Post\text{-}Discharge\ MSPB\ Costs_{CBSA,t}$ measure. Panels A and C offer the default rates, while Panels B 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.

Figure 1 shows that a representative ZIP-code level consumer is 16.4% more likely to default if they reside in high versus low healthcare costs CBSAs. The lowest credit score decile

consumers experience a 9.95% default rate in the bottom HCC quartile CBSAs and 11.58% in the top HCC quartile CBSAs, resulting in a 1.63% default rate differential. This default rate differential monotonically declines to 0.19% in the top credit score decile group. Similar effects are observable for DTIs (Panels C and D of Figure 1). The default rate differential across the top and bottom HCC quartiles is 2.77% for the top DTI decile consumers and only 0.7% for the bottom DTI decile consumers. 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.

We confirm these findings using the following regression equation.

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

where $Default_{ZIP,t+1}$ is the share of consumers 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 the three healthcare cost measures advanced in this study.

Figure 5 summarizes our empirical predictions. On the one hand, policymakers argue that imperfect medical liabilities data recorded in credit files create a downward bias in consumer creditworthiness assessment, i.e., it unfairly deflates credit scores and inflates DTI. This view suggests that consumers exposed to high healthcare costs are expected to default less than their credit score estimates would suggest. These effects would be felt more acutely by riskier consumers who are more likely to borrow to cover their medical care expenses. Policymakers' view corresponds to $\beta_1 < 0$ and $\beta_2 > 0$ in the case of credit scores ($\beta_1 > 0$ and $\beta_2 < 0$ in the case of DTIs).

The lending industry advocates, on the other hand, argue that imperfect information has the opposite effect. Hidden medical liabilities lead to credit scores and DTIs underpredicting future default rates, particularly for riskier consumers. In this case, we would expect $\beta_1 > 0$ and $\beta_2 < 0$ for credit scores ($\beta_1 < 0$ and $\beta_2 > 0$ for DTIs).

Regression analysis allows us 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 fewer 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. Irrespective of the healthcare costs measure used, we find that consumers residing in high HCC 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 magnitudes of the coefficients do not significantly change as we saturate the model with controls.

The effects are economically meaningful. In column 2 of Panel A, we find that an interquartile increase in healthcare costs is associated with a 0.21% higher default rate for the 25th credit score percentile consumers and a 0.04% lower default rate for the 75th credit score percentile consumers. For comparison, the sample average default rate is 5.03% (Panel C of Table 1). The economic magnitudes of these effects increase once we expand the potential default window to 12 months (Appendix Table A2).

Table 4 presents similar results based on DTIs. As in Table 3, each panel focuses on one of the three MSPB HCC measures, and the dependent variable is the 6-month default rates. Appendix Table A3 explores the 12-month default rates. The results uniformly suggest that (riskier) high DTI consumers residing in high HCC markets are more likely to default than similar consumers residing in low HCC markets ($\beta_2 > 0$). The effects are economically significant. An interquartile increase in healthcare costs is associated with a 0.19% higher default rate for 75th DTI percentile consumers and a 0.13% higher default rate for 25th DTI percentile consumers. For comparison, the sample average default rate is 5.03% (Panel C of Table 1).

Overall, the results documented in Tables 3 and 4 are consistent with the notion that as healthcare costs rise, the credit scores (DTIs) exhibit upward (downward) bias, underestimating consumer defaults and overestimating their creditworthiness.

One can argue that the above results are not necessarily inconsistent with policymakers' claims that the creditworthiness assessment of consumers *with* available medical liabilities data is downward biased limiting their access to credit. To this point, our analysis reflects the average effect across all consumers, both with and without such records, leaving open the possibility that a downward bias exists among those with reported medical liabilities. If so, we should expect to observe the opposite pattern within this subgroup.

To address this concern, we assess the documented effects for consumers *with* and *without* recorded medical liabilities separately. Specifically, we create two sub-samples of ZIP-code representative consumers: one based solely on consumers with non-zero medical liabilities recorded in credit bureau files and another that excludes them. Table 5 presents the results for credit scores (Panel A) and DTIs (Panel B). Odd-numbered columns report estimates for the sub-sample of consumers with medical liabilities, while even-numbered columns correspond to those without. Columns (1) and (2) use *MSPB Costs*, (3) and (4) use *Post-Discharge MSPB Costs*, and (5) and (6) use the *Post- to Pre-Discharge MSPB Costs* to capture the heterogeneity in the HCC.

The results presented in Table 5 confirm that our core results are driven by the group of consumers without medical liability accounts in their credit files (even-numbered columns). Yet we do not find support for the policymakers' claims. Irrespective of the healthcare costs measure used we find no evidence that credit scores (DTIs) are downward (upward) biased in their ability to predict defaults of consumers with medical liabilities (odd-numbered columns). If anything, the coefficients for the "*With*" sample, while not statistically significant, align in sign and magnitude to those reported for "*Without*" sample. This suggests that available medical liabilities data does not systematically distort consumer creditworthiness assessment.

2022 Medical Liabilities Policy Shift

The core results presented in Tables 3 and 4 are largely consistent with the argument that information friction undermines the accuracy of the traditional creditworthiness measures to overestimate consumers' creditworthiness. However, they might be subject to alternative interpretations: high healthcare costs might affect consumer default rates via the cash flow channel rather than the information friction channel. Consumers residing in high healthcare costs markets are more likely to incur higher medical bills in the future, which should lead them to borrow more and/or hamper their ability to repay existing debt, thus making current creditworthiness assessment less accurate in predicting future defaults.

To isolate the information friction channel, we employ the 2022 policy shift (discussed in Section 2.2) 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 how this policy shift affected medical liabilities data recorded by the credit bureau. The plot shows the total amount of registered medical collections in our sample dropping precipitously starting from the first half of 2022, providing a clear indication of the reform's impact. Table 6 reports the results of regression analysis that confirms this effect. Here we explore the impact of the 2022 policy shift on the share of consumers with medical collection accounts. In this analysis we focus on a narrow (post-COVID) window surrounding the policy shift date. To mitigate the potential anticipation effects, we exclude the first half of 2022 and focus

on two semiannual observations before the shift (S1 and S2 of 2021) and two periods after (S2 of 2022 and S1 of 2023).

The results presented in Table 6 confirm that the policy shift had a significant impact on the credit bureau records. It shows that the share of consumers with medical debt collection accounts declined by about 4% in following the 2022 policy shift (column 1). Columns (2) and (4) further show that the effect grew over time. While there is no statistically or economically significant difference between S1 of 2021 and S2 of 2021 share of consumers with medical debt collection accounts, this number drops by 2.4% in the second half of 2022 and by another 6.2% in the first half of 2023. This is a significant decline as the average share of consumers with medical collections accounts in our sample is 13%.

We utilize this policy shock to confirm the information friction channel. Specifically, we modify our regression equation (3) to:

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

Two additional interaction terms $-HCC_{CBSA,t} \times D_{Post\ 2022}$ and $Credit\ Score_{ZIP,t} \times HCC_{CBSA,t} \times D_{Post\ 2022}$ – capture the incremental effects of limiting access to medical liabilities data on the ability of credit scores and DTIs to predict consumer defaults. As before, 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 7 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 previously documented upward

bias in the traditional creditworthiness assessment measures, leading them to underestimate the default rates more, particularly so for higher risk consumers, those with lower credit scores and higher DTIs. The reform amplified the economic magnitudes of the main coefficients of interest. In Panel A, the baseline estimates of 0.302 for β_1 and -0.042 for β_2, are similar to those reported in Table 3 (column 2 of Panel A). After the reform, the coefficients' magnitudes increase to 0.395 (0.302 + 0.093) for β_1 and -0.044 (-0.042 - 0.012) for β_2, reflecting a 30.8% to 28.6% increase in magnitude correspondingly.

Table 8 presents similar results based on DTIs. Once again, we find that the core coefficients of interest are amplified post 2022 policy shift. For instance, in Panel A, the baseline estimates are 0.194 for β_2 is similar to one reported in Table 4 (in column 2 of Panel A). After the reform, the β_2 coefficient increases to 0.259 (0.194 + 0.065), reflecting a 33.5% increase in magnitude. All these findings are robust to the inclusion of the CBSA fixed effects.

Overall, the results presented in Tables 5 and 6 are consistent with the notion that the medical debt information frictions create upward bias in the traditional creditworthiness indicators in their ability 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 HCC-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.[14] To capture the credit supply decision, we focus on mortgage acceptance rates. We aim to isolate the credit supply effect by examining the within *lender-year-loan type* mortgage acceptance rates decisions across different HCC markets while controlling for an array of borrower and loan characteristics. We do not rely on consumer leverage or loan origination amounts as borrowers facing high healthcare costs may seek additional debt to cover medical expenses (KFF, 2024) or postpone repayment of existing obligations.

As in the case of credit bureau data, we aggregate HMDA data to ZIP-code-lender-loan type-year level observations that allow us to capture lenders' credit supply decisions at a granular level. We map this loan applicant data to available HCC measures at CBSA-year level, local economic conditions, and ZIP-code consumer financial characteristics provided by both HMDA and credit bureau data.

