Are hospital bills hazardous to your financial health? *

Jash Jain†

June 22, 2025

Abstract

This paper studies the effect of hospital prices on the financial health of individuals. I construct a novel zip-level measure of prices hospitals charge for their services using detailed healthcare micro-data and state hospital cost reports obtained via a series of Freedom of Information Act (FOIA) requests. Using an instrumental variable strategy that captures insurers' market power, the findings reveal a causal link between higher hospital prices and adverse financial outcomes, including a rise in personal bankruptcy filings, reduced demand and increased application denials for home mortgages, and increased use of credit cards and home equity line of credit. I provide evidence that these results are not driven by declining income, deteriorating health, or over-utilization of health services in the local area. I show that such price increases disproportionately impact areas with individuals particularly exposed to healthcare prices, such as areas with a higher percentage of uninsured individuals, lower Medicare/Medicaid enrollment, and areas with a higher population concentration of people of color. Furthermore, I show that home equity mitigates some of these effects. The results are robust to alternative specifications and the use of an alternative instrument that exploits price changes induced by hospital peer effects in a geographic area.

Keywords: Healthcare finance, hospital prices, personal bankruptcies, consumer credit, mortgage, home equity.
JEL classification: G21, G51, I11, I13, I15, R21, R32

*This paper is a revised version of Chapter 1 of my dissertation titled "The Economic Consequences of Rising Healthcare Costs". I am grateful to my advisors Andy Winton, Richard Thakor, Pinar Karaca-Mandic, and Cyrus Aghamolla for their continued support, guidance and encouragement. I would also like to thank Jacelly Cespedes, Tony Whited and seminar participants at Business Advancement Center for Health (BACH), University of Minnesota, Indian School of Business, Chinese University of Hong Kong and Hong Kong University of Science and Technology for helpful discussion and comments. I acknowledge the support from NBER in providing access to the HCUP Database and computing resources.

†Indian School of Business. E-mail: jash_jain@isb.edu.

1 Introduction

The incessant rise in healthcare prices has been the centerpiece of policy and political debates (NYT (2023)). This is unsurprising given that the total healthcare spending in the U.S. accounts for 18-20% of GDP. An important aspect of rising healthcare costs is the prices hospitals charge patients for their services. Hospital spending represented close to a third of all health spending in 2021. The cost of hospital stays averaged $14,912 in 2020, representing a 250% growth since the turn of the century (AHRQ (2020)). Moreover, the costs are prevalent even in the presence of insurance due to increased cost-sharing, the gaps in plan coverage, the rising incidence of harmful billing practices, the pervasiveness of high-deductible plans[1], and the financial burden it imposes.[2] Despite the potential negative impact of rising healthcare prices on consumers, the effect on household finances remains understudied. The primary objective of the paper is to investigate: 1) Do increases in hospital prices push more households to bankruptcy? 2) Do higher hospital prices change households' demand and ability to access credit?

While the question is straightforward, empirically establishing the impact of hospital prices on households' financial outcomes poses significant hurdles. To begin with, it is difficult to measure commercial hospital prices accurately. Hospital prices charged to private insurance companies and individuals are unregulated and determined by negotiations between hospitals and health insurance companies, as well as the complexity of the patient's diagnosis, both of which are private information. To address this measurement challenge, I exploit data from a patient-level database and information on discounts offered to commercial insurers through multiple state hospital cost reports obtained via a series of Freedom of Information Act (FOIA) requests. It helps accurately measure commercial hospital prices adjusted for patient complexity. Second, patients self-select hospitals based on proximity, hospital quality, and the cost of care, among others, which invariably induces bias in the analysis, given that the unobservable factors driving patient choice might be correlated with the patient's financial health. To mitigate these concerns, I leverage the exogenous variation of distance between patients and hospitals as an instrumental variable for estimating regional market shares, which in turn is used for aggregating hospital prices at the zip-code level.

First, I establish that increases in hospital prices are associated with a meaningful rise in

[1] See Claxton et al. (2016). In 2017, one in 100 Americans under age 64 spent $5,000 or more out of pocket for medical services. (Glied and Zhu (2020))

[2] Abdus et al. (2016) find that 7.3% adults with employer-sponsored insurance have total family out-of-pocket health expenses exceeding 20% of their disposable income. This figure inflates to 20.6% for low-income enrollees.

personal bankruptcies at the five-digit zip level. However, examining the causal link between hospital prices and household financial outcomes is challenging due to endogeneity issues. First, hospitals determine their pricing strategies by considering the economic conditions and demographics of the regions where they operate. More importantly, market environment conditions can lead to concurrent changes in both hospital prices and the financial conditions of its prospective patients.[3] Unlike other cost components of hospitals, which are confounded with local economic factors, the discounts offered by hospitals to insurers are primarily dependent on their relative bargaining power. Insurance companies operate across geographies, making their bargaining power plausibly exogenous to common local economic conditions.

I use the medical loss ratio (MLR) of insurance companies as a proxy for their market power[4]. Medical loss ratio, defined as the ratio of total claims that insurers pay to the total premiums that insurers charge to those they offer coverage, is a measure of price-cost margin for the insurer. The insurer's market power impacts the medical loss ratio in two ways. First, an insurer's ability to negotiate with healthcare providers depends on its market power. An increase (decrease) in the insurer's bargaining power would lead to a decrease (increase) in the negotiated claim amounts. Second, insurers operating in concentrated markets charge higher premiums and provide lower dollar value of coverage for the premiums charged. Consequently, a higher medical loss ratio signals intensifying competition in the market that weakens the bargaining power of insurers vis-à-vis healthcare providers. I validate these arguments by showing that insurance companies that have a monopoly over more geographical markets tend to have a lower medical loss ratio.[5,6]

The main results are as follows. I document that an increase in instrumented hospital prices leads to a significant increase in personal bankruptcy filings at the five-digit zip-code level. A 1% increase in hospital prices leads to a 1.77% increase in personal bankruptcies. To contextualize this magnitude, a back-of-the-envelope calculation suggests that this effect is comparable to a 2% reduction in Medicaid eligibility[7]. These estimates underscore that

[3] Dranove et al. (2017) find that the average non-profit hospital did not increase prices during the financial crisis. However, those with substantial market power did so. More recently, Aghamolla et al. (2022) documents that hospitals resort to specific cost-cutting and revenue-enhancing strategies, such as increasing admissions and procedures, in response to disruption in their credit access.

[4] The instrumental variable strategy detailed in Section 3 relies on a national conglomerate level MLR measure. This is to ensure that the measure is not driven by changes in any particular local area.

[5] Karaca-Mandic et al. (2015) also demonstrates the validity of medical loss ratio as a measure of price-cost margin and that competitive markets have a higher medical loss ratio than their monopoly counterparts.

[6] The Affordable Care Act (ACA) imposed a floor of 85% on the medical loss ratio. I discuss its implication on hospital prices at length in Section 3

[7] Using variation from state Medicaid expansions, Gross and Notowidigdo (2011) estimate that a 10%

the effects are not only statistically significant but also economically meaningful. To examine if an increase in hospital prices leads to changes in the characteristics of the marginal bankruptcy filer, I look at the chapter of bankruptcy filed and the amount and composition of debt they hold. The eligibility for Chapter 7 bankruptcy filing is contingent on a means test. Chapter 7 bankruptcy typically results in the liquidation of non-exempt assets, rendering it more prevalent among individuals characterized by lower incomes and fewer assets. I establish that Chapter 13 bankruptcies are more responsive to changes in hospital prices than Chapter 7 bankruptcies. Furthermore, the marginal bankruptcy filer reports a higher debt-to-income ratio and a higher proportion of secured debt. I also provide evidence that the average income of the marginal bankruptcy filer is higher. These have two noteworthy implications. First, the negative welfare consequences of higher hospital prices may not be limited to low-income individuals.[8,9] Notably, individuals with more substantial assets are more likely to file Chapter 13 and hold health insurance. Therefore, the results suggest that rising hospital prices exacerbate the extent of underinsurance, pushing individuals toward bankruptcy. Second, it provides evidence that the results are not driven by a decline in income in the local area.

Patients who face higher medical bills might incur debt to cover these bills (Kluender et al. (2021)) or to supplement other expenditures in the face of reduced financial resources (Kaiser Family Foundation (2022)). This, in turn, can change their appetite for additional credit. Individuals burdened with debt also might find it difficult to secure further credit (Dobbie et al. (2020)). In contrast, others might modify their spending and credit behavior in anticipation of these financial constraints (De Nardi et al. (2010), Kalda (2020)). I investigate these dynamics using data on the universe of all US residential mortgage applications. The analysis reveals a decline in mortgage origination and an increase in application denial rates in the face of increased hospital prices. Additionally, there is a significant decline in mortgage applications. In particular, a 1% increase in instrumented hospital prices in a zip leads to a 1.26% decline in mortgage originations. Notably, financial institutions increasingly cite the debt-to-income ratio as the primary reason for application denial. I also look at credit card debt and home equity lines of credit to provide evidence for household indebtedness. The results demonstrate that an increase in hospital prices makes households hold more credit cards. Furthermore, more households obtain home equity lines of credit and rely more

increase in Medicaid eligibility reduces personal bankruptcy filings by 8%.

[8] See Adelino et al. (2018) for a review of literature documenting evidence that the housing crisis emanated from the middle of the income distribution.

[9] This is in contrast to Dranove and Millenson (2006) , who argue that medical bills are a contributing factor more than those whose income tends to be closer to poverty levels.

on auto loans for automobile purchases. These results suggest that medical debt may be absorbed into general consumer debt, potentially obscuring its true nature. This mechanism may help explain why Kluender et al. (2025) find limited effects of medical debt forgiveness. These findings underscore that mounting medical bills heighten household debt burdens, reducing both their appetite for mortgage credit and their ability to access it.

While the adverse financial consequences of higher hospital prices are evident, these alone do not establish that such price increases are welfare-reducing. If patients are self-selecting into unnecessary and costly care that subsequently leads to financial distress, the interpretation of the results would differ vastly. To address this concern, I examine patterns in hospital discharges across regions exposed to higher hospital prices. I find a decline in overall discharges, driven primarily by a reduction in elective procedures. This suggests that patients are not engaging in excessive or discretionary care that harms them financially. Rather, the evidence suggests that patients reduce utilization in response to higher prices, implying that the observed financial distress is not due to underlying differences in health status across regions. More importantly, the decline in elective procedures points to a behavioral adjustment in care-seeking behavior. In particular, patients appear to delay or forgo treatment in response to rising prices. To examine the consequences of such delays, I study rates of lower limb amputations among diabetic patients, a condition widely considered avoidable with timely medical intervention[10]. I find that the incidence of these procedures increases in high-price regions, providing evidence that delays in care induced by higher prices have tangible and potentially severe health consequences.

Lack of insurance can lead to a significant decline in an individual's financial security when their health deteriorates (Carlos et al. (2018)). Without insurance coverage, individuals have no safety cushion against hospital bills. This makes it more likely for them to be directly affected when prices increase. I use variations in the proportion of individuals without insurance coverage over time and across different zip codes to underscore the financial implications of lacking insurance or sufficient coverage. The findings suggest that regions with a higher proportion of uninsured individuals experience more pronounced increases in bankruptcy filings and a sharper decline in mortgage demand when faced with elevated hospital prices. Furthermore, I exploit the geographic disparities in Medicare and Medicaid enrollment, driven by variation in population composition across geographies and varying eligibility criteria across states, to show that public health insurance programs such as Medi-

[10]This procedure is included in the AHRQ's Prevention Quality Indicator (PQI) set. It is particularly useful for this analysis because, unlike other complications that may take years to develop, the effects of delayed care on amputation risk tend to manifest more immediately.

care and Medicaid offer a certain level of protection to eligible patients against increases in hospital prices.

Areas that face shocks to health might see higher hospital utilization, making them more exposed to hospital prices and the negative financial consequences. I test it directly by using the number of high-temperature days in a zip code as an exogenous source of variation. I find that areas with a greater frequency of days with temperatures exceeding 90 degrees Fahrenheit and potentially more likely to see an exogenous increase in hospital utilization, have higher bankruptcy filings and worse credit outcomes.

I run additional heterogeneity tests across various dimensions, specifically the concentration of people of color and median household income. The findings suggest that hospital prices disproportionately affect regions with a higher concentration of people of color. This underscores the merit of considering proposals to expand public health insurance coverage, emphasizing the necessity of conducting a comprehensive cost-benefit analysis that accounts for the broader spillover effects of hospital prices on household financial well-being, particularly within historically underserved communities. I also find that areas with higher median household income report higher bankruptcies when faced with higher hospital prices. These regions are more likely to have higher existing debt in their balance sheets and, hence, can be pushed across the default boundary when faced with unanticipated hospital bills. This is corroborated by the fact that even though their demand or access to mortgage credit is not severely impacted, financial institutions increasingly cite the debt-to-income ratio as a reason for mortgage application denial.

The increase in the use of the home equity line of credit indicates how individuals might seek credit against their home values to meet liquidity needs when faced with hospital bills. Consequently, home equity can help mitigate the severe adverse impacts of rising hospital prices on an individual's financial health. I investigate whether or not home values provide a sufficient cushion against healthcare costs. Household credit and default spillovers to the broader economy have been well-documented in the literature (Mian et al. (2013)). When faced with financial constraints, homeowners often turn to their homes as collateral to obtain credit (Aladangady (2017)). Consequently, their capacity to access credit becomes closely linked to the value of their properties (Mian and Sufi (2011)). However, the impact of hospital prices on home values has not been well documented. Higher hospital prices can potentially dampen home values either by diminishing the attractiveness of nearby properties or through the decline in mortgage demand documented above.[11] I show the decrease in home values in

[11] The reduced demand for mortgages can exert downward pressure on home values (Favara and Imbs (2015), Blickle (2022))

regions where hospital prices increase. In particular, a 1% increase in instrumented hospital prices leads to a -0.20% decline in home values. This decrease in home equity can, in turn, further tighten the credit constraints faced by the households.

The fact that hospital prices dampen home values introduces endogeneity in the analysis, making it difficult to establish a link between home equity and its ability to help households mitigate the impacts of higher hospital prices. I employ the plausibly exogenous variation in the propensity of a region to be subject to investor speculation to examine this question. Nathanson and Zwick (2018) hypothesize that areas where the land supply is elastic in the short run and inelastic in the long run are susceptible to investor speculation. Thus, regions with an intermediate amount of available land often witness home builders bidding up land prices. Given that land is a pivotal input for home construction, home prices also tend to increase (Lutz and Sand (2022)). Consequently, markets prone to speculation might have exogenously higher land values. They, hence, may experience a lesser decline in home prices when confronted with a demand shock induced by higher hospital prices. In particular, I posit that speculative land markets have higher home equity, which dampens the adverse impacts of hospital price increases. To test this, I utilize the dispersion in geographical constraints on construction in the spirit of Saiz (2010). Areas with moderate levels of geographical constraints are the areas that might have an elastic land supply in the short run. However, anticipated future constraints create an attractive market for investors looking to speculate on future price increases. My findings corroborate the hypothesis, demonstrating that in regions characterized by a higher incidence of land market speculation, the effects of hospital prices are comparatively weaker. This is consistent with Gupta et al. (2018), who document that home equity attenuates the financial consequences of a cancer diagnosis. However, there are two distinctive aspects of my findings. First, by reducing home values, higher hospital prices weaken the effectiveness of the very resources individuals may rely on to cope with these price increases. Second, adverse effects of hospital prices can propagate to the broader economy through the home equity channel, affecting even those who were not directly exposed to higher hospital prices through hospitalizations.

For external validation and as a robustness exercise, I exploit price changes induced by hospital competition in a geographic area to instrument hospital prices. Hospitals operating in the same geographical region are peers to each other. The co-movement in their prices captures the changing competitive landscape of the region. I define the peer of a target hospital to be a hospital that has overlap in their geographies of operation. However, the prices of the peer hospitals suffer from the same endogeneity issue since they both operate in the same local market. The omitted peer of a hospital is a peer of a peer who does not operate in the same region as the hospital. Given the geographical separation, the key to establishing the validity of the exclusion restriction, it is unlikely that the local economic conditions would influence the pricing process of the omitted peer in areas where the hospital operates. The underlying assumption is that the omitted-peer prices impact the price of the hospital only through their common peer, thus capturing changes in market competitiveness while remaining orthogonal to the local economic conditions. In particular, I expect the price of the omitted-peer hospital to affect the prices for several reasons. First, common patterns can emerge due to peer effects on technical efficiency (Ferrier and Valdmanis (2005), Bloom et al. (2015)) and technology adoption (Angst et al. (2010)). Second, there might be concurrent changes in negotiated prices of hospitals with common insurers (Liu (2022)). Most importantly, evolving competitive landscapes might beget non-price competition (Cooper et al. (2011)), technology adoption (Wright et al. (2016), Karaca-Mandic et al. (2017)), and price competition (for a review see Gaynor and Town (2011)). These, in effect, establish a positive correlation between the respective prices.

The results in this paper are subject to the overarching concern that they might be driven by the local economic conditions. The validity of the exclusion restriction in the instrumental variable analysis relies on the assumption that the hospital in question, its omitted peer, and insurers operating in the region are not simultaneously exposed to identical economic shocks. While geographical separation and heterogeneity ensure that this holds, I exclude the years affected by the financial crisis as a robustness check. In additional tests, I also added time-varying economic variables as controls. The results are consistent with my main specification. It is also important to note that I do not find a decline in income among those filing for bankruptcy. These findings are inconsistent with the hypothesis that local economic conditions drive the outcomes.

Related literature

This paper relates to a growing literature that studies the causal relationship between health events and financial well-being, including Ramsey et al. (2013), who find a higher incidence of bankruptcy among cancer patients. Morrison et al. (2013) establish a correlation between an individual's pre-health shock financial condition and car crashes. They are not able to identify a causal effect of health shocks on bankruptcy. Carlos et al. (2018) find that the incidence of bankruptcy increases among the hospitalized. Gupta et al. (2018) find that home equity dampens the effect of health shocks, improving both financial and mortality outcomes. I diverge from these studies in that my analysis does not hinge on the occurrence of specific health shocks to individuals, which can be confounded by loss of income and employment. Instead, I document the consequences of changes in the price of care, circumventing the issue of diagnosis complexity and its impact on an individual's labor outcomes.

A concurrent literature, Gross and Notowidigdo (2011), Finkelstein et al. (2012), Mazumder and Miller (2016), Hu et al. (2018), Brevoort et al. (2020), Rhodes et al. (2020), Callison and Walker (2021) studies the financial implications of Medicaid expansion on household distress; this empirical literature finds that states that expanded Medicaid eligibility witness a decline in bankruptcy and improved credit outcomes. This paper makes a significant contribution to this literature in two key aspects. First, I highlight the consequences of changes in the price of care. By examining hospital prices for the privately insured, this paper underscores the presence of underinsurance within the healthcare system, emphasizing that insurance coverage may be inadequate to protect individuals against healthcare expenses. Secondly, it sheds light on the fact that hospital prices can impose significant financial burdens even on individuals with relatively higher income levels. It highlights the broader implications of rising healthcare costs beyond low-income populations, which generally benefit from Medicaid expansion.

Several papers examine the welfare consequences of rising healthcare costs, including (Baicker and Chandra (2006), Kolstad and Kowalski (2016), Arnold and Whaley (2020)) who find a decline in wages and employment in the face of increased burden of health insurance premiums on firms. More recently, Gao et al. (2022) found a decline in employment and technology investment decisions following increased health insurance premiums. Using private equity buyouts of U.S. hospital systems as a shock to healthcare costs, Aghamolla et al. (2023) documents higher insurance premiums, which lead to increased business bankruptcy, slower establishment and employment growth, and decline in innovation. There is a related broader literature at the intersection of healthcare and consumer finance, starting with Domowitz and Sartain (1999), which documents medical debt to be an important determinant of consumer bankruptcy decisions. Brevoort and Kambara (2015) show that medical collections are less predictive of future credit performance. Kluender et al. (2021) document that an estimated 17.8% individuals had medical debt in collections on their credit reports. I add to this literature by highlighting important credit consequences of healthcare costs, particularly the decline in consumers' ability to access credit.

Finally, this paper also relates to the household finance literature that studies the impact of home equity. Mian and Sufi (2011), Aladangady (2017), and Agarwal and Qian (2017) document a positive relation between home equity and consumption. Adelino et al. (2015) highlights the role of home equity in the growth of small business employment. Donaldson et al. (2019) and Bernstein (2021) show that negative home equity can lead to a decline in labor supply. Bernstein and Struyven (2022) documents the decline in household mobility due to negative home equity. I contribute to this literature by highlighting how home equity acts as a cushion against medical expenses. Furthermore, I underline how hospital prices can lead to a decline in home equity, accentuating the financial consequences of rising healthcare costs on households.

