Hidden Medical Debt and Consumer Access to Credit

Elena Loutskina, University of Virginia*

and

Joonsung Won, University of Virginia**

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ABSTRACT

Credit bureaus face significant frictions in collecting consumer medical debt data, which spurred an intense policy debate. We leverage novel healthcare costs proxies based on Medicare spending data to evaluate the impact of hidden medical debt 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 36.3% 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 intensified the medical debt information collection frictions. Our findings suggest that limiting the flow of medical debt data undermines the predictive accuracy of standard credit metrics, impairs the value of credit bureau data, and leads to less efficient credit allocation.

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* Corresponding Author: LoutskinaE@darden.virginia.edu; Darden School of Management University of Virginia, 100 Darden Boulevard, 22903;
** WonJ@darden.virginia.edu; Darden School of Management University of Virginia, 100 Darden Boulevard, 22903

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 2024, U.S. households held about $220 billion in medical debt (KFF, 2024) with 21% of the households having past-due medical bills (Fulford and Wilson, 2025). Yet credit bureaus (CBs) observe only a fraction of this debt due to numerous information collection frictions (Section II). This paper sheds light on how this incomplete and noisy medical debt data affects consumer creditworthiness assessment and access to credit.

Improving the information flows to better account for medical debt should not be controversial. Other forms of debt are already accounted for in consumers' credit files. Consumer advocates, however, argue that CBs should disregard even available medical debt data, viewing such data as prone to errors, disputes, insurance adjustments, and delayed updates. Small medical debt also does not meaningfully predict consumer defaults (Duarte et al. 2025; CFPB 2025a). In Q1 of 2022, CFPB called to restrict the use of medical collections in credit scoring, arguing that usage of such data "disproportionately harms low-income Americans" — lowering credit scores and restricting access to credit.[1] Removing such noisy credit data may improve the credit-score precision and credit availability for underserved groups (Blattner and Nelson, 2021). Lending industry advocates countered that while excluding negative credit events may expand access to credit for *direct beneficiaries* (e.g., Dobbie et al., 2020a; Liberman, 2016), incomplete medical debt information might lead to risk pooling (Chatterjee et al., 2023) and a reduction in aggregate access to credit (e.g., Liberman et al., 2018), thus lowering social welfare (Jansen et al., 2024).

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

This paper contributes to this debate by examining how medical debt affects consumer access to credit. The core empirical challenge we face is that medical debt is (mostly) *hidden*.[2] We address this issue by exploiting novel healthcare costs (HCC) measures that are consistently measured across markets and are positively associated with the accumulation of medical debt, which we verify using available, albeit incomplete, CB data. We further enhance our identification by leveraging the 2022 policy shift that sharply reduced the reporting of medical collections to CBs without affecting consumers' balance sheets.

Our results suggest that hidden medical debt is associated with upward bias in standard creditworthiness indicators and restricts consumer access to credit. Conditional on credit scores and debt-to-income ratios (DTIs), consumers in high-HCC CBSAs are 36.3% more likely to default than those in low-HCC CBSAs (Figure 1). The effects are most pronounced among riskier consumers — those with low credit scores and high DTIs. Lenders appear to internalize this, as mortgage rejection rates are higher in high-HCC CBSAs, particularly for riskier applicants (Figure 2). Both effects intensify following the 2022 policy shift, consistent with increased adverse selection due to greater information frictions. Collectively, our findings suggest that the hidden medical debt compromises the predictive ability of CB data and further restricts consumers' access to credit.

Our empirical design is built on novel HCC proxies based on hospital-level Medicare Spending Per Beneficiary (MSPB) data from 2017 to 2023.[3] MSPB data offers several advantages.

[2] CFPB (2022) estimates that only $88 billion of the medical debt was accounted for in 2021 consumer credit files compared to $250 billion KFF estimate of the total outstanding medical debt. The credit bureau data utilized in this paper suggests that in 2021, consumers carried about $60.6 billion in medical debt, or 24.2% of the amounts reported by KFF (2024). 98% this debt is recorded in the medical debt *collection* accounts. Fulford and Wilson (2025) document that while 36% of households had medical debt, only 12% had medical debt collection records in credit files.

[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

These costs are reported per hospitalization, spanning three days before admission through 30 days after discharge (Das et al. 2016) and, hence, are *unaffected* by healthcare utilization rates (Anderson, Dobkin, and Gross 2012; Finkelstein, Gentzkow, and Williams 2016). CMS adjusts MSPB costs for differences in Medicare reimbursement rates (Clemens and Gottlieb, 2014) and local population health risk factors. Effectively, the core variation in the MSPB costs stems from hospital (in)efficiencies, care quality (e.g., post-operative infection rates), and (over- or under-) provision of services (Norton et al. 2018), which are factors that influence all patients, not only Medicare recipients (Ferro et al. 2019).

Although our MSPB-based HCC proxies do not fully capture the heterogeneity in HCC across CBSAs, they represent a driver of HCC that is arguably largely unrelated to local consumers' financial conditions and credit demand.[4] 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). We further validate our MSPB-based HCC proxies by documenting that consumers residing in high HCC markets accumulate higher medical debt as per CB data.

In the first part of the paper, we employ the MSPB-based HCC measures to assess whether hidden medical debt affects the informativeness of the traditional creditworthiness indicators for consumer defaults. We find that representative ZIP code level consumers residing in the top

[4] We acknowledge that our MSPB-based HCC measures are not exogenous to local *economic* conditions. Hospitals located in rapidly growing labor markets or markets with high insurance coverage are likely to have better equipment and more modern (and more expensive) healthcare services as compared to rural markets. Our identification stems from the policy shock that amplified medical debt information collection frictions and affected high HCC markets to a larger extent.

quartile HCC markets exhibit a 1.53% higher 6-month default rate than those in the bottom quartile HCC markets (Figure 1). This differential represents 36.3% of the sample's average default rate from the bottom quartile HCC markets (4.21%). The default-rate differential declines (increases) monotonically across credit score (DTI) deciles. Specifically, the differential is 1.59% among the lowest credit score decile consumers but only 0.19% among those in the highest decile.[5] We confirm these effects in a regression setting where we control for an array of local economic fundamentals, consumer financial conditions, and demographic characteristics. These effects are strongest among consumers *without* any reported medical debt data in CB data, underscoring the role of information collection frictions.

One can argue that HCC may affect consumer defaults through a cash-flow channel rather than an information friction channel. High HCC and related medical expenses are likely to impede consumers' ability to pay their bills or might correspond to more time spent seeking treatment and away from the workplace. To isolate the role of the information frictions, we leverage the 2022 policy shift that further impeded CBs' access to medical debt data. On July 1st, 2022, CBs stopped considering (a) repaid medical tradelines and (b) debt transferred to collectors within the prior 12 months. By 2023, they also stopped considering (c) unpaid medical collections below $500. We find that this policy shift amplified the adverse effect of healthcare costs on the predictive ability of credit scores and DTIs. These results highlight that hidden medical debt introduces an upward bias in the traditional creditworthiness measures. Broadly, they suggest that limiting the availability of medical debt information weakens the quality of CB data and impairs lenders' ability to assess borrower risk.

[5] The default rate differential is 2.70% for the highest DTI decile consumers and 0.7% for the lowest DTI decile consumers.

In the second part of the paper, we examine whether lenders recognize 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. We analyze ZIP code-level mortgage acceptance rates to capture lenders' credit allocation decisions across different HCC markets *within lender-year-loan type*, conditional on loan and borrower characteristics.

We find that lenders are about 3.47% more likely to reject new mortgage applications in top-quartile HCC markets relative to bottom-quartile markets (Figure 2), more so for riskier borrowers. This is sizeable relative to the 18.7% sample average rejection rate. These effects increase by about 47.3% following the 2022 policy shift, further supporting the information collection frictions channel. Confronted with growing uncertainty regarding borrowers' true financial health, lenders appear to internalize this by broadly restricting access to credit in higher HCC markets, irrespective of individual exposure to medical liabilities. Such a response by lenders potentially reduces the efficiency of credit allocation and might negatively affect consumer welfare.

Our paper contributes to several strands of academic inquiry. First, we add to the literature exploring the impact of medical debt on consumer financial health. Several papers have documented that medical debt is a significant contributor 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* improves consumers' credit scores (Kluender et al, 2024). We add to this

literature by documenting the impact of the *hidden* medical debt on consumers' credit scoring and access to credit.

Second, we contribute to the literature that explores the impact of information deletion from consumer credit files. Several studies show that limits on public information increase access to credit for the *direct beneficiaries* (Dobbie et al., 2020b; Gross, Notowidigdo, and Wang 2020; Herkenhoff, Phillips, and Cohen-Cole, 2021). Yet, incomplete credit information is associated with lower overall social welfare (Jansen et al., 2024), as adverse selection leads to a reduction in aggregate access to credit (Liberman et al., 2018) and job prospects (Agan and Starr, 2017; Corbae and Glover, 2025) due to risk pooling (Chatterjee et al. 2023). In this line of academic inquiry, Duarte et al., (2025) is the closest study to ours. It documents that removing medical collection accounts below $500 from CB files did not impact defaults and access to credit of *direct beneficiaries*. We augment this literature by exploring the broader impact of the 2022 policy shift that amplified information frictions and led to adverse selection and risk pooling in credit markets.

Third, 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. 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). Our measure adds to this array as it helps explain the variation in consumer medical debt and links HCC with geographic heterogeneity in individual economic outcomes (Keys, Mahoney, and Yang 2022).

Finally, we contribute to the policy debate with profound implications for lenders and consumers alike. On January 7th, 2025, the CFPB called to remove all medical debt from the credit reports (CFPB, 2025), without eliminating the underlying medical debt. On July 15th, 2025, the

U.S. Eastern District Court of Texas effectively voided this ruling. Our results indicate that limiting CBs' access to medical debt data weakens the quality of information available to lenders and restricts consumers' access to credit.

II. Medical Debt in Consumer Credit Files

II.1 Institutional Details

As of December 2021, Americans owed approximately $220 billion in medical debt (KFF, 2024). The KFF survey estimated that around 21 million U.S. adults carried medical debt, with 52% of them owing more than $2,000 to healthcare providers. However, consumer medical debt is not systematically incorporated into CBs' files. As of September 2021, the closest date available to us, credit files of a major CB used in this study recorded only $60.6 billion in mostly (98%) medical collection balances, substantially below the $220 billion estimated by KFF.[6] Fulford and Wilson (2025) use data from two 2024 surveys to document that 36.3% of US households (39% of households with some uninsured members) had medical debt; 23% were paying a medical bill over time to a provider; and 16.9% used another credit product to pay their medical bills. Only 12% of households had medical collections in their credit records.[7]

There are several reasons why medical debt in CB files can be incomplete and frequently 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, healthcare providers frequently engage in

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

[7] 13% of consumers (not households) have medical debt or medical collection accounts in our CB files data.

debt renegotiations and restructuring to enhance recovery rates (NPR, 2023) and typically process medical debt in-house. "… *hospitals become frequent collection agents*" (Richman et al., 2023). However, providers rarely have direct reporting relationships with CBs (Consumer Reports, 2018).