Mortgage Acceptance Rate Analysis

First, we evaluate whether healthcare costs affect lenders' willingness to supply credit. Figure 2 illustrates our results graphically. Similar to Figure 1, it plots the unconditional mortgage rejection rates across credit scores (DTI) deciles and healthcare cost quartiles based on $Post\text{-}Discharge\ MSPB\ Costs_{CBSA,t}$. Panels A and C plot the rejection rates, while Panels B and D offer the difference in rejection rates across consumers residing in top- versus bottom quartile healthcare cost CBSAs.

Panels A and B of Figure 2 show that lenders are about 3.47% more likely to reject mortgage applications of the lowest credit score decile consumers if they reside in the top HCC

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

quartile CBSAs compared to the bottom HCC quartile CBSAs. This rejection rate differential decreases to 1.96% for applicants in the top credit score decile. Panels C and D show similar results based on DTI. The rejection rate differential between the highest and the lowest healthcare costs CBSAs quartiles is 2.40% for the top DTI decile mortgage applicants and declines monotonically to 1.54% for the bottom DTI decile applicants. For comparison, the average rejection rate in our sample is 18.77%. Figure 2 suggests that lenders are aware of the healthcare costs related to distortions in the traditional creditworthiness measures.

We confirm these results using the regression analysis, where we control for a wide array of local economic fundamentals and consumer financial characteristics.

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

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. 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. Ideally, we would like to utilize the mortgage-applicant-level measures of creditworthiness – credit scores and DTIs. Yet HMDA data only provides us with the 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.

$\gamma_{lender \times loan\ type \times t}$ fixed effects allow us to isolate the effects on the healthcare costs on credit supply. Effectively we rely on the within the same lender, year, and loan type variation in mortgage approval rates across U.S. ZIP-codes with different HCC exposure. The set of control variables includes CBSA-level economic characteristics, ZIP-code consumer financials, as well as

mortgage application characteristics supplied by HMDA: the natural logarithm of the average loan amount, loan maturity, log applicant income, share of minority applicants, average DTI, and loan-to-value ratio.

Table 9 reports the results based on average ZIP-code credit scores supplied by the credit bureau data, while Table 10 reports the results based on mortgage applicants' DTIs supplied by HMDA. We report the results for the $Post\text{-}Discharge\ MSPB\ Costs_{CBSA,t}$ measure, though the results are qualitatively and quantitatively similar if we employ other measures. Column (2) of Table 9 suggests that a one percentage point increase in healthcare costs is associated with a 30 basis point 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 3.9 basis points. The results are robust to the inclusion of CBSA fixed effects.

Table 10 offers similar findings around DTIs. We find that the negative relationship between DTIs and the mortgage acceptance rates is more pronounced in areas with high healthcare costs. Column (2) suggests that mortgage applicants at the 75th percentile of the DTI distribution face a 0.78 percentage point higher rejection rate if they reside in the top quartile HCC CBSAs as compared to those residing in the bottom HCC quartile CBSAs. This rejection rate differential becomes economically negligible for applicants with DTI at or below the 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 loan approval results might be due to the cash flow channel rather than the information collection channel. To isolate the role of the information collection frictions, we exploit the 2022 policy shift (discussed in Section 2.2). If lenders' differential credit

supply across areas with varying healthcare costs is driven by information frictions, then the reporting reform should intensify lenders' reactions documented in Tables 9 and 10.

To test this, we add two interaction terms to the regression equation (5) that capture the incremental effects of 2002 policy shift:

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

The results are presented in Table 11. We find that the effect of the healthcare costs on the mortgage approval decisions is amplified post-2022 when an individual applicant's medical liabilities are less likely to be recorded in credit bureau files. Panel A reports the results for credit scores. The baseline estimate of β_1 (-0.227) increases to -0.404 (-0.227 - 0.177), or a 78.0% increase in magnitude. The baseline estimate of β_2 (0.029) increases to 0.052 (0.029 + 0.023) or 76.3% increases in magnitude.

Table 12 offers a similar analysis using DTIs. Like in the case of credit scores, we find that the effect of healthcare costs on lenders' mortgage approval decisions intensifies after the reporting reform. The core coefficients of interest increase in magnitude by 59.0%.

Overall, the results presented in this section suggest that lenders are aware of and internalize the distortions in the creditworthiness assessment available to them. They react by restricting access to (mortgage) credit for consumers residing in higher HCC markets. Notably, without direct access to complete medical liabilities data, lenders are likely to limit credit supply indiscriminately to all consumers, those with and without medical liabilities. As such, the frictions in collecting medical liabilities information are likely to impede the efficient allocation of consumer credit.

V. Conclusion

This paper shows that information frictions stemming from incomplete medical liabilities data can compromise the integrity of the traditional credit risk indicators– credit scores and DTIs – especially in high healthcare cost markets. Lenders appear to be aware of the distortions in the creditworthiness assessment available to them and impose potentially undue credit constraints on borrowers residing in markets where healthcare-related financial strain is most acute. These credit constraints particularly disadvantage borrowers with lower credit scores and higher DTIs.

These effects are exacerbated after the 2022 regulatory shift that restricted the use of medical liabilities data by credit bureaus without eliminating the underlying liabilities from consumer balance sheets. Lenders responded to this incremental information collection friction by further restricting access to credit for higher-risk borrowers residing in higher HCC markets. These results further emphasize the role of the hidden medical debt and its impact on consumer access to credit. The post-2022 results thus offer a cautionary tale about blanket policies aiming to remove medical debt from the credit risk assessment process.

Our findings thus contribute to the ongoing policy debate regarding the role of medical liabilities in credit reporting as they shed light on the tradeoffs between protecting consumers from the punitive effects of illness-driven debt and ensuring lenders have sufficient data to allocate credit efficiently. This becomes particularly important in light of the January 7th, 2025 CFPB rule that called to remove *all* medical liabilities from consideration in consumer creditworthiness assessment. During the rule announcement, Vice President Kamala Harris stated that the CFPB's rule banning unpaid medical bills from credit reports 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" (Washington Post, January 7, 2025).

More recently, Judge Sean Jordan of the U.S. District Court for the Eastern District of Texas ruled that the CFPB exceeded its authority under the Fair Credit Reporting Act in its attempt to remove medical debt from consumer credit reports. This decision aligns with the position of two major industry associations that initiated the lawsuit, later supported by the Trump administration.[15]

This paper challenges the narrative that removing medical debt from credit files will unambiguously improve consumer outcomes. Our results suggest that this policy is likely to further undermine credit bureaus' ability to provide quality information to lenders and, by extension, is likely to adversely affect consumers' access to credit irrespective of their medical liabilities. The results highlight the trade-offs behind such policy decisions and suggest improving the accuracy and completeness of medical liabilities reporting—rather than eliminating it—may better balance consumer protection with credit market efficiency.

Our paper offers 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.

[15] CNN, July 15th, 2025.

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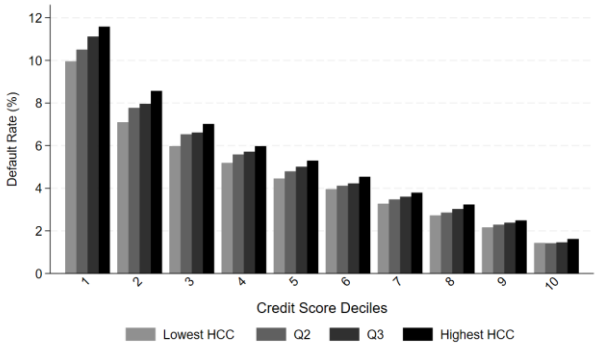
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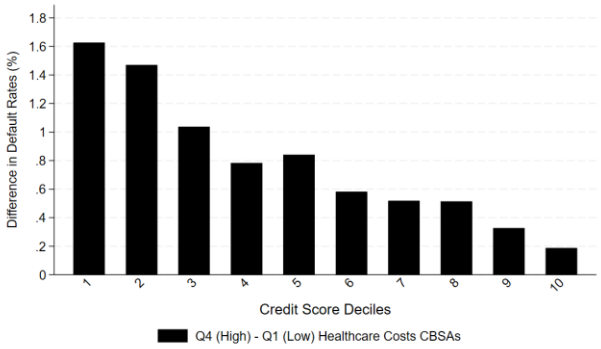
Figure 1
Consumer Default Rates and Healthcare Costs

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.