The paper is organized as follows. In Section 2, I begin by discussing the institutional background on the U.S. healthcare system. In Section 3, I describe the empirical strategy and datasets used in this paper. In Section 4, I discuss the empirical findings. I introduce an alternative identification strategy in Section 5. I discuss the heterogenity tests in Section 6. In Section 7, I discuss the home equity channel. I establish the robustness of my results in Section 8. Section 9 concludes the paper.

2 Institutional Background and Conceptual Framework

Hospital Bills for the Privately Insured

Hospital pricing is a complex exercise. Unlike grocery stores or restaurants, where listed prices directly translate into the final payable amount, the amount that a patient pays to a hospital depends on various factors, including health insurance coverage, type of insurer, and the specific terms of their insurance plan that govern the sharing of medical expenses with the insurer.

Private health insurance coverage continues to be more prevalent than coverage through public insurance programs such as Medicare and Medicaid in the U.S., at 65.6% and 36.1%, respectively. Of the subtypes of health insurance coverage, employment-based insurance was the most common, covering 54.5% of the population, followed by Medicaid (18.8 %) and Medicare (18.7%) (Keisler-Stankey and Bunch (2021)). To the extent an expense is covered, prices that enrollees pay under public insurance programs are extensively regulated. Medicare, for instance, is generally premium-free and imposes a fixed deductible per hospital benefit period. In the case of Medicaid, while co-payments and deductibles vary by state, there exists a federal limit on the extent to which these insurance cost-sharing measures can be imposed. However, given that Medicare provides coverage to older adults, the average utilization by an enrollee under Medicare is much higher than that of Medicaid. While these programs reduce exposure to commercial hospital prices to a large extent, Medicare still has substantial coverage gaps. An estimated 7.7 million people, primarily ages 65 and older, used paid long-term service and support in 2020, according to CBO (2020). In 2021, the median annual cost for such care in the U.S. was $108,405, which is generally not covered by Medicare. In the absence of Medicaid eligibility or supplementary insurance among such Medicare enrollees, a substantive portion of these costs would be borne by the individuals. The higher utilization and gaps in Medicare coverage are substantiated by the fact that average out-of-pocket expenditure for those with coverage under Medicaid is almost a tenth of those under Medicare (Catlin et al. (2015)).

Barring a few states, hospital prices under private health plans are largely unregulated. The negotiations between insurance companies and hospitals determine 1) the network, that is, whether or not patients can use their insurance coverage to access care at a particular hospital, and 2) the price that insurance companies will reimburse to hospitals for the services rendered by it to the patients (in this paper, referred to as commercial hospital prices). While smaller employers typically provide a single health plan option, larger employers provide employees with a selection from a range of alternative health plans. The choice of health plan determines the portion of the hospital bill that the individual is responsible for in the event of an adverse health event. Most plans require the insured to pay up to a specific contracted amount (commonly referred to as deductibles) before coverage kicks in. The insured may also be obligated to pay a fixed percentage or amount (co-insurance) of the total incurred bill. Most plans also have an upper bound on the total out-of-pocket expenditure made by those insured (out-of-pocket limit). These two sets of negotiations, in which the insured typically has little or no influence, are instrumental in defining their financial burden in the event of hospitalization. Deductibles, co-insurance commitments, and out-of-pocket limits all have been increasing, putting a substantial burden of the increasing hospital prices on the patients.

This intricate web of contract negotiations and arrangements can lead to situations that are financially exploitative for the patients. One such outcome is surprise medical billing. This can arise in a variety of situations, including when a hospital is in-network (covered by insurance), but patients unavoidably receive out-of-network care (not covered by insurance) when physicians at the hospitals are not in-network (Hall et al. (2016)). I borrowed a case from *KFF Health News* to illustrate surprise billing in the example below:

> *Josephine "Joey" Trumble needed neonatology physician services including*

> *tube feeding and ventilator care to provide oxygen in 2020 and was covered by her mother's health plan through her employer, an advertising agency. For 2019, it was an Aetna plan, and for 2020, it was a plan from Blue Cross and Blue Shield of Illinois. The staff physician at Ann & Robert H. Lurie Children's Hospital of Chicago treated Joey at Northwestern Medicine Prentice Women's Hospital. Lurie is independent of Northwestern Medicine, but it is physically connected to Prentice Women's by an enclosed walkway. Lurie has a collaboration agreement with Northwestern Medicine to provide neonatology and pediatric physician services to Prentice Women's patients. Aetna paid for nearly all of Joey and her mother's hospital and physician charges in December, while Blue Cross picked up nearly all of Joey's hospital charges in January. Physician charges from Lurie in January totaled $14,624.55, of which the family was asked to pay $12,531.58 after payments from Blue Cross. It took Kearney months of calls to Blue Cross and the two hospitals to find out why Lurie billed more than $14,000 for physician services: The physicians treating her daughter at Prentice Women's — an in-network hospital under her health plan — actually worked for a separate, out-of-network hospital.*[12]

Using the entry/exit of a market-leading Emergency Department outsourcing firm in a hospital, Cooper et al. (2020) shows an increase in patients' cost-sharing burden in such scenarios. In other circumstances, such as emergencies where insurers are required to cover out-of-network costs, the insurer and the hospital might not agree on a reasonable amount, putting the onus of payment of the balance on the patient. The No Surprises Act is a federal law that went into effect on January 1, 2022, and was designed to protect individuals from such circumstances. Apart from the federal law, many states offer various legal protections to patients. However, ingenious methods to circumvent such laws have already become prevalent. Out-of-network providers are evading surprise-billing laws by being contracted as "participating providers" (Meyer (2023)). In emergencies, if the facility were out-of-network, laws would prohibit charges from being passed to the patient. However, insurance companies are contracting high co-insurance rates with the erstwhile out-of-network facility (now the participating providers). Apart from these, differences in the classification of what constitutes an emergency, coverage, or lack thereof of specific procedures might inflate the balance borne by the patient.

[12] KFF Health News publishes "Bill of the Month" highlighting such scenarios. See https://kffhealthnews.org/news/tag/bill-of-the-month/.

Insurer Market Power

Unlike the somber words weaved by Nobel Laureate Rabindranath Tagore in his poem"The Last Bargain", in the market economy no one bargains to be hired for nothing in exchange for freedom. As such, the contract negotiation between the insurer and the hospital depends on the strength of their bargaining chips, which is mainly driven by their market power in a given geography. Liu (2022) shows that private equity with a reputation for closing distressed borrowers can use the threat of hospital closure to extract higher reimbursements. A hospital closure induces higher market power among the remaining hospitals within a market, raising their bargaining power and incentivizing insurers to prevent hospital closure by providing higher reimbursement rates. Liu (2022) find that negotiated prices increase by an average of 32% following the private equity acquisition of a hospital. Barrette et al. (2022) document that the healthcare industry exhibits a unique vertical structure where the market power of insurers acts as a source of countervailing bargaining power to hospitals and other medical providers. That is to say, the reimbursement schemes for treating privately insured patients could be lower if insurance companies have substantive market power vis-à-vis hospitals. In particular, they show that a typical hospital merger that would raise prices by 4.3% at the 25th percentile of insurer concentration is able to raise prices only by 0.97% at the 75th percentile.

There is compelling evidence to suggest that increases in hospital prices will ultimately result in increases in the cost of health plans (insurance premiums), reductions in the breadth of coverage, particularly in terms of provider networks, and increased co-insurance obligations placed on policyholders. Aghamolla et al. (2023) shows that insurers are able to pass part of the burden of increased reimbursement rates onto the local communities in the form of higher premiums. Apart from these, the rent-seeking behavior due to substantial insurer market power might be detrimental to those they provide coverage to, even if they are able to contain increases in reimbursement rates. Thus, an insurer's market power determines not only the hospital prices but also an insured individual's exposure to it.

3 Research Design and Data

3.1 Hospital Prices

In most cases, researchers have access to hospital charges (or listed prices) rather than the actual prices billed to insurance companies or patients. To accurately measure inpatient prices that can be compared across different hospitals, I need to consider the discounts negotiated with commercial insurers (contractual discounts) for inpatient services. Additionally, some hospitals may, whether by design or by chance, admit patients with higher diagnosis complexity, necessitating greater resources for treatment and consequently resulting in inherently higher costs. Therefore, the prices reported by these hospitals may be inflated due to patient case-mix factors, making it essential to adjust for the average patient diagnosis complexity at the hospital.

The standard approximation used in the literature for commercial hospital prices is the "Dafny measure". Dafny (2009) employs the Healthcare Provider Cost Reporting Information System (HCRIS), hosted by the U.S. Centers for Medicare & Medicaid Services (CMS), to estimate prices based on hospital charges. However, the limitations of this measure stem from several sources. First, HCRIS provides data on aggregate contractual discounts, encompassing discounts extended to Medicare/Medicaid patients and covering both inpatient and outpatient discharges. Second, the revenue figures obtained from HCRIS cannot be adjusted to account for Medicaid revenue and discharges. Lastly, the measure of patient complexity is derived from CMS Impact Files, calculated primarily for Medicare patients. The complexity of Medicare patients may differ significantly from that of commercial patients, introducing potential bias into the analysis.

In this paper, I enhance the Dafny measure through several improvements. First, to accurately account for price negotiation between commercial insurers and hospitals, I acquired the state hospital cost reports of Massachusetts, New York, New Jersey, Vermont, Maryland, Wisconsin, Nevada, and Florida via a series of Freedom of Information Act (FOIA) requests. These reports provide comprehensive and detailed information about the discounts applied to inpatient and outpatient services for Medicare, Medicaid, commercial insurers, and self-pay patients, as opposed to the aggregate contractual discounts available in HCRIS. Second, the data on hospital charges for the universe of hospital inpatient discharges for a subset of US states comes from the State Inpatient Databases (SID) developed for the Healthcare Cost and Utilization Project (HCUP). It includes information on the patient's demographic, including their zip code location, their payer type, and diagnosis/procedure codes. I restrict my sample to patients with commercial insurance, thus adjusting the revenue for all other insurer types.

Lastly, to account for the diagnosis complexity of patients under commercial insurance, I exploit the MS-DRG code that has been assigned to every discharge in the HCUP-SID files. MS-DRG or Medicare Severity Diagnosis-Related Groups is defined by a particular set of patient attributes, which include principal diagnosis, specific secondary diagnoses, procedures, sex, and discharge status. Each MS-DRG is assigned a time-varying weight that represents the average resources required to care for cases in that particular DRG, relative to the average resources used to treat cases in all DRGs. The average DRG weight is one. The data for DRG weights comes from CMS Impact Files. The average patient diagnosis complexity for commercially insured patients for hospital h a year t as measured by the Case-Mix Index, is calculated as follows:

$$\text{CCMI}_{h,t} = \frac{\sum_{i=1}^{\text{Discharge}_{ht}} \text{DRGWeight}_{iht}}{\text{Discharge}_{ht}} \tag{1}$$

where Discharge_{ht} is the total number of commercial inpatient discharges, and DRGWeight_{iht} is the MS-DRG weight for discharge i. I aggregate the charges to get the total commercial inpatient revenue, which I then adjust for contractual discount and the Case-Mix-Index calculated above. The commercial hospital price for hospital h in a year t is calculated as follows:

$$HospPrice_{h,t} = \frac{\text{Commercial Inpatient Revenue}_{h,t} * (1 - \text{Commercial Contractual Discounts}_{h,t})}{\text{Discharge}_{h,t} * \text{CCMI}_{h,t}} \tag{2}$$

The correlation between the prices calculated above and my estimation using the method described in Dafny (2009) is 0.42. Transaction data with detailed insurance reimbursements such as those used and described in Cooper et al. (2019) is costly and not easily accessible. Consequently, leveraging data from state hospital cost reports presents a valuable alternative that can help address measurement concerns.

I aggregate hospital prices at the five-digit zip level to capture the geographic variation in exposure to hospital prices. I first define the geographical market of a hospital to be all the zip codes that lie within a fixed radius of the hospital. The underlying assumption is that the majority of patients who visit a particular hospital live or work in proximity to the hospital. One way of constructing the zip-level measure of hospital price would be to simply aggregate prices using the number of discharges as weights. However, this introduces a major endogeneity concern as patients self-select a hospital. Patient choices regarding hospitals are driven by factors such as hospital quality, coverage provided by their health plan, and the individual's financial constraints. These factors are unobservables to the researcher and could potentially be correlated with the financial outcome under study.

In the spirit of Kessler and McClellan (2000), Gowrisankaran and Town (2003), and

Karaca-Mandic et al. (2017), I construct a measure of market share of a hospital in a zip that is independent from the unobserved factors. I assume the distance between the patient and the hospital to be exogenous, in that they determine choice but not the financial outcome of the patient. As in Berry (1994), I run a conditional logit model of patient's choice of hospital. For each zip z, I define the choice set to be the hospitals that are within a 25 mile radius. I run the following regression separately for each year:

$$ln(sh_{hzt}) - ln(sh_{0zt}) \equiv \delta_{h,z,t} = \beta_1 \text{Distance}_{h,z} + \beta_2 \text{Distance}^2_{h,z} + \gamma_h + \epsilon_{h,z} \tag{3}$$

where sh_{hz} is the market share of hospital h in zip z, sh_{0z} is the market share of hospitals outside the 25-mile radius, $Distance_{h,z}$ is the geographic distance between the hospital and the zip, and γ_h is the hospital fixed effect. Since the HCUP-SID files do not have data for all the states, for consistency, I consider discharge at an out-of-state hospital to be outside the choice set. Using the predicted $\hat{\delta}_{h,z,t}$, I calculate the predicted market share as:

$$\alpha_{h,z,t} = \frac{e^{\hat{\delta}_{h,z,t}}}{\sum_{\text{h in z}} e^{\hat{\delta}_{h,z,t}}} \tag{4}$$

Hence, the hospital price aggregated at the zip code level is given by:

$$ZipPrice_{z,t} = \sum_{\text{h in z}} \alpha_{h,z,t} HospPrice_{h,t} \tag{5}$$

For robustness, I recalculate markets shares and by extension prices by defining the choice set to include all hospitals within a 50-mile radius.

3.2 Identification Strategy

Insurer's Medical Loss Ratio Instrumental Variable

To estimate the causal effect of hospital prices on household financial outcomes, I use the medical loss ratio of an insurance company weighted by their market share in a zip as an instrument for hospital prices. Medical loss ratio or MLR is the share of total health care premiums spent on medical claims and/or efforts to improve the quality of care. For the exclusion restriction to hold, the only channel through which insurers' medical loss ratio can impact individuals' financial outcomes is through hospital prices. I assert that the exclusion restriction is met for two main reasons. Firstly, insurance companies in my sample are large firms that span multiple geographical areas, making it highly improbable for a specific zip code to affect an insurer's gap between claims and premiums. Secondly, insurance premiums in most cases are negotiated between insurance companies and an individual's employer, reducing the likelihood that premiums are influenced by the financial circumstances of a particular zip code.

I establish the relevance of the instrument on several fronts. The insurer's market power impacts the medical loss ratio in two ways. First, an insurer's ability to negotiate with healthcare providers depends on its market power. An increase (decrease) in the insurer's bargaining power would lead to a decrease (increase) in the negotiated claim amounts (inpatient hospital claim amounts are commercial hospital prices in this paper). Second, insurers operating in concentrated markets charge higher premiums and/or provide lower dollar value of coverage for the premiums charged. Consequently, a higher medical loss ratio signals intensifying competition in the market and thus weakened bargaining power of insurers vis-a-vis the healthcare providers. Karaca-Mandic et al. (2015) demonstrates that the medical cost ratio is a valid measure of an insurer's price-cost margin. They also find that monopoly markets tend to have significantly lower medical loss ratios compared to more competitive markets. Decreasing medical loss ratios, thus can serve as indicators of insurer market power. A recent literature starting with Gowrisankaran et al. (2015) models insurers' negotiations with healthcare providers. In particular, Barrette et al. (2022) illustrates how insurance market power can act as a countervailing force against hospital market power, mitigating the impact of hospital mergers on prices. Consequently, a higher medical loss ratio could signal intensifying competition in the market, which would, in turn, weaken the bargaining power of insurers in negotiations with healthcare providers. This could lead to higher commercial hospital prices.

The Affordable Care Act (ACA), since 2012, has enforced a floor of 85% on the medical loss ratio to curb excess profitability and counter the effects of insurer market power. Zhao (2021) illustrates that this regulation may inadvertently reduce insurers' incentives to negotiate lower prices with healthcare providers. While the medical loss ratio (MLR) places a cap on insurers' profits relative to premiums, it doesn't directly regulate their absolute profits. Consequently, instead of decreasing premiums and claim denials, insurers may find ways to work around the regulation's intent. They can achieve this by increasing the amounts they pay to hospitals per medical event on one hand, and shifting part of these costs to patients through less patient-friendly co-insurance arrangements on the other. Abraham et al. (2014) demonstrated that the initial response of insurers to the regulation was mostly driven by increases in claim amounts. While the initial response could have been an artifact of the time constraint to comply, Cicala et al. (2017) documents that these effects persist. Their results are in tune with Zhao (2021) in that they find that claims rose nearly one-to-one for distance below the threshold, with no significant effect on premium. This combination of reduced market power and diminished incentives for cost negotiation connects a higher medical loss ratio to higher prices negotiated between hospitals and insurance companies.

To empirically validate that the medical loss ratio captures the insurer's market power, I test whether or not insurers who have a monopoly in more geographical markets in which they operate have lower medical loss ratios. To that end, I run the following specification:

$$MLR_{n,t} = \alpha + \beta MonopolyMarkets_{n,t} + \kappa_n + \gamma_t + \varepsilon_{n,t}. \tag{6}$$

I define $MonopolyMarkets_{n,t}$ as the proportion of counties in which the insurer has a monopoly out of all the counties that the insurer operates in. $MLR_{n,t}$ is the medical loss ratio of the insurer n at a given year t. I include both insurer and year fixed effects. The standard errors are clustered at the insurer level. Table 2 reports the results for this specification. Column (1) presents results for the entire sample, and Column (2) presents results for the sample before the implementation of ACA provisions. I find strong evidence that insurer market power is negatively related to their medical loss ratio. In other words, insurers operating in less concentrated markets have lower medical loss ratios.

The construction of the instrument is in the spirit of Gao et al. (2022), who use it to instrument firm-level insurance premiums. They argue that the recent insurer losses put pressure on the insurance firms to raise premiums for short-term liquidity. My findings underline that this might in fact be an artifact of higher negotiated prices between insurance companies and healthcare providers (Zeller (2023), Aghamolla et al. (2023)). This is in line with the predictions of Zhao (2021) who show that consumers end up paying more out of pocket costs for health care services and premiums.

The data for medical loss ratios comes from S&P CapitalIQ Pro's Insurance Statutory Financial(U.S.). I calculate a zip's exposure to an insurance company, using Form 5500 reports filed with the Department of Labor. Each firm files an individual Schedule A report for every insurance contract they have for an employer-sponsored health plan. This has information on the insurance carrier, premiums, number of insured, and type of welfare benefits provided under the contract. I include only insurance contracts that indicate the presence of health coverage and exclude standalone dental, vision, life, and other ancillary insurance contracts. I match the insurer information on Form 5500 and the medical loss ratio using the National Association of Insurance Commissioners (NAIC) codes. I further match NAIC codes to their group counterparts, using medical loss ratio at the conglomerate level. The medical loss ratio IV for zip z in the year t is given by:

$$MLR_{z,t,t-2} = \sum_{n=1}^{k} \omega_{n,z,t} \frac{\textit{Total Medical Claim}_{n,t,t-2}}{\textit{Net Premium Written}_{n,t,t-2}} \tag{7}$$

where $\omega_{n,z,t}$ is the share of the insurance company n among those enrolled in zip z at time t. The exposure to the zip is defined if the firm is situated within a 25-mile radius of the zip. $\textit{Total Medical Claim}_{n,t,t-2}$ and $\textit{Net Premium Written}_{n,t,t-2}$ is the total medical claims less reinsurance and the net premium written amount for the conglomerate holding insurance company n incurred between the years $t-2$ and t. In tune with ACA regulations, I put a floor of 85% on the insurer's MLR if it is below the threshold. In particular, post-2011, the medical loss ratio IV for zip z in the year t is given by:

$$MLR_{z,t,t-2} = \sum_{n=1}^{k} \omega_{n,z,t} \ \max(85, \frac{\textit{Total Medical Claim}_{n,t,t-2}}{\textit{Net Premium Written}_{n,t,t-2}}) \tag{8}$$

3.3 Data Description and Summary Statistics

Table 1 provides summary statistics for the variables of interest. Panel A summarizes the hospital price measure, the MLR instrument, and the omitted-peer instrument. My main sample spans from 2005 to 2019[13], encompassing all the state-year combinations for which I have access to state hospital cost reports data. To ensure price and service comparability, I restrict the sample to include only short-term acute-care hospitals. Following the existing literature, I exclude government hospitals since they receive direct government funding and potentially have a different incentive structure than the one relevant for my study. The final sample includes 782 hospitals that operate in a total of 6553 zip codes.