Second, major contributors of the medical debt information in CB 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 finalized and no longer disputed (Kluender et al., 2021). As of September 2021, $59.8 billion out of $60.6 billion of medical debt cited above are medical debt *collection* balances.

Third, 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.

Finally, even data provided by collection agencies is subject to distortions and errors. The medical debt collection industry is highly fragmented, with approximately 1,400 different agents (CFPB, 2014).[8] Relationships between collectors and CBs are largely voluntary, creating frictions that lead to delayed or inconsistent reporting.[9] Moreover, medical debt collectors might be incentivized to underreport repayment (Lyons, 2020) 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).

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

[9] Gibbs et al. (2025) report that debt collection agencies only *sometimes* furnish collection accounts to credit reporting agencies, suggesting that the reporting process is largely voluntary and not automatic.

These factors contribute to significant frictions in collecting medical debt information, leading to incomplete and noisy medical debt data in consumer credit files. Yet, when available, this information significantly affects consumers' creditworthiness assessment (Kluender et al., 2024; Brevoort, Grodzicki, and Hackmann, 2020) and by extension, 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 debt data is unreliable and *should not* be factored into consumer creditworthiness assessment due to inaccuracies and outdated reporting. CFPB contends that credit scores incorporating available medical debt data systematically *underestimate* borrower quality, leading to unjustified credit rationing. CFPB also cites evidence that small medical debt collections are poor predictors of default (CFPB 2025a). Excluding medical debt 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 debt data from credit reports would undermine the informativeness of CBs' data, weaken underwriting, and expand risky lending (WSJ 2024). The lending industry advocates further argue that 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 CBs announced that they would dramatically curtail the use of medical debt data in credit assessment. Specifically, starting July 1st, 2022, CBs stopped considering (a) repaid medical debt and collection 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 about 70% of medical debt tradelines (i.e., accounts) from credit files without changing consumers' financial obligations to healthcare providers and collectors.

The rule was followed by a rapid decline in recorded medical debt data that, even by CFPB's own admission, far exceeded the expected decline in medical debt collections (CFPB, Sandler and Blizard 2024). Our 5% CB data shows that medical debt collection tradelines dropped from $4.22 billion in September 2021 to $2.97 billion in September 2022, even before the "below $500" limit went into effect (Figure 5), as "furnishers decided not to furnish certain tradelines" (CFPB, Sandler and Blizard, 2024). An independent study by the Urban Institute suggests that the 2022 move improved the VantageScores of subprime consumers by about 30 points while leaving the credit scores of prime consumers unaffected (Blavin, Braga, and Karpman 2023). We exploit this information friction shock in our empirical design.[10]

More recently, in January 2025, the outgoing Administration announced a new CFPB Rule that mandated CRAs to fully exclude medical debt data from consumer credit files. The rule was expected to remove an estimated $49 billion in medical bills and collections from consumer credit reports of about 15 million Americans" (CFPB, 2025). While announcing the rule, Vice President Kamala Harris stated that this would be "life-changing" for millions of families as "no one should

[10] Our contract with a credit bureau data provider limits our ability to conduct commensurate analysis of the effects of omitted medical debt data on consumer credit scores.

be denied economic opportunity because they got sick or experienced a medical emergency." On July 15th, 2025, the U.S. Eastern District Court of Texas effectively voided this ruling, thus keeping the debate ongoing.

III. Data and Sample Selection

To support the call to remove medical debt from CB files, CFPB conducted a study that compared the unconditional frequency of derogatory events among consumers with and without medical debt data recorded in consumer credit files (CFPB, 2014). This empirical approach presents two key issues. First, it implicitly assumes that medical debt 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 debt data 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 debt data, we focus on healthcare costs — the core driver of (observed and hidden) medical debt. We argue that the impact of medical debt on consumer financial health should be more pronounced in high healthcare cost markets and for at-risk consumers, those with low credit scores and high DTIs.

III.1 Healthcare Costs Proxies

We advance novel factors that contribute to heterogeneity in healthcare costs across U.S. markets, built 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, during, and 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 were designed to enable comparisons of hospitals' cost efficiency (Norton et al., 2018; Currie et al., 2023). To ensure comparability between hospitals, the MSPB data rely on CMS-designed standardization procedures.[11] First, the measure is adjusted for the local population health risk factors, including age, severity of illness, comorbidities, and other characteristics.[12] Second, it is also price-standardized, meaning regional payment differences (e.g., local wage indexes) are adjusted out. Third, the data is also free of potential biases stemming from geographical variations in healthcare utilization by patients, as it relies on *per-hospitalization incident* costs and fully ignores the patient demand for healthcare services (Skinner, 2011). 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. Importantly, 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). Ultimately, the core variation in the MSPB data captures the heterogeneity in the care quality (e.g., rate of costly post-op infections) and the (over-) provision of medical services across U.S. hospitals.

We acknowledge that MSPB data does not fully capture the heterogeneity in HCC across CBSAs. Rather, it captures one of the drivers of local HCC stemming from the standards of care established for Medicaid patients. Amounting to about 21% of total U.S. healthcare spending,

[11] 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.

[12] We independently verify that MSPB costs are not driven by local population health or hospitals' ability to provide complex procedures using the case complexity index provided by the American Hospital Association data. The index captures hospitals' exposure to a higher number of more complex, resource-intensive cases.

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).

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:[13]

$$MSPB\ Costs_{CBSA,t} = Avg_{CBSA,t}\left(\frac{MSPB\ Costs_{Hospital,t}}{National\ Avg_{t}}\right). \quad (1a)$$

Second, we investigate post-hospital-discharge MSPB costs. These costs (e.g., post-acute care, skilled nursing facilities) represent 42.1% 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, our second measure focuses on the *Post-Discharge MSPB Costs*:

[13] We have conducted an array of robustness tests defining a healthcare market for a representative consumer using a group of hospitals located within 25-, 50-, and 100-mile radius of a given ZIP code. We find all the results reported in this paper to be robust to these alternative healthcare market definitions.

$$Post\text{-}Discharge\ MSPB\ Costs_{CBSA,t} = Avg_{CBSA,t}\left(\frac{Post\text{-}Discharge\ MSPB\ Costs_{Hospital,t}}{National\ Avg_t}\right). \quad (1b)$$

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 may still be affected by local patient health and local hospitals' ability to provide complex medical services. To further account for heterogeneity in local health demographic factors and hospital capabilities, we advance a *third* HCC measure where we normalize the CBSA-average post-discharge MSPB costs by the CBSA-average pre-discharge MSPB costs:

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

Normalization aims to eliminate any residual effects of in-hospital care complexity 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 and over- or under-provision of services after hospitalization.[14]

Panel A of Table 1 reports the summary statistics for our measures. The sample average Medicare Spending per Beneficiary is $20,335, with post-discharge spending averaging $8,524 — 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.[15] 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.

[14] 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)

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

III.2 Consumer Financials Data and Sample Selection

Consumer Credit Panel

To capture consumer financial characteristics, we rely on data from one of the major U.S. CBs. We utilize data about a 5% representative sample of U.S. consumers observed at the end of March and September each year from 2017 to 2023. These data offer detailed information about consumer debt, including delinquent and derogatory events and balances, credit scores, income level, leverage relative to income, a proxy for consumer age, and 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 debt.

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 13% of consumers have medical debt accounts (medical debt and/or medical collection accounts).

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 mortgage applications for single-family, site-built residential properties (excluding manufactured housing), including

home purchase, home improvement, and refinance loans. Throughout our analysis, we use 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 CB and HMDA data using multiple other data sources. We account for the variation in the local access to health insurance by utilizing (a) the share of the local population that is older than 65 and hence has access to Medicare; and (b) the county-level share of the insured population under age 65 provided by the U.S. Census Bureau's Small Area Health Insurance Estimates (SAHIE). We further collect the hospital-level case mix index from the Center for Medicare and Medicaid Services (CMS) and aggregate it at the CBSA level to control for the average clinical severity of the local patient population. Lastly, we utilize 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.

III.3 Healthcare Measures Validation Tests

We first and foremost use the CB data to confirm that the proposed healthcare cost measures do contribute to the accumulation of consumer medical debt. This analysis is based on (arguably incomplete and noisy) medical debt data recorded in consumer credit files. The identifying assumption underlying this analysis is that these data, while noisy and downward-biased, are not randomly distributed across U.S. markets. Specifically, we focus on two observed

medical debt characteristics of ZIP code representative consumers: (a) the share of consumers with medical debt; and (b) the average medical debt balances. Panel B of Table 1 offers summary statistics for these variables. Medical debt is present for 13% of U.S. consumers, with an average observed balance of $333 per consumer.

Figure 4 reports the bin-scatter plots of the observed medical debt characteristics against — $Post\text{-}Discharge\ MSPB\ Costs_{CBSA,t}$.[16] Panel A suggests that for an average consumer, a 1 percentage point increase in *Post-Discharge MSPB Costs* leads to a 0.246% increase in the share of consumers with observed medical debt. Panel B indicates that for an average consumer, a 1 percentage point increase in *Post-Discharge MSPB Costs* leads to a 0.797% increase in observed average consumer medical debt. The figures suggest that the effect works through both intensive and extensive margins.

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

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

The analysis incorporates a wide set of control variables that account for ZIP code representative consumers' financial characteristics, local insurance levels, and CBSA-level local economic conditions described above. The identifying assumption is that, while the medical debt data in CB files is incomplete, it is not randomly distributed across U.S. ZIP codes.

Table 2 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

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

debt collections dimensions, even after controlling for a host of factors, potentially affecting the accumulation of medical debt by consumers. Specifically, the set of controls includes the consumer financial conditions based on CB data, local insurance coverage based on SAHIE estimates, local economic fundamentals based on employment and wages data, and the case mix index, provided by CMS, that captures the complexity of local healthcare services.

Column 1 of Panel A indicates that for an average consumer, a one percentage point increase in $MSPB\ Costs_{CBSA,t}$ is associated with an 0.107 percentage point increase in the share of consumers with medical debt accounts. Column 4 of Panel A shows that for an average consumer, a one percentage point increase in $MSPB\ Costs_{CBSA,t}$ is associated with a 1.623% increase in the ZIP code-level average medical debt balances. Panels B and C, which examine the other two measures of HCC, show similar statistical and economic magnitudes in explaining the heterogeneity of medical debt across regions. Overall, results reported in Table 2 validate our core identifying assumption — our healthcare cost measures contribute to the heterogeneity in medical debt across U.S. markets.

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 how the traditional creditworthiness measures 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 15.9% more likely to default if they reside in high versus low healthcare costs CBSAs. The lowest credit score decile consumers experience a 9.98% default rate in the bottom HCC quartile CBSAs and 11.57% in the top HCC quartile CBSAs, resulting in a 1.59% 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 2.75% for the top DTI decile consumers and only 0.7% for the bottom DTI decile consumers. These findings support the notion that credit scores and DTIs — based on imperfect medical debt 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.

