Are hospital bills hazardous to your financial health?

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October 30, 2023

Abstract

Healthcare price increases have been a frequent topic of public debate, but little is understood about how such increases impact consumers. I study the effect of hospital prices on the financial health of individuals. Instrumenting for patient choice using their proximity to hospitals, I construct a novel zip-level measure of prices that hospitals charge for their services using detailed healthcare microdata and state hospital cost reports obtained via a series of Freedom of Information Act (FOIA) requests. Using the insurer's ratio of medical claims to premiums (medical loss ratio) as an instrument for hospital prices, the findings reveal a causal link between higher hospital prices and adverse financial outcomes, including a rise in personal bankruptcy filings, reduced demand for home mortgages, an increase in credit card debt, and increased use of home equity line of credit. I provide evidence that financial institutions are less inclined to approve mortgage applications due to elevated debt-to-income ratios resulting from escalating hospital prices. Furthermore, I provide evidence 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. However, the presence of home equity mitigates some of these effects, as areas that experienced plausibly exogenous increases in house prices are less impacted by increases in hospital prices. The results are robust to alternative specifications and use of an alternative instrument that exploits price changes induced by hospital competition in a geographic area.

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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 under 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 and intuitive, empirically establishing the impact of hospital prices on households' financial outcomes poses significant challenges. 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 the hospitals and the health insurance companies and 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 demography 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. 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 their 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-a-vis healthcare providers. I validate these arguments by showing that insurance companies that have a monopoly over more geographical markets tend to have lower medical loss ratio.[4,5]

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 1.39% increase in personal bankruptcies. 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

[3] Dranove et al. (2017) find that the average non-profit hospitals did not increase prices during the financial crisis. However, those with substantial market power did so. More recently, Aghamolla et al. (2022) document 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] Karaca-Mandic et al. (2015) also demonstrate the validity of medical loss ratio as a measure of price-cost margin and that competitive markets have higher medical loss ratio than their monopoly counterparts.

[5] 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

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 does not change. These have two noteworthy implications. First, the negative welfare consequences of higher hospital prices may not be limited to low-income individuals.[6,7] Notably, individuals with more substantial assets are both 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.

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 0.84% decline in mortgage originations. Notably, financial institutions increasingly cite 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 card debt. Furthermore, more households obtain home equity lines of credit. These findings underscore that mounting medical bills heighten household debt burdens, reducing both their appetite for mortgage credit and their ability to access it.

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

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

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

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

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 under-served 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 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.[8] I show the decline in home

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

values in regions where hospital prices increase. In particular, a 1% increase in instrumented hospital prices leads to a -0.19% 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 their 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 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.

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, as a robustness check, I exclude the years affected by the financial crisis. In additional tests, I also add 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.

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 implication of Medicaid expansion on household distress; this empirical literature finds that states that expanded Medicaid eligibility witness a decline in bankruptcy and improve 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) document higher insurance premiums, which lead to increased business bankruptcy, slower establishment and employment growth, and lower wages. 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 positive relation between home equity and consumption. Adelino et al. (2015)

highlight 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) document 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-payment 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 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 hospitalizations. 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 borrow 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.[9]

Using entry/exit of a market-leading Emergency Department outsourcing firm in a hospital, Cooper et al. (2020) shows an increase in patient's 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 the 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 to be 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.

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

Insurer Market Power

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 viz-a-viz 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) show 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 acquire 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 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 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 at 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 at 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 majority of patients that 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 endogenity concern as patients self-select 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 seperately 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 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 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 insurance company's lagged medical loss ratio 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 quality of care. For the exclusion restriction to hold the only channel through which insurer's medical loss ratio can impact individual's 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 market power impacts the medical loss ratio in two ways. First, an insurer's ability to negotiate with the healthcare providers depends on their market power. An increase (decrease) in the insurer's bargaining power, would lead to an 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 starting with Gowrisankaran et al. (2015) models insurers' negotiations with healthcare providers. In particular, Barrette et al. (2022) illustrate 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 have 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) demonstrate that the initial response of insurers to the regulation was mostly driven by increases in claim amount. While the initial response could have been an artifact of a the time constraint to comply, Cicala et al. (2017) document 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 monopoly on 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 monopoly out of all the counties that the insurer operates in. $MLR_{n,t}$ is the the medical loss ratio of insurer n at 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) present results for the entire sample and Column (2) for the sample before the implementation of ACA provisions. I find strong evidence that insurer market power is negatively related with their medical loss ratio. In other words, insurer operating in less concentrated markets have lower medical loss ratio.