Data for personal bankruptcies comes from the Federal Judicial Center Integrated Database. This dataset includes fundamental filing information such as the zip code, filing date, and the specific chapter under which a bankruptcy petition has been filed. Additionally, it provides a schedule of assets and liabilities, offering details on the type and amount of debt, as well as the filer's income, expenses, and asset availability. The dataset spans the period from 2007 to 2019. Panel B summarizes key outcome variables derived from the database. The bankruptcy counts have been aggregated at the zip code level. Debt-to-income ratios,

[13] I exclude data from 2020 to avoid potential confounding from the COVID-19 pandemic. Moreover, the dataset contains only a single state-year observation for 2020, further limiting its analytical value. However, the results are robust to inclusion of 2020.

ratio of secured and unsecured liability to total liability, total debt, and average monthly income and expenses are at the bankruptcy filer level. Given that the self-reported nature of supplementary data can occasionally exhibit noise, the financial data has been winsorized at the 1% level to address extreme values in the dataset.

Data for mortgage application and origination comes from the Home Mortgage Disclosure Act (HMDA) database hosted by the Consumer Financial Protection Bureau. Under the Home Mortgage Disclosure Act, financial institutions are required to provide mortgage data to the public. Files prior to 2007 have been taken from the US Archives. Panel C summarizes key outcome variables derived from the database. These outcomes have been aggregated at the zip code level and encompass counts of mortgage applications, origination, and denials, among others. Data for credit card and home equity line of credit has been taken from S&P CapitalIQ Pro's Geographic Intelligence Data. Additionally, data from the Census, Policy Maps, IRS, and CMS are used as controls and/or heterogeneity tests.

3.4 Empirical Specification

The primary objective of this paper is to study the impact of hospital prices on household's financial outcomes. Before, I deal with the endogenity issue extensively discussed above, I run the following OLS specification to highlight some salient facts in the data.

$$Y_{z,t} = \alpha + \beta ZipPrice_{z,t} + \kappa_z + \gamma_{st} + \varepsilon_{i,t}. \tag{9}$$

Equation (9) examines the effect of hospital prices *ZipPrice* on household financial outcomes Y for zip z, state s , and year t. I include zip and state-year fixed effects, and the standard errors are clustered at the zip level.

For my main specification, I employ an instrumental variable approach using a two stage least square (2SLS) design. In the first stage, I instrument for zip-level hospital prices (5) using a three-year average of medical loss ratio as defined in (7) . Next, I study the impact of the instrumented hospital price on financial outcomes to establish causality.

$$ZipPrice_{z,t} = \beta MLR_{z,t,t-2} + \tau_z + \mu_{st} + \varepsilon_{i,t}. \tag{10}$$

$$Y_{z,t} = \lambda \widehat{ZipPrice}_{z,t} + \kappa_z + \gamma_{st} + \varepsilon_{i,t}. \tag{11}$$

where z is a zip code and t is a year. The outcome variables $Y_{z,t}$ include counts of bankruptcy filings, bankruptcy filer characteristics such as ratio of secured and unsecured liability to total debt, log of average income and expenses among the bankruptcy filers, log number of mortgage applications and originations, mortgage application denial rate, among others.[14]

I incorporate fixed effects for both zip codes and time-varying state fixed effects to account for potential confounding factors introduced by cross-sectional differences among zip codes and macroeconomic trends over time. Standard errors are clustered at the zip-code level. It is important to note that the legal and institutional frameworks under which hospitals operate can vary significantly from state to state and are subject to ongoing changes, such as the staggered expansion of Medicaid or the implementation of laws to address surprise billing in certain states. Medicaid eligibility is also subject to state-specific criteria that can change over time. Inclusion of state-year fixed effects is crucial to control for the aforementioned state-specific trends.

4 Results

4.1 Personal Bankruptcies

I begin by establishing certain salient facts on household distress that emerge from the data. Table 3 provides the results of zip-level estimation for the bankruptcy outcomes following the specification outlined in (9). The dependent variables of interest include the number of Chapter 7 (liquidation), Chapter 13 (reorganization), total personal bankruptcies, and filings by individuals with a prior bankruptcy record in a given zip code and year. The results show that increases in hospital prices are associated with a meaningful rise in personal bankruptcies. Having established this correlation between hospital prices and financial outcomes, I now proceed to implement my identification strategy in order to establish causality. Utilizing the two-stage least squares (2SLS) approach, I first validate the relevance of the medical loss ratio instrument. Column (1) of Table 4 presents results for the first stage of the main specification as specified in Equation (10). The findings demonstrate that an increase in medical loss ratio exhibits a positive and statistically significant relation with hospital prices. The results indicate that a percentage point increase in insurer's medical loss ratio leads to a 1.25% increase in hospital prices.

Columns (2)-(5) of Table 4 present results for the second stage. The estimates from the

[14] Following Chen and Roth (2024), wherever necessary, I apply the transformation $m(y)$, defined as $m(y) = \log\left(\frac{y}{\min_{y>0} y}\right)$ if $y > 0$, and $m(y) = -x$ if $y = 0$, instead of taking the log of the outcome. This imposes that the extensive-margin effect of moving from 0 to the minimum of non-negative y is equivalent to a $100x\%$ increase in y. The results are robust to using standard logarithmic transformations, and the full set of results is available upon request.

headline specification in (11) imply a bankruptcy-price elasticity of 1.77. In other words, every \$124 increase in hospital prices leads to a unit increase in total personal bankruptcy filings per zip code on average. To provide a practical perspective on the magnitude of this price increase, it is important to note that the prices reflect patients with average diagnosis complexity (MS-DRG weight = 1). This equates to a \$1240 increase in the cost of a liver transplant and an \$3348 increase for a heart transplant.

Interestingly, the elasticity of Chapter 13 bankruptcy filings with respect to hospital prices is higher than that of Chapter 7. I also find that those with prior bankruptcy filings are more adversely impacted by hospital price rises. This is intuitive, since many individuals with prior bankruptcy filings are those who currently are trying to adhere to a reorganization plan following Chapter 13.

To examine the characteristics of those filing bankruptcies and whether these characteristics change in response to higher hospital prices, I look at measures constructed from supplementary information that the bankruptcy filers need to furnish when submitting their petition. Table 5 examines the debt-to-income ratio, proportion of secured, unsecured-non-priority debt out of total debt, total debt, and average income and expenses of the bankruptcy filers. The findings reveal that the marginal bankruptcy filer, on average, reports higher debt-to-income ratios and higher debt when exposed to higher hospital prices. The results show that the marginal bankruptcy filer has a higher income. This indicates that the results are not driven by income composition effects and that the negative welfare consequences of higher hospital prices may not be limited to low-income individuals. This is consistent with Fisher (2019) who finds that middle-income groups are most likely to file for bankruptcy. Bankruptcy filers also report a higher proportion of secured debt on average, indicating the presence of more substantial assets.

4.2 Effect on Credit Outcome

In this section, I analyze the household response to an increase in hospital prices by examining changes in their demand for mortgages. Concurrently, I also study if their ability to access credit is impeded by hospital price induced financial obligations.

Column (1) in Table 6 replicates the first stage regression in specifications (14) and (10) for the HMDA sample. The results are statistically significant and consistent with prior findings in Table 4. Columns (2) - (5) of Table 6 present results for the second stage. The dependent variable of interest is the number of mortgage applications, originations, proportion of second lien mortgage applications, and application denial rate in a given zip and year. The estimates from the headline specification provide evidence that increased hospital prices lead to a decline in demand for mortgage loans. Specifically, a \$23 increase in hospital prices corresponds to one fewer mortgage application in a zip code. I also document a decline in mortgage originations. In particular, a \$49 increase in hospital prices leads to one fewer mortgage origination. The more pronounced effect on mortgage applications may reflect a preemptive response by households anticipating higher out-of-pocket healthcare expenditures due to rising medical prices. The results also document an increase in mortgage application denials by financial institutions. Furthermore, there is an increase in the proportion of second-lien mortgage applications, which suggests that borrowers are increasingly trying to tap into their home equity to meet their demand for credit.

The increase in denial rates prompts the question of why these applications are being denied. Analyzing the reasons for denials can offer insights into how hospital prices affect credit access. Table 7 presents the second-stage results regarding the reasons for mortgage application denial cited by the financial institutions. The results indicate that the debt-to-income ratio and insufficient cash are increasingly cited as reasons for loan denials when hospital prices increase. This suggests that a potential increase in medical debt following higher hospital prices might lead to higher debt-to-income ratios and insufficient liquidity among potential borrowers. Importantly, the results show that employment, credit history, and collateral are not the primary reasons for application denials. This implies that the increased denials are not primarily driven by local economic conditions but rather by the potential financial challenges arising from mounting medical debt.

I test whether the increase in denial rates are only limited to lower income groups. Table 8 presents results for the second stage specification studying the denial rates across applicant income quintiles. The results indicate that while the applications of those on lower income quintiles are disproportionately denied, the increase in denial rates is still substantial among those in the higher income quintiles. Next, I examine whether historically underserved communities experience a more pronounced decline in credit access. Table 9 reports results from the second-stage specification, focusing on the share of mortgage applications and originations of Black applicants as well as their corresponding denial rates. The estimates indicate that the share of Black applicants declines in both the application and origination pools, suggesting that rising hospital prices may disproportionately deter or exclude them from the mortgage market.

Additionally, I look at supplementary credit measures available from S&P CapitalIQ Pro's Geographic Intelligence datasets. Table 10 presents results for the second stage specifications studying the number of households holding credit cards[15], home equity line of credit, and auto loans. The results indicate that an increase in hospital prices leads to increases in credit card use. This shows that medical debt can masquerade as credit card debt. This mechanism may help explain why Kluender et al. (2025) find limited effects of medical debt forgiveness. The results also document that more households utilize home equity lines of credit, demonstrating the role of home equity in helping households cope with increases in hospital bills.

4.3 Patient Outcomes

Lastly, I examine whether higher hospital prices affect patients' access to care. Table 11 presents second-stage estimates where the outcomes are the number of total discharges, discharges for elective and non-elective procedures, and lower limb amputation among diabetic patients per 1,000 residents at the ZIP code level. The results indicate a contemporaneous decline in total discharges following an increase in hospital prices, suggesting that patients defer care when faced with higher costs.

This finding has two important implications. First, it helps rule out the possibility that rising hospital prices reflect higher demand or increased utilization at the local level. Second, the decline is concentrated among elective procedures, indicating that the effect is not driven by an increase in discretionary or non-essential care.

Importantly, I also find evidence that such delays in care have adverse consequences. In the year following a price increase, there is a rise in the incidence of lower limb amputations among diabetic patients. This is a form of preventable hospitalization that is typically avoidable with timely medical intervention. This underscores the broader health costs associated with diminished access to affordable care.

5 Alternative Identification Strategy

Omitted-Peer Instrumental Variable

Alternatively, I exploit changes in prices induced by hospital competition in a geographic area to instrument for hospital prices. Hospitals operating in the same geographical region are peers to each other. The co-movement in their prices captures the changing competitive

[15] The data provides separate figures for the number of households with VISA, Mastercard, and Discover. Since households might use one or many credit cards, I do not aggregate it.

landscape of the region. However, the prices of the peer hospital suffer from the same endogeneity issue as the hospital prices, given that they operate in the same local market. An omitted peer, in this context, refers to a hospital that is a peer of the peer hospital, but does not serve any of the geographical areas in which the target hospital operates. This concept is depicted in Figure A1.1. The underlying assumption is that the omitted-peer prices impact the price of the hospital only through their common peer, thus capturing changes in market competitiveness while remaining orthogonal to the local economic conditions. There are several reasons to believe that the exclusion restriction, a key IV assumption, holds. First, the geographical and market separation between the two hospitals makes it highly unlikely for the local economic conditions of a particular zip code where the target hospital operates to influence the pricing strategy of the omitted peer hospital. Second, the process by which a hospital is matched with its omitted peer is largely exogenous, adding further credibility to the validity of this instrument. Additionally, in order to account for potential macroeconomic shocks or trends induced by changes in the state's healthcare regulation, I incorporate time-varying state-fixed effects into the analysis.

In addition to the benefit of market separation, the concept of omitted peers also contributes to a cleaner and more precise identification of peer effects in the analysis. Standard peer effect models, as discussed by Manski (1993), are susceptible to the "reflection problem". This challenge arises from the difficulty of distinguishing the influence of peers on an individual from the influence of the individual on their peers when both are simultaneously determined. By introducing partially overlapping peer groups, the omitted peer eliminates the problem of all peers in a group having the same set of peers. This is demonstrated in prior research by Bramoullé et al. (2009), Angelucci and De Giorgi (2009), Aghamolla and Thakor (2022).

I establish the relevancy of the instrument on two accounts. First, there is a large literature in economics and finance that studies different channels through which peers influence behavior. In the healthcare finance literature, the role of peers in improving technical efficiency has been studied by Ferrier and Valdmanis (2005). They find that an 10% increase in peer efficiency translates into a 2% increase in hospital's own efficiency. Angst et al. (2010) study how peer-effects influenced adoption of Electronic Medical Records(EMR) across hospitals. Hence, peer effects can induce correlation between their costs and, by extension, prices.

Second, the hospital and its omitted-peer operate in the same institutional environment, such as legal regulations and healthcare market structure. These institutional elements are plausibly exogenous to the financial outcome of a particular zip. Dafny (2009) finds a sizeable one-time increase in prices following the merger of a neighboring hospital. A related literature studies how changes in hospital market structure can lead to improvement in hospital quality (Cooper et al. (2011)). Wright et al. (2016) show that increased market competition was associated with increased use of robotic-assisted surgery. Karaca-Mandic et al. (2017) find faster technology diffusion among cardiologists facing higher competitive pressure. Liu (2022) documents the increase in insurer-negotiated hospital prices following a hospital's private equity buyout. More importantly, they show that neighboring hospitals that are not private equity owned raise their negotiated price following the buyout.

To ensure sufficient geographical separation, the definition of market served by a hospital extends beyond the previously defined 25-mile radius criterion. Instead, it encompasses all zip codes with at least 1% of all discharges at the target hospital. Though far and few, I do make an exception and exclude an omitted peer if it happens to fall within a 25-mile radius of the target hospital to maintain adequate separation. On average, there is a substantial distance of 104 miles between a hospital and its omitted peer. It's important to note that a hospital may have multiple peers and, consequently, multiple omitted peers. To create the instrumental variable, I calculate a rank-weighted average of the omitted peer prices. These ranks are determined based on the number of zip codes that overlap between the omitted peer and its peer, as well as the peer and the target hospital. In particular, the zip-level instrumented prices are given by:

$$OmittedZipPrice_{z,t} = \sum_{\text{h in z}} \alpha_{h,z,t} OmittedPrice_{h,t} \tag{12}$$

where

$$OmittedPrice_{h,t} = \sum_{\text{k in } o_h} \omega_{k,h,t} HospPrice_{k,t} \tag{13}$$

where, o_h is the set of all omitted peers of hospital h, $\omega_{k,h,t}$ is the rank-weight of omitted peer k for target hospital h. Alternatively, I compute weights using discharge-overlap among hospitals or by selecting the omitted peer whose peer exhibits the strongest overlap with the target hospital. Importantly, the results remain robust across different approaches to averaging prices. Note that the market shares used to aggregate these prices at the zip level remain unchanged.

The following specifications mirror (10) and (11) for the omitted-peer instrument as defined in (12):

$$
\begin{aligned}
ZipPrice_{z,t} &= \beta OmittedZipPrice_{z,t} + \tau_z + \mu_{st} + \varepsilon_{i,t}. && (14)\\
Y_{z,t} &= \lambda \widehat{ZipPrice}_{z,t} + \kappa_z + \gamma_{st} + \varepsilon_{i,t}. && (15)
\end{aligned}
$$

where z is a zip code and t is a year. I incorporate fixed effects for both zip codes and time-varying state fixed effects.

Column (1) of Table A1.1 reports the estimates from the first stage. I find a positive and statistically significant relation between the two prices. In particular, a 10% rise in omitted-peer prices leads to an 1% increase in hospital prices in a zip z. Tables A1.1, A1.2, A1.3, and A1.4 correspond to Tables 4, 5, 6, and 7 , respectively, using the omitted-peer instrument. The results are broadly consistent, both in magnitude and significance.

6 Heterogeneity Tests

In this section, I extend my analysis to further explore the heterogeneous effects of hospital prices on the financial outcomes to reinforce evidence for the underlying mechanism driving the established results.

The lack of insurance coverage can lead to a significant decline in an individual's financial security when their health deteriorates. While prior research documents that uninsured patients pay prices lower than those negotiated with the insurers, those with sufficient coverage on average have lower out-of-pocket costs (Jiang et al. (2021)). Hospital and state-run programs designed for the uninsured often prove insufficient in preventing deterioration in a patient's financial health. In particular, Carlos et al. (2018) documents that uninsured individuals face more financial strains as a consequence of hospitalizations than their insured counterparts. Hence, they are more likely to be directly affected when the price increases. Leveraging the variation in the proportion of individuals without any insurance coverage in a county, I examine the impact of commercial hospital prices in zip codes that fall below the median uninsured rate compared to those that fall above it. Table 12 reports the results for instrumented prices interacting with an indicator for whether a zip code has an uninsured rate below or above the median in a given year. The findings are consistent with the hypothesis that lack of coverage aggravates the impact of hospital prices, leading to higher bankruptcy filings in regions with a higher rate of uninsured. I also find a stronger decline in demand for home mortgages.

There is an extensive body of literature that examines the impact of public insurance coverage on the financial well-being of individuals in the United States. (Miller et al. (2021), Hu et al. (2018)). Medicare, a federally administered social insurance program, provides coverage primarily to the elderly, who exhibit higher rates of hospital utilization and, in the absence of coverage, would face significantly greater out-of-pocket expenditures than younger populations. Table 14 reports the results for instrumented prices interacting with an indicator for whether a zip code has Medicare enrollment below or above the median in a given year. The results indicate that regions with higher Medicare enrollment experience significantly lower bankruptcy rates and better credit outcomes, consistent with Medicare coverage mitigating financial distress.

While Medicare targets the elderly group, Medicaid was targeted towards the low-income population. Medicaid came into being as a result of the Social Security Amendments of 1965. Under this program, the spending by state governments in providing medical assistance to certain eligible residents was matched by funds from the federal government. Many states expanded their Medicaid programs to include low-income adults. The Affordable Care Act (ACA), enacted in 2010, introduced provisions aimed at expanding Medicaid eligibility to include low-income adults who were previously ineligible. This expansion sought to counter the adverse effects of high hospital prices on individuals without insurance coverage. However, the Supreme Court's ruling in National Federation of Independent Business et al v. Sebelius allowed states the option to opt out of Medicaid expansion, introducing complexities into its implementation. Using the geographic variation in enrollment in the program, I investigate the extent to which Medicaid safeguards individuals against commercial hospital prices. Table 13 reports the results for instrumented prices interacting with an indicator for whether a zip code has medicaid enrollment below or above the median in a given year. In contrast to the findings for Medicare, the evidence for Medicaid is more nuanced. I find that higher Medicaid enrollment attenuates the increase in bankruptcy filings following medical price shocks, suggesting that Medicaid provides partial protection against severe financial distress. However, credit outcomes deteriorate in areas with higher Medicaid enrollment. This pattern is likely driven by selection since individuals in these regions may have had limited access to credit even prior to the shock, leaving less room for observable declines in credit outcomes.

Racial disparity in healthcare access in the United States is a well-documented fact. This disparity has multiple dimensions, including both health insurance coverage and access to care. People of color are more likely to be uninsured, which hinders their access to primary and preventive care, potentially leading to worse health outcomes. Additionally, people of color have a higher incidence of cardiovascular diseases and diabetes, among others. These disparities have persisted despite the implementation of the Affordable Care Act. Therefore, the increase in hospital prices can disproportionately impact the financial outcomes of people of color. I investigate this by considering the interaction between hospital prices and historical population concentrations of people of color in a zip code. Table 15 reports the results for instrumented prices interacting with an indicator for whether a zip code has a population of people of color below or above their median value in any given year. Zip codes with higher concentrations exhibit the most pronounced effects of rising hospital prices, both on bankruptcy and credit outcomes.