Arguably, omitted negative credit file data creates an upward bias in consumer creditworthiness assessment, i.e., it unfairly inflates credit scores and deflates DTIs for consumers exposed to the risk of medical debt accumulation. This upward bias in the traditional

creditworthiness assessment should be felt more acutely by riskier consumers. Consistently, we would expect $\beta_1 > 0$ and $\beta_2 < 0$ in the case of credit scores ($\beta_1 > 0$ and $\beta_2 > 0$ in the case of DTIs).

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 the 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 insurance coverage differences across geographies, we incorporate the share of the local population aged 65 and older and the share of insured population data provided by SAHIE (Section III.2). The local economic conditions are accounted for via the (natural logarithm of) total local employment and average wage, past employment and wage growth, and 2-digit NAICS industry labor shares that capture the local industry composition. The CBSA-level average case mix index allows us to control for the average clinical severity of the patient population. Finally, time fixed effects (γ_t) control for macroeconomic conditions such as overall consumer credit conditions, business cycles, and shifts in Medicare policies. To ensure that some unobserved CBSA-specific heterogeneity drives our results, in a subset of tests, we include CBSA fixed effects (μ_{CBSA}), and for robustness, the CBSA-time fixed effects.

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. Column 4 of Panel B suggests that an average 700 credit score consumer does not exhibit a difference in defaults across high and low HCC markets. The HCC coefficient of interest for an average consumer is effectively zero (0.233 – 0.033 × 700/100). For every 100-point decline in credit scores, however, consumers are 0.56% (0.033 × 0.17) more likely to default if they reside in the top quartile HCC market vs the bottom quartile HCC market. Credit scores underpredict defaults more in high HCC markets, particularly so for low-credit-score consumers. For comparison, the average 6-month default rate in our sample is 5.03% (Panel C of Table 1). The magnitudes of these effects increase once we expand the potential default window to 12 months.[17]

Table 4 presents a similar analysis focused 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.[18] 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 ($\beta_2 > 0$). While β_1 is negative, the average effect of HCC on defaults is still positive. Column 4 of Panel B implies that for every ten percentage points increase in DTI, consumers residing in top quartile HCC markets default 0.19% more (0.113 × 0.17 × 0.1) than those residing in bottom quartile HCC markets.

[17] These results, as well as all other robustness tests cited in this study, are available upon request.

[18] Similar results are observed for 12-month default rates. These results are not reported and are available upon request.

To this point, our analysis reflects the average effect across all consumers, both with and without medical debt records, leaving open the possibility that the bias in the consumer creditworthiness measures exists solely among those with reported medical debt, rather than those with hidden medical debt. To address this concern, we assess the documented effects for consumers *with* and *without* recorded medical debt separately. Specifically, we create two sub-samples of ZIP code representative consumers: one based solely on consumers with non-zero medical debt recorded in CB 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 debt, while even-numbered columns correspond to those *without* medical debt in credit files. For brevity, Table 5, as well as all subsequent tables, reports the results based on the $Post\text{-}Discharge\ MSPB\ Costs_{CBSA,t}$ measure of HCC. The results based on the other two HCC measures are consistent with those reported in the paper and are available upon request.

Table 5 shows that our core results are driven by the group of consumers *without* medical debt accounts in their credit files (even columns). We find no evidence that credit scores (DTIs) are biased in predicting defaults for consumers *with* medical debt tradelines (odd columns). This suggests that available medical debt data does not systematically distort consumer creditworthiness assessment.

Overall, the results documented in Tables 3 through 5 are consistent with the notion that as healthcare costs rise, the credit scores (DTIs) exhibit upward (downward) bias, underestimating defaults and potentially overestimating their creditworthiness for consumers residing in higher HCC markets. These effects seem to be driven by unobserved medical debt proxied for by HCC measures.

2022 Medical Collections Policy Shift

The core results presented in Tables 3 through 5 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 the current creditworthiness assessment less accurate in predicting future defaults. It is also possible that MSPB costs are fully unrelated to local economic conditions despite our extensive set of controls.[19]

To isolate the information friction channel, we employ the 2022 policy shift (discussed in Section 2.2) that effectively led CBs to delete a number of medical collection accounts and delayed the furnishers' ability to provide information on others (CFPB: Data Spotlight 2024). This quasi-natural experiment offers a great setting to confirm the role of the information frictions as the shift increased the information collection frictions specific to the medical collections, but it did not eliminate the underlying collections from consumer balance sheets.

Figure 5 illustrates the impact of this policy shift on the aggregate medical collections in CB files. Panel A shows the total amount of registered medical collections in our sample declining precipitously starting from the first half of 2022, providing a clear indication of the reform's impact. Panel B illustrates the analogous declining patterns in the number of accounts.

[19] In an unreported set of tests, we verify that, if anything, MSPB HCC measures are higher, not lower, in markets with higher share of insured population and higher incomes. MSPB HCC measures also do not exhibit any economically meaningful correlation with local credit scores and DTIs.

Table 6 reports the results of regression analysis that confirm 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 after (S2 of 2022 and S1 of 2023). Table 6 shows that, following the 2022 policy shift, the share of consumers with medical debt collection accounts declined by about 3.7% (column 1). This is a significant decline, as the average share of consumers with medical debt accounts in our sample is 13%. 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 2.1% in the second half of 2022 (16% relative to the mean of 13%) and by 6.1% in the first half of 2023 (47% relative to the mean of 13%).

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

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

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 debt data on the ability of credit scores and DTIs to predict consumer defaults after the policy shock. 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 the *Post-Discharge MSPB Costs*; the findings remain robust across alternative HCC measures. In Panel A, we observe that the policy shock amplified the previously documented HCC-driven upward bias in the credit scores. In high HCC markets, credit scores underestimate the default rates, particularly so for higher risk consumers — those with lower credit scores. The reform amplified the economic magnitudes of the main coefficients of interest. In Panel A, the baseline estimates of 0.248 for β_1 and -0.035 for β_2, are similar to those reported in Table 3 (column 2 of Panel B). After the reform, the coefficients' magnitudes increase to 0.325 (0.248 + 0.077) for β_1 and -0.046 (-0.035 - 0.011) for β_2, reflecting a 31.0% and 31.4% increase in magnitude, respectively.

Panel B of Table 7 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 column 1, the baseline estimate of 0.094 for β_2 is similar to one reported in Table 4 (in column 4 of Panel B). After the reform, the β_2 coefficient increases to 0.164 (0.094 + 0.068), reflecting a 72% increase in magnitude.

To validate this analysis, we also conduct parallel trend tests. Specifically, we augment the regression equation (4) to have five sets of additional interaction terms for each semiannual period between Q3 of 2020 and Q1 of 2023. Q1 of 2020 serves as a benchmark sample.[20] Figure 6 graphically reports the dynamic changes in the core coefficient of interest — β_2. Panel A (B) reports the results based on credit scores (DTIs). The results confirm that our empirical design meets parallel trend tests. Both panels document an increase in the (negative) magnitude of the core coefficient of interest only after the policy shift.

[20] Parallel trend results are quantitatively similar when Q1 of 2021 serves as the benchmark sample.

Overall, the results presented in Table 7 are consistent with the notion that the unobserved medical debt creates upward bias in the traditional creditworthiness indicators in their ability to predict consumer defaults.

IV.2 Healthcare Costs and Access to Credit

In this section, we address arguably a more important question of whether lenders recognize these HCC-related distortions in creditworthiness assessments and adjust their lending decisions accordingly. If lenders are indeed aware, the hidden medical debt-induced asymmetric information should amplify the agency problem and lead to more credit rationing for consumers.

We analyze this question using the mortgage acceptance rates provided by HMDA data from 2018 to 2023.[21] Acceptance rates allow us to isolate the credit supply effect by examining the within *lender-year-loan type* mortgage approval decisions across different HCC markets while controlling for an array of borrower and loan characteristics. We do not use consumer leverage or loan volumes, 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 CB 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 the CBSA-year level, local insurance coverage and economic conditions data, and ZIP code consumer financial characteristics provided by both HMDA and CB data.

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

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 new mortgage applications with the lowest credit score decile consumers if they reside in the top HCC quartile CBSAs compared to the bottom HCC quartile CBSAs. This rejection rate differential decreases to 1.98% for applicants in the top credit score decile ZIP codes. Panels C and D show similar results based on DTI. The rejection rate differential between the highest and the lowest HCC CBSAs quartiles is 2.44% for the top DTI decile mortgage applicants and declines monotonically to 1.52% for the bottom DTI decile applicants. For comparison, the average rejection rate of new loans in our sample is 10.84%. Overall, 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 across 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. While HMDA data provides us with the *applicants' DTIs*, it does not offer their credit scores. Consistently, we supplement HMDA data with average ZIP code-year-level average credit scores supplied by the CB data.

The $\gamma_{lender \times loan\ type \times t}$ fixed effects allow us to isolate the effects of 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 insurance coverage variables, 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.

Panel A of Table 8 reports the results of ZIP code-year-level based on credit scores supplied by the CB data, while Panel B reports the results based on mortgage applicants' DTIs provided by HMDA. For brevity, we only report the results for the *Post-Discharge MSPB Costs* measure, though the results are qualitatively and quantitatively similar if we employ other HCC measures. Panel A shows that the positive relationship between credit scores and mortgage acceptance rates is stronger in high HCC markets, i.e., lenders are more likely to reject low credit score applicants in high HCC markets. Column (2) of Panel A suggests that an average 700 credit score consumer in our sample has the same access to credit in high and low HCC markets. The HCC coefficient of interest for an average consumer is effectively zero (-0.433 + 0.061 × 700/100 = - 0.006). For every 100-point decline in credit scores, consumers are 0.67% (0.061 × 0.11) less likely to have

their mortgage application approved if they reside in the top quartile HCC market vs the bottom quartile HCC market. For comparison, the average mortgage rejection rate is 18.8%.

Panel B offers the analysis centered on 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 for every standard deviation increase in applicant DTIs (0.06), consumers residing in top quartile HCC markets are 0.26% less likely to have their mortgage application approved than consumers with the same DTIs and credit scores residing in bottom quartile HCC markets (-0.398 × 0.11 × 0.06).

Overall, our findings are consistent with the notion that lenders are aware of the healthcare cost-related distortions in creditworthiness indicators.

2022 Medical Collections Reporting Policy Shift

Again, one can argue that the loan approval results might be due to economic channels different from the information collection channel. To isolate the role of the information collection frictions, we exploit the 2022 policy shift. 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 Table 8 when the information asymmetry intensifies.

To test this, we add two interaction terms to the regression equation (5) that capture the incremental effects of the 2022 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 9. We find that the effect of the healthcare cost-related distortions on the mortgage approval decisions is amplified post-2022 when the information

frictions associated with medical collections are higher. Panel A reports the results for credit scores. In column 1, the baseline estimate of β_1 (-0.383) increases to -0.593 (-0.383 -0.210) after 2022, or a 54.8% increase in magnitude. The baseline estimate of β_2 (0.055) increases to 0.083 (0.055 + 0.028) after 2022, or 47.3% increases in magnitude. Panel B of Table 9 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 42.8%.