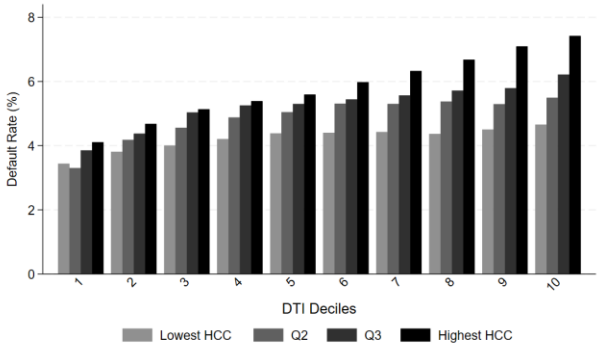
Panel A: Default Rates Across Credit Score Deciles



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

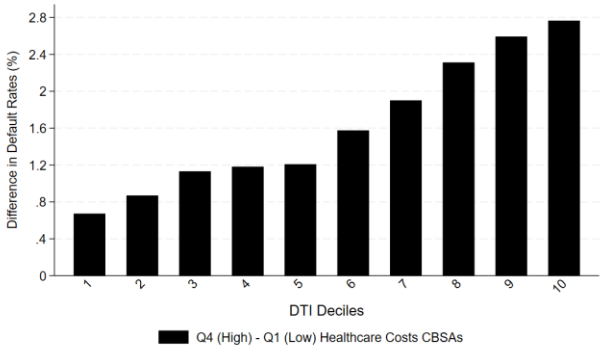
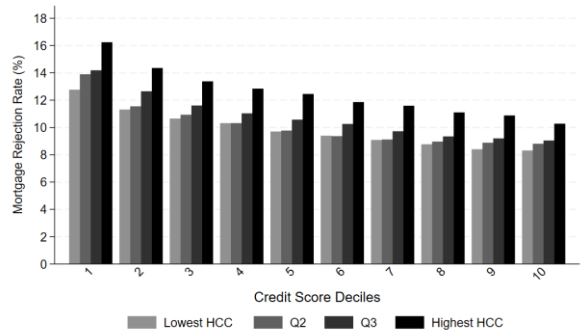


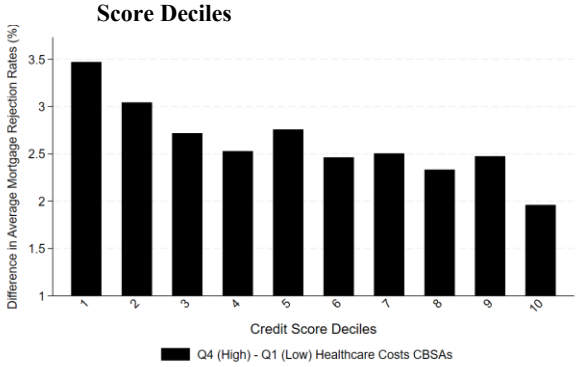
Figure 2
Mortgage Rejection Rates and Healthcare Costs

Panels A and B show the differences in mortgage rejection 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 (C) plots the average mortgage rejection by credit score (DTI) deciles and healthcare costs quartiles. Panel B (D) shows the difference in mortgage rejection rates between the highest and lowest healthcare cost quartiles for each credit score (DTI) decile. The analysis utilizes the 2018 – 2023 Home Mortgage Disclosure Act (HMDA) data and 5% consumer credit panel from one of the top credit bureaus.

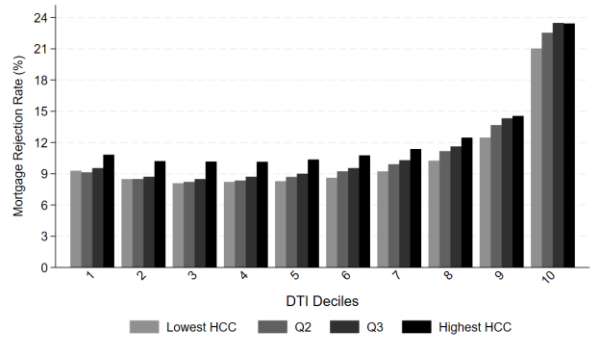
Panel A: Rejection Rates Across Credit Score Deciles



Panel B: Differences in Rejection Rates Across Credit Score Deciles



Panel C: Rejection Rates Across DTI Deciles



Panel D: Differences in Rejection Rates Across DTI Deciles

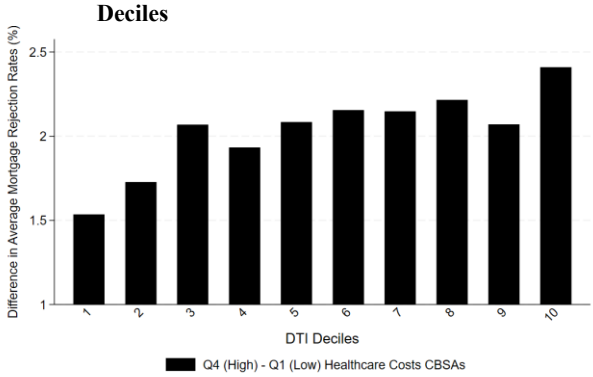
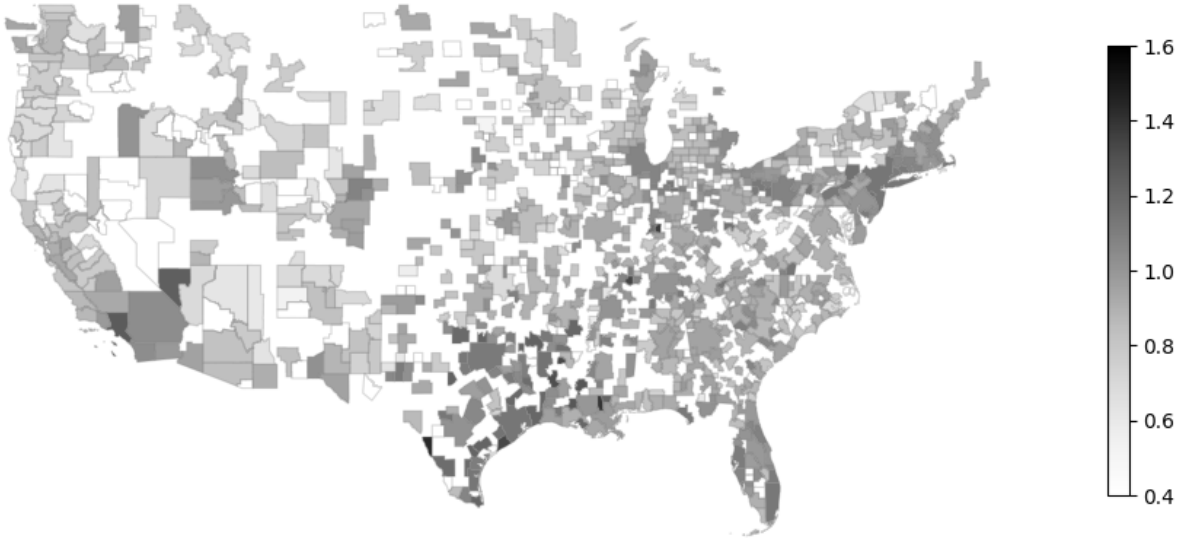


Figure 3
Heatmaps: Medicare Spending Per Beneficiary

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 Mspb Healthcare Costs Heatmap at the Start of the Sample Period, 2017



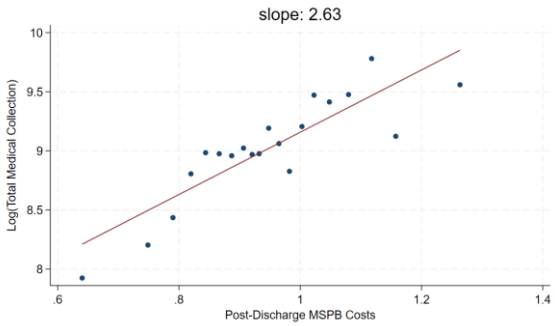
Panel B: MSPB Healthcare Costs Heatmap at the End of the Sample Period, 2023



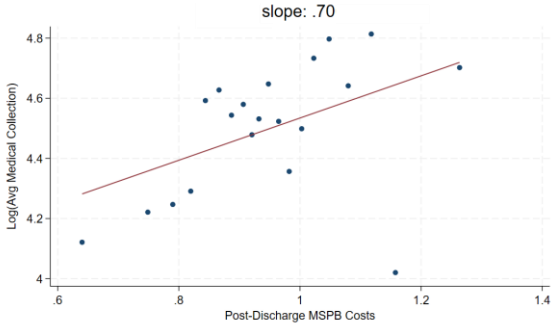
Figure 4
Validation of Medicare-Spending-per-Beneficiary Based Healthcare Costs Measures

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 and average medical collections, respectively. Panels C and D plot healthcare costs against the natural logarithm of total and average medical debt, respectively.

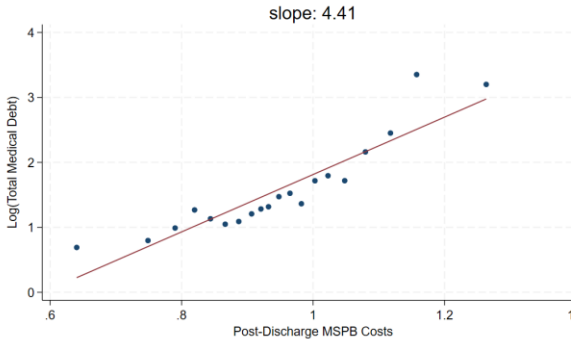
Panel A: Healthcare Costs and Total Medical Collection



Panel B: Healthcare Costs and Average Medical Collection



Panel C: Healthcare Costs and Total Medical Debt



Panel D: Healthcare Costs and Average Medical Debt

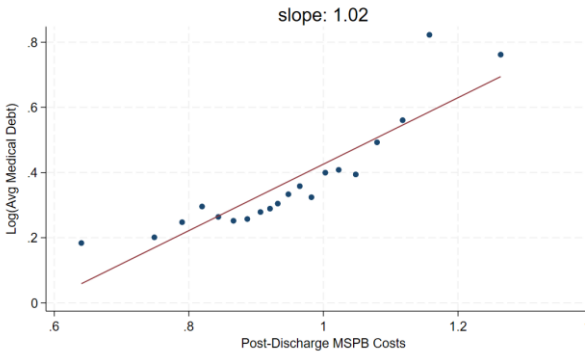
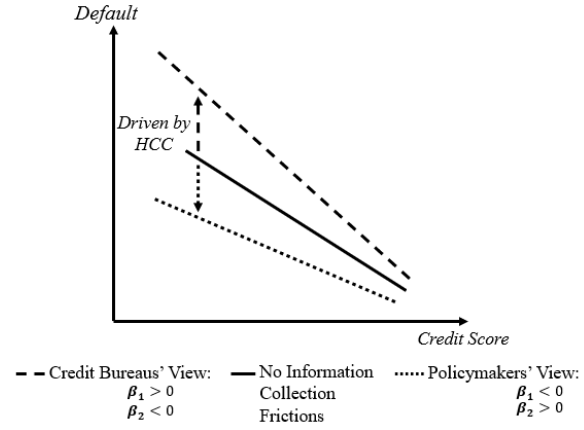


Figure 5
Empirical Design and Predictions

Panels A and B present predictions from our empirical design using the OLS regression specification below. Panel A uses credit scores 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 no information collection frictions in medical liabilities data, while dashed and dotted lines reflect the perspectives of credit bureaus and policymakers, respectively.