Individuals in higher income brackets are more likely to have insurance coverage, either through their employers or direct purchases. However, it is challenging to assess whether they are adequately insured. While higher income provides a buffer against higher hospital bills, either through the availability of liquid funds or the ability to access credit, the burden can be steep, especially in the presence of existing debt. Table 16 reports the results for instrumented prices interacting with an indicator for whether a zip code has a median household income below or above its median value in any given year. Two interesting facts emerge. First, the relationship between bankruptcy and the differential impact of household income on hospital prices is negative. This indicates both the presence of underinsurance and how costly medical bills can be for individuals with existing debt. Second, the adverse impact on both credit demand and credit access is decreasing with increasing median household income. Thus, higher income does provide individuals with some protection against higher hospital bills by not significantly deteriorating their ability to access credit.

A large literature (ex. Lin et al. (2009),Michelozzi et al. (2009)) examines the effects of extreme temperatures on health outcomes. Regions experiencing a greater frequency of high temperature days, particularly those exceeding 90 degrees Fahrenheit, are more susceptible to higher hospital utilization, thereby increasing exposure to medical costs and the associated financial risks. Table 17 presents estimates from a specification that interacts instrumented hospital prices with an indicator for whether a ZIP code experiences an above-median number of such hot days in a given year. The results are consistent with the hypothesis that greater exposure to extreme heat amplifies the financial consequences of medical price shocks.

7 Home Equity Channel

In this section, I explore whether home equity helps mitigate the severe adverse impacts of rising hospital prices. Numerous studies have explored the spillover effects of household credit and default on the broader economy. When individuals face higher medical expenses, a common recourse is to leverage their homes to secure credit. This access to credit is contingent upon the underlying value of their homes, specifically their home equity. Aladangady (2017) has demonstrated that additional home equity collateral can alleviate borrowing constraints.

While the proximity of homes to hospitals and healthcare facilities has been associated with elevated property values, the direct influence of hospital prices on home values has not been well documented. Hospital prices can potentially impact home values through two primary mechanisms. Firstly, higher hospital prices may diminish the attractiveness of properties near the hospital, thereby exerting downward pressure on property prices. Secondly, as my findings indicate, higher hospital prices can lead to heightened borrowing constraints, resulting in reduced demand for mortgages and, consequently, a decline in home values.

To investigate this, I use the house price index constructed by Zillow. The findings are summarized in Table 18. Column (1) reports the first-stage regression. I find results to be consistent both statistically and in magnitude. Column (2) reports the results for the second stage. I find that a \$ 100 increase in instrumented commercial hospital prices corresponds to a statistically significant \$445 decline in home values. However, it's crucial to interpret this result in light of a feedback effect. In essence, while higher hospital prices lead to an increase in bankruptcies (potentially resulting in more foreclosures) and a decrease in demand for mortgages, consequently lowering home values (Mian et al. (2015)), these reduced home values further weaken household balance sheets and their ability to access credit (Ramcharan and Crowe (2013)). That the decline in home equity can further tighten the borrowing constraints of the already constrained borrower is noteworthy. Those with unpaid mortgages may find themselves with negative home equity, where the outstanding mortgage balance exceeds the home's value. Prior research suggests that a reduction in home equity could reduce household mobility (Bernstein and Struyven (2022)), decrease labor supply (Bernstein (2021)), and lead to lower labor income (Gopalan et al. (2021)). In particular, Agarwal and Qian (2017) finds that reduced credit access on account of home equity leads to a significant negative consumption response. The lack of access to liquidity in the face of higher hospital bills consequently results in further deterioration in household financial well-being. This feedback effect exacerbates the financial strain experienced by households.

In particular, in the presence of the feedback effect I posit that hospital prices would have a more negative impact on household's financial outcomes in areas where there is a stronger decline in home values. Conversely, individuals in areas with steady home values will be able to mitigate the impact of hospital price increases by drawing down credit against their home equity. Any empirical exercise undertaken to establish this link would require the home values to be orthogonal to hospital prices. We've already established that hospital prices have a negative impact on home values. However, it's also plausible that hospitals set their prices based on the local housing market conditions, which could create a two-way relationship. To overcome this issue, I use geographical land unavailability to instrument for the housing supply elasticity in the spirit of Saiz (2010). In particular, Saiz (2010) documents that MSAs in which housing supply in regarded as inelastic are severely land-constrained by their geography. Mian et al. (2013) document that the land unavailability in a good instrument for housing net worth. Nonetheless, some recent critiques of this approach have emerged. Guren et al. (2021) argued that the Saiz elasticity instrument lacks predictive power for house prices, and Davidoff (2015) highlighted the potential correlation between the Saiz measure and demand factors. Addressing these concerns, Lutz and Sand (2022) constructed a zip-code level instrument using high-resolution satellite imagery. This instrument offers an improved approach for addressing the endogeneity issue, as it overcomes the criticisms previously associated with the Saiz measure.

The relation between land supply elasticity and its impact on house prices needs further discussion. Mian and Sufi (2009) found that areas characterized by a higher inelastic supply of land experienced the most significant housing boom during the period from 2002 to 2006. Gao et al. (2015) highlights that regions with intermediate levels of supply elasticity witnessed larger booms or busts in the housing market. Nathanson and Zwick (2018) reconciled these facts and argued that land impacts house price booms in two opposing ways. First, more land availability begets new construction, softening house price increases, in what they call the *classical channel*. At the same time, through the *speculative channel*, land availability also provides fertile grounds for a speculative market, driving up land prices. Since land is a critical input for house construction, this in turn leads to house price booms. They demonstrate that the classical channel dominates in regions that are either far from the constraint or already on it. Given the standard demand-supply argument, the impact of a demand shock on price is stronger in the area that is on the constraint than in those far from it. The speculation channel dominates in areas that are approaching the constraint. This is because regions with presently elastic land supply but anticipated future constraints create an attractive market for investors looking to speculate on future price increases.

In this paper, higher hospital prices behave akin to a negative demand shock to the housing market. Therefore, it is in the intermediate range of land supply elasticity, typically areas approaching the constraint, where we would anticipate the speculative channel to have the most significant impact, resulting in the least decline in house prices. To investigate this, I divide zip codes into deciles based on the measure of land unavailability provided by Lutz and Sand (2022). I examine the impact of hospital prices, interacted with an indicator variable for whether a zip code fell into a specific decile, on home values. Figure 1 presents the coefficients associated with each decile. Consistent with the hypothesis, the findings reveal that regions with intermediate land supply elasticity experience a smaller decline in house prices compared to regions at either end of the spectrum. Notably, the effects tend to level out as we approach areas with the highest land unavailability. This suggests that prices in saturated housing markets may not be as sensitive to hospital prices.

Next, I test the home equity channel. Figure 1 displays the coefficients for hospital prices, interacted with an indicator variable denoting whether a zip code falls into a particular land unavailability decile, on my primary outcome variables. A couple of interesting patterns emerge. Firstly, the demand for mortgages, as indicated by mortgage applications, follows a speculative pattern. This means that areas approaching land supply constraints exhibit the smallest decline in demand for mortgages. Secondly, bankruptcy filings exhibit patterns similar to home values across the ten deciles. In simpler terms, areas experiencing the smallest decline in home values also see the least increase in bankruptcy filings.

These findings suggest that home equity can offer some protection against the adverse effects of rising hospital prices. This is consistent with Gupta et al. (2018) who demonstrates that home equity can help alleviate some of the financial burdens associated with a cancer diagnosis. However, it's crucial to emphasize a distinctive aspect of my findings: higher hospital prices weaken the effectiveness of the very resource individuals may rely on to cope with these price increases.

8 Robustness

In this section, I provide a number of robustness and additional tests. All of the results in this section are included in the Appendix.

Alternative specifications

The results are robust to a number of alternative specifications. Some of the outcome variables - i.e., the number of bankruptcies, mortgage applications, and originations are discrete count variables. As has been documented by the econometrics literature, using linear regression models may introduce bias in estimates involving count variables. To address this potential concern, for robustness, I re-estimate the results by scaling these variables using the total zip population. The results as provided in Appendix Table A2.1 are similar to the earlier findings.

Second, in my main specification, I do not include zip-level control variables. I verify that the results hold when including zip-level controls for zip population, median household income, and percentage of uninsured population. Appendix Table A2.2 provides results with controls for bankruptcy filings, and Appendix Table A2.3 provides results with controls for mortgage outcomes. The results are very similar to those of the main specifications.

Alternative Choice Set

Throughout the paper, the choice set of hospitals for a household has been defined as the set of hospitals located within a 25-mile radius of a household's reported location. As robustness, I broaden the choice set to include hospitals within a 50-mile radius. I re-estimate the regional market shares and re-calculate hospital prices at the zip-level. Appendix Table A2.4 and A2.5 provide results for prices calculated using the broader choice set. These results are similar both in magnitude and significance to the baseline hospital choice set.

Sample selection

One potential concern stems from the fact that large macroeconomic shocks can confound both household financial outcomes and hospital prices. While the geographic separation and heterogeneity offered by both the instruments and time-varying zip controls sufficiently deal with the issue, to show that the results are not driven by the inclusion of large macroeconomic shocks, I drop the financial crisis years of 2008 and 2009. Appendix Table A2.6 and A2.7 report the results for the sample without the financial crisis years. The findings are in line with the main specifications.

Alternate Construction of the MLR Instrument

Given the novelty of the instruments used in this analysis, one might be concerned that the way these variables are constructed could be influencing the strength of the results. To address this, I use two alternative versions of the medical loss ratio (MLR) instrument.

Appendix Tables A2.8 and A2.9 present results using a lagged three-year average of the MLR as an instrument for hospital prices. Meanwhile, Appendix Tables A2.10 and A2.11 show results using the contemporaneous MLR—that is, the MLR in the same year, without averaging across years or applying legal caps.

In both cases, the results remain consistent, demonstrating that the findings are robust to alternative constructions of the MLR instrument.

Alternate Price Measure

In the main specifications, hospital prices are adjusted for patient complexity using the case mix index. However, one concern is that while the case mix index captures overall complexity, it may not fully account for changes in the composition of diagnoses across time and regions.

To address this, I construct a hedonic price measure. The dataset includes charge information (i.e., listed prices) for each patient discharge. I estimate the following regression:

$$HospCharges_{i(h,z),t} = \Gamma[X_{i(h,z),t}] + \lambda_{zip3,t} + \tau_{DRG,t} + \mu_{h,t} \tag{16}$$

where$HospCharges_{i(h,z),t}$ are the hospital charges for the patient i, each uniquely related to zip z, and hospital h, $X_{i(h,z),t}$ are the set of patient characteristics used as controls, such as age, sex, and race. Additionally, I control for 3-digit zip code - year and DRG-year fixed effects. The hospital-year fixed effects ($\mu_{h,t}$), normalized to match the overall mean, are then used as the hospital-level price measure. These hedonic price estimates are further adjusted for contractual discounts following the method in Equation 5. Appendix Tables A2.12 and A2.13 present results using the hedonic measure of hospital prices described above. The results are robust to the use of this alternative measure[16]

[16]The results are robust to other variations of the estimated prices. This includes using the price of the nearest hospital instead of aggregating prices using market share. These results are available upon request.

9 Concluding Remarks

This paper explores the impact of increases in hospital prices on household financial health. I construct a novel measure of hospital prices using detailed healthcare patient-level data and state hospital cost reports obtained via a series of FOIA requests. I aggregate the hospital prices at the zip-code level using regional market shares instrumented using the distance between patients and hospitals, which are plausibly exogenous to patients' financial outcomes. This method assists in alleviating concerns related to self-selection, where latent factors influencing patients' choice of hospital might be interlinked with their financial health.

Given that hospital pricing strategies are influenced by local economic conditions and that market environment factors could confound hospital prices and household finances, I employ an instrumental variable approach. I use the insurer's medical loss ratio, which captures changes in the relative bargaining power of the insurer and the hospital in determining hospital prices, to instrument the zip-level hospital prices. My analysis reveals that an increase in instrumented hospital prices leads to an increase in personal bankruptcy filings. Moreover, I provide compelling evidence that such price increases lead to a diminished demand for mortgages, higher rates of mortgage application denials, and a noticeable increase in financial institutions' rejections based on high debt-to-income ratios. Additionally, I explore various credit-related outcomes and illustrate that households tend to increase the use of credit cards and home equity lines of credit. To shed light on the mechanisms underpinning these outcomes, I conduct a variety of heterogeneity tests. I establish that these effects disproportionately affect areas where residents are more exposed to hospital price variations. Specifically, regions with a higher percentage of uninsured individuals, lower enrollment in public health insurance programs like Medicare and Medicaid, and areas with a higher population concentration of people of color experience more severe consequences resulting from increases in hospital prices. My findings also suggest that individuals carrying higher levels of pre-existing debt are more susceptible to crossing the threshold into financial default when faced with hospital price increases. I provide evidence that changes in patient choice, utilization rates, or health status of the local population do not drive these results.

In additional analysis, I illustrate that hospital prices dampen home equity values. By employing geographical constraints on construction as an instrument, I demonstrate that areas vulnerable to land market speculation experience plausibly exogenous increases in house prices. Consequently, these regions witness a lesser decline in home values when confronted with rising hospital prices. I demonstrate that the presence of home equity mitigates some of the effects of increases in hospital prices, in that households in the speculative areas are least impacted by increases in hospital prices.

This study highlights the negative economic consequences of higher healthcare prices on households. The findings reveal how higher hospital bills can contribute to severe deterioration in consumers' financial well-being and underline the role of home equity as a cushion against it. Lastly, the study underscores the limitations of public insurance programs and how hospital prices can have detrimental consequences even for those with insurance coverage.

References

Abdus, S., T. M. Selden, and P. Keenan (2016): "The financial burdens of high-deductible plans," *Health Affairs*, 35, 2297–2301.

Abraham, J. M., P. Karaca-Mandic, and K. Simon (2014): "How has the Affordable Care Act's medical loss ratio regulation affected insurer behavior?" *Medical care*, 370–377.

Adelino, M., A. Schoar, and F. Severino (2015): "House prices, collateral, and self-employment," *Journal of Financial Economics*, 117, 288–306.

——— (2018): "The role of housing and mortgage markets in the financial crisis," *Annual Review of Financial Economics*, 10, 25–41.

Agarwal, S. and W. Qian (2017): "Access to home equity and consumption: Evidence from a policy experiment," *Review of Economics and Statistics*, 99, 40–52.

Aghamolla, C., J. Jain, and R. T. Thakor (2023): "When Private Equity Comes to Town: The Local Economic Consequences of Rising Healthcare Costs," *Available at SSRN*.

Aghamolla, C., P. Karaca-Mandic, X. Li, and R. T. Thakor (2022): "Merchants of death: The effect of credit supply shocks on hospital outcomes," *Available at SSRN 3827246*.

Aghamolla, C. and R. T. Thakor (2022): "IPO peer effects," *Journal of Financial Economics*, 144, 206–226.

AHRQ (2020): "Agency for Healthcare Research and Quality, Number of people in thousands, United States, 1996 to 2020. Medical Expenditure Panel Survey," https://meps.ahrq.gov/mepsweb.

Aladangady, A. (2017): "Housing wealth and consumption: evidence from geographically linked microdata," *American Economic Review*, 107, 3415–3446.

Angelucci, M. and G. De Giorgi (2009): "Indirect effects of an aid program: how do cash transfers affect ineligibles' consumption?" *American economic review*, 99, 486–508.

Angst, C. M., R. Agarwal, V. Sambamurthy, and K. Kelley (2010): "Social contagion and information technology diffusion: The adoption of electronic medical records in US hospitals," *Management Science*, 56, 1219–1241.

Arnold, D. and C. Whaley (2020): "Who pays for health care costs? The effects of health care prices on wages," *The Effects of Health Care Prices on Wages (July 21, 2020).*

Baicker, K. and A. Chandra (2006): "The labor market effects of rising health insurance premiums," *Journal of Labor Economics*, 24, 609–634.

Barrette, E., G. Gowrisankaran, and R. Town (2022): "Countervailing market power and hospital competition," *Review of Economics and Statistics*, 104, 1351–1360.

Bernstein, A. (2021): "Negative home equity and household labor supply," *The Journal of Finance*, 76, 2963–2995.

Bernstein, A. and D. Struyven (2022): "Housing lock: Dutch evidence on the impact of negative home equity on household mobility," *American Economic Journal: Economic Policy*, 14, 1–32.

Berry, S. T. (1994): "Estimating discrete-choice models of product differentiation," *The RAND Journal of Economics*, 242–262.

Blickle, K. (2022): "Local banks, credit supply, and house prices," *Journal of Financial Economics*, 143, 876–896.

Bloom, N., C. Propper, S. Seiler, and J. Van Reenen (2015): "The impact of competition on management quality: evidence from public hospitals," *The Review of Economic Studies*, 82, 457–489.

Bramoullé, Y., H. Djebbari, and B. Fortin (2009): "Identification of peer effects through social networks," *Journal of econometrics*, 150, 41–55.

Brevoort, K., D. Grodzicki, and M. B. Hackmann (2020): "The credit consequences of unpaid medical bills," *Journal of Public Economics*, 187, 104203.

Brevoort, K. P. and M. Kambara (2015): "Are all collections equal? The case of medical debt," *Journal of Credit Risk*, 11.

Callison, K. and B. Walker (2021): "Medicaid expansion and medical debt: evidence from Louisiana, 2014–2019," *American Journal of Public Health*, 111, 1523–1529.

Carlos, D., F. Amy, and K. Raymond (2018): "Notowidigdo Matthew J. The economic consequences of hospital admissions," *American Economic Review*, 108, 308–52.

Catlin, M. K., J. A. Poisal, and C. A. Cowan (2015): "Out-of-pocket health care expenditures, by insurance status, 2007–10," *Health Affairs*, 34, 111–116.

CBO (2020): "Analyzes the Costs of Proposals for Single-Payer Health Care Systems That Are Based on Medicare's Fee-for-Service Program: Working Paper 2020-08 [Internet]. Congressional Budget Office;[cited 2021 Jan 30]," .

Chen, J. and J. Roth (2024): "Logs with zeros? Some problems and solutions," *The Quarterly Journal of Economics*, 139, 891–936.

Cicala, S., E. M. Lieber, and V. Marone (2017): "Cost of service regulation in US health care: Minimum medical loss ratios," Tech. rep., National Bureau of Economic Research.

Claxton, G., L. Levitt, and M. Long (2016): "Payments for cost sharing increasing rapidly over time," *Peterson-Kaiser Health System Tracker Insight Brief, April*, 12.

Cooper, Z., S. V. Craig, M. Gaynor, and J. Van Reenen (2019): "The price ain't right? Hospital prices and health spending on the privately insured," *The quarterly journal* *of economics*, 134, 51–107.

Cooper, Z., S. Gibbons, S. Jones, and A. McGuire (2011): "Does hospital competition save lives? Evidence from the English NHS patient choice reforms," *The Economic Journal*, 121, F228–F260.

Cooper, Z., F. Scott Morton, and N. Shekita (2020): "Surprise! Out-of-network billing for emergency care in the United States," *Journal of Political Economy*, 128, 3626–3677.

Dafny, L. (2009): "Estimation and identification of merger effects: An application to hospital mergers," *The Journal of Law and Economics*, 52, 523–550.

Davidoff, T. (2015): "Supply constraints are not valid instrumental variables for home prices because they are correlated with many demand factors," *Available at SSRN 2400833*.

De Nardi, M., E. French, and J. B. Jones (2010): "Why Do the Elderly Save? The Role of Medical Expenses," *Journal of Political Economy*, 118, 39–75.

Dobbie, W., P. Goldsmith-Pinkham, N. Mahoney, and J. Song (2020): "Bad credit, no problem? Credit and labor market consequences of bad credit reports," *The Journal of Finance*, 75, 2377–2419.

Domowitz, I. and R. L. Sartain (1999): "Determinants of the consumer bankruptcy decision," *The Journal of Finance*, 54, 403–420.

Donaldson, J. R., G. Piacentino, and A. Thakor (2019): "Household debt overhang and unemployment," *The Journal of Finance*, 74, 1473–1502.

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

Dranove, D. and M. L. Millenson (2006): "Medical Bankruptcy: Myth Versus Fact: This response to a widely cited paper by David Himmelstein and colleagues challenges the basis of its conclusions." *Health Affairs*, 25, W74–W83.

Favara, G. and J. Imbs (2015): "Credit supply and the price of housing," *American Economic Review*, 105, 958–992.

Ferrier, G. D. and V. G. Valdmanis (2005): "Peer effects and efficiency: the influence of competitors' performance on hospital efficiency," *Cost Eff Resour Alloc*, 14, 7.