Panels C and D of Figure 6 report the results of parallel trends tests. Specifically, we examine the dynamic changes in the core coefficient of interest (β_2) by augmenting the regression equation (6) with two sets of additional interaction terms in 2021 and 2023 (2022 is omitted from the sample). 2020 serves as a benchmark year. Figure 6 graphically reports how β_2 changes over time. Panel C (D) reports the results based on credit scores (DTIs). These results confirm that our empirical designs meet the parallel trends tests. Both panels document an increase in the magnitude of the core coefficient of interest only after the 2022 policy shift.

Adverse Selection vs. Information Production

Overall, the results presented in this section suggest that lenders internalize the HCC-induced bias in the creditworthiness assessment available to them. They react by restricting access to (mortgage) credit for consumers residing in high HCC markets. Consistent with the agency problem, we argue that without direct access to complete medical debt data, lenders limit credit supply indiscriminately to all consumers, those with and without medical debt (risk pooling). As such, the frictions in collecting medical debt information impede the efficient allocation of consumer credit.

One can argue, however, that the mortgage acceptance rate results are also consistent with lenders independently producing information about consumer medical debt and not relying on arguably biased credit scores and DTIs provided by CBs. Under this hypothesis, lenders discriminate between borrowers without medical debt, thus improving the credit allocation.

One aspect of our analysis directly undermines the information production hypothesis. Namely, our mortgage approval results rely on applicant DTIs (reported in HMDA) rather than the DTIs provided by the CB. If lenders were to produce information about consumer medical debt, this information must be incorporated into mortgage applicants' DTIs. If lenders were to produce full consumer medical debt information, we should not observe lending decisions to differ across HCC markers for the same DTI loan applicants. Even if lenders were producing information about medical debt imperfectly, we should not observe an increase in lenders restricting access to credit in high HCC markets post 2022. The 2022 shock should not affect the lender's ability to generate information. If anything, this shock should amplify lenders' incentives to collect information, thus reducing, not amplifying, the DTI-driven credit constraints in the high HCC markets.

V. Conclusion

This paper shows that information frictions stemming from hidden medical debt 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 financially vulnerable borrowers — those with lower credit scores and higher DTIs.

These effects are exacerbated after the 2022 regulatory shift that restricted the use of medical debt data by CBs without eliminating the underlying debt from consumer balance sheets. Lenders responded to these incremental information collection frictions by further restricting access to credit for higher-risk borrowers residing in higher HCC markets. These results emphasize the role of the hidden medical debt and its impact on consumer access to credit.

Our findings thus contribute to the ongoing policy debate regarding the role of medical debt 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 considering the January 7th, 2025, CFPB rule that calls to remove *all* medical collections 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, 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.[22]

Our paper offers important implications for this policy debate as it underscores the need for a more nuanced approach to integrating medical debt information into credit evaluations. The results challenge the narrative that removing medical debt from credit files will unambiguously

[22] "Judge nixes a Biden rule in order to keep medical debt on credit reports" (CNN, July 15th ,2025)

improve consumer outcomes. Rather, they suggest that this policy is likely to undermine CBs' ability to provide quality information to lenders and, by extension, to adversely affect consumers' access to credit due to risk pooling. We do not argue that the elimination of information friction is the most effective policy to balance consumer protection and credit market efficiency. Rather, we aim to provide a social planner with clear trade-offs behind such policy decisions.

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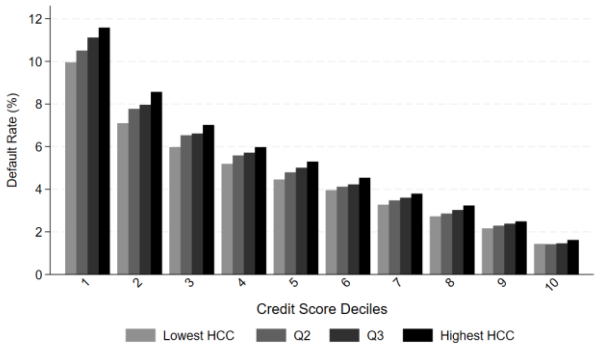
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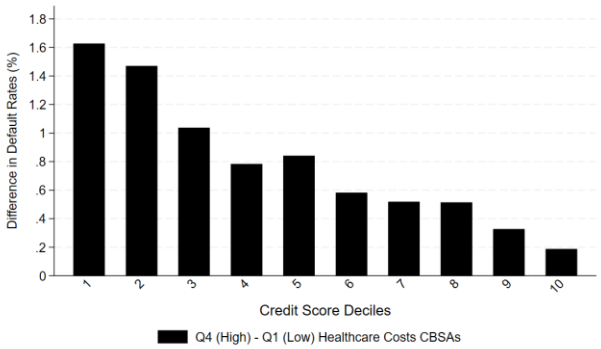
Figure 1
Consumer Default Rates and Healthcare Costs

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 CBs.

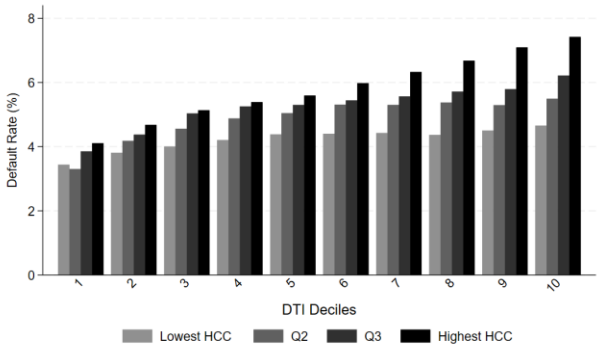
Panel A: Default Rates Across Credit Score Deciles



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

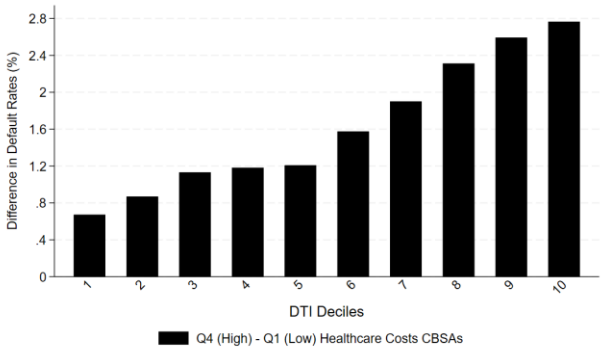
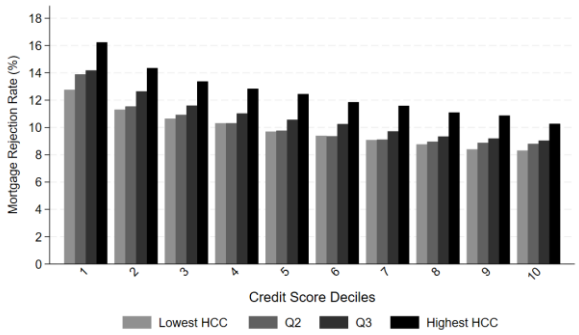


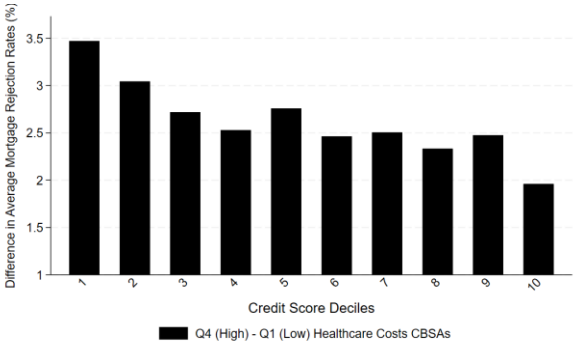
Figure 2
Mortgage Rejection Rates and Healthcare Costs

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 CBs.

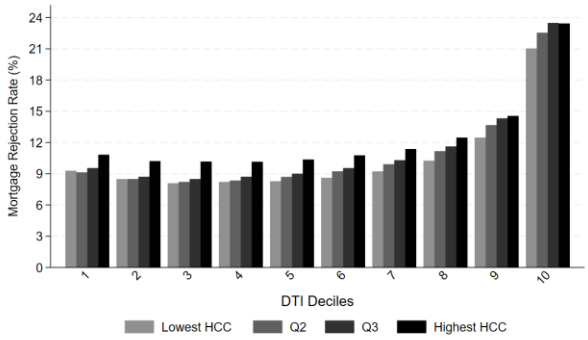
Panel A: Rejection Rates Across Credit Score Deciles



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

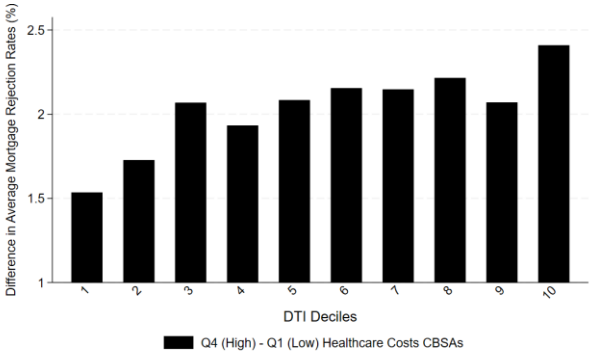
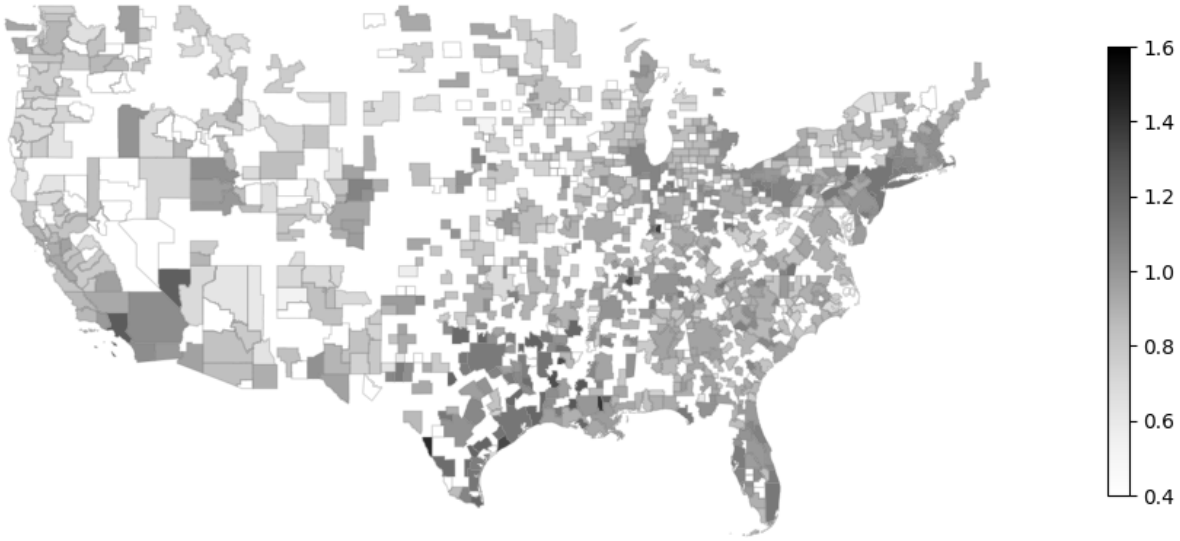