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

Panel A. Credit Score



Panel B. Debt-to-Income Ratio

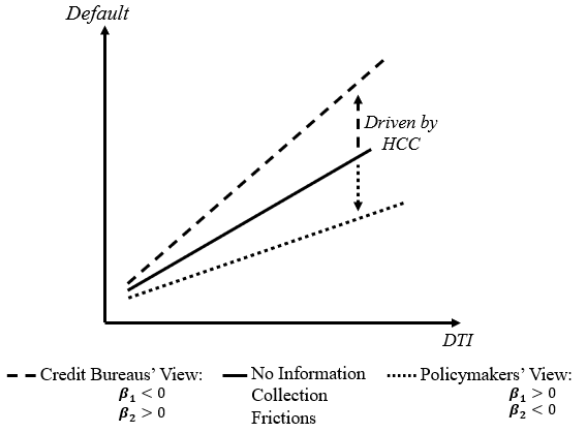


Figure 6
Total Medical Debt Collection Balances

The 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.

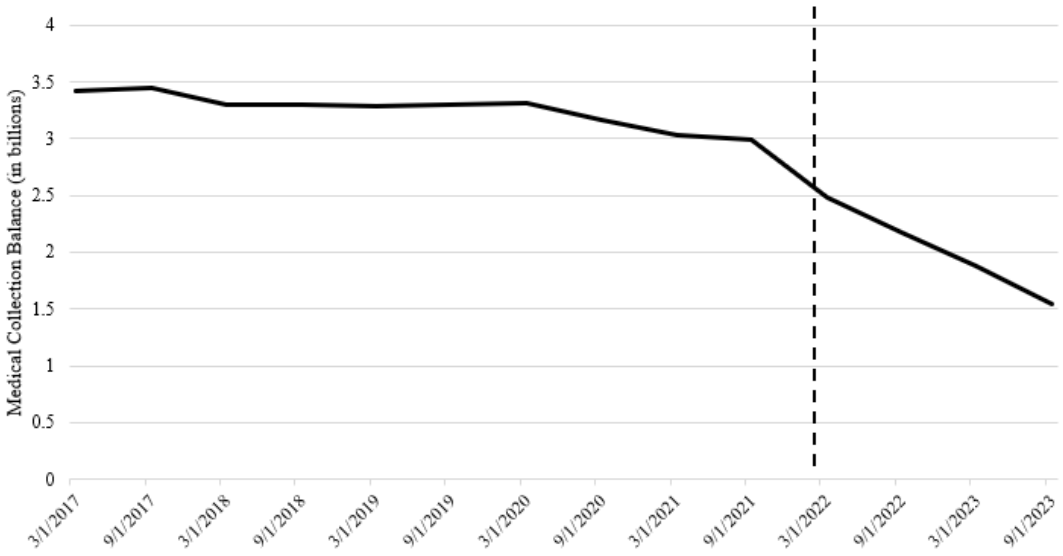


Table 1
Summary Statistics

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 mortgage applicants. Panel F 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	0.02	0.04	0	0.01	0.03
Average(medical debt) ($)	345,696	726.32	3637.40	0	125	623
Average(medical debt / total debt) (%)	345,696	1.23%	4.65%	0.00%	0.19%	0.96%
Share of consumers with medical collection accounts	345,696	0.13	0.11	0.05	0.11	0.18
Average(medical collections) ($)	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: Mortgage Applicant Related Variables (ZIP-Code-lender-year-loan type level) 2018 - 2023						
Mortgage Approval Rate	4,259,047	0.81	0.20	0.71	0.86	1.00
Debt-to-income ratio	4,259,047	0.36	0.06	0.32	0.35	0.39
Loan to value ratio	4,259,047	71.60	13.99	63.04	71.47	81.14
Loan Amount ($)	4,259,047	279635	231580	158750	231667	324063
Loan Maturity (months)	4,259,047	317	52	293	330	360
Minority	4,259,047	0.13	0.19	0.00	0.05	0.19
Panel F: Local Economic Fundamentals (CBSA-semiannual level) 2017 - 2023						
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 collections. Columns (2) and (3) use the natural logarithm of average and total medical collections (plus one), respectively. Column (4) uses the percentage of consumers with medical debt as the dependent variable. Columns (5) and (6) use the natural logarithm of average and total medical debt (plus one), respectively. Consumer financial information (at the ZIP-code level) includes the credit score, the average debt-to-income ratio, the natural logarithm of average income, the natural logarithm of the oldest account, the 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 med collections *(1)*	Log (avg med collections + 1) *(2)*	Log (total med collections + 1) *(3)*	% consumers with medical debt *(4)*	Log (avg med debt +1) *(5)*	Log (total med debt + 1) *(6)*
Panel A: HCC Proxy = MSPB Costs						
MSPB $Costs_{(CBSA,\ t)}$	0.061***	1.085***	1.155**	0.001***	0.430***	1.753***
	(2.94)	(2.96)	(2.21)	(2.66)	(3.69)	(3.90)
Consumer 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	0.42	0.24	0.15	0.01	0.08	0.12
Panel B: HCC Proxy = Post-Discharge MSPB Costs						
Post-Discharge MSPB $Costs_{(CBSA,\ t)}$	0.039***	0.787***	1.410***	0.001***	0.544***	2.107***
	(3.29)	(3.52)	(4.64)	(5.06)	(7.03)	(7.38)
Consumer 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	0.43	0.24	0.15	0.01	0.08	0.12
Panel C: HCC Proxy = Post- to Pre-Discharge MSPB Costs						
Post- to Pre-Discharge MSPB $Costs_{(CBSA.\ t)}$	0.018**	0.380**	0.889***	0.001***	0.351***	1.335***
	(2.24)	(2.35)	(4.02)	(4.63)	(6.50)	(6.73)
Consumer 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	0.42	0.24	0.15	0.01	0.08	0.12

Table 3
Healthcare Costs and Distortions in the Credit Score Reliability

The table presents results on healthcare costs and distortion in 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. 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. Consumer financial information (at the ZIP-code level) includes the credit score, the average debt-to-income ratio, the natural logarithm of average income, the natural logarithm of the oldest account, the 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*			
	(1)	*(2)*	*(3)*	*(4)*
Panel A: HCC Proxy = MSPB Costs				
MSPB Costs$_{(CBSA, t)}$	-	0.318***	-	0.321***
		(5.72)		(4.59)
Credit Score/100 $_{(ZIP, t)}$ ×	-	-0.044***	-	-0.046***
MSPB Costs$_{(CBSA, t)}$		(5.62)		(4.64)
Credit Score/100 $_{(ZIP, t)}$	-0.058***	-0.018**	-0.058***	-0.015
	(29.50)	(2.54)	(28.81)	(1.64)
Consumer financials $_{(ZIP, t)}$ including DTI	Y	Y	Y	Y
Local economy controls $_{(CBSA, t)}$	Y	Y	Y	Y
CBSA FEs	-	-	Y	Y
Time FEs	Y	Y	Y	Y
Observations	345,279	345,279	345,279	345,279
R-squared	0.28	0.28	0.30	0.30
Panel B: HCC Proxy = Post-Discharge MSPB Costs				
Post-Discharge MSPB Costs$_{(CBSA, t)}$	-	0.284***	-	0.242***
		(5.95)		(4.46)
Credit Score/100 $_{(ZIP, t)}$ ×	-	-0.039***	-	-0.034***
Post-Discharge MSPB Costs$_{(CBSA, t)}$		(5.92)		(4.47)
Credit Score/100 $_{(ZIP, t)}$	-0.058***	-0.022***	-0.058***	-0.025***
	(29.50)	(3.75)	(28.81)	(3.59)
Consumer financials $_{(ZIP, t)}$ including DTI	Y	Y	Y	Y
Local economy controls $_{(CBSA, t)}$	Y	Y	Y	Y
CBSA FEs	-	-	Y	Y
Time FEs	Y	Y	Y	Y
Observations	345,279	345,279	345,279	345,279
R-squared	0.28	0.29	0.30	0.30
Panel C: HCC Proxy = Post- to Pre-Discharge MSPB Costs				
Post- to Pre-Discharge MSPB Costs$_{(CBSA, t)}$	-	0.135***		0.108***
		(4.60)		(3.21)
Credit Score/100 $_{(ZIP, t)}$ ×	-	-0.018***		-0.015***
Post- to Pre-Discharge MSPB Costs$_{(CBSA, t)}$		(4.51)		(3.20)
Credit Score/100 $_{(ZIP, t)}$	-0.058***	-0.039***	-0.058***	-0.042***
	(29.50)	(8.63)	(28.81)	(7.98)
Consumer financials $_{(ZIP, t)}$ including DTI	Y	Y	Y	Y
Local economy controls $_{(CBSA, t)}$	Y	Y	Y	Y
CBSA FEs	-	-	Y	Y
Time FEs	Y	Y	Y	Y
Observations	345,279	345,279	345,279	345,279
R-squared	0.28	0.28	0.30	0.30