Finkelstein, A., S. Taubman, B. Wright, M. Bernstein, J. Gruber, J. P. Newhouse, H. Allen, K. Baicker, and O. H. S. Group (2012): "The Oregon health insurance experiment: evidence from the first year," *The Quarterly journal of economics*, 127, 1057–1106.

Fisher, J. D. (2019): "Who files for personal bankruptcy in the United States?" *Journal of Consumer Affairs*, 53, 2003–2026.

Gao, J., S. Ge, L. Schmidt, and C. Tello-Trillo (2022): "How Do Health Insurance Costs Affect Firm Labor Composition and Technology Investment?" *Available at SSRN 4496766*.

Gao, Z., M. Sockin, and W. Xiong (2015): "Learning about the neighborhood: The role of supply elasticity for housing cycles," in *Unpublished working paper*, Princeton University.

Gaynor, M. and R. J. Town (2011): "Competition in health care markets," *Handbook of health economics*, 2, 499–637.

Glied, S. A. and B. Zhu (2020): "Catastrophic out-of-pocket health care costs: A problem mainly for middle-income Americans with employer coverage," *The Commonwealth Fund*.

Gopalan, R., B. H. Hamilton, A. Kalda, and D. Sovich (2021): "Home equity and labor income: The role of constrained mobility," *The Review of Financial Studies*, 34, 4619–4662.

Gowrisankaran, G., A. Nevo, and R. Town (2015): "Mergers when prices are negotiated: Evidence from the hospital industry," *American Economic Review*, 105, 172–203.

Gowrisankaran, G. and R. J. Town (2003): "Competition, payers, and hospital quality 1," *Health services research*, 38, 1403–1422.

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

Gupta, A., E. Morrison, C. R. Fedorenko, and S. D. Ramsey (2018): "Home equity mitigates the financial and mortality consequences of health shocks: Evidence from cancer diagnoses," *New York University, Stern School of Business*.

Guren, A. M., A. McKay, E. Nakamura, and J. Steinsson (2021): "Housing wealth effects: The long view," *The Review of Economic Studies*, 88, 669–707.

Hall, M. A., P. B. Ginsburg, S. M. Lieberman, L. Adler, C. Brandt, and M. Darling (2016): "Solving surprise medical bills," *The Schaeffer Initiative for Innovation in Health Policy, A Brookings Institution–USC Schaeffer Center Partnership*.

Hu, L., R. Kaestner, B. Mazumder, S. Miller, and A. Wong (2018): "The effect of the affordable care act Medicaid expansions on financial wellbeing," *Journal of public economics*, 163, 99–112.

Jiang, J. X., M. A. Makary, and G. Bai (2021): "Comparison of US hospital cash prices and commercial negotiated prices for 70 services," *JAMA Network Open*, 4, e2140526–e2140526.

Kaiser Family Foundation (2022): "KFF Health Care Debt Survey," Tech. rep.

Kalda, A. (2020): "Peer Financial Distress and Individual Leverage," *Review of Financial Studies*, 33, 3391–3391.

Karaca-Mandic, P., J. M. Abraham, and K. Simon (2015): "Is the medical loss ratio a good target measure for regulation in the individual market for health insurance?" *Health Economics*, 24, 55–74.

Karaca-Mandic, P., R. J. Town, and A. Wilcock (2017): "The effect of physician and hospital market structure on medical technology diffusion," *Health services research*, 52, 579–598.

Keisler-Stankey, K. and L. N. Bunch (2021): "Health Insurance Coverage in the United States: 2020," *United States Census Bureau, Current Population Report. P60-274*.

Kessler, D. P. and M. B. McClellan (2000): "Is hospital competition socially wasteful?" *The Quarterly Journal of Economics*, 115, 577–615.

Kluender, R., N. Mahoney, F. Wong, and W. Yin (2021): "Medical debt in the US, 2009-2020," *JAMA*, 326, 250–256.

——— (2025): "The effects of medical debt relief: Evidence from two randomized experiments," *The Quarterly Journal of Economics*, 140, 1187–1241.

Kolstad, J. T. and A. E. Kowalski (2016): "Mandate-based health reform and the labor market: Evidence from the Massachusetts reform," *Journal of health economics*, 47, 81–106.

Lin, S., M. Luo, R. J. Walker, X. Liu, S.-A. Hwang, and R. Chinery (2009): "Extreme high temperatures and hospital admissions for respiratory and cardiovascular diseases," *Epidemiology*, 20, 738–746.

Liu, T. (2022): "Bargaining with private equity: Implications for hospital prices and patient welfare," *Available at SSRN 3896410*.

Lutz, C. and B. Sand (2022): "Highly disaggregated land unavailability," *Available at SSRN 3478900*.

Manski, C. F. (1993): "Identification of endogenous social effects: The reflection problem," *The review of economic studies*, 60, 531–542.

Mazumder, B. and S. Miller (2016): "The effects of the Massachusetts health reform on household financial distress," *American Economic Journal: Economic Policy*, 8, 284–313.

Meyer, H. (2023): "A surprise-billing law loophole? Her pregnancy led to a six-figure hospital bill," .

Mian, A., K. Rao, and A. Sufi (2013): "Household balance sheets, consumption, and the economic slump," *The Quarterly Journal of Economics*, 128, 1687–1726.

Mian, A. and A. Sufi (2009): "The consequences of mortgage credit expansion: Evidence from the US mortgage default crisis," *The Quarterly journal of economics*, 124, 1449–1496.

——— (2011): "House prices, home equity–based borrowing, and the us household leverage crisis," *American Economic Review*, 101, 2132–2156.

Mian, A., A. Sufi, and F. Trebbi (2015): "Foreclosures, house prices, and the real economy," *The Journal of Finance*, 70, 2587–2634.

Michelozzi, P., G. Accetta, M. De Sario, D. D'Ippoliti, C. Marino, M. Baccini, A. Biggeri, H. R. Anderson, K. Katsouyanni, F. Ballester, et al. (2009): "High temperature and hospitalizations for cardiovascular and respiratory causes in 12 European cities," *American journal of respiratory and critical care medicine*, 179, 383–389.

Miller, S., L. Hu, R. Kaestner, B. Mazumder, and A. Wong (2021): "The ACA Medicaid expansion in Michigan and financial health," *Journal of Policy Analysis and Management*, 40, 348–375.

Morrison, E. R., A. Gupta, L. Olson, L. Cook, and H. Keenan (2013): "Health and financial fragility: Evidence from car crashes and consumer bankruptcy," *University of Chicago Coase-Sandor Institute for Law & Economics Research Paper*, 13–81.

Nathanson, C. G. and E. Zwick (2018): "Arrested Development: Theory and Evidence of Supply-Side Speculation in the Housing Market," *The Journal of Finance*, 73, 2587–2633.

NYT (2023): "The Cost of Care," *The New York Times*.

Ramcharan, R. and C. Crowe (2013): "The impact of house prices on consumer credit: evidence from an internet bank," *Journal of Money, Credit and Banking*, 45, 1085–1115.

Ramsey, S., D. Blough, A. Kirchhoff, K. Kreizenbeck, C. Fedorenko, K. Snell, P. Newcomb, W. Hollingworth, and K. Overstreet (2013): "Washington State cancer patients found to be at greater risk for bankruptcy than people without a cancer diagnosis," *Health affairs*, 32, 1143–1152.

Rhodes, J. H., T. C. Buchmueller, H. G. Levy, and S. S. Nikpay (2020): "Heterogeneous effects of the ACA Medicaid expansion on hospital financial outcomes," *Contemporary Economic Policy*, 38, 81–93.

Saiz, A. (2010): "The geographic determinants of housing supply," *The Quarterly Journal of Economics*, 125, 1253–1296.

Wright, J. D., A. I. Tergas, J. Y. Hou, W. M. Burke, L. Chen, J. C. Hu, A. I. Neugut, C. V. Ananth, and D. L. Hershman (2016): "Effect of regional hospital competition and hospital financial status on the use of robotic-assisted surgery," *JAMA surgery*, 151, 612–620.

Zeller, S. (2023): "Effect of Increasing Healthcare Costs on Small Firms: Evidence from Private Equity Acquisitions of Hospitals," *Working paper*.

Zhao, X. (2021): "Medical Loss Ratio Regulation and Insurer Pricing," *Working paper*.

Figure 1: Supply Elasticity, Home Values, and the Home Equity Channel

This figure provides coefficients for instrument prices interacted with an indicator for the decile of land unavailability in a ZIP for the Zillow house price index. The price $\log(ZipPrice_{z,t})$ is instrumented by $MLR_{z,t,t-2}$, which is the three-year average medical loss ratio weighted by the insurer's market share in ZIP z in the year t. I include time-varying controls for income, total population, Medicaid and Medicare enrollment, and uninsured population.

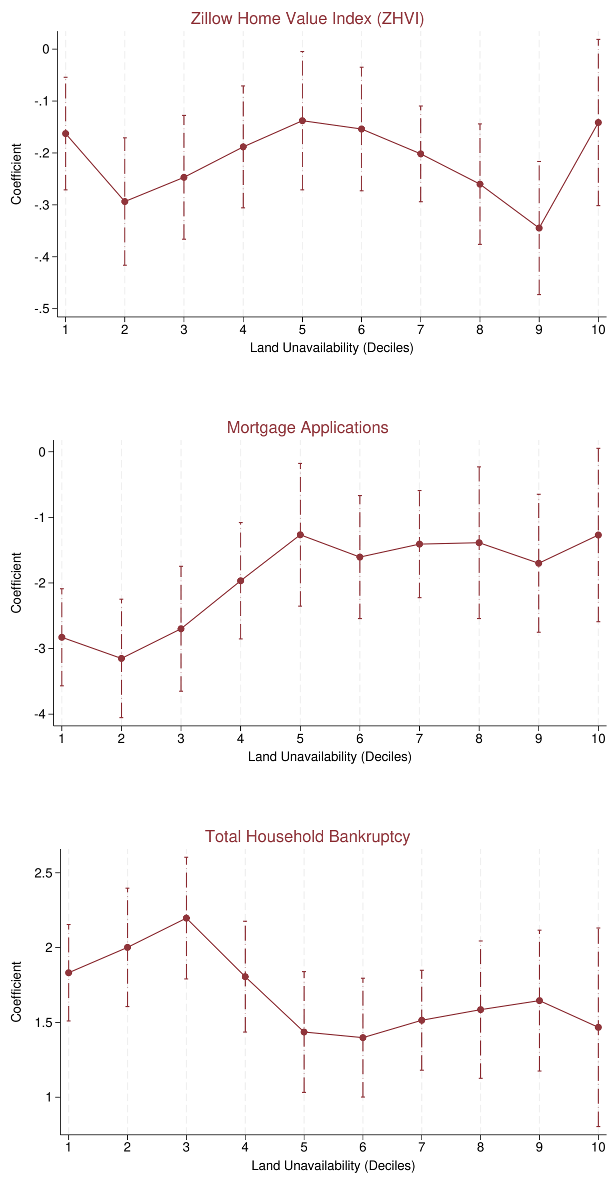

Table 1: Summary Statistics

This table provides summary statistics for the variables used in this study.

	N	Mean	SD	p10	p25	Median	p75	p90
Panel A: Hospital Prices								
$ZipPrice_{z,t}$	71791	10764.51	4016.96	6173.50	7858.81	10181.12	13062.45	16204.77
$MLR_{z,t,t-2}$	69998	0.86	0.02	0.84	0.85	0.86	0.88	0.89
$OmittedZipPrice_{z,t}$	71791	9914.18	2856.96	6241.99	7737.76	9647.21	11954.95	13773.16
Panel B: FJCID								
Ch7 Bankruptcy	62887	22.77	38.88	0.00	1.00	6.00	28.00	67.00
Ch13 Bankruptcy	62887	8.51	17.27	0.00	0.00	2.00	9.00	25.00
Total Bankruptcy	62887	31.28	53.42	0.00	2.00	9.00	38.00	92.00
Bankruptcy w prior filing	62887	3.75	9.47	0.00	0.00	1.00	4.00	11.00
Debt-to-Income Ratio	49673	5.74	6.76	1.04	1.92	3.81	6.60	11.64
Non-Priority Unsec/Liability	49593	0.96	0.14	0.88	1.00	1.00	1.00	1.00
Secured/Liability	50764	0.49	0.37	0.00	0.06	0.57	0.82	0.94
Total Debt	50257	210675.67	225936.28	27006.00	53974.08	134415.00	279172.00	493015.91
Average Monthly Income	51191	3341.72	2079.92	1137.00	1885.38	2949.52	4373.07	6100.97
Average Monthly Expense	51190	3308.13	1921.23	1285.00	1965.74	2939.39	4239.00	5824.50
Panel C: HMDA Database								
Mortgage Application	71791	244.31	430.97	0.00	12.00	76.00	304.00	672.00
Mortgage Origination	71791	176.59	316.96	0.00	8.00	51.00	213.00	495.00
Mortgage Application Denial	71791	67.72	128.57	0.00	4.00	21.00	84.00	176.00
Denial Rate	61750	0.30	0.14	0.15	0.21	0.28	0.37	0.48
% Second Lien Application	61750	0.09	0.08	0.00	0.03	0.06	0.13	0.22
Denial DTI	60390	0.18	0.12	0.00	0.11	0.18	0.25	0.33
Denial CRH	60390	0.19	0.13	0.00	0.11	0.18	0.25	0.33
Denial Collateral	60390	0.15	0.11	0.00	0.09	0.14	0.21	0.28
Denial Employment	60390	0.01	0.02	0.00	0.00	0.00	0.01	0.02
Denial Insufficient	60390	0.01	0.02	0.00	0.00	0.00	0.02	0.03
Panel D: SPCIQ Credit								
Line of Credit HHs	25619	1138.81	1251.71	74.00	188.00	650.00	1757.00	2914.00
Discover Credit HHs	25619	1223.98	1309.19	88.00	221.00	716.00	1892.00	3074.00
Mastercard Credit HHs	25619	2586.71	2949.07	162.00	409.00	1424.00	3923.00	6576.00
Visa Credit HHs	25619	3376.40	3776.58	217.00	537.00	1858.00	5269.00	8719.00
Auto Loans HHs	25619	1449.06	1540.45	107.00	275.00	811.00	2265.00	3740.00

Table 2: Insurance Market Competition and Medical Loss Ratio

This table presents regression results from the OLS specification on Medical Loss Ratio. Observations are at the insurer-year level. The regressor is $MonopolyMarkets_{n,t}$ which is the proportion of counties in which the insurer n holds a monopoly position out of all counties that it operates in a year t. $MLR_{n,t}$ is the medical loss ratio of insurer n in year t. Column (1) reports results for the full sample. Column (2) restricts the sample to before the implementation of the Affordable Care Act. Regressions are run at the insurer-year level. Standard errors are clustered at the insurer level, and fixed effects are included, as indicated. *** indicates significance at the 1% level, ** significance at the 5% level, and * significance at the 10% level.

	$MLR_{n,t}$	
	2004-20	2004-10
	(1)	(2)
$MonopolyMarkets_{n,t}$	-0.045**	-0.088**
	(0.018)	(0.042)
Insurer FE	Y	Y
Year FE	Y	Y
N	6856	3031
adj. R^2	0.519	0.675

Table 3: OLS Specification

This table presents regression results from the OLS specification on bankruptcy outcomes using a transformation of the dependent variable $m(y)$ following Chen and Roth (2024). In particular, $m(y) = log(y/\min_{y>0}(y))$ if $y > 0$ and $m(y) = -x$ if $y = 0$. The table reports the results for the case of $x = -0.01$. Observations are at the zip-year level. The regressor is $log(ZipPrice_{z,t})$ which is the log of hospital prices in zip z in the year t. $Ch\,7$ is the number of Chapter 7 personal bankruptcies, $Ch\,13$ is the number of Chapter 13 personal bankruptcies, $Total$ is the total number of personal bankruptcies, $Prior$ is the total number of personal bankruptcies filed by individuals who had a prior bankruptcy filing in the last 7 years in zip z in the year t. Regressions are run at the zip-year level. Standard errors are clustered at the zip-code level, and fixed effects are included, as indicated. *** indicates significance at the 1% level, ** significance at the 5% level, and * significance at the 10% level.

	Ch7	Ch13	Total	Prior
	(1)	(2)	(3)	(4)
$log(ZipPrice_{z,t})$	0.041***	0.032***	0.045***	0.073***
	(0.011)	(0.011)	(0.011)	(0.009)
Zip-Code FE	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y
N	61427	61427	61427	61427
adj. R^2	0.936	0.893	0.944	0.840

Table 4: IV Specification: Bankruptcy Filings

This table presents regression results from the IV specification on bankruptcy outcomes using a transformation of the dependent variable $m(y)$ following Chen and Roth (2024). In particular, $m(y) = log(y/\min_{y>0}(y))$ if $y > 0$ and $m(y) = -x$ if $y = 0$. The table reports the results for the case of $x = -0.01$. Observations are at the zip-year level. Column (1) reports the result for the first-stage instrumental variable regression. The table reports results where $log(ZipPrice_{z,t})$ is instrumented by $MLR_{z,t,t-2}$ which is a three-year average medical loss ratio weighted by the insurer's market share in the zip z. Columns (2)-(5) report the results for the second-stage instrumental variable regressions. $Ch\,7$ is the number of Chapter 7 personal bankruptcies, $Ch\,13$ is the number of Chapter 13 personal bankruptcies, $Total$ is the total number of personal bankruptcies, $Prior$ is the total number of personal bankruptcies filed by individuals who had a prior bankruptcy filing in the last 7 years in zip z in the year t. Regressions are run at the zip-year level. Standard errors are clustered at the zip-code level, and fixed effects are included, as indicated. *** indicates significance at the 1% level, ** significance at the 5% level, and * significance at the 10% level.

	First Stage	Second Stage			
	$log(ZipPrice_{z,t})$	log(Ch7)	log(Ch13)	log(Total)	log(Prior)
	(1)	(2)	(3)	(4)	(5)
Medical Loss Ratio IV					
$MLR_{z,t,t-2}$	1.249***				
	(0.084)				
$log(\widehat{ZipPrice}_{z,t})$		0.821***	2.786***	1.773***	2.488***
		(0.139)	(0.237)	(0.173)	(0.213)
Zip-Code FE	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y
N	59565	59565	59565	59565	59565
KP rk Wald F-stat	218.58				

Table 5: IV Specification: Bankruptcy Filer Characteristics

This table presents regression results from the IV specification on bankruptcy filer characteristics. Observations are at the zip-year level. The table reports results where $log(ZipPrice_{z,t})$ is instrumented by $MLR_{z,t,t-2}$ which is a three-year average medical loss ratio weighted by the insurer's market share in the zip z in the year t. Columns (1)-(6) report the results for the second-stage instrumental variable regressions. $Debt - to - Income\,Ratio$ is the average debt-to-income ratio, $NP - Unsecured/Liability$ is the proportion of total non-priority unsecured liability in total liability, $Secured/Liability$ is the proportion of total secured liability in total liability, $Total\,Debt$ is the total secured and unsecured debt, $Income$ is the average monthly income, and $Expense$ is the average monthly expense of the bankruptcy filers in zip z in the year t. Regressions for columns (1), (4)-(6) are run using a transformation of the dependent variable $m(y)$ following Chen and Roth (2024). In particular, $m(y) = log(y/\min_{y>0}(y))$ if $y > 0$ and $m(y) = -x$ if $y = 0$. The table reports the results for the case of $x = -0.01$. Data has been winsorized at 1%. Regressions are run at the zip-year level. Standard errors are clustered at the zip-code level, and fixed effects are included, as indicated. *** indicates significance at the 1% level, ** significance at the 5% level, and * significance at the 10% level.