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 rake up 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 zip's exposure to an insurance company, using Form 5500 reports filed with Department of Labor. Each firm files an individual Schedule A report for every insurance contract they have for 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 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 year t is given by:

$$MLR_{z,t-1,t-3} = \sum_{n=1}^{k} \omega_{n,z,t-1} \frac{Total\ Medical\ Claim_{n,t-1,t-3}}{Net\ Premium\ Written_{n,t-1,t-3}} \tag{7}$$

where $\omega_{n,z,t-1}$ is the share of insurance company n in those enrolled in zip z in time $t-1$. The exposure to the zip is defined if the firm is situated within the 25 miles radius of the zip. $\textit{Total Medical Claim}_{n,t-1,t-3}$ and $\textit{Net Premium Written}_{n,t-1,t-3}$ is the total medical claims less reinsurance and the net premium written amount for the conglomerate holding insurance company n incurred between the years $t-3$ and $t-1$. 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 year t is given by:

$$MLR_{z,t-1,t-3} = \sum_{n=1}^{k} \omega_{n,z,t-1} \ \max(85, \frac{\textit{Total Medical Claim}_{n,t-1,t-3}}{\textit{Net Premium Written}_{n,t-1,t-3}}) \tag{8}$$

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 2020, 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 existent literature, I exclude government hospitals since they receive direct government funding and potentially have different incentive structure than the one relevant for my study. The final sample includes 793 hospitals that operate in a total of 6602 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 2020. 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, ratio of secured and unsecured liability to total liability, total debt and average monthly income and expenses are at 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 dateset.

Data for mortgage application and origination comes from 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 application, 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 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 in 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 using a lagged 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.

$$ZipPrice_{z,t} = \beta MLR_{z,t-1,t-3} + \tau_z + \mu_{st} + \varepsilon_{i,t}. \tag{10}$$
$$Y_{z,t} = \lambda \widehat{ZipPrice}_{z,t} + \kappa_z + \gamma_{st} + \varepsilon_{i,t}. \tag{11}$$

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.

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 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 are crucial to control for the aforementioned state-specific trends.

4 Results

4.1 Personal Bankruptcies

I begin by establishing certain salient facts 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 and year. The results show that increases in hospital prices are associated with 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 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 lagged insurer's medical loss ratio leads to a 2.3% increase in hospital prices.

Columns (2)-(5) of Table 4 present results for the second stage. The estimates from the headline specification in (11) imply a unit bankruptcy-price elasticity. In other words, every \$256 increase in hospital prices leads to a unit increase in total personal bankruptcy filings per zip-code on an 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 \$2560 increase in the cost of a liver transplant and an \$6912 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 either low-income individuals or are currently 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 an average report higher debt-to-income ratios and higher debt when exposed to higher hospital prices. The results show no decline in the reported 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. Bankruptcy filers also report higher proportion of secured debt on an 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 presents 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. Column (2) - (5) of Table 6 present results for the second stage. The dependent variable of interest are 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 \$64 increase in hospital prices corresponds to one fewer mortgage application in a zip code. The decline in mortgage originations are even more pronounced, suggesting that mortgage application are denied more often. In particular, a \$69 increase in hospital prices leads to one fewer mortgage origination. 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 debt-to-income ratio and insufficient cash are increasingly cited as reasons for loan denials when hospital price increases. 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 are still substantial among those in the higher income quintiles.