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

The table presents results on healthcare costs 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. 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. Consumer financial information (at the ZIP-code level) includes the credit score, the average debt-to-income ratio, the natural logarithm of average income, the natural logarithm of the oldest account, the 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*			
	(1)	*(2)*	*(3)*	*(4)*
Panel A: HCC Proxy = MSPB Costs				
MSPB $Costs_{(CBSA,\ t)}$	-	-0.005	-	-0.011
		(0.65)		(1.31)
$DTI_{(ZIP,\ t)}$ ×	-	0.172***	-	0.081
$MSPB\ Costs_{(CBSA,\ t)}$		(2.74)		(1.24)
$DTI_{(ZIP,\ t)}$	0.029***	-0.133**	0.026***	-0.050
	(4.30)	(2.24)	(3.66)	(0.82)
Consumer financials $_{(ZIP,\ t)}$ including Credit Score	Y	Y	Y	Y
Local economy controls $_{(CBSA,\ t)}$	Y	Y	Y	Y
CBSA FEs	-	-	Y	Y
Time FEs	Y	Y	Y	Y
Observations	345,279	345,279	345,279	345,279
R-squared	0.28	0.28	0.30	0.30
Panel B: HCC Proxy = Post-Discharge MSPB Costs				
Post-Discharge $MSPB\ Costs_{(CBSA,\ t)}$	-	-0.010*	-	-0.012**
		(1.87)		(2.26)
$DTI_{(ZIP,\ t)}$ ×	-	0.198***	-	0.113**
Post-Discharge $MSPB\ Costs_{(CBSA,\ t)}$		(4.99)		(2.56)
$DTI_{(ZIP,\ t)}$	0.029***	-0.156***	0.026***	-0.081*
	(4.30)	(4.14)	(3.66)	(1.94)
Consumer financials $_{(ZIP,\ t)}$ including Credit Score	Y	Y	Y	Y
Local economy controls $_{(CBSA,\ t)}$	Y	Y	Y	Y
CBSA FEs	-	-	Y	Y
Time FEs	Y	Y	Y	Y
Observations	345,279	345,279	345,279	345,279
R-squared	0.28	0.28	0.30	0.30
Panel C: HCC Proxy = Post- to Pre-Discharge MSPB Costs				
Post- to Pre-Discharge $MSPB\ Costs_{(CBSA,\ t)}$	-	-0.005	-	-0.007*
		(1.17)		(1.73)
$DTI_{(ZIP,\ t)}$ ×	-	0.107***	-	0.071**
Post- to Pre-Discharge $MSPB\ Costs_{(CBSA,\ t)}$		(3.51)		(2.24)
$DTI_{(ZIP,\ t)}$	0.029***	-0.079**	0.026***	-0.046
	(4.30)	(2.49)	(3.66)	(1.41)
Consumer financials $_{(ZIP,\ t)}$ including Credit Score	Y	Y	Y	Y
Local economy controls $_{(CBSA,\ t)}$	Y	Y	Y	Y
CBSA FEs	-	-	Y	Y
Time FEs	Y	Y	Y	Y
Observations	345,279	345,279	345,279	345,279
R-squared	0.28	0.28	0.30	0.30

Table 5
Healthcare Costs and Distortions:
By Consumers With and Without Medical Debt

The table examines distortions in the reliability of consumer creditworthiness metrics for consumers with and without medical debt. Panel A reports results for credit score reliability, while Panel B focuses on DTI reliability. Odd-numbered columns present results for consumers with medical debt, and even-numbered columns are for those without. Columns (1) and (2) use *MSPB Costs* as the measure of local healthcare costs, Columns (3) and (4) use *Post-Discharge MSPB Costs*, and Columns (5) and (6) use *Post- to Pre-Discharge MSPB Costs*. The dependent variable is the proportion of consumers in an area who have outstanding medical collection balances. Consumer financial information (at the ZIP-code level) includes the credit score, the average debt-to-income ratio, the natural logarithm of average income, the natural logarithm of the oldest account, the 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	*Healthcare Costs Proxies (CBSA, t)*					
	MSPB Costs		*Post-Discharge MSPB Costs*		*Post- to Pre-Discharge MSPB Costs*	
Medical Debt Accounts:	*With*	*Without*	*With*	*Without*	*With*	*Without*
Panel A: Credit Score Analysis						
Local Healthcare Costs$_{(CBSA, t)}$	0.111	0.267***	0.071	0.187***	0.026	0.072**
	(1.17)	(4.35)	(1.19)	(4.94)	(0.58)	(2.52)
Credit Score/100$_{(ZIP, t)}$ × Local Healthcare Costs$_{(CBSA, t)}$	-0.018	-0.038***	-0.012	-0.026***	-0.005	-0.010**
	(-1.21)	(-4.41)	(-1.29)	(-5.01)	(-0.72)	(-2.51)
Credit Score/100$_{(ZIP, t)}$	-0.065***	-0.015*	-0.070***	-0.025***	-0.077***	-0.040***
	(-4.54)	(-1.89)	(-7.63)	(-5.10)	(-9.88)	(-8.96)
Consumer financials$_{(ZIP, t)}$	Y	Y	Y	Y	Y	Y
Local economy controls$_{(CBSA, t)}$	Y	Y	Y	Y	Y	Y
CBSA FEs	Y	Y	Y	Y	Y	Y
Time FEs	Y	Y	Y	Y	Y	Y
Observations	290,173	344,277	290,173	344,277	290,173	344,277
R-squared	0.11	0.22	0.11	0.22	0.11	0.21
Panel B: DTI Analysis						
Local Healthcare Costs$_{(CBSA, t)}$	0.016	-0.013*	-0.010	-0.010**	-0.015*	-0.004
	(0.80)	(-1.84)	(-0.78)	(-2.41)	(-1.67)	(-1.17)
DTI$_{(ZIP, t)}$ × Local Healthcare Costs$_{(CBSA, t)}$	-0.114	0.099*	0.044	0.092***	0.069	0.041
	(-1.16)	(1.72)	(0.68)	(2.63)	(1.52)	(1.54)
DTI$_{(ZIP, t)}$	0.025	-0.060	-0.122**	-0.053	-0.151***	-0.008
	(0.28)	(-1.09)	(-2.02)	(-1.61)	(-3.26)	(-0.30)
Consumer financials$_{(ZIP, t)}$	Y	Y	Y	Y	Y	Y
Local economy controls$_{(CBSA, t)}$	Y	Y	Y	Y	Y	Y
CBSA FEs	Y	Y	Y	Y	Y	Y
Time FEs	Y	Y	Y	Y	Y	Y
Observations	290,173	344,277	290,173	344,277	290,173	344,277
R-squared	0.11	0.21	0.11	0.22	0.11	0.21

Table 6
The 2022 Policy Shift: Shock Validation

The table validates the 2022 policy shift. The dependent variable is the proportion of consumers in an area who have outstanding medical collection balances. Consumer financial information (at the ZIP-code level) includes the credit score, the average debt-to-income ratio, the natural logarithm of average income, the natural logarithm of the oldest account, the 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 = % of consumers with medical collection accocunts $_{(ZIP,\ t)}$			
Subsample: 2021S1-2023S1	*(1)*	*(2)*	*(3)*	*(4)*
Post 2022 Dummy	-0.040***		-0.013***	
	(15.35)		(4.77)	
D(Year2021 S2)		-0.002		-0.000
		(1.48)		(0.18)
D(Year2022 S1)		*omitted from the sample*		
D(Year2022 S2)		-0.024***		-0.014***
		(8.95)		(4.30)
D(Year2023 S1)		-0.062***		-0.051***
		(21.60)		(11.42)
Consumer financials $_{(ZIP,\ t)}$	Y	Y	Y	Y
Local economy controls $_{(CBSA,\ t)}$	Y	Y	Y	Y
CBSA FEs	-	-	Y	Y
Observations	105,186	105,186	105,186	105,186
R-squared	0.36	0.38	0.48	0.49