Figure 3
Heatmaps: Medicare Spending Per Beneficiary

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



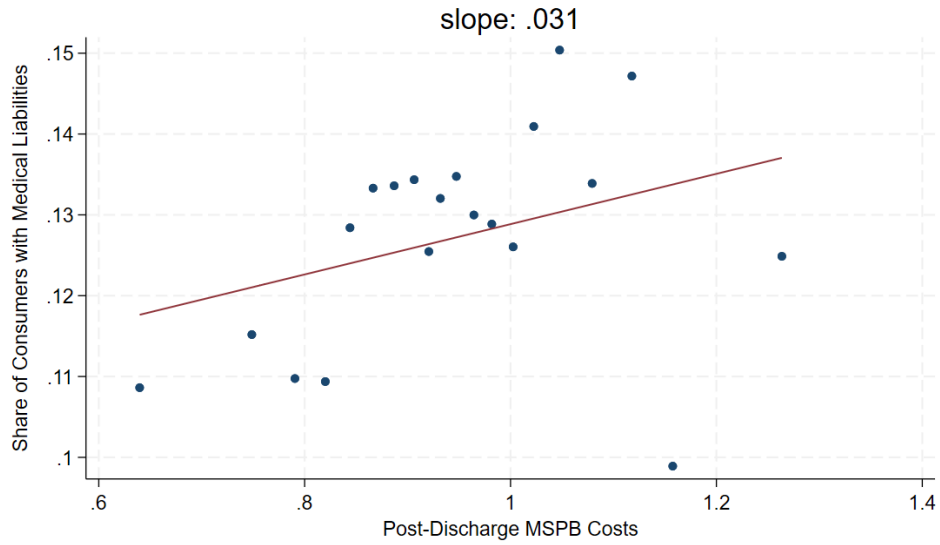
Panel B: MSPB Healthcare Costs Heatmap at the End of the Sample Period, 2023



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

Panels A and B present binned scatter plots examining the relationship between our healthcare cost measure and medical debt. Healthcare costs are measured as the average post-discharge Medicare Spending Per Beneficiary (MSPB), scaled by the national average from Equation (1b). Panel A plots healthcare costs against the share of consumers with medical debt. Panel B plots healthcare costs against the natural logarithm of average medical debt.

Panel A: Healthcare Costs and the Share of Consumers with Medical Debt



Panel B: Healthcare Costs and the Average Medical Debt

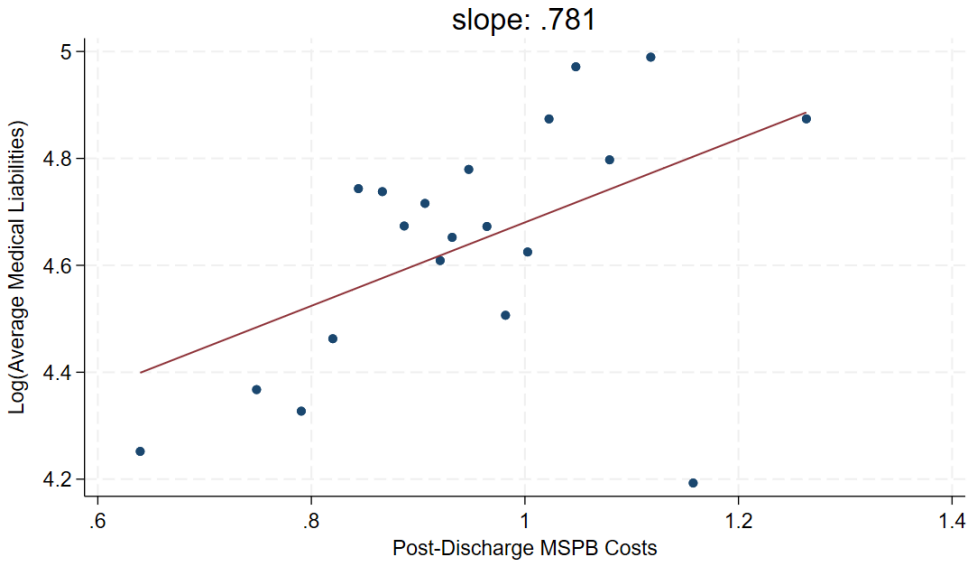
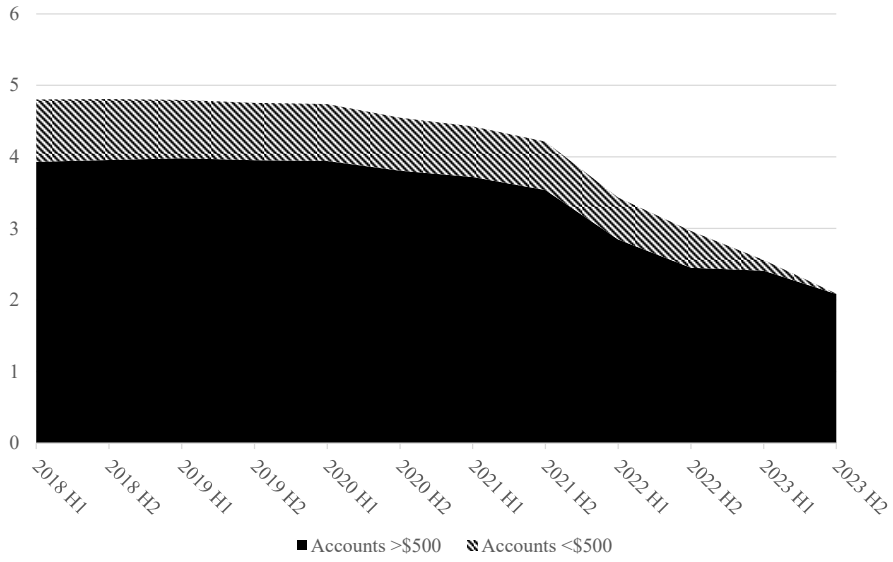


Figure 5
Medical Debt Collections

Panels A and B present medical debt in collections (billions of dollars) and the number of medical collection accounts, respectively, based on a 5% random sample of consumer credit files from a major CB. In Panel A, the solid shaded area denotes balances from accounts exceeding $500, while the striped area denotes balances from accounts of $500 or less. In Panel B, the solid line represents accounts exceeding $500, and the dashed line represents accounts of $500 or less. Data are observed semiannually (March and September) from 2017 to 2023.

Panel A: Medical Debt Collection Balances ($Billions)



Panel B: Number of Medical Debt Collection Accounts (in Millions)

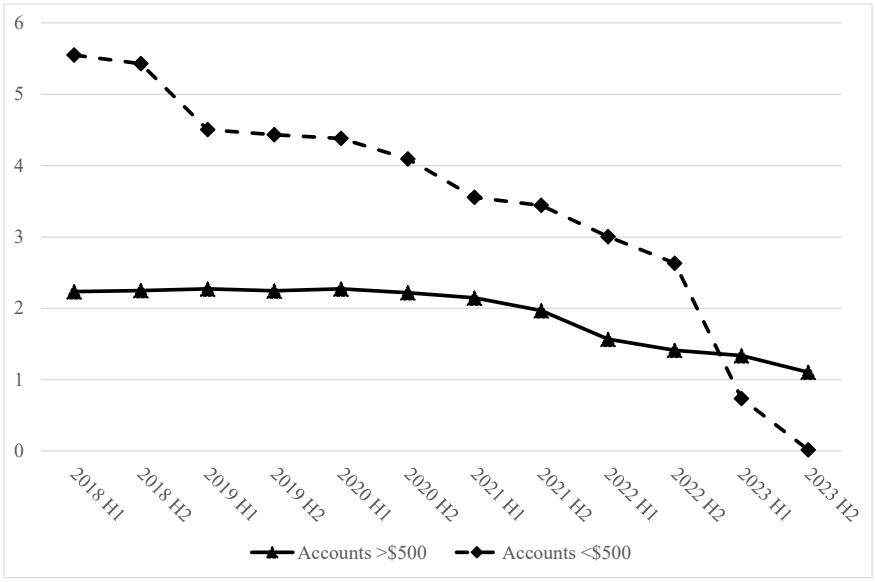


Figure 6
The 2022 Policy Shift: Parallel Trends Tests

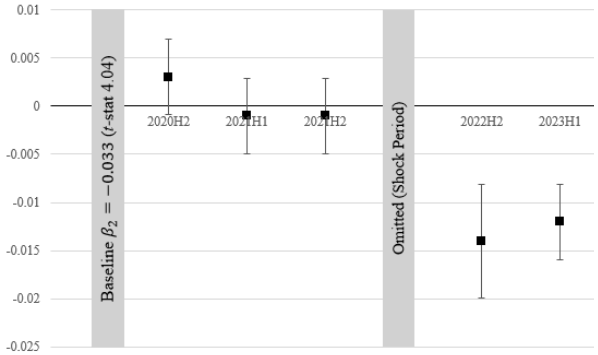
This figure reports the dynamic coefficients of healthcare costs' impact on consumer defaults (Panels A and B) and mortgage acceptance rates (Panels C and D). Panels A and B report the results based on the extension of the regression specification (4). They report the semiannual changes in the core coefficient of interest between March 2020 and September 2023:

$$Default_{ZIP,t+1} = \boldsymbol{\beta_{2,Baseline}} \times Credit\ Score_{ZIP,t} \times HCC_{CBSA,t} + \sum_{k=Q3\ 2020}^{Q1\ 2023} \beta_{2,k} \times D_k \times Credit\ Score_{ZIP,k} \times HCC_{CBSA,k}$$

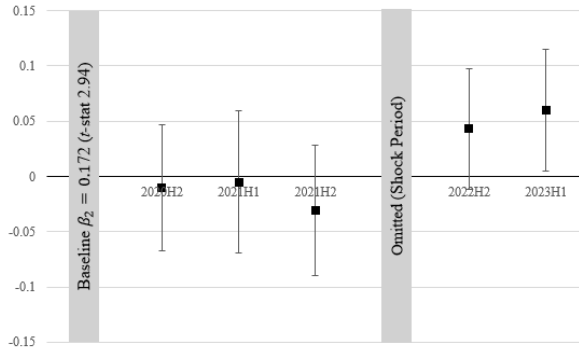
$$+\beta_0 Credit\ Score_{ZIP,t} + \beta_1 HCC_{CBSA,t} + \sum_k \beta_{1,k} \times D_k \times HCC_{CBSA,k} + Controls + \gamma_t + \mu_{CBSA} + \varepsilon_{ZIP,t+1}.$$

Panels C and D utilize a similar extension to the regression specification (6). They report the dynamics of the core coefficients of interest utilizing 2020- 2023 annual mortgage originations data.