Additionally, I look at supplementary credit measures available from S&P CapitalIQ Pro's Geographic Intelligence datasets. Table 9 presents results for the second stage specifications studying the number of households holding credit card[10], home equity line of credit and average balance on these credits. The results indicate that an increase in hospital prices lead to increases in households' average credit card balance. This shows that medical debt can masquerade as credit card debt. The results also document that more households utilize home equity line of credit, demonstrating the role of home equity in helping households cope with increases in hospital bills.

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 capture the changing competitive landscape of the region. However, the prices of the peer hospital suffers 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

[10]The data provides separate figures for number of households with AMEX, VISA, Mastercard, Discover or bank credit card. Since bank credit card can overlap with the earlier four categories, I do not aggregate it.

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 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 "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 shows that neighboring hospitals which 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 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):

$$ZipPrice_{z,t} = \beta OmittedZipPrice_{z,t} + \tau_z + \mu_{st} + \varepsilon_{i,t}. \tag{14}$$

$$Y_{z,t} = \lambda \widehat{ZipPrice}_{z,t} + \kappa_z + \gamma_{st} + \varepsilon_{i,t}. \tag{15}$$

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 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 an average have lower out-of-pockets 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) document 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 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. The table reports the results for instrumented prices interacting with an indicator for whether a zip code has uninsured rate below or above the median in a given year. Regions with higher uninsured populations also tend to be economically disadvantaged. These areas also have higher take-up rates of Medicare and Medicaid. I include controls for zip code income, population, and Medicare and Medicaid coverage to isolate the impact of a lack of insurance coverage on financial outcomes. Figure 1 illustrates the findings from Table 10. 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 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)) Medicaid came into being as a result of the Social Security Amendments of 1965. Under this program, the spending by states governments in providing medical assistance to certain eligible residents were 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 11 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. I include time-varying controls for zip-level income, uninsured, medicare enrollment and population. Figure 2 illustrate the findings from the table. I find that Medicaid protects individuals severe financial deterioration, in that these regions see lower increases in bankruptcy. These regions also fair better in credit outcomes.

While Medicaid was targeted towards the low-income group, Medicare is a social insurance program funded by the federal government primarily focused on the elderly. Unlike Medicaid, the eligibility criteria for Medicare isn't state varying. Table 12 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. As before, I include time-varying controls. Figure 3 illustrate the findings from the table. Like Medicaid, Medicare does provide protection against severe financial deterioration. However, we see slightly higher mortgage application denials in regions with higher Medicare enrollment, more of them citing a high debt-to-income ratio. This could be an artifact of gaps in Medicare coverage. A majority of individuals enrolled under Medicare take additional coverage in the form of Medigap. These plans help enrolles share of cost covered by the original Medicare. However, these plans don't cover long-term care (like in a nursing home) which has a significant bearing on the cost of care borne by the elderly.

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 13 reports the results for instrumented prices interacting with an indicator for whether a zip code has people of color population below or above their median value in 2000. Figure 4 illustrate the findings from the table. 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 availability of liquid funds or the ability to access credit, the burden can steep specially in the presence of existing debt. Table 14 reports the results for instrumented prices interacting with an indicator for whether a zip code has median household income below or above their median value in 2000. Figure 5 illustrate the findings from the table. 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.

7 Home Equity Channel

In this section, I explore if 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 to 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 15. 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) find 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) highlight that regions with intermediate levels of supply elasticity witnessed larger booms or busts in the housing market. Nathanson and Zwick (2018) reconcile these facts and argue that land impact house price booms in two opposing ways. First, more land availability begets new construction softening house price increases, in what they call as 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 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 6 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 7 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. 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 and mortgage application denials 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 and loan application denials by financial institutions.

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 specification. Some of the outcome variables - i.e. the number of bankruptcies, mortgage application 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, percentage of uninsured population, percentage enrollment in Medicare and Medicaid insurance programs. 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.

Altenative 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 shock, 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.

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 patient's 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 financial, 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 accumulate more credit card debt and increasingly resort to 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.

In additional analysis, I illustrate that hospital prices have a dampening effect on 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 the financial well-being of consumers and underlines 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.

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Figure 1: Heterogeneity Tests: % Uninsured Population

This figure provides coefficients for instrument prices interacted with an indicator for below and above the median of percentage uninsured population