Table 7
The 2022 Policy Shift: Credit Score Distortion

The table examines the distortion in the credit score reliability around the 2022 policy shift. 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. Consumer financial information (at the ZIP-code level) includes the credit score, the average debt-to-income ratio, the natural logarithm of average income, the natural logarithm of the oldest account, the 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: HCC Proxy = MSPB Costs				
MSPB Costs$_{(CBSA, t)}$	0.302***	0.093***	0.356***	0.082***
	(3.75)	(5.75)	(3.45)	(4.89)
Credit Score/100 $_{(ZIP, t)}$ ×	-0.042***	-0.012***	-0.051***	-0.011***
MSPB Costs$_{(CBSA, t)}$	(3.79)	(5.52)	(3.52)	(4.76)
Consumer 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		0.27		0.28
Panel B: HCC Proxy = Post-Discharge MSPB Costs				
Post-Discharge MSPB Costs$_{(CBSA, t)}$	0.276***	0.078***	0.256***	0.078***
	(4.49)	(5.01)	(3.45)	(4.89)
Credit Score/100 $_{(ZIP, t)}$ ×	-0.037***	-0.011***	-0.036***	-0.011***
Post-Discharge MSPB Costs$_{(CBSA, t)}$	(4.52)	(5.44)	(3.45)	(5.24)
Consumer 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 C: HCC Proxy = Post- to Pre-Discharge MSPB Costs				
Post- to Pre-Discharge MSPB Costs$_{(CBSA, t)}$	0.120***	0.076***	0.091**	0.074***
	(3.41)	(5.62)	(2.13)	(5.40)
Credit Score/100$_{(ZIP, t)}$ ×	-0.016***	-0.011***	-0.012**	-0.011***
Post- to Pre-Discharge MSPB Costs$_{(CBSA, t)}$	(3.27)	(6.04)	(2.03)	(5.76)
Consumer 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 8
The 2022 Policy Shift: Debt-to-Income Ratio Distortion

The table examines the distortion in the debt-to-income ratio reliability around the 2022 policy shift. 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. Consumer financial information (at the ZIP-code level) includes the credit score, the average debt-to-income ratio, the natural logarithm of average income, the natural logarithm of the oldest account, the 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: HCC Proxy = MSPB Costs				
MSPB Costs$_{(CBSA, t)}$	-0.016	0.001	-0.019	-0.001
	(1.39)	(0.16)	(1.56)	(0.26)
DTI $_{(ZIP, t)}$ ×	0.194**	0.065***	0.123	0.067***
MSPB Costs$_{(CBSA, t)}$	(2.28)	(3.39)	(1.36)	(3.44)
Consumer 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: HCC Proxy = Post-Discharge MSPB Costs				
Post- to Pre-Discharge MSPB Costs$_{(CBSA, t)}$	-0.011	-0.007**	-0.011	-0.007**
	(1.39)	(2.17)	(1.41)	(2.24)
DTI (ZIP, t) ×	0.183***	0.062***	0.100*	0.066***
Post- to Pre-Discharge MSPB Costs$_{(CBSA, t)}$	(3.26)	(3.26)	(1.68)	(3.41)
Consumer 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 C: HCC Proxy = Post- to Pre-Discharge MSPB Costs				
Post- to Pre-Discharge MSPB Costs$_{(CBSA, t)}$	-0.001	-0.009***	-0.002	-0.009***
	(0.22)	(3.61)	(0.34)	(3.47)
DTI $_{(ZIP, t)}$ ×	0.078*	0.057***	0.039	0.059***
Post- to Pre-Discharge MSPB Costs$_{(CBSA, t)}$	(1.75)	(3.37)	(0.86)	(3.45)
Consumer 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 9
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, the proportion of minorities, the average debt-to-income ratio of mortgage applicants, and the average loan-to-value ratio. Consumer financial information (at the ZIP-code level) includes the credit score, the average debt-to-income ratio, the natural logarithm of average income, the natural logarithm of the oldest account, the 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)*
Post- to Pre-Discharge MSPB Costs$_{(CBSA, t)}$	-	-0.296***	-	-0.359***
		(3.31)		(3.21)
Credit Score/100 $_{(ZIP, t)}$ ×	-	0.039***	-	0.051***
Post- to Pre-Discharge MSPB		(3.16)		(3.22)
Credit Score/100$_{(ZIP, t)}$	0.047***	0.008	0.043***	-0.008
	(12.48)	(0.63)	(9.91)	(0.47)
Other loan characteristics$_{(ZIP,t)}$	Y	Y	Y	Y
Local consumer financials $_{(ZIP, t)}$	Y	Y	Y	Y
Local economy controls $_{(CBSA, t)}$	Y	Y	Y	Y
CBSA FEs	-	-	Y	Y
Lender x year x loan type FEs	Y	Y	Y	Y
Observations	4,251,896	4,251,896	4,251,896	4,251,896
R-squared	0.64	0.64	0.64	0.64

Table 10
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, the proportion of minorities, the average debt-to-income ratio of mortgage applicants, and the average loan-to-value ratio. Consumer financial information (at the ZIP-code level) includes the credit score, the average debt-to-income ratio, the natural logarithm of average income, the natural logarithm of the oldest account, the 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)*
Post- to Pre-Discharge MSPB Costs$_{(CBSA, t)}$	-	0.096***	-	0.113***
		(4.49)		(5.39)
DTI $_{(ZIP, t)}$ x	-	-0.324***	-	-0.315***
Post- to Pre-Discharge MSPB Costs$_{(CBSA, t)}$		(4.89)		(5.40)
DTI $_{(ZIP, t)}$	-0.851***	-0.514***	-0.841***	-0.518***
	(47.83)	(8.30)	(46.09)	(9.75)
Credit Score/100$_{(ZIP, t)}$	0.047***	0.046***	0.043***	0.043***
	(12.48)	(11.96)	(9.91)	(9.83)
Other loan characteristics$_{(ZIP,t)}$	Y	Y	Y	Y
Local consumer financials $_{(ZIP, t)}$	Y	Y	Y	Y
Local economy controls $_{(CBSA, t)}$	Y	Y	Y	Y
Lender x year x loan type FEs	Y	Y	Y	Y
CBSA FEs	-	-	Y	Y
Observations	4,251,896	4,251,896	4,251,896	4,251,896
R-squared	0.64	0.64	0.64	0.64

Table 11
Healthcare Costs and Access to Credit: The 2022 Policy Shift

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 policy shift. Panel A examines the distortion in 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, the proportion of minorities, the average debt-to-income ratio of mortgage applicants, and the average loan-to-value ratio. Consumer financial information (at the ZIP-code level) includes the credit score, the average debt-to-income ratio, the natural logarithm of average income, the natural logarithm of the oldest account, the 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*
Post- to Pre-Discharge MSPB Costs$_{(CBSA, t)}$	-0.227***	-0.177***	-0.269**	-0.178***
	(2.78)	(11.76)	(2.56)	(11.73)
Credit Score/100$_{(ZIP, t)}$ ×	0.029***	0.023***	0.039***	0.023***
Post- to Pre-Discharge MSPB Costs$_{(CBSA, t)}$	(2.63)	(10.84)	(2.68)	(11.96)
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 12
Healthcare Costs and Access to Credit: The 2022 Policy Shift and DTI

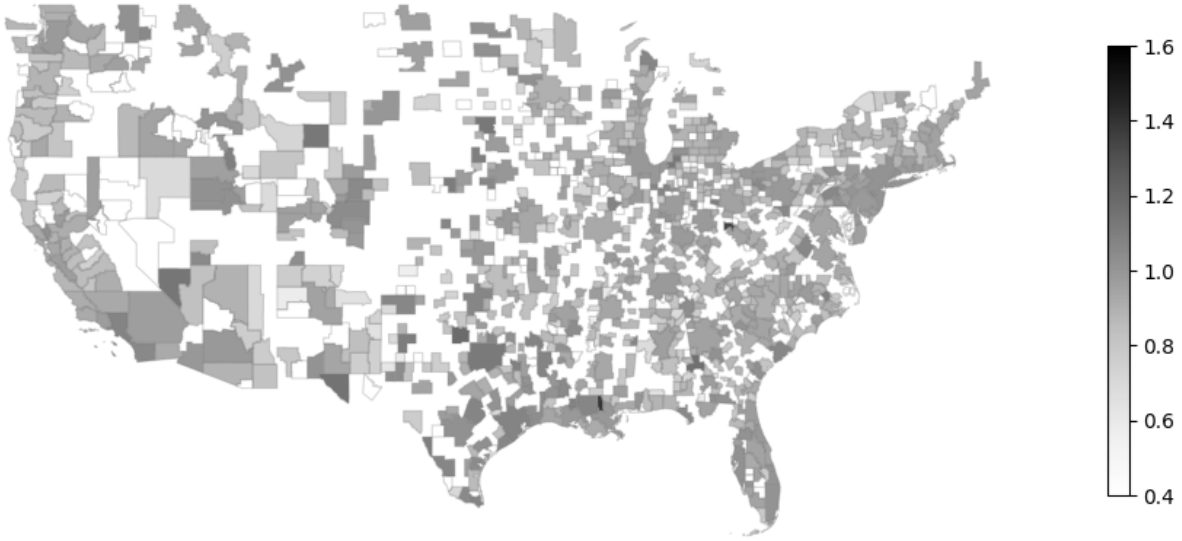
The table examines the association between the distortion in the credit score (and the debt-to-income ratio) reliability and consumers' access to credit around the 2022 policy shift. Panel A examines the distortion in credit score reliability. Panel B examines the distortion in the debt-to-income ratio 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, the proportion of minorities, the average debt-to-income ratio of mortgage applicants, and the average loan-to-value ratio. Consumer financial information (at the ZIP-code level) includes the credit score, the average debt-to-income ratio, the natural logarithm of average income, the natural logarithm of the oldest account, the 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*
Post- to Pre-Discharge MSPB Costs$_{(CBSA, t)}$	0.065***	0.049***	0.088***	0.049***
	(3.20)	(7.84)	(4.01)	(8.80)
DTI $_{(ZIP, t)}$ ×	-0.235***	-0.139***	-0.225***	-0.138***
Post- to Pre-Discharge MSPB Costs$_{(CBSA, t)}$	(3.72)	(13.38)	(3.81)	(13.30)
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	