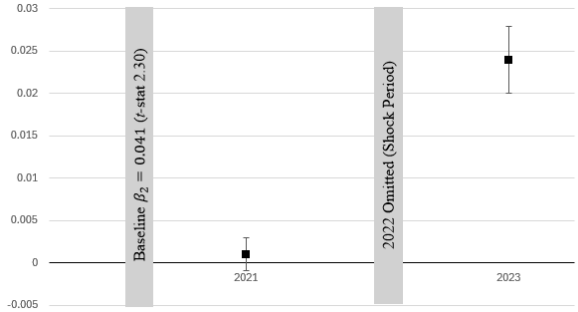
Panel A: Credit Score-based Analysis of Defaults



Panel B: DTI-based Analysis of Defaults



Panel C: Credit Score-based Analysis of Mortgage Approval Rates



Panel D: DTI-based Analysis of Mortgage Approval Rates

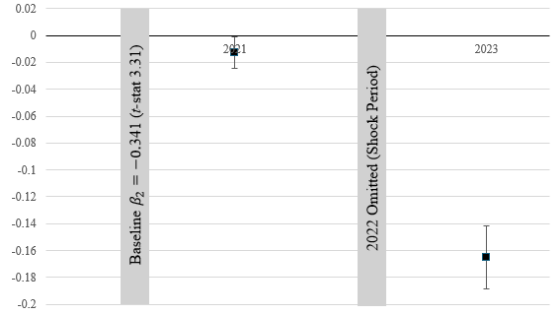


Table 1
Summary Statistics

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 observed medical debt. 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) 2017 - 2023						
Medicare Spending ($)	341,673	20,349	2,259	19,055	20,347	21,793
MSPB Costs	341,673	0.94	0.09	0.89	0.95	1.00
Post-Discharge Medicare Spending ($)	341,673	8,526	1,360	7,676	8,468	9,348
Post-Discharge MSPB Costs	341,673	0.95	0.14	0.86	0.94	1.03
Post- to Pre-Discharge MSPB Costs	341,673	1.03	0.20	0.90	1.02	1.16
Panel B: Observed Medical Debt (ZIP-code-semiannual level) 2017 - 2023						
Share of Consumers with Medical Debt	341,673	0.13	0.11	0.05	0.11	0.18
Average(Medical Debt) ($)	341,673	333	826	48	165	395
Panel C: Consumer Default Rates (ZIP-code-semiannual level) 2017 - 2023						
% Delinquency or Default in the Next 6 Months	341,673	5.03%	5.56%	1.59%	4.00%	6.98%
% Delinquency or Default in the Next 12 Months	290,505	7.53%	6.73%	3.23%	6.37%	10.38%
Panel D: Consumer Financial Characteristics (ZIP-code-semiannual level) 2017 - 2023						
Avg. Credit Score	341,673	702.5	40.0	677.9	705.7	730.8
Avg. Debt-to-Income Ratio	341,673	0.12	0.03	0.10	0.12	0.13
ln (Avg. Income)	341,673	4.46	0.30	4.27	4.44	4.63
Avg. Oldest Account Age (years)	341,673	17.84	4.00	15.56	17.89	20.10
ln (Avg. Total Debt Balance)	341,673	10.84	0.89	10.50	10.94	11.36
ln (Avg. Nonmedical Collections Balance)	341,673	5.00	1.78	4.72	5.47	6.02
Share of Consumers With Accounts in Nonmedical Collectior	341,673	0.15	0.11	0.07	0.13	0.20
Panel E: Mortgage Applicant Related Variables (ZIP-Code-lender-year-loan type level) 2018 - 2023						
Mortgage Approval Rate	4,238,951	0.81	0.20	0.71	0.86	1.00
Debt-to-income ratio	4,238,951	0.36	0.06	0.32	0.35	0.39
Loan to Value Ratio	4,238,951	71.60	13.98	63.04	71.46	81.14
Loan Amount ($)	4,238,951	279,903	231,694	159,000	232,111	324,655
Loan Maturity (months)	4,238,951	317	52	293	330	360
Minority	4,238,951	0.13	0.19	0.00	0.05	0.19
Panel F: Local Economic Fundamentals (CBSA-semiannual level) 2017 - 2023						
ln(Total Local Employment)	341,673	14.12	2.45	12.78	14.42	16.05
ln(Average Local Wages)	341,673	6.33	0.49	5.93	6.44	6.73
Δ ln (Total Local Employment)	341,673	0.39	4.30	-1.76	0.52	2.65
Δ ln (Average Local Wages)	341,673	2.74	7.77	-2.07	2.27	7.29
Average Case Mix Index	341,673	1.69	0.20	1.58	1.69	1.80

Table 2
Validation: Healthcare Costs and Medical Debt

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. Columns (1) to (3) use the share of consumers with medical debt as the dependent variable. Columns (4) to (6) use the natural logarithm of average medical debt as the dependent variable. 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 insurance coverage controls (at the county level) include the share of the population under the age of 65 with insurance coverage, the share of the population aged 65 and over, and the case mix index. 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)	*Share of Consumers With Medical Debt*			*ln(Average Medical Debt)*		
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Panel A: HCC Proxy = MSPB Costs						
MSPB Costs$_{(CBSA, t)}$	0.107***	0.096***	0.092***	1.646***	1.532***	1.144**
	(3.69)	(3.85)	(3.27)	(3.54)	(3.64)	(2.40)
Consumer Financials$_{(ZIP, t)}$	-	Y	Y	-	Y	Y
Insurance Coverage Controls$_{(County, t)}$	-	-	Y	-	-	Y
Local Economy Controls $_{(CBSA, t)}$	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Observations	341,673	341,673	341,673	341,673	341,673	341,673
R-squared	0.13	0.29	0.33	0.08	0.15	0.19
Within R-squared	0.09	0.26	0.30	0.07	0.13	0.17
Panel B: HCC Proxy = Post-Discharge MSPB Costs						
Post-Discharge MSPB Costs$_{(CBSA, t)}$	0.099***	0.071***	0.040***	1.498***	1.169***	0.610***
	(5.90)	(4.90)	(3.20)	(5.44)	(4.61)	(2.84)
Consumer Financials$_{(ZIP, t)}$	-	Y	Y	-	Y	Y
Insurance Coverage Controls$_{(County, t)}$	-	-	Y	-	-	Y
Local Economy Controls $_{(CBSA, t)}$	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Observations	341,673	341,673	341,673	341,673	341,673	341,673
R-squared	0.14	0.29	0.33	0.09	0.15	0.19
Within R-squared	0.10	0.26	0.30	0.07	0.13	0.17
Panel C: HCC Proxy = Post- to Pre-Discharge MSPB Costs						
Post- to Pre-Discharge MSPB Costs$_{(CBSA, t)}$	0.058***	0.037***	0.030***	0.855***	0.606***	0.492***
	(5.00)	(3.79)	(3.13)	(4.28)	(3.35)	(2.92)
Consumer Financials$_{(ZIP, t)}$	-	Y	Y	-	Y	Y
Insurance Coverage Controls$_{(County, t)}$	-	-	Y	-	-	Y
Local Economy Controls $_{(CBSA, t)}$	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Observations	341,673	341,673	341,673	341,673	341,673	341,673
R-squared	0.13	0.29	0.33	0.09	0.15	0.19
Within R-squared	0.10	0.26	0.30	0.07	0.13	0.17

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 insurance coverage controls (at the county level) include the share of the population under the age of 65 with insurance coverage, the share of the population aged 65 and over, and the case mix index. 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. The CBSA-level average case mix index is included to control for the average clinical severity of the patient population. 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 Months*					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Panel A: HCC Proxy = MSPB Costs						
$\text{MSPB Costs}_{(CBSA,\ t)}$	-	0.329***	-	0.308***	-	-
		(6.11)		(4.40)		
$\text{Credit Score/100}_{(ZIP,\ t)}$ ×	-	-0.044***	-	-0.043***	-	-0.045***
$\text{MSPB Costs}_{(CBSA,\ t)}$		(5.91)		(4.41)		(4.22)
$\text{Credit Score/100}_{(ZIP,\ t)}$	-0.056***	-0.016**	-0.057***	-0.016*	-0.057***	-0.015
	(30.09)	(2.36)	(30.15)	(1.83)	(29.81)	(1.51)
Consumer Financials Including DTI	Y	Y	Y	Y	Y	Y
Local Economy and Insurance Controls	Y	Y	Y	Y	Y	Y
CBSA FEs	-	-	Y	Y	-	-
Time FEs	Y	Y	Y	Y	-	-
CBSA × Year FEs	-	-	-	-	Y	Y
Observations	341,673	341,673	341,673	341,673	341,651	341,651
R-squared	0.29	0.29	0.30	0.30	0.30	0.30
Within R-squared	0.28	0.28	0.20	0.20	0.21	0.21
Panel B: HCC Proxy = Post-Discharge MSPB Costs						
$\text{Post-Discharge MSPB Costs}_{(CBSA,\ t)}$	-	0.269***	-	0.233***	-	-
		(5.87)		(4.32)		
$\text{Credit Score/100}_{(ZIP,\ t)}$ ×	-	-0.037***	-	-0.033***	-	-0.034***
$\text{Post-Discharge MSPB Costs}_{(CBSA,\ t)}$		(5.89)		(4.33)		(4.15)
$\text{Credit Score/100}_{(ZIP,\ t)}$	-0.056***	-0.022***	-0.057***	-0.026***	-0.057***	-0.025***
	(30.09)	(3.86)	(30.15)	(3.71)	(29.81)	(3.23)
Consumer Financials Including DTI	Y	Y	Y	Y	Y	Y
Local Economy and Insurance Controls	Y	Y	Y	Y	Y	Y
CBSA FEs	-	-	Y	Y	-	-
Time FEs	Y	Y	Y	Y	-	-
CBSA × Time FEs	-	-	-	-	Y	Y
Observations	341,673	341,673	341,673	341,673	341,651	341,651
R-squared	0.29	0.29	0.30	0.30	0.30	0.30
Within R-squared	0.28	0.28	0.20	0.20	0.21	0.21
Panel C: HCC Proxy = Post- to Pre-Discharge MSPB Costs						
$\text{Post- to Pre-Discharge MSPB Costs}_{(CBSA,\ t)}$	-	0.119***	-	0.105***	-	-
		(4.18)		(3.11)		
$\text{Credit Score/100}_{(ZIP,\ t)}$ ×	-	-0.016***	-	-0.015***	-	-0.016***
Post- to Pre-Discharge MSPB		(4.07)		(3.13)		(3.16)
$\text{Credit Score/100}_{(ZIP,\ t)}$	-0.056***	-0.040***	-0.057***	-0.042***	-0.057***	-0.040***
	(30.09)	(8.81)	(30.15)	(7.87)	(29.81)	(7.14)
Consumer Financials Including DTI	Y	Y	Y	Y	Y	Y
Local Economy and Insurance Controls	Y	Y	Y	Y	Y	Y
CBSA FEs	-	-	Y	Y	Y	Y
Time FEs	Y	Y	Y	Y	-	-
CBSA × Time FEs	-	-	-	-	Y	Y
Observations	341,673	341,673	341,673	341,673	341,651	341,651
R-squared	0.29	0.29	0.30	0.30	0.30	0.30
Within R-squared	0.28	0.28	0.20	0.20	0.21	0.21