	Debt-to-Income Ratio	Secured/Liability	NP-Unsecured/Liability	Total Debt	Income	Expense
	(1)	(2)	(3)	(4)	(5)	(6)
Medical Loss Ratio IV						
$log(\widehat{ZipPrice}_{z,t})$	0.545***	0.447***	-0.042**	0.687***	0.387*	0.206*
	(0.148)	(0.061)	(0.019)	(0.165)	(0.211)	(0.109)
Zip-Code FE	Y	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y	Y
N	52206	52333	52225	52275	52365	52359
KP rk Wald F-stat	194.222	195.141	193.754	193.885	194.414	194.425

Table 6: IV Specification: Mortgage Applications and Denials

This table presents regression results from the IV specification on mortgage outcomes. Observations are at the zip-year level. Column (1) reports the result for the first-stage instrumental variable regression. The table reports results where $log(ZipPrice_{z,t})$ is instrumented by $MLR_{z,t,t-2}$ which is the three-year average medical loss ratio weighted by the insurer's market share in the zip z in the year t. Columns (2)-(5) report the results for the second-stage instrumental variable regressions. $Mort\,App$ is the total number of mortgage applications, $Mort\,Org$ is the total number of mortgage originations, $\%\,Second\,Lien\,App$ is the percentage of second lien mortgage applications as a percentage of total applications, and $DenialRate$ is the ratio of mortgage applications denied to total mortgage applications in zip z in the year t. Regressions for columns (2)-(3) are run using a transformation of the dependent variable $m(y)$ following Chen and Roth (2024). In particular, $m(y) = log(y/\min_{y>0}(y))$ if $y > 0$ and $m(y) = -x$ if $y = 0$. The table reports the results for the case of $x = -0.01$. Regressions are run at the zip-year level. Standard errors are clustered at the zip-code level, and fixed effects are included, as indicated. *** indicates significance at the 1% level, ** significance at the 5% level, and * significance at the 10% level.

	First Stage	Second Stage			
	$log(ZipPrice_{z,t})$	Mort App	Mort Org	% Second Lien App	Denial Rate
	(1)	(2)	(3)	(4)	(5)
Medical Loss Ratio IV					
$MLR_{z,t,t-2}$	1.491***				
	(0.092)				
$log(\widehat{ZipPrice}_{z,t})$		-1.189***	-1.256***	0.030***	0.241***
		(0.253)	(0.236)	(0.010)	(0.022)
Zip-Code FE	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y
N	68542	68542	68542	58910	58910
KP rk Wald F-stat	262.362				

Table 7: IV Specification: Reasons for Mortgage Application Denials

This table presents regression results from the IV specification on reasons for mortgage application denials. Observations are at the zip-year level. The table reports results where $log(ZipPrice_{z,t})$ is instrumented by $MLR_{z,t,t-2}$ which is the three-year average medical loss ratio weighted by the insurer's market share in the zip z in the year t. Columns (1)-(5) report the results for the second-stage instrumental variable regressions. $Debt-to-Income$ is the total proportion of mortgage application denials citing high debt-to-income ratio for denial, $Credit\,History$ is the total proportion of mortgage application denials citing bad credit history for denial, $Collateral$ is the total proportion of mortgage application denials citing inadequate collateral for denial, $Employment$ is the total proportion of mortgage application denials citing employment history for denial, $Insufficent$ is the total proportion of mortgage application denials citing insufficient cash for denial, in zip z in year t. Regressions are run at the zip-year level. Standard errors are clustered at the zip-code level, and fixed effects are included, as indicated. *** indicates significance at the 1% level, ** significance at the 5% level, and * significance at the 10% level.

	Reasons for Application Denial				
	Debt-to-Income	Credit History	Collateral	Employment	Insufficient
	(1)	(2)	(3)	(4)	(5)
Medical Loss Ratio IV					
$log(\widehat{ZipPrice}_{z,t})$	0.055***	0.027	-0.122***	-0.006	0.001
	(0.020)	(0.021)	(0.021)	(0.004)	(0.004)
Zip-Code FE	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y
N	57628	57628	57628	57628	57628
KP rk Wald F-stat	259.262	259.262	259.262	259.262	259.262

Table 8: IV Specification: Mortgage Application Denials across Income Quintiles

This table presents regression results from the IV specification on mortgage application denials across income quintiles using a transformation of the dependent variable $m(y)$ following Chen and Roth (2024). In particular, $m(y) = log(y/\min_{y>0}(y))$ if $y > 0$ and $m(y) = -x$ if $y = 0$. The table reports the results for the case of $x = -0.01$. Observations are at the zip-year level. The table reports results where $log(ZipPrice_{z,t})$ is instrumented by $MLR_{z,t,t-2}$ which is the three-year average medical loss ratio weighted by the insurer's market share in the zip z in the year t. Columns (1)-(5) report the results for the second-stage instrumental variable regressions. $Income\,Qi$ is the denial rate for applications where the applicant's income falls in quintile i, in zip z in the year t. Regressions are run at the zip-year level. Standard errors are clustered at the zip-code level, and fixed effects are included, as indicated. *** indicates significance at the 1% level, ** significance at the 5% level, and * significance at the 10% level.

	Application Denials				
	Income Q1	Income Q2	Income Q3	Income Q4	Income Q5
	(1)	(2)	(3)	(4)	(5)
Medical Loss Ratio IV					
$log(\widehat{ZipPrice}_{z,t})$	0.556***	0.295***	0.211***	0.139***	0.000
	(0.048)	(0.036)	(0.036)	(0.035)	(0.047)
Zip-Code FE	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y
N	56336	56316	56033	55220	52195
KP rk Wald F-stat	255.745	254.277	242.592	240.995	211.984

Table 9: IV Specification: Mortgage among Black Population

This table presents regression results from the IV specification on mortgage application denials across income quintiles. Observations are at the zip-year level. The table reports results where $log(ZipPrice_{z,t})$ is instrumented by $MLR_{z,t,t-2}$ which is the three-year average medical loss ratio weighted by the insurer's market share in the zip z in the year t. Columns (1)-(3) report the results for the second-stage instrumental variable regressions. *Denial Rate* is the denial rate for applications where the race of the applicant is Black. % *App* and % *Org* is the percentage of applications and originations where the race of the applicant is black. Regressions are run at the zip-year level. Standard errors are clustered at the zip-code level, and fixed effects are included, as indicated. *** indicates significance at the 1% level, ** significance at the 5% level, and * significance at the 10% level.

	Second Stage		
	% *App*	% *Org*	Denial Rate
	(1)	(2)	(3)
Medical Loss Ratio IV			
$log(\widehat{ZipPrice}_{z,t})$	-0.046***	-0.047***	0.254**
	(0.008)	(0.009)	(0.099)
Zip-Code FE	Y	Y	Y
State-Year FE	Y	Y	Y
N	58910	58468	35520
KP rk Wald F-stat	263.143	258.618	130.411

Table 10: IV Specification: Additional Credit Outcomes

This table presents regression results from the IV specification on additional credit outcomes using a transformation of the dependent variable $m(y)$ following Chen and Roth (2024). In particular, $m(y) = log(y/\min_{y>0}(y))$ if $y > 0$ and $m(y) = -x$ if $y = 0$. The table reports the results for the case of $x = -0.01$. Observations are at the zip-year level. The table reports results where $log(ZipPrice_{z,t})$ is instrumented by $MLR_{z,t,t-2}$ which is the three-year average medical loss ratio weighted by the insurer's market share in the zip z in the year t. Columns (1)-(5) report the results for the second-stage instrumental variable regressions. $HELOC$ is the number of households with home equity line of credit (HELOC), $Discover\,CC$, $Visa\,CC$, $Mastercard\,CC$ is the number of households with Discover, VISA, or Mastercard credit cards, and $Auto$ is the number of households with auto loans in zip z in the year t. Regressions are run at the zip-year level. Standard errors are clustered at the zip-code level, and fixed effects are included, as indicated. *** indicates significance at the 1% level, ** significance at the 5% level, and * significance at the 10% level.

	Second Stage				
	HELOC	Discover CC	Visa CC	Mastercard CC	Auto
	(1)	(2)	(3)	(4)	(5)
Medical Loss Ratio IV					
$log(\widehat{ZipPrice}_{z,t})$	0.688***	0.402***	0.286**	0.138	0.296**
	(0.197)	(0.152)	(0.136)	(0.124)	(0.142)
Zip-Code FE	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y
N	24908	24908	24908	24908	24908
KP rk Wald F-stat	24.339	24.339	24.339	24.339	24.339

Table 11: IV Specification: Patient Discharge Rates and Outcome

This table presents regression results from the IV specification on discharge rates and avoidable hospitalization. Observations are at the zip-year level. The table reports results where $log(ZipPrice_{z,t})$ is instrumented by $MLR_{z,t,t-2}$ which is the three-year average medical loss ratio weighted by the insurer's market share in the zip z in the year t. Columns (1)-(8) report the results for the second-stage instrumental variable regressions. *Elective* is the rate of discharges with elective procedures, $Non - Elective$ is the rate of discharges with non-elective discharges, *Discharges* is the rate of discharges, and *Diabetic Amputations* is the rate of lower limb amputations in diabetic patients for every 1000 people living in zip z in a year t. Regressions are run at the zip-year level. Standard errors are clustered at the zip-code level, and fixed effects are included, as indicated. *** indicates significance at the 1% level, ** significance at the 5% level, and * significance at the 10% level.

	Second Stage							
	Elective		Non-Elective		Discharges		Diabetic Amputations	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Medical Loss Ratio IV								
$log(\widehat{ZipPrice}_{z,t})$	-4.299**		-1.217		-5.516***		-0.054	
	(1.882)		(0.762)		(2.079)		(0.063)	
$log(\widehat{ZipPrice}_{z,t-1})$		0.579		-0.868		-0.432		0.079*
		(2.517)		(0.758)		(2.713)		(0.044)
N	57547	52876	57547	52876	57547	52938	57537	52824
Zip-Code FE	Y	Y	Y	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y	Y	Y	Y
KP rk Wald F-stat	260.096	205.952	260.096	205.952	260.096	206.537	259.679	207.380

Table 12: Heterogeneity Test: % Uninsured Population

This table presents regression results from the IV specification on bankruptcy filer characteristics. Observations are at the zip-year level. The table reports results where $log(ZipPrice_{z,t})$ is instrumented by $MLR_{z,t,t-2}$ which is the three-year average medical loss ratio weighted by the insurer's market share in the zip z in the year t. The price has been interacted with an indicator variable $\mathbf{1}[X_{z,t} > Median]$ which takes the value 1 if the zip z has an uninsured rate above the median value in the year t, and 0 otherwise. Columns (1)-(6) report the results for the second-stage instrumental variable regressions. $Ch\,7$ is the number of Chapter 7 personal bankruptcies, $Ch\,13$ is the number of Chapter 13 personal bankruptcies, $Total$ is the total number of personal bankruptcies, $DenialRate$ is the ratio of mortgage applications denied to total mortgage applications, $Mort\,App$ is the total number of mortgage applications, and $DenialDTI$ is the total proportion of mortgage application denials citing high debt-to-income ratio for denial in zip z in year t. Regressions for columns (1)-(3) and (4) are run using a transformation of the dependent variable $m(y)$ following Chen and Roth (2024). In particular, $m(y) = log(y/\min_{y>0}(y))$ if $y > 0$ and $m(y) = -x$ if $y = 0$. The table reports the results for the case of $x = -0.01$. Regressions are run at the zip-year level. Standard errors are clustered at the zip-code level, and fixed effects are included, as indicated. *** indicates significance at the 1% level, ** significance at the 5% level, and * significance at the 10% level.

	$X_{z,t}$ = % Uninsured$_{z,t}$					
	Ch7	Ch13	Total	Denial Rate	Mort App	Denial DTI
	(1)	(2)	(3)	(4)	(5)	(6)
Medical Loss Ratio IV						
$\mathbf{1}[X_{z,t} < Median] \times log(\widehat{ZipPrice}_{z,t})$	0.526***	2.485***	1.437***	0.241***	-0.958***	0.044**
	(0.130)	(0.212)	(0.154)	(0.021)	(0.227)	(0.020)
$\mathbf{1}[X_{z,t} > Median] \times log(\widehat{ZipPrice}_{z,t})$	1.102***	3.136***	2.037***	0.245***	-1.406***	0.052***
	(0.178)	(0.312)	(0.222)	(0.024)	(0.258)	(0.020)
$\mathbf{1}[X_{z,t} > Median]$	-5.272***	-6.007***	-5.502***	-0.032	4.003***	-0.079
	(1.386)	(2.181)	(1.629)	(0.134)	(1.491)	(0.119)
Zip-Code FE	Y	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y	Y
N	53651	53651	53651	54943	62374	53739
KP rk Wald F-stat	65.240	65.240	65.240	119.263	125.849	119.376

Table 13: Heterogeneity Test: % Medicaid Enrollment

This table presents regression results from the IV specification on bankruptcy filer characteristics. Observations are at the zip-year level. The table reports results where $log(ZipPrice_{z,t})$ is instrumented by $MLR_{z,t,t-2}$ which is the three-year average medical loss ratio weighted by the insurer's market share in the zip z in the year t. The price has been interacted with an indicator variable $\mathbf{1}[X_{z,t} > Median]$ which takes the value 1 if the zip z has medicaid enrollment above the median value in the year t, and 0 otherwise. Columns (1)-(6) report the results for the second-stage instrumental variable regressions. $Ch\,7$ is the number of Chapter 7 personal bankruptcies, $Ch\,13$ is the number of Chapter 13 personal bankruptcies, $Total$ is the total number of personal bankruptcies, $DenialRate$ is the ratio of mortgage applications denied to total mortgage applications, $Mort\,App$ is the total number of mortgage applications, and $DenialDTI$ is the total proportion of mortgage application denials citing high debt-to-income ratio for denial in zip z in year t. Regressions for columns (1)-(3) and (4) are run using a transformation of the dependent variable $m(y)$ following Chen and Roth (2024). In particular, $m(y) = log(y/\min_{y>0}(y))$ if $y > 0$ and $m(y) = -x$ if $y = 0$. The table reports the results for the case of $x = -0.01$. Regressions are run at the zip-year level. Standard errors are clustered at the zip-code level, and fixed effects are included, as indicated. *** indicates significance at the 1% level, ** significance at the 5% level, and * significance at the 10% level.

	$X_{z,t}$ = Medicaid Enrollment$_{z,t}$					
	Ch7	Ch13	Total	Denial Rate	Mort App	Denial DTI
	(1)	(2)	(3)	(4)	(5)	(6)
Medical Loss Ratio IV						
$\mathbf{1}[X_{z,t} < Median]\times log(\widehat{ZipPrice}_{z,t})$	0.872***	2.811***	1.774***	0.239***	-0.274	0.040**
	(0.126)	(0.218)	(0.152)	(0.022)	(0.167)	(0.019)
$\mathbf{1}[X_{z,t} > Median]\times log(\widehat{ZipPrice}_{z,t})$	0.799***	2.572***	1.568***	0.301***	-1.636***	0.023
	(0.159)	(0.264)	(0.188)	(0.027)	(0.181)	(0.023)
$\mathbf{1}[X_{z,t} > Median]$	0.679	2.183	1.907*	-0.573***	12.560***	0.148*
	(0.834)	(1.372)	(0.990)	(0.110)	(0.840)	(0.090)
Zip-Code FE	Y	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y	Y
N	47412	47412	47412	50751	55192	49791
KP rk Wald F-stat	91.538	91.538	91.538	111.342	117.286	111.621

Table 14: Heterogeneity Test: % Medicare Enrollment

This table presents regression results from the IV specification on bankruptcy filer characteristics. Observations are at the zip-year level. The table reports results where $log(\mathit{ZipPrice}_{z,t})$ is instrumented by $MLR_{z,t,t-2}$ which is the three-year average medical loss ratio weighted by the insurer's market share in the zip z in the year t. The price has been interacted with an indicator variable $\mathbf{1}[X_{z,t} > Median]$ which takes the value 1 if the zip z has medicare enrollment above the median value in the year t, and 0 otherwise. Columns (1)-(6) report the results for the second-stage instrumental variable regressions. $Ch\,7$ is the number of Chapter 7 personal bankruptcies, $Ch\,13$ is the number of Chapter 13 personal bankruptcies, $Total$ is the total number of personal bankruptcies, $DenialRate$ is the ratio of mortgage applications denied to total mortgage applications, $Mort\,App$ is the total number of mortgage applications, and $DenialDTI$ is the total proportion of mortgage application denials citing high debt-to-income ratio for denial in zip z in year t. Regressions for columns (1)-(3) and (4) are run using a transformation of the dependent variable $m(y)$ following Chen and Roth (2024). In particular, $m(y) = log(y/\min_{y>0}(y))$ if $y > 0$ and $m(y) = -x$ if $y = 0$. The table reports the results for the case of $x = -0.01$. Regressions are run at the zip-year level. Standard errors are clustered at the zip-code level, and fixed effects are included, as indicated. *** indicates significance at the 1% level, ** significance at the 5% level, and * significance at the 10% level.

	$X_{z,t}$ = Medicare Enrollment$_{z,t}$					
	Ch7	Ch13	Total	Denial Rate	Mort App	Denial DTI
	(1)	(2)	(3)	(4)	(5)	(6)
Medical Loss Ratio IV						
$\mathbf{1}[X_{z,t} < Median] \times log(\widehat{ZipPrice}_{z,t})$	1.027***	2.893***	1.905***	0.255***	-0.532***	0.029
	(0.132)	(0.233)	(0.162)	(0.022)	(0.176)	(0.019)
$\mathbf{1}[X_{z,t} > Median] \times log(\widehat{ZipPrice}_{z,t})$	0.553***	2.538***	1.450***	0.238***	-0.353**	0.052**
	(0.144)	(0.236)	(0.171)	(0.022)	(0.155)	(0.021)
$\mathbf{1}[X_{z,t} > Median]$	4.388***	3.253**	4.196***	0.158	-1.664*	-0.216**
	(0.911)	(1.486)	(1.078)	(0.100)	(0.861)	(0.093)
Zip-Code FE	Y	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y	Y
N	47412	47412	47412	50751	55192	49791
KP rk Wald F-stat	121.497	121.497	121.497	135.186	138.909	136.785

Table 15: Heterogeneity Test: % People of Color

This table presents regression results from the IV specification on bankruptcy filer characteristics. Observations are at the zip-year level. The table reports results where $log(ZipPrice_{z,t})$ is instrumented by $MLR_{z,t,t-2}$ which is the three-year average medical loss ratio weighted by the insurer's market share in the zip z in the year t. The price has been interacted with an indicator variable $\mathbf{1}[X_{z,t} > Median]$ which takes the value 1 if the zip z has a population of people of color above the median value in the year t, and 0 otherwise. Columns (1)-(6) report the results for the second-stage instrumental variable regressions. $Ch\,7$ is the number of Chapter 7 personal bankruptcies, $Ch\,13$ is the number of Chapter 13 personal bankruptcies, $Total$ is the total number of personal bankruptcies, $DenialRate$ is the ratio of mortgage applications denied to total mortgage applications, $Mort\,App$ is the total number of mortgage applications, and $DenialDTI$ is the total proportion of mortgage application denials citing high debt-to-income ratio for denial in zip z in year t. Regressions for columns (1)-(3) and (4) are run using a transformation of the dependent variable $m(y)$ following Chen and Roth (2024). In particular, $m(y) = log(y/\min_{y>0}(y))$ if $y > 0$ and $m(y) = -x$ if $y = 0$. The table reports the results for the case of $x = -0.01$. Regressions are run at the zip-year level. Standard errors are clustered at the zip-code level, and fixed effects are included, as indicated. *** indicates significance at the 1% level, ** significance at the 5% level, and * significance at the 10% level.

	$X_{z,t}$ = % People of Color$_{z,t}$					
	Ch7	Ch13	Total	Denial Rate	Mort App	Denial DTI
	(1)	(2)	(3)	(4)	(5)	(6)
Medical Loss Ratio IV						
$\mathbf{1}[X_{z,t} < Median] \times log(\widehat{ZipPrice}_{z,t})$	0.089	2.801***	1.280***	0.184***	-0.610	0.085**
	(0.223)	(0.377)	(0.256)	(0.035)	(0.575)	(0.040)
$\mathbf{1}[X_{z,t} > Median] \times log(\widehat{ZipPrice}_{z,t})$	0.825***	3.093***	1.836***	0.123***	-1.984***	0.071***
	(0.143)	(0.259)	(0.168)	(0.024)	(0.383)	(0.027)
$\mathbf{1}[X_{z,t} > Median]$	-6.822***	-2.704	-5.145***	0.567***	12.735***	0.124
	(1.077)	(1.802)	(1.229)	(0.168)	(2.913)	(0.182)
Zip-Code FE	Y	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y	Y
N	47374	47374	47374	45599	47499	45120
KP rk Wald F-stat	45.980	45.980	45.980	54.867	43.200	53.947

Table 16: Heterogeneity Test: Median Household Income

This table presents regression results from the IV specification on bankruptcy filer characteristics. Observations are at the zip-year level. The table reports results where $log(ZipPrice_{z,t})$ is instrumented by $MLR_{z,t,t-2}$ which is the three-year average medical loss ratio weighted by the insurer's market share in the zip z in the year t. The price has been interacted with an indicator variable $\mathbf{1}[X_{z,t} > Median]$ which takes the value 1 if the zip z has a median household income above the median value in the year t, and 0 otherwise. Columns (1)-(6) report the second-stage instrumental variable regression results. $Ch7$ is the number of Chapter 7 personal bankruptcies, $Ch13$ is the number of Chapter 13 personal bankruptcies, $Total$ is the total number of personal bankruptcies, $DenialRate$ is the ratio of mortgage applications denied to total mortgage applications, $MortApp$ is the total number of mortgage applications, and $DenialDTI$ is the total proportion of mortgage application denials citing high debt-to-income ratio for denial in zip z in year t. Regressions for columns (1)-(3) and (4) are run using a transformation of the dependent variable $m(y)$ following Chen and Roth (2024). In particular, $m(y) = log(y/\min_{y>0}(y))$ if $y > 0$ and $m(y) = -x$ if $y = 0$. The table reports the results for the case of $x = -0.01$. Regressions are run at the zip-year level. Standard errors are clustered at the zip-code level, and fixed effects are included, as indicated. *** indicates significance at the 1% level, ** significance at the 5% level, and * significance at the 10% level.