Figure A1
Heatmaps: Medicare Spending Per Beneficiary
Using *MSPB Costs*

Panels A and B show the geographic variation in healthcare costs across CBSAs. Healthcare costs are measured as the average Medicare Spending Per Beneficiary (MSPB), scaled by the national average from Equation (1a). 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

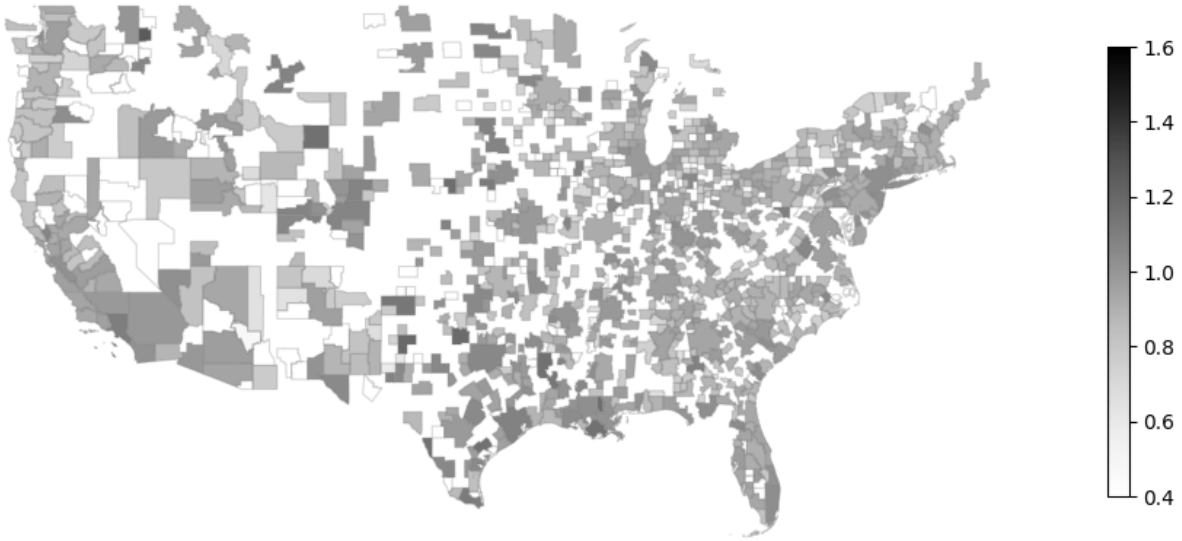
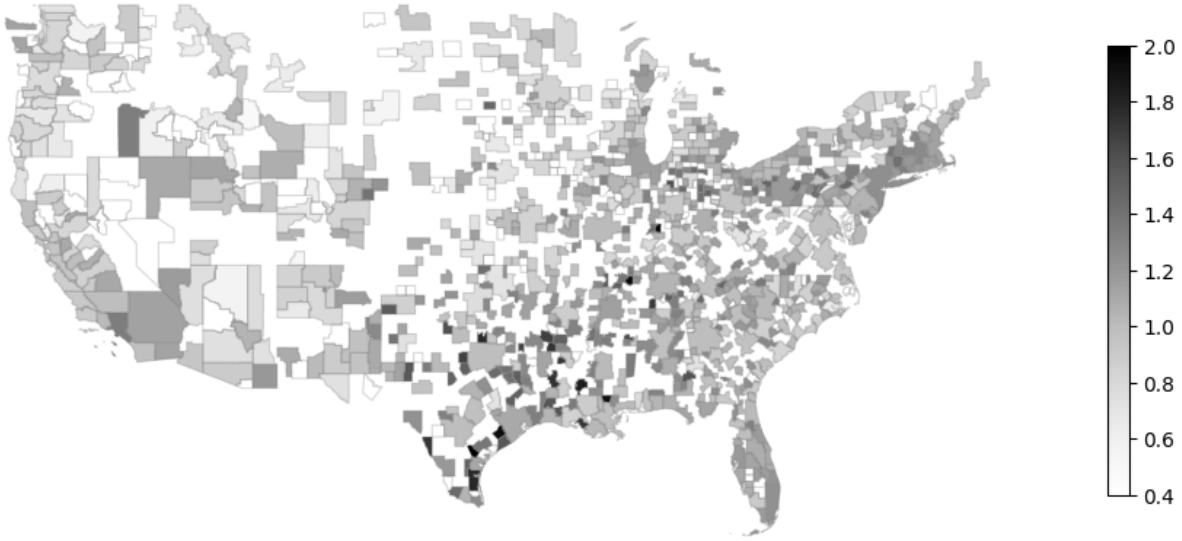


Figure A2
Heatmaps: Medicare Spending Per Beneficiary
Using *Post- to Pre-Discharge MSPB Costs*

Panels A and B show the geographic variation in healthcare costs across CBSAs. Healthcare costs are measured as the post- to pre-discharge average Medicare Spending Per Beneficiary (MSPB), scaled by the national average from Equation (1c). 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



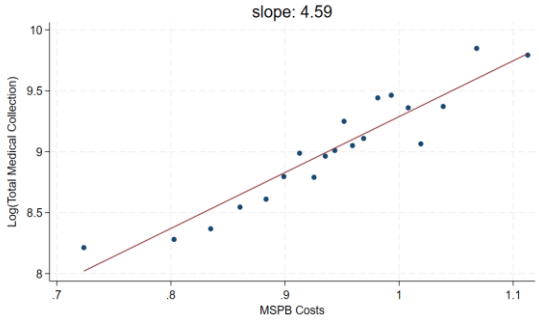
Panel B: MSPB Healthcare Costs Heatmap at the End of the Sample Period, 2023



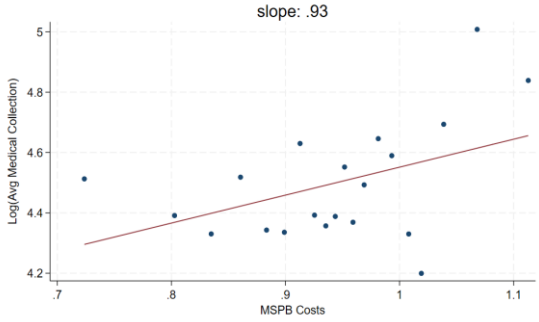
Figure A3
Validation of Medicare-Spending-per-Beneficiary Based Healthcare Costs Proxy: Using *MSPB Costs*

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 Medicare Spending Per Beneficiary (MSPB), scaled by the national average from Equation (1a). Panels A and B plot healthcare costs against the natural logarithm of total and average medical collections, respectively. Panels C and D plot healthcare costs against the natural logarithm of total and average medical debt, respectively.

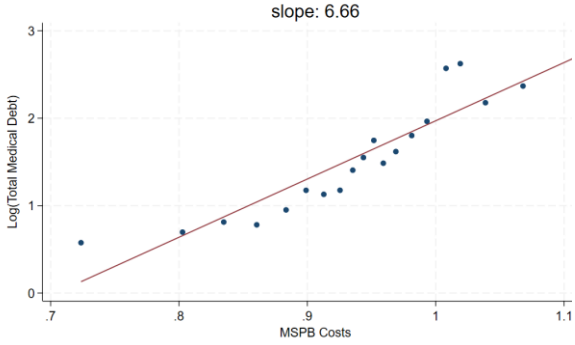
Panel A: Healthcare Costs and Total Medical Collection



Panel B: Healthcare Costs and Average Medical Collection



Panel C: Healthcare Costs and Total Medical Debt



Panel D: Healthcare Costs and Average Medical Debt

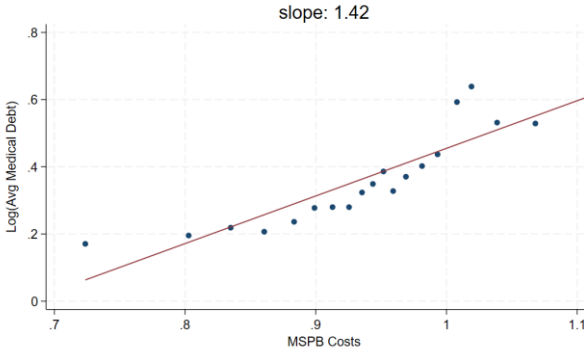
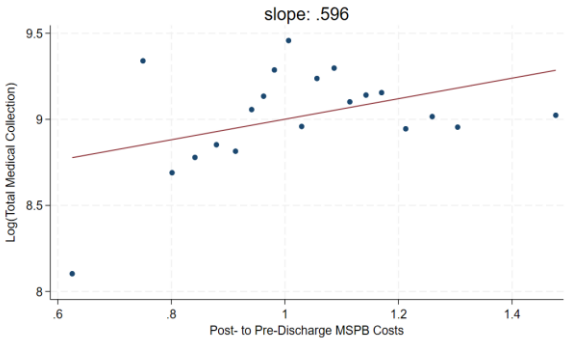