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

The table presents results on healthcare costs and the 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 insurance coverage controls (at the county level) include the share of the population under the age of 65 with insurance coverage, the share of the population aged 65 and over, and the case mix index. 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. The CBSA-level average case mix index is included to control for the average clinical severity of the patient population. 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 Months*					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Panel A: HCC Proxy = MSPB Costs						
$\text{MSPB Costs}_{(CBSA, t)}$	-	0.001	-	-0.008	-	-
		(0.08)		(0.89)		
$\text{DTI}_{(ZIP, t)} \times$	-	0.192***	-	0.089	-	0.088
$\text{MSPB Costs}_{(CBSA, t)}$		(2.97)		(1.33)		(1.28)
$\text{DTI}_{(ZIP, t)}$	0.028***	-0.151**	0.025***	-0.059	0.025***	-0.059
	(4.11)	(2.49)	(3.53)	(0.93)	(3.41)	(0.90)
Consumer Financials Including Credit Score	Y	Y	Y	Y	Y	Y
Local Economy and Insurance Controls	Y	Y	Y	Y	Y	Y
CBSA FEs	-	-	Y	Y	-	-
Time FEs	Y	Y	Y	Y	-	-
CBSA × Time FEs	-	-	-	-	Y	Y
Observations	341,673	341,673	341,673	341,673	341,651	341,651
R-squared	0.29	0.29	0.30	0.30	0.30	0.30
Within R-squared	0.28	0.28	0.20	0.20	0.21	0.21
Panel B: HCC Proxy = Post-Discharge MSPB Costs						
$\text{Post-Discharge MSPB Costs}_{(CBSA, t)}$	-	-0.012**	-	-0.012**	-	-
		(2.27)		(2.24)		
$\text{DTI}_{(ZIP, t)} \times$	-	0.186***	-	0.113**	-	0.114**
$\text{Post-Discharge MSPB Costs}_{(CBSA, t)}$		(4.72)		(2.55)		(2.50)
$\text{DTI}_{(ZIP, t)}$	0.028***	-0.146***	0.025***	-0.081*	0.025***	-0.083*
	(4.11)	(3.88)	(3.53)	(1.94)	(3.41)	(1.92)
Consumer Financials Including Credit Score	Y	Y	Y	Y	Y	Y
Local Economy and Insurance Controls	Y	Y	Y	Y	Y	Y
CBSA FEs	-	-	Y	Y	-	-
Time FEs	Y	Y	Y	Y	-	-
CBSA × Time FEs	-	-	-	-	Y	Y
Observations	341,673	341,673	341,673	341,673	341,651	341,651
R-squared	0.29	0.29	0.30	0.30	0.30	0.30
Within R-squared	0.28	0.28	0.20	0.20	0.21	0.21
Panel C: HCC Proxy = Post- to Pre-Discharge MSPB Costs						
$\text{Post- to Pre-Discharge MSPB Costs}_{(CBSA, t)}$	-	-0.004	-	-0.007*	-	-
		(0.90)		(1.88)		
$\text{DTI}_{(ZIP, t)} \times$	-	0.097***	-	0.066**	-	0.069**
$\text{Post- to Pre-Discharge MSPB Costs}_{(CBSA, t)}$		(3.19)		(2.09)		(2.09)
$\text{DTI}_{(ZIP, t)}$	0.028***	-0.070**	0.025***	-0.042	0.025***	-0.045
	(4.11)	(2.21)	(3.53)	(1.28)	(3.41)	(1.32)
Consumer Financials Including Credit Score	Y	Y	Y	Y	Y	Y
Local Economy and Insurance Controls	Y	Y	Y	Y	Y	Y
CBSA FEs	-	-	Y	Y	Y	Y
Time FEs	Y	Y	Y	Y	-	-
CBSA × Time FEs	-	-	-	-	Y	Y
Observations	341,673	341,673	341,673	341,673	341,651	341,651
R-squared	0.29	0.29	0.30	0.30	0.30	0.30
Within R-squared	0.28	0.28	0.20	0.20	0.21	0.21

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 columns present results for consumers with medical debt, and even columns are for those without. The local healthcare costs are captured by the *Post-Discharge MSPB Costs* measure. 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 insurance coverage controls (at the county level) include the share of the population under the age of 65 with insurance coverage, the share of the population aged 65 and over, and the case mix index. 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. The CBSA-level average case mix index is included to control for the average clinical severity of the patient population. 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 Months*			
Medical Debt Accounts:	*With*	*Without*	*With*	*Without*
Panel A: Credit Score Analysis				
Local Healthcare Costs$_{(CBSA, t)}$	0.074	0.176***	-	-
	(1.24)	(4.86)		
Credit Score/100 $_{(ZIP, t)}$ ×	-0.013	-0.025***	-0.012	-0.026***
Local Healthcare Costs$_{(CBSA, t)}$	(1.34)	(4.93)	(0.97)	(4.81)
Credit Score/100 $_{(ZIP, t)}$	-0.069***	-0.027***	-0.070***	-0.026***
	(7.43)	(5.48)	(6.07)	(4.96)
Consumer Financial Controls	Y	Y	Y	Y
Local Economy and Insurance Controls	Y	Y	Y	Y
CBSA FEs	Y	Y	-	-
Time FEs	Y	Y	-	-
CBSA × Time FEs	-	-	Y	Y
Observations	287,326	340,693	287,267	340671
R-squared	0.11	0.11	0.12	0.22
Within R-squared	0.04	0.04	0.04	0.17
Panel B: DTI Analysis				
Local Healthcare Costs$_{(CBSA, t)}$	-0.011	-0.010**	-	-
	(0.85)	(2.40)		
DTI $_{(ZIP, t)}$ ×	0.052	0.091***	0.074	0.088**
Local Healthcare Costs$_{(CBSA, t)}$	(0.79)	(2.65)	(1.08)	(2.49)
DTI $_{(ZIP, t)}$	-0.128**	-0.052	-0.151**	-0.050
	(2.11)	(1.59)	(2.38)	(1.47)
Consumer Financial Controls	Y	Y	Y	Y
Local Economy and Insurance Controls	Y	Y	Y	Y
CBSA FEs	Y	Y	-	-
Time FEs	Y	Y	-	-
CBSA × Time FEs	-	-	Y	Y
Observations	287,326	340,693	287,326	340,671
R-squared	0.11	0.11	0.12	0.22
Within R-squared	0.04	0.04	0.04	0.16

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 insurance coverage controls (at the county level) include the share of the population under the age of 65 with insurance coverage, the share of the population aged 65 and over, and the case mix index. 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. The CBSA-level average case mix index is included to control for the average clinical severity of the patient population. 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 $_{(ZIP,\ t)}$			
2021 - 2023 subsample	*(1)*	*(2)*	*(3)*	*(4)*
Post 2022 Dummy	-0.037***		-0.010***	
	(14.09)		(3.84)	
D(Year2021 S2)		-0.001		-0.001
		(0.82)		(0.59)
D(Year2022 S1)		*(Omitted from the Sample)*		
D(Year2022 S2)		-0.021***		-0.015***
		(7.98)		(4.53)
D(Year2023 S1)		-0.060***		-0.051***
		(19.37)		(11.64)
Consumer Financial Controls	Y	Y	Y	Y
Local Economy and Insurance Controls	Y	Y	Y	Y
CBSA FEs	-	-	Y	Y
Observations	104,018	104,018	104,018	104,018
R-squared	0.39	0.40	0.49	0.50
Within R-squared	0.39	0.40	0.29	0.30

Table 7
The 2022 Policy Shift: Credit Score and DTI Distortion

The table examines the distortion in the credit score (and the debt-to-income ratio) reliability 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 local healthcare costs are captured by the *Post-Discharge MSPB Costs* measure. 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 insurance coverage controls (at the county level) include the share of the population under the age of 65 with insurance coverage, the share of the population aged 65 and over, and the case mix index. 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. The CBSA-level average case mix index is included to control for the average clinical severity of the patient population. 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 Months*			
2021 - 2023 Subsample	*Main Effect*	*Incremental Effect Post 2022*	*Main Effect*	*Incremental Effect Post 2022*
Panel A: Credit Score Analysis				
Local Healthcare Costs$_{(CBSA, t)}$	0.248***	0.077***	-	-
	(3.40)	(4.82)		
Credit Score/100 $_{(ZIP, t)}$ ×	-0.035***	-0.011***	-0.035***	-0.013***
Local Healthcare Costs$_{(CBSA, t)}$	(3.41)	(5.14)	(3.21)	(5.01)
Consumer Financial Controls		Y		Y
Local Economy and Insurance Controls		Y		Y
CBSA FEs		Y		-
Time FEs		Y		-
CBSA × Time FEs		-		Y
Observations		104,018		104,012
R-squared		0.29		0.28
Within R-squared		0.20		0.20
Panel B: Debt-to-Income Ratio Analysis				
Local Healthcare Costs$_{(CBSA, t)}$	-0.010	-0.007**	-	-
	(1.32)	(2.39)		
DTI $_{(ZIP, t)}$ ×	0.094	0.068***	0.094	0.069***
Local Healthcare Costs$_{(CBSA, t)}$	(1.57)	(3.47)	(1.56)	(3.27)
Consumer Financial Controls		Y		Y
Local Economy and Insurance Controls		Y		Y
CBSA FEs		Y		-
Time FEs		Y		-
CBSA × Time FEs		-		Y
Observations		104,018		104,012
R-squared		0.28		0.28
Within R-squared		0.20		0.20