	$X_{z,t}$ = % Median Household Income$_{z,t}$					
	Ch7	Ch13	Total	Denial Rate	Mort App	Denial DTI
	(1)	(2)	(3)	(4)	(5)	(6)
Medical Loss Ratio IV						
$\mathbf{1}[X_{z,t} < Median] \times log(\widehat{ZipPrice}_{z,t})$	0.533**	2.394***	1.342***	0.154***	-6.460***	0.016
	(0.259)	(0.442)	(0.309)	(0.043)	(1.084)	(0.045)
$\mathbf{1}[X_{z,t} > Median] \times log(\widehat{ZipPrice}_{z,t})$	0.822***	2.894***	1.736***	0.126***	-3.710***	0.053*
	(0.159)	(0.274)	(0.190)	(0.026)	(0.668)	(0.028)
$\mathbf{1}[X_{z,t} > Median]$	-2.666**	-4.571**	-3.615**	0.264	-25.466***	-0.341
	(1.197)	(2.093)	(1.434)	(0.207)	(4.839)	(0.217)
Zip-Code FE	Y	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y	Y
N	47343	47343	47343	45582	47466	45099
KP rk Wald F-stat	29.947	29.947	29.947	37.135	27.788	38.012

Table 17: Heterogeneity Test: High Temperature

This table presents regression results from the IV specification on bankruptcy filer characteristics. Observations are at the zip-year level. The table reports results where $log(ZipPrice_{z,t})$ is instrumented by $MLR_{z,t,t-2}$ which is the three-year average medical loss ratio weighted by the insurer's market share in the zip z in the year t. The price has been interacted with an indicator variable $\mathbf{1}[X_{z,t} > Median]$ which takes the value 1 if the zip z has the number of days with temperature greater than 90 degrees Fahrenheit above the median in the year t, and 0 otherwise. Columns (1)-(6) report the results for the second-stage instrumental variable regressions. $Ch\,7$ is the number of Chapter 7 personal bankruptcies, $Ch\,13$ is the number of Chapter 13 personal bankruptcies, $Total$ is the total number of personal bankruptcies, $DenialRate$ is the ratio of mortgage applications denied to total mortgage applications, $Mort\,App$ is the total number of mortgage applications, and $DenialDTI$ is the total proportion of mortgage application denials citing high debt-to-income ratio for denial in zip z in year t. Regressions for columns (1)-(3) and (5) are run using a transformation of the dependent variable $m(y)$ following Chen and Roth (2024). In particular, $m(y) = log(y/\min_{y>0}(y))$ if $y > 0$ and $m(y) = -x$ if $y = 0$. The table reports the results for the case of $x = -0.01$. Regressions are run at the zip-year level. Standard errors are clustered at the zip-code level, and fixed effects are included, as indicated. *** indicates significance at the 1% level, ** significance at the 5% level, and * significance at the 10% level.

	$X_{z,t}$ = Days with Temperature $\geq 90F_{z,t}$					
	Ch7	Ch13	Total	Denial Rate	Mort App	Denial DTI
	(1)	(2)	(3)	(4)	(5)	(6)
Medical Loss Ratio IV						
$\mathbf{1}[X_{z,t} < Median] \times log(\widehat{ZipPrice}_{z,t})$	0.093	2.088***	1.005***	0.238***	-0.891***	0.046*
	(0.156)	(0.248)	(0.184)	(0.025)	(0.317)	(0.027)
$\mathbf{1}[X_{z,t} > Median] \times log(\widehat{ZipPrice}_{z,t})$	1.486***	4.342***	2.834***	0.262***	-1.013***	0.061**
	(0.266)	(0.504)	(0.357)	(0.027)	(0.319)	(0.025)
$\mathbf{1}[X_{z,t} > Median]$	-12.978***	-21.126***	-17.078***	-0.221*	1.160	-0.136
	(2.786)	(5.388)	(3.800)	(0.127)	(1.439)	(0.108)
Zip-Code FE	Y	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y	Y
N	51091	51091	51091	57925	50056	48995
KP rk Wald F-stat	40.597	40.597	40.597	89.916	94.695	92.346

Table 18: IV Specification: Zillow Home Value Index

This table presents regression results from the IV specification on mortgage outcomes. Observations are at the zip-year level. Column (1) reports the result for the first-stage instrumental variable regression. The table reports results where $log(ZipPrice_{z,t})$ is instrumented by $MLR_{z,t,t-2}$ which is the three-year average medical loss ratio weighted by the insurer's market share in the zip z in the year t. Columns (2) report the results for the second-stage instrumental variable regressions. $ZHVI$ is the Zillow House Price Index in zip z in the year t. Regressions for column (2) are run using a transformation of the dependent variable $m(y)$ following Chen and Roth (2024). In particular, $m(y) = log(y/\min_{y>0}(y))$ if $y > 0$ and $m(y) = -x$ if $y = 0$. The table reports the results for the case of $x = -0.01$. Regressions are run at the zip-year level. Standard errors are clustered at the zip-code level, and fixed effects are included, as indicated. *** indicates significance at the 1% level, ** significance at the 5% level, and * significance at the 10% level.

	First Stage	Second Stage
	$log(ZipPrice_{z,t})$	ZHVI
	(1)	(2)
Medical Loss Ratio IV		
$MLR_{z,t,t-2}$	1.734***	
	(0.102)	
$log(\widehat{ZipPrice}_{z,t})$		-0.198***
		(0.038)
Zip-Code FE	Y	Y
State-Year FE	Y	Y
N	50553	50553
KP rk Wald F-stat	287.424	287.424

Appendix

A.1 Alternative Identification Strategy

Figure A1.1: Omitted Peer of a Hospital

This figure depicts the omitted peer for Hospital A. Hospitals A, B, and C have geographical overlap in the markets they operate in. Namely, Hospital A and Hospital B both operate in ZIP4. Hospital A and C both operate in ZIP2. Hospital D is a peer of Hospital B and Hospital C, but not of A. Likewise, Hospital E is a peer of Hospital B, but not of Hospital C. Both Hospital D and Hospital E are peer-of-peer to A, but do not operate in the same zip code as Hospital A itself. Hence, Hospital D and Hospital E are the omitted-peer of Hospital A.

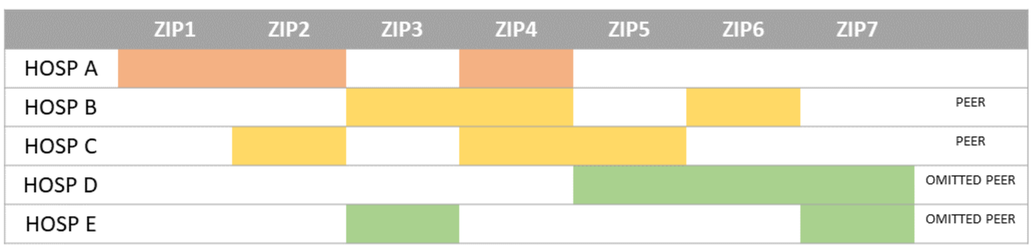

Table A1.1: IV Specification: Bankruptcy Filings

This table presents regression results from the IV specification on bankruptcy outcomes using a transformation of the dependent variable $m(y)$ following Chen and Roth (2024). In particular, $m(y) = log(y/\min_{y>0}(y))$ if $y > 0$ and $m(y) = -x$ if $y = 0$. The table reports the results for the case of $x = -0.01$. Observations are at the zip-year level. Column (1) reports the result for the first-stage instrumental variable regression. This table reports results when $log(ZipPrice_{z,t})$ which is the log of hospital price is instrumented by $log(OmittedZipPrice_{z,t})$ which is the log of omitted peer hospital price in zip z in the year t. Columns (2)-(5) report the results for the second-stage instrumental variable regressions. $Ch\,7$ is the number of Chapter 7 personal bankruptcies, $Ch\,13$ is the number of Chapter 13 personal bankruptcies, $Total$ is the total number of personal bankruptcies, $Prior$ is the total number of personal bankruptcies filed by individuals who had a prior bankruptcy filing in the last 7 years in zip z in the year t. Regressions are run at the zip-year level. Standard errors are clustered at the zip-code level, and fixed effects are included, as indicated. *** indicates significance at the 1% level, ** significance at the 5% level, and * significance at the 10% level.

	First Stage	Second Stage			
	$log(ZipPrice_{z,t})$	log(Ch7)	log(Ch13)	log(Total)	log(Prior)
	(1)	(2)	(3)	(4)	(5)
Omitted Peer Price IV					
$log(OmittedZipPrice_{z,t})$	0.276***				
	(0.017)				
$log(\widehat{ZipPrice}_{z,t})$		0.579***	1.070***	0.847***	1.447***
		(0.097)	(0.124)	(0.099)	(0.139)
Zip-Code FE	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y
N	61427	61427	61427	61427	61427
KP rk Wald F-stat	271.837				

Table A1.2: IV Specification: Bankruptcy Filer Characteristics

This table presents regression results from the IV specification on bankruptcy filer characteristics. Observations are at the zip-year level. This table reports results when $log(ZipPrice_{z,t})$ which is log of hospital price is instrumented by $log(OmittedZipPrice_{z,t})$ which is the log of omitted peer hospital price in zip z in the year t. $Debt-to-Income\,Ratio$ is the average debt-to-income ratio, $NP-Unsecured/Liability$ is the proportion of total non-priority unsecured liability in total liability, $Secured/Liability$ is the proportion of total secured liability in total liability, $Total\,Debt$ is the total secured and unsecured debt, $Income$ is the average monthly income, and $Expense$ is the average monthly expense of the bankruptcy filers in zip z in the year t. Regressions for columns (1), (4)-(6) are run using a transformation of the dependent variable $m(y)$ following Chen and Roth (2024). In particular, $m(y) = log(y/\min_{y>0}(y))$ if $y > 0$ and $m(y) = -x$ if $y = 0$. The table reports the results for the case of $x = -0.01$. Data has been winsorized at 1%. Regressions are run at the zip-year level. Standard errors are clustered at the zip-code level, and fixed effects are included, as indicated. *** indicates significance at the 1% level, ** significance at the 5% level, and * significance at the 10% level.

	Debt-to-Income Ratio	Secured/Liability	NP-Unsecured/Liability	Total Debt	Income	Expense
	(1)	(2)	(3)	(4)	(5)	(6)
Omitted Peer Price IV						
$log(\widehat{ZipPrice}_{z,t})$	0.225**	0.137***	-0.054***	0.140	0.088	-0.011
	(0.104)	(0.036)	(0.014)	(0.107)	(0.258)	(0.163)
Zip-Code FE	Y	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y	Y
N	53468	53598	53598	53541	53632	53626
KP rk Wald F-stat	297.693	296.862	295.374	299.229	299.276	299.240

Table A1.3: IV Specification: Mortgage Applications and Denials

This table presents regression results from the IV specification on mortgage outcomes. Observations are at the zip-year level. Column (1) reports the result for the first-stage instrumental variable regression. This table reports results when $log(ZipPrice_{z,t})$ which is log of hospital price is instrumented by $log(OmittedZipPrice_{z,t})$ which is the log of omitted peer hospital price in zip z in the year t. Columns (2)-(5) report the results for the second-stage instrumental variable regressions. $Mort\,App$ is the total number of mortgage applications, $Mort\,Org$ is the total number of mortgage originations, $\%\,Second\,Lien\,App$ is the percentage of second lien mortgage applications as a percentage of total applications, and $DenialRate$ is the ratio of mortgage applications denied to total mortgage applications in zip z in the year t. Regressions for columns (2)-(3) are run using a transformation of the dependent variable $m(y)$ following Chen and Roth (2024). In particular, $m(y) = log(y/\min_{y>0}(y))$ if $y > 0$ and $m(y) = -x$ if $y = 0$. Regressions are run at the zip-year level. Standard errors are clustered at the zip-code level, and fixed effects are included, as indicated. *** indicates significance at the 1% level, ** significance at the 5% level, and * significance at the 10% level.

	First Stage	Second Stage			
	$log(ZipPrice_{z,t})$	Mort App	Mort Org	% Second Lien App	Denial Rate
	(1)	(2)	(3)	(4)	(5)
Omitted Peer Price IV					
$log(OmittedZipPrice_{z,t})$	0.153***				
	(0.009)				
$log(\widehat{ZipPrice}_{z,t})$		-0.141	-0.430**	-0.014	0.268***
		(0.185)	(0.173)	(0.009)	(0.020)
Zip-Code FE	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y
N	70325	70325	70325	60388	60388
KP rk Wald F-stat	496.196				

Table A1.4: IV Specification: Reasons for Mortgage Application Denials

This table presents regression results from the IV specification on reasons for mortgage application denials. Observations are at the zip-year level. This table reports results when $log(ZipPrice_{z,t})$ which is log of hospital price is instrumented by $log(OmittedZipPrice_{z,t})$ which is the log of omitted peer hospital price in zip z in the year t. Columns (1)-(5) report the results for the second-stage instrumental variable regressions. $Debt-to-Income$ is the total proportion of mortgage application denials citing high debt-to-income ratio for denial, $Credit\,History$ is the total proportion of mortgage application denials citing bad credit history for denial, $Collateral$ is the total proportion of mortgage application denials citing inadequate collateral for denial, $Employment$ is the total proportion of mortgage application denials citing employment history for denial, $Insufficent$ is the total proportion of mortgage application denials citing insufficient cash for denial, in zip z in year t. Regressions are run at the zip-year level. Standard errors are clustered at the zip-code level, and fixed effects are included, as indicated. *** indicates significance at the 1% level, ** significance at the 5% level, and * significance at the 10% level.

	Reasons for Application Denial				
	Debt-to-Income	Credit History	Collateral	Employment	Insufficient
	(1)	(2)	(3)	(4)	(5)
Omitted Peer Price IV					
$log(\widehat{ZipPrice}_{z,t})$	0.037**	-0.100***	-0.070***	-0.004	0.010**
	(0.018)	(0.021)	(0.017)	(0.003)	(0.004)
Zip-Code FE	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y
N	59044	59044	59044	59044	59044
KP rk Wald F-stat	409.299	409.299	409.299	409.299	409.299

A.2 Robustness Tests

Table A2.1: Robustness: Population Scaled Count Variables

This table presents regression results from the IV specification on count variables scaled by total population. Observations are at the zip-year level. The table reports results where $log(ZipPrice_{z,t})$ is instrumented by $MLR_{z,t,t-2}$ which is the three-year average medical loss ratio weighted by the insurer's market share in the zip z in the year t. Columns (1)-(6) report the results for the second-stage instrumental variable regressions. $Ch\,7$ is the number of Chapter 7 personal bankruptcies, $Ch\,13$ is the number of Chapter 13 personal bankruptcies, $Total$ is the total number of personal bankruptcies, $Prior$ is the total number of personal bankruptcies filed by individuals who had a prior bankruptcy filing in the last 7 years, $Mort\,App$ is the total number of mortgage applications, $Mort\,Org$ is the total number of mortgage originations, scaled by total population in zip z in year t. Regressions are run at the zip-year level. Standard errors are clustered at the zip-code level, and fixed effects are included, as indicated. *** indicates significance at the 1% level, ** significance at the 5% level, and * significance at the 10% level.

	Second Stage					
	Ch7	Ch13	Total	Prior	Mort App	Mort Org
	(1)	(2)	(3)	(4)	(5)	(6)
Medical Loss Ratio IV						
$log(\widehat{ZipPrice}_{z,t})$	1.813***	2.640***	4.453***	1.269***	-17.934***	-16.739***
	(0.349)	(0.247)	(0.480)	(0.132)	(4.617)	(3.267)
Zip-Code FE	Y	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y	Y
N	48940	48940	48940	48940	58410	58410
KP rk Wald F-stat	246.900	246.900	246.900	246.900	263.244	263.244

Table A2.2: Robustness: IV Specification with Controls - Bankruptcy Filings

This table presents regression results from the IV specification with zip-level time-varying controls on bankruptcy outcomes using a transformation of the dependent variable $m(y)$ following Chen and Roth (2024). In particular, $m(y) = log(y/\min_{y>0}(y))$ if $y > 0$ and $m(y) = -x$ if $y = 0$. The table reports the results for the case of $x = -0.01$. Observations are at the zip-year level. The table reports results where $log(ZipPrice_{z,t})$ is instrumented by $MLR_{z,t,t-2}$ which is the three-year average medical loss ratio weighted by the insurer's market share in the zip z in the year t. Columns (1)-(4) report the results for the second-stage instrumental variable regressions. $Ch7$ is the number of Chapter 7 personal bankruptcies, $Ch13$ is the number of Chapter 13 personal bankruptcies, $Total$ is the total number of personal bankruptcies, $Prior$ is the total number of personal bankruptcies filed by individuals who had a prior bankruptcy filing in the last 7 years in zip z in the year t. Regressions are run at the zip-year level. Standard errors are clustered at the zip-code level, and fixed effects are included, as indicated. *** indicates significance at the 1% level, ** significance at the 5% level, and * significance at the 10% level.

	Second Stage			
	Ch7	Ch13	Total	Prior
	(1)	(2)	(3)	(4)
Medical Loss Ratio IV				
$log(\widehat{ZipPrice}_{z,t})$	0.822***	3.128***	1.840***	2.562***
	(0.146)	(0.274)	(0.183)	(0.239)
Controls	Y	Y	Y	Y
Zip-Code FE	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y
N	47330	47330	47330	47330
KP rk Wald F-stat	205.285	205.285	205.285	205.285

Table A2.3: Robustness: IV Specification with Controls - Mortgage Outcomes

This table presents regression results from the IV specification with zip-level time-varying controls on mortgage outcomes. Observations are at the zip-year level. Column (1) reports the result for the first-stage instrumental variable regression. The table reports results where $log(ZipPrice_{z,t})$ is instrumented by $MLR_{z,t,t-2}$ which is the three-year average medical loss ratio weighted by the insurer's market share in the zip z in the year t. Columns (1)-(9) report the results for the second-stage instrumental variable regressions. $Mort\,App$ is the total number of mortgage applications, $Mort\,Org$ is the total number of mortgage originations, $\%\,Second\,Lien\,App$ is the percentage of second lien mortgage applications as a percentage of total applications, $DenialRate$ is the ratio of mortgage applications denied to total mortgage applications, $Debt-to-Income$ is the total proportion of mortgage application denials citing high debt-to-income ratio for denial, $Credit\,History$ is the total proportion of mortgage application denials citing bad credit history for denial, $Collateral$ is the total proportion of mortgage application denials citing inadequate collateral for denial, $Employment$ is the total proportion of mortgage application denials citing employment history for denial, $Insufficent$ is the total proportion of mortgage application denials citing insufficient cash for denial in zip z in year t. Regressions for columns (1)-(2) are run using a transformation of the dependent variable $m(y)$ following Chen and Roth (2024). In particular, $m(y) = log(y/\min_{y>0}(y))$ if $y > 0$ and $m(y) = -x$ if $y = 0$. The table reports the results for the case of $x = -0.01$. Regressions are run at the zip-year level. Standard errors are clustered at the zip-code level, and fixed effects are included, as indicated. *** indicates significance at the 1% level, ** significance at the 5% level, and * significance at the 10% level.