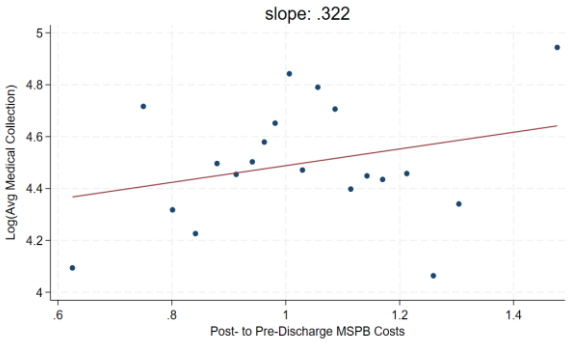
Figure A4
Validation of Medicare-Spending-per-Beneficiary Based Healthcare Costs Proxy: Using *Post- to Pre-Discharge MSPB Costs*

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- to pre-discharge Medicare Spending Per Beneficiary (MSPB), scaled by the national average from Equation (1c). Panels A and B plot healthcare costs against the natural logarithm of total and average medical collections, respectively. Panels C and D plot healthcare costs against the natural logarithm of total and average medical debt, respectively.

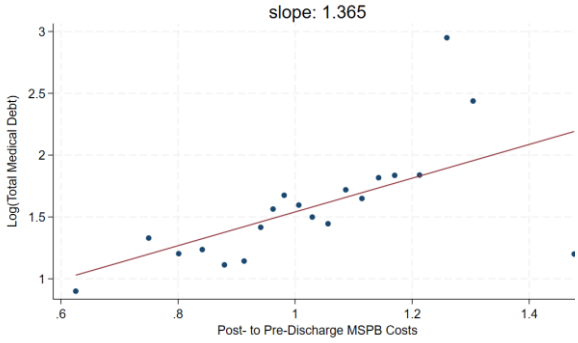
Panel A: Healthcare Costs and Total Medical Collection



Panel B: Healthcare Costs and Average Medical Collection



Panel C: Healthcare Costs and Total Medical Debt



Panel D: Healthcare Costs and Average Medical Debt

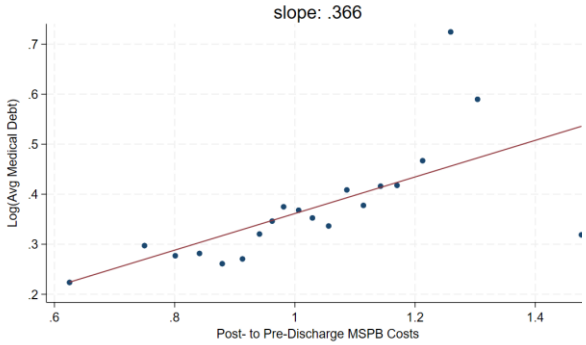


Table A1
Distribution of Medicare Spending per Beneficiary Across Periods of Treatment

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%

Table A2
Healthcare Costs and Distortions in the Credit Score Reliability (12 months)

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. 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 over the next twelve months. Consumer financial information (at the ZIP-code level) includes the credit score, the average debt-to-income ratio, the natural logarithm of average income, the natural logarithm of the oldest account, the 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 12 month*			
	(1)	*(2)*	*(3)*	*(4)*
Panel A: HCC Proxy = MSPB Costs				
MSPB Costs$_{(CBSA, t)}$	-	0.274***	-	0.316***
		(3.74)		(3.48)
Credit Score/100 $_{(ZIP, t)}$ ×	-	-0.036***	-	-0.045***
MSPB Costs$_{(CBSA, t)}$		(3.56)		(3.49)
Credit Score/100 $_{(ZIP, t)}$	-0.070***	-0.037***	-0.068***	-0.026**
	(29.20)	(3.89)	(28.45)	(2.16)
Consumer financials $_{(ZIP, t)}$	Y	Y	Y	Y
Local economy controls $_{(CBSA, t)}$	Y	Y	Y	Y
CBSA FEs	-	-	Y	Y
Time FEs	Y	Y	Y	Y
Observations	293,364	293,364	293,364	293,364
R-squared	0.38	0.38	0.40	0.40
Panel B: HCC Proxy = Post-Discharge MSPB Costs				
Post-Discharge MSPB Costs$_{(CBSA, t)}$	-	0.317***	-	0.285***
		(5.31)		(4.26)
Credit Score/100 $_{(ZIP, t)}$ ×	-	-0.042***	-	-0.040***
Post-Discharge MSPB Costs$_{(CBSA, t)}$		(5.15)		(4.22)
Credit Score/100 $_{(ZIP, t)}$	-0.070***	-0.031***	-0.068***	-0.030***
	(29.20)	(4.25)	(28.45)	(3.52)
Consumer financials $_{(ZIP, t)}$	Y	Y	Y	Y
Local economy controls $_{(CBSA, t)}$	Y	Y	Y	Y
CBSA FEs	-	-	Y	Y
Time FEs	Y	Y	Y	Y
Observations	293,364	293,364	293,364	293,364
R-squared	0.38	0.38	0.40	0.40
Panel C: HCC Proxy = Post- to Pre-Discharge MSPB Costs				
Post- to Pre-Discharge MSPB Costs$_{(CBSA, t)}$		0.184***		0.151***
		(5.08)		(3.67)
Credit Score/100 $_{(ZIP, t)}$ ×		-0.024***		-0.021***
Post- to Pre-Discharge MSPB		(4.87)		(3.58)
Credit Score/100 $_{(ZIP, t)}$	-0.070***	-0.045***	-0.068***	-0.047***
	(29.20)	(8.31)	(28.45)	(7.50)
Consumer financials $_{(ZIP, t)}$	Y	Y	Y	Y
Local economy controls $_{(CBSA, t)}$	Y	Y	Y	Y
Time FEs	Y	Y	Y	Y
Observations	293,364	293,364	293,364	293,364
R-squared	0.38	0.38	0.40	0.40

Table A3
Healthcare Costs and Distortions in the Debt-to-Income Ratio Reliability (12 months)

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. 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 over the next twelve months. Consumer financial information (at the ZIP-code level) includes the credit score, the average debt-to-income ratio, the natural logarithm of average income, the natural logarithm of the oldest account, the 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 12 month*			
	(1)	*(2)*	*(3)*	*(4)*
Panel A: HCC Proxy = MSPB Costs				
MSPB Costs$_{(CBSA, t)}$	-	0.003	-	-0.005
		(0.23)		(0.40)
DTI $_{(ZIP, t)}$ ×	-	0.150	-	0.045
MSPB Costs$_{(CBSA, t)}$		(1.46)		(0.42)
DTI $_{(ZIP, t)}$	0.047***	-0.093	0.046***	0.004
	(5.36)	(0.95)	(4.99)	(0.04)
Consumer financials $_{(ZIP, t)}$	Y	Y	Y	Y
Local economy controls $_{(CBSA, t)}$	Y	Y	Y	Y
CBSA FEs	-	-	Y	Y
Time FEs	Y	Y	Y	Y
Observations	293,364	293,364	293,364	293,364
R-squared	0.37	0.37	0.39	0.39
Panel B: HCC Proxy = Post-Discharge MSPB Costs				
Post-Discharge MSPB Costs$_{(CBSA, t)}$	-	-0.001	-	-0.007
		(0.17)		(0.87)
DTI $_{(ZIP, t)}$ ×	-	0.204***	-	0.093
Post-Discharge MSPB Costs$_{(CBSA, t)}$		(3.52)		(1.45)
DTI $_{(ZIP, t)}$	0.047***	-0.141**	0.046***	-0.042
	(5.36)	(2.53)	(4.99)	(0.68)
Consumer financials $_{(ZIP, t)}$	Y	Y	Y	Y
Local economy controls $_{(CBSA, t)}$	Y	Y	Y	Y
CBSA FEs	-	-	Y	Y
Time FEs	Y	Y	Y	Y
Observations	293,364	293,364	293,364	293,364
R-squared	0.37	0.37	0.39	0.39
Panel C: HCC Proxy = Post- to Pre-Discharge MSPB Costs				
Post- to Pre-Discharge MSPB Costs$_{(CBSA, t)}$	-	0.002	-	-0.002
		(0.31)		(0.35)
DTI $_{(ZIP, t)}$ ×	-	0.109***	-	0.058
Post- to Pre-Discharge MSPB Costs$_{(CBSA, t)}$		(2.64)		(1.35)
DTI $_{(ZIP, t)}$	0.047***	-0.061	0.046***	-0.013
	(5.36)	(1.41)	(4.99)	(0.29)
Consumer financials $_{(ZIP, t)}$	Y	Y	Y	Y
Local economy controls $_{(CBSA, t)}$	Y	Y	Y	Y
CBSA FEs	-	-	Y	Y
Time FEs	Y	Y	Y	Y
Observations	293,364	293,364	293,364	293,364
R-squared	0.37	0.37	0.39	0.39