Table 8
Healthcare Costs and Access to Credit

The table examines the relationship between mortgage approval rates and creditworthiness indicators across different HCC markets. The local HCCs are captured by the *Post-Discharge MSPB Costs*. The dependent variable is the ZIP code-year-lender-loan type level mortgage approval rate. Loan application controls include the natural logarithm of the loan amount, the natural logarithm of the loan maturity, the natural logarithm of the income of the mortgage applicants, the proportion of minorities, the debt-to-income ratio of mortgage applicants, and the loan-to-value ratio. Consumer financials are the credit score, the applicant DTI, log(average consumer income), log(oldest account age), the proportion of consumers with collections, and the ratio of total collections to total debt balance. Local insurance coverage controls (at the county level) include the share of the population under the age of 65 with insurance coverage, the share of the population aged 65 and over, and the case mix index. Local economy controls (at the CBSA-level) are log(wage), log(employment), wage growth, employment growth, and the fraction of employment in the set of two-digit NAICS industries. Each (*CBSA, time, lender, loan type*) group contains, on average, 76 (*ZIP, time, lender, loan type*) observations. 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)*
Panel A: Credit Score Analysis				
Local Healthcare Costs$_{(CBSA,\ t)}$	-	-0.433**	-	-
		(2.55)		
Credit Score/100 $_{(ZIP,\ t)}$ ×	-	0.061**	-	0.063**
Local Healthcare Costs$_{(CBSA,\ t)}$		(2.53)		(2.52)
Credit Score/100$_{(ZIP,\ t)}$	0.066***	0.067***	0.066***	0.066***
	(36.20)	(38.60)	(35.81)	(38.24)
Other Loan Characteristics	Y	Y	Y	Y
Local Consumer Financials	Y	Y	Y	Y
Local Economy and Insurance Coverage Controls	Y	Y	Y	Y
Lender × Time × Loan Type FEs	Y	Y	Y	Y
CBSA FEs	Y	Y	-	-
CBSA × Time FEs	-	-	Y	Y
Observations	4,236,291	4,236,291	4,236,289	4,236,289
R-squared	0.64	0.64	0.64	0.64
Within R-squared	0.13	0.13	0.13	0.13
Panel B: Debt-to-Income Ratio Analysis				
Local Healthcare Costs$_{(CBSA,\ t)}$	-	0.140***	-	-
		(4.21)		
Applicant DTI $_{(ZIP,\ t)}$ ×	-	-0.398***	-	-0.383***
Local Healthcare Costs$_{(CBSA,\ t)}$		(4.26)		(3.97)
Applicant DTI $_{(ZIP,\ t)}$	-0.841***	-0.456***	-0.841***	-0.470***
	(45.84)	(5.40)	(45.56)	(5.40)
Other Loan Characteristics	Y	Y	Y	Y
Local Consumer Financials	Y	Y	Y	Y
Local Economy and Insurance Coverage Controls	Y	Y	Y	Y
Lender × Time × Loan Type FEs	Y	Y	Y	Y
CBSA FEs	Y	Y	-	-
CBSA × Time FEs	-	-	Y	Y
Observations	4,236,291	4,236,291	4,236,289	4,236,289
R-squared	0.64	0.64	0.64	0.64
Within R-squared	0.13	0.13	0.13	0.13

Table 9
Healthcare Costs and Access to Credit: The 2022 Policy Shift

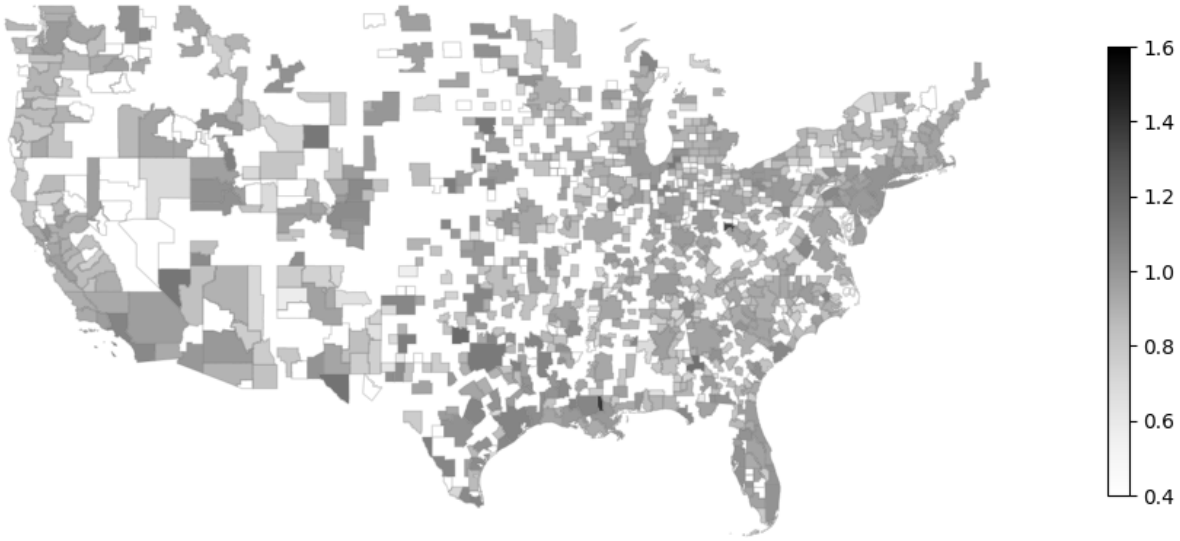
The table examines the association between the distortion in the credit score (and the debt-to-income ratio) reliability and consumers' access to credit around the 2022 policy shift. Panel A examines the distortion in credit score reliability. Panel B examines the distortion in the debt-to-income ratio reliability. The local healthcare costs are captured by the *Post-Discharge MSPB Costs* measure. 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 insurance coverage controls (at the county level) include the share of the population under the age of 65 with insurance coverage, the share of the population aged 65 and over, and the case mix index. 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. The CBSA-level average case mix index is included to control for the average clinical severity of the patient population. 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)*			
2021 - 2023 subsample	*Main Effect*	*Incremental Effect: Post 2022*	*Main Effect*	*Incremental Effect: Post 2022*
Panel A: Credit Score Analysis				
Local Healthcare Costs$_{(CBSA, t)}$	-0.383**	-0.210***	-	-
	(2.27)	(12.73)		
Credit Score/100 $_{(ZIP, t)}$ ×	0.055**	0.026***	0.055**	0.028***
Local Healthcare Costs$_{(CBSA, t)}$	(2.34)	(12.17)	(2.33)	'(13.33)
Other Loan Characteristics		Y		Y
Local Consumer Financials		Y		Y
Local Economy and Insurance Coverage Controls		Y		Y
Lender × Time × Loan Type FEs		Y		Y
CBSA FEs		Y		-
CBSA × Time FEs		-		Y
Observations		1,449,428		1,449,427
R-squared		0.64		0.64
Within R-squared		0.13		0.13
Panel B: Debt-to-Income Ratio Analysis				
Local Healthcare Costs$_{(CBSA, t)}$	0.118***	0.050***	-	-
	(3.46)	(6.67)		
Applicant DTI $_{(ZIP, t)}$ ×	-0.326***	-0.149***	-0.332***	-0.142***
Local Healthcare Costs$_{(CBSA, t)}$	(3.43)	(13.56)	(3.47)	(12.34)
Other Loan Characteristics		Y		Y
Local Consumer Financials		Y		Y
Local Economy and Insurance Coverage Controls		Y		Y
Lender × Time × Loan Type FEs		Y		Y
CBSA FEs		Y		-
CBSA × Time FEs		-		Y
Observations		1,475,848		1,475,848
R-squared		0.64		0.64
Within R-squared		0.13		0.13

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

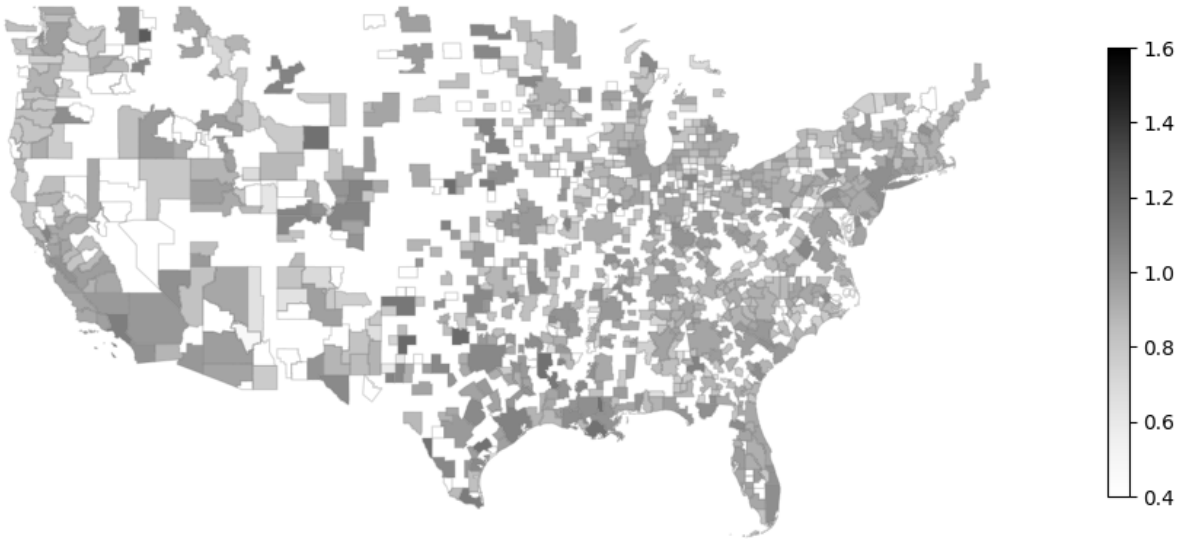
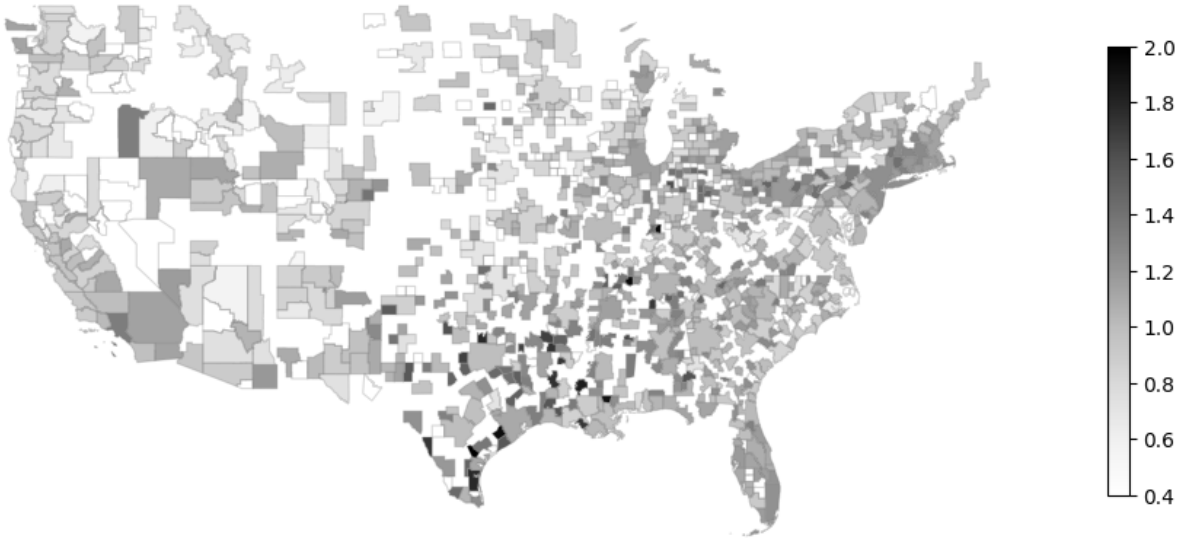


Figure A2
Heatmaps: Medicare Spending Per Beneficiary
Using *Post- to Pre-Discharge MSPB Costs*

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



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%