	Second Stage								
	log(Mort App)	log(Mort Org)	Denial Rate	% Second Lien App	Debt-to-Income	Credit History	Collateral	Employment	Insufficient
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Medical Loss Ratio IV									
$log(\widehat{ZipPrice}_{z,t})$	-2.296***	-2.042***	0.104***	0.100***	0.055**	0.108***	-0.281***	-0.003	-0.004
	(0.412)	(0.376)	(0.022)	(0.015)	(0.027)	(0.030)	(0.032)	(0.005)	(0.006)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Zip-Code FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	47351	47351	45822	45822	45516	45516	45516	45516	45516
KP rk Wald F-stat	204.975	204.975	210.178	210.178	204.901	204.901	204.901	204.901	204.901

Table A2.4: Robustness: Broader Hospital Market - Bankruptcy Filings

This table presents regression results from the IV specification on bankruptcy outcomes, where the choice set of hospitals used to estimate prices is defined to be a 50-mile circle around the centroid of the zip. The specification is run using a transformation of the dependent variable $m(y)$ following Chen and Roth (2024). In particular, $m(y) = log(y/\min_{y>0}(y))$ if $y > 0$ and $m(y) = -x$ if $y = 0$. The table reports the results for the case of $x = -0.01$. Observations are at the zip-year level. The table reports results where $log(ZipPrice_{z,t})$ is instrumented by $MLR_{z,t,t-2}$ which is the three-year average medical loss ratio weighted by the insurer's market share in the zip z in the year t. Columns (1)-(4) report the results for the second-stage instrumental variable regressions. $Ch\,7$ is the number of Chapter 7 personal bankruptcies, $Ch\,13$ is the number of Chapter 13 personal bankruptcies, $Total$ is the total number of personal bankruptcies, $Prior$ is the total number of personal bankruptcies filed by individuals who had a prior bankruptcy filing in the last 7 years in zip z in the year t. Regressions are run at the zip-year level. Standard errors are clustered at the zip-code level, and fixed effects are included, as indicated. *** indicates significance at the 1% level, ** significance at the 5% level, and * significance at the 10% level.

	Second Stage			
	Ch7	Ch13	Total	Prior
	(1)	(2)	(3)	(4)
Medical Loss Ratio IV				
$log(\widehat{ZipPrice}_{z,t})$	0.856***	2.957***	1.897***	2.646***
	(0.151)	(0.245)	(0.184)	(0.220)
Zip-Code FE	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y
N	60800	60800	60800	60800
KP rk Wald F-stat	254.117	254.117	254.117	254.117

Table A2.5: Robustness: Broader Market Definition - Mortgage Outcomes

This table presents regression result from the IV specification on mortgage outcomes, where the choice set of hospitals used to estimate prices is defined to be a 50-mile circle around the centroid of the zip. Observations are at the zip-year level. Column (1) reports the result for the first-stage instrumental variable regression. The table reports results where $log(ZipPrice_{z,t})$ is instrumented by $MLR_{z,t,t-2}$ which is the three-year average medical loss ratio weighted by the insurer's market share in the zip z in the year t. Columns (1)-(9) report the results for the second-stage instrumental variable regressions. $Mort\,App$ is the total number of mortgage applications, $Mort\,Org$ is the total number of mortgage originations, $\%\,Second\,Lien\,App$ is the percentage of second lien mortgage applications as a percentage of total applications, $DenialRate$ is the ratio of mortgage applications denied to total mortgage applications, $Debt-to-Income$ is the total proportion of mortgage application denials citing high debt-to-income ratio for denial, $Credit\,History$ is the total proportion of mortgage application denials citing bad credit history for denial, $Collateral$ is the total proportion of mortgage application denials citing inadequate collateral for denial, $Employment$ is the total proportion of mortgage application denials citing employment history for denial, $Insufficent$ is the total proportion of mortgage application denials citing insufficient cash for denial in zip z in year t. Regressions for columns (1)-(2) are run using a transformation of the dependent variable $m(y)$ following Chen and Roth (2024). In particular, $m(y) = log(y/\min_{y>0}(y))$ if $y > 0$ and $m(y) = -x$ if $y = 0$. The table reports the results for the case of $x = -0.01$. Regressions are run at the zip-year level. Standard errors are clustered at the zip-code level, and fixed effects are included, as indicated. *** indicates significance at the 1% level, ** significance at the 5% level, and * significance at the 10% level.

	Second Stage								
	Mort App	Mort Org	Denial Rate	% Second Lien App	Debt-to-Income	Credit History	Collateral	Employment	Insufficient
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Medical Loss Ratio IV									
$log(\widehat{ZipPrice}_{z,t})$	-1.272***	-1.348***	0.278***	0.035***	0.066***	0.030	-0.150***	-0.008*	0.001
	(0.286)	(0.268)	(0.025)	(0.012)	(0.023)	(0.025)	(0.025)	(0.004)	(0.005)
Zip-Code FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	69776	69776	60098	60098	58798	58798	58798	58798	58798
KP rk Wald F-stat	274.560	274.560	271.187	271.187	267.675	267.675	267.675	267.675	267.675

Table A2.6: Robustness: Without Financial Crisis Years - Bankruptcy Filings

This table presents regression results from the IV specification, dropping the financial crisis years of 2008 & 2009 on bankruptcy outcomes using a transformation of the dependent variable $m(y)$ following Chen and Roth (2024). In particular, $m(y) = log(y/\min_{y>0}(y))$ if $y > 0$ and $m(y) = -x$ if $y = 0$. The table reports the results for the case of $x = -0.01$. Observations are at the zip-year level. The table reports results where $log(ZipPrice_{z,t})$ is instrumented by $MLR_{z,t,t-2}$ which is the three-year average medical loss ratio weighted by the insurer's market share in the zip z in the year t. Columns (1)-(4) report the results for the second-stage instrumental variable regressions. $Ch\,7$ is the number of Chapter 7 personal bankruptcies, $Ch\,13$ is the number of Chapter 13 personal bankruptcies, $Total$ is the total number of personal bankruptcies, $Prior$ is the total number of personal bankruptcies filed by individuals who had a prior bankruptcy filing in the last 7 years in zip z in the year t. Regressions are run at the zip-year level. Standard errors are clustered at the zip-code level, and fixed effects are included, as indicated. *** indicates significance at the 1% level, ** significance at the 5% level, and * significance at the 10% level.

	Second Stage			
	Ch7	Ch13	Total	Prior
	(1)	(2)	(3)	(4)
Medical Loss Ratio IV				
$log(\widehat{ZipPrice}_{z,t})$	0.671***	2.990***	1.719***	2.714***
	(0.156)	(0.273)	(0.194)	(0.251)
Zip-Code FE	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y
N	50899	50899	50899	50899
KP rk Wald F-stat	205.146	205.146	205.146	205.146

Table A2.7: Robustness: Without Financial Crisis Years - Mortgage Outcomes

This table presents regression results from the IV specification, dropping the financial crisis years of 2008 & 2009, on mortgage outcomes. Observations are at the zip-year level. Column (1) reports the result for the first-stage instrumental variable regression. The table reports results where $log(ZipPrice_{z,t})$ is instrumented by $MLR_{z,t,t-2}$ which is the three-year average medical loss ratio weighted by the insurer's market share in the zip z in the year t. Columns (1)-(9) report the results for the second-stage instrumental variable regressions. $Mort\,App$ is the total number of mortgage applications, $Mort\,Org$ is the total number of mortgage originations, $\%\,Second\,Lien\,App$ is the percentage of second lien mortgage applications as a percentage of total applications, $DenialRate$ is the ratio of mortgage applications denied to total mortgage applications, $Debt-to-Income$ is the total proportion of mortgage application denials citing high debt-to-income ratio for denial, $Credit\,History$ is the total proportion of mortgage application denials citing bad credit history for denial, $Collateral$ is the total proportion of mortgage application denials citing inadequate collateral for denial, $Employment$ is the total proportion of mortgage application denials citing employment history for denial, $Insuff icent$ is the total proportion of mortgage application denials citing insufficient cash for denial in zip z in year t. Regressions for columns (1)-(2) are run using a transformation of the dependent variable $m(y)$ following Chen and Roth (2024). In particular, $m(y) = log(y/\min_{y>0}(y))$ if $y > 0$ and $m(y) = -x$ if $y = 0$. The table reports the results for the case of $x = -0.01$. Regressions are run at the zip-year level. Standard errors are clustered at the zip-code level, and fixed effects are included, as indicated. *** indicates significance at the 1% level, ** significance at the 5% level, and * significance at the 10% level.

	Second Stage								
	Mort App	Mort Org	Denial Rate	% Second Lien App	Debt-to-Income	Credit History	Collateral	Employment	Insufficient
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Medical Loss Ratio IV									
$log(\widehat{ZipPrice}_{z,t})$	-0.522**	-0.735***	0.253***	0.012	0.076***	0.003	-0.078***	-0.008*	0.001
	(0.219)	(0.207)	(0.023)	(0.010)	(0.021)	(0.022)	(0.021)	(0.004)	(0.004)
Zip-Code FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	59936	59936	52139	52139	51026	51026	51026	51026	51026
KP rk Wald F-stat	261.744	261.744	248.514	248.514	248.988	248.988	248.988	248.988	248.988

Table A2.8: Robustness: Lagged Medical Loss IV - Bankruptcy Filings

This table presents regression results from the IV specification on bankruptcy outcomes using a transformation of the dependent variable $m(y)$ following Chen and Roth (2024). In particular, $m(y) = log(y/\min_{y>0}(y))$ if $y > 0$ and $m(y) = -x$ if $y = 0$. The table reports the results for the case of $x = -0.01$. Observations are at the zip-year level. The table reports results where $log(ZipPrice_{z,t})$ is instrumented by $MLR_{z,t-1,t-3}$ which is the lagged three-year average medical loss ratio weighted by the insurer's market share in the zip z in the year t. Columns (1)-(4) report the results for the second-stage instrumental variable regressions. $Ch\,7$ is the number of Chapter 7 personal bankruptcies, $Ch\,13$ is the number of Chapter 13 personal bankruptcies, $Total$ is the total number of personal bankruptcies, $Prior$ is the total number of personal bankruptcies filed by individuals who had a prior bankruptcy filing in the last 7 years in zip z in the year t. Regressions are run at the zip-year level. Standard errors are clustered at the zip-code level, and fixed effects are included, as indicated. *** indicates significance at the 1% level, ** significance at the 5% level, and * significance at the 10% level.

	Second Stage			
	Ch7	Ch13	Total	Prior
	(1)	(2)	(3)	(4)
Medical Loss Ratio IV				
$log(\widehat{ZipPrice}_{z,t})$	0.608***	3.257***	1.786***	2.968***
	(0.179)	(0.347)	(0.231)	(0.322)
Zip-Code FE	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y
N	56876	56876	56876	56876
KP rk Wald F-stat	118.362	118.362	118.362	118.362

Table A2.9: Robustness: Lagged Medical Loss IV - Mortgage Outcomes

This table presents regression results from the IV specification on mortgage outcomes. Observations are at the zip-year level. Column (1) reports the result for the first-stage instrumental variable regression. The table reports results where $log(ZipPrice_{z,t})$ is instrumented by $MLR_{z,t-1,t-3}$ which is the lagged three-year average medical loss ratio weighted by the insurer's market share in the zip z in the year t. Columns (1)-(9) report the results for the second-stage instrumental variable regressions. $Mort\,App$ is the total number of mortgage applications, $Mort\,Org$ is the total number of mortgage originations, $\%\,Second\,Lien\,App$ is the percentage of second lien mortgage applications as a percentage of total applications, $DenialRate$ is the ratio of mortgage applications denied to total mortgage applications, $Debt-to-Income$ is the total proportion of mortgage application denials citing high debt-to-income ratio for denial, $Credit\,History$ is the total proportion of mortgage application denials citing bad credit history for denial, $Collateral$ is the total proportion of mortgage application denials citing inadequate collateral for denial, $Employment$ is the total proportion of mortgage application denials citing employment history for denial, $Insufficent$ is the total proportion of mortgage application denials citing insufficient cash for denial in zip z in year t. Regressions for columns (1)-(2) are run using a transformation of the dependent variable $m(y)$ following Chen and Roth (2024). In particular, $m(y) = log(y/\min_{y>0}(y))$ if $y > 0$ and $m(y) = -x$ if $y = 0$. The table reports the results for the case of $x = -0.01$. Regressions are run at the zip-year level. Standard errors are clustered at the zip-code level, and fixed effects are included, as indicated. *** indicates significance at the 1% level, ** significance at the 5% level, and * significance at the 10% level.

	Second Stage								
	Mort App	Mort Org	Denial Rate	% Second Lien App	Debt-to-Income	Credit History	Collateral	Employment	Insufficient
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Medical Loss Ratio IV									
$log(\widehat{ZipPrice}_{z,t})$	-1.572***	-1.312***	0.075***	0.068***	0.057*	0.114***	-0.198***	-0.009	0.017**
	(0.299)	(0.276)	(0.028)	(0.015)	(0.030)	(0.038)	(0.034)	(0.005)	(0.007)
Zip-Code FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	62133	62133	54174	54174	53067	53067	53067	53067	53067
KP rk Wald F-stat	158.185	158.185	163.183	163.183	163.434	163.434	163.434	163.434	163.434

Table A2.10: Robustness: Alternate MLR Measure - Bankruptcy Filings

This table presents regression results from the IV specification on bankruptcy outcomes using a transformation of the dependent variable $m(y)$ following Chen and Roth (2024). In particular, $m(y) = log(y/\min_{y>0}(y))$ if $y > 0$ and $m(y) = -x$ if $y = 0$. The table reports the results for the case of $x = -0.01$. Observations are at the zip-year level. The table reports results where $log(ZipPrice_{z,t})$ is instrumented by $MLR_{z,t}$ which is the medical loss ratio weighted by the insurer's market share in the zip z in the year t. Columns (1)-(4) report the results for the second-stage instrumental variable regressions. $Ch\,7$ is the number of Chapter 7 personal bankruptcies, $Ch\,13$ is the number of Chapter 13 personal bankruptcies, $Total$ is the total number of personal bankruptcies, $Prior$ is the total number of personal bankruptcies filed by individuals who had a prior bankruptcy filing in the last 7 years in zip z in the year t. Regressions are run at the zip-year level. Standard errors are clustered at the zip-code level, and fixed effects are included, as indicated. *** indicates significance at the 1% level, ** significance at the 5% level, and * significance at the 10% level.

	Second Stage			
	Ch7	Ch13	Total	Prior
	(1)	(2)	(3)	(4)
Medical Loss Ratio IV				
$log(\widehat{ZipPrice}_{z,t})$	0.383*	2.658***	1.370***	2.101***
	(0.222)	(0.390)	(0.264)	(0.325)
Zip-Code FE	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y
N	60587	60587	60587	60587
KP rk Wald F-stat	76.888	76.888	76.888	76.888

Table A2.11: Robustness: Alternate MLR Measure - Mortgage Outcomes

This table presents regression results from the IV specification on mortgage outcomes. Observations are at the zip-year level. Column (1) reports the result for the first-stage instrumental variable regression. The table reports results where $log(ZipPrice_{z,t})$ is instrumented by $MLR_{z,t}$ which is the medical loss ratio weighted by the insurer's market share in the zip z in the year t. Columns (1)-(9) report the results for the second-stage instrumental variable regressions. $Mort\,App$ is the total number of mortgage applications, $Mort\,Org$ is the total number of mortgage originations, $\%\,Second\,Lien\,App$ is the percentage of second lien mortgage applications as a percentage of total applications, $DenialRate$ is the ratio of mortgage applications denied to total mortgage applications, $Debt-to-Income$ is the total proportion of mortgage application denials citing high debt-to-income ratio for denial, $Credit\,History$ is the total proportion of mortgage application denials citing bad credit history for denial, $Collateral$ is the total proportion of mortgage application denials citing inadequate collateral for denial, $Employment$ is the total proportion of mortgage application denials citing employment history for denial, $Insufficent$ is the total proportion of mortgage application denials citing insufficient cash for denial in zip z in year t. Regressions for columns (1)-(2) are run using a transformation of the dependent variable $m(y)$ following Chen and Roth (2024). In particular, $m(y) = log(y/\min_{y>0}(y))$ if $y > 0$ and $m(y) = -x$ if $y = 0$. The table reports the results for the case of $x = -0.01$. Regressions are run at the zip-year level. Standard errors are clustered at the zip-code level, and fixed effects are included, as indicated. *** indicates significance at the 1% level, ** significance at the 5% level, and * significance at the 10% level.

	Second Stage								
	Mort App	Mort Org	Denial Rate	% Second Lien App	Debt-to-Income	Credit History	Collateral	Employment	Insufficient
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Medical Loss Ratio IV									
$log(\widehat{ZipPrice}_{z,t})$	-2.585***	-2.390***	0.157***	0.076***	0.119***	0.231***	-0.224***	-0.016**	0.003
	(0.601)	(0.556)	(0.038)	(0.022)	(0.045)	(0.053)	(0.051)	(0.008)	(0.009)
Zip-Code FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	69566	69566	59892	59892	58594	58594	58594	58594	58594
KP rk Wald F-stat	54.772	54.772	71.760	71.760	70.101	70.101	70.101	70.101	70.101

Table A2.12: Robustness: Alternate Price Measure - Bankruptcy Filings

This table presents regression results from the IV specification on bankruptcy outcomes using a transformation of the dependent variable $m(y)$ following Chen and Roth (2024). The prices have been estimated using the equation 16. In particular, $m(y) = log(y/\min_{y>0}(y))$ if $y > 0$ and $m(y) = -x$ if $y = 0$. The table reports the results for the case of $x = -0.01$. Observations are at the zip-year level. The table reports results where $log(ZipPrice_{z,t})$ is instrumented by $MLR_{z,t,t-2}$ which is the three-year average medical loss ratio weighted by the insurer's market share in the zip z in the year t. Columns (1)-(4) report the results for the second-stage instrumental variable regressions. $Ch\,7$ is the number of Chapter 7 personal bankruptcies, $Ch\,13$ is the number of Chapter 13 personal bankruptcies, $Total$ is the total number of personal bankruptcies, $Prior$ is the total number of personal bankruptcies filed by individuals who had a prior bankruptcy filing in the last 7 years in zip z in the year t. Regressions are run at the zip-year level. Standard errors are clustered at the zip-code level, and fixed effects are included, as indicated. *** indicates significance at the 1% level, ** significance at the 5% level, and * significance at the 10% level.

	Second Stage			
	Ch7	Ch13	Total	Prior
	(1)	(2)	(3)	(4)
Medical Loss Ratio IV				
$log(\widehat{ZipPrice}_{z,t})$	0.836***	2.710***	1.748***	2.481***
	(0.136)	(0.227)	(0.170)	(0.207)
Zip-Code FE	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y
N	60234	60234	60234	60234
KP rk Wald F-stat	221.423	221.423	221.423	221.423

Table A2.13: Robustness: Alternate Price Measure - Mortgage Outcomes

This table presents regression results from the IV specification on mortgage outcomes where the prices have been estimated using the equation 16. Observations are at the zip-year level. Column (1) reports the result for the first-stage instrumental variable regression. The table reports results where $log(ZipPrice_{z,t})$ is instrumented by $MLR_{z,t,t-2}$ which is the three-year average medical loss ratio weighted by the insurer's market share in the zip z in the year t. Columns (1)-(9) report the results for the second-stage instrumental variable regressions. $Mort\,App$ is the total number of mortgage applications, $Mort\,Org$ is the total number of mortgage originations, $\%\,Second\,Lien\,App$ is the percentage of second lien mortgage applications as a percentage of total applications, $DenialRate$ is the ratio of mortgage applications denied to total mortgage applications, $Debt-to-Income$ is the total proportion of mortgage application denials citing high debt-to-income ratio for denial, $Credit\,History$ is the total proportion of mortgage application denials citing bad credit history for denial, $Collateral$ is the total proportion of mortgage application denials citing inadequate collateral for denial, $Employment$ is the total proportion of mortgage application denials citing employment history for denial, $Insufficent$ is the total proportion of mortgage application denials citing insufficient cash for denial in zip z in year t. Regressions for columns (1)-(2) are run using a transformation of the dependent variable $m(y)$ following Chen and Roth (2024). In particular, $m(y) = log(y/\min_{y>0}(y))$ if $y > 0$ and $m(y) = -x$ if $y = 0$. The table reports the results for the case of $x = -0.01$. Regressions are run at the zip-year level. Standard errors are clustered at the zip-code level, and fixed effects are included, as indicated. *** indicates significance at the 1% level, ** significance at the 5% level, and * significance at the 10% level.

	Second Stage								
	Mort App	Mort Org	Denial Rate	% Second Lien App	Debt-to-Income	Credit History	Collateral	Employment	Insufficient
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Medical Loss Ratio IV									
$log(\widehat{ZipPrice}_{z,t})$	-0.891***	-0.959***	0.228***	0.003	0.063***	0.027	-0.098***	-0.009***	0.002
	(0.215)	(0.200)	(0.019)	(0.009)	(0.018)	(0.020)	(0.018)	(0.003)	(0.004)
Zip-Code FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	68157	68157	58799	58799	57523	57523	57523	57523	57523
KP rk Wald F-stat	415.840	415.840	422.285	422.285	407.409	407.409	407.409	407.409	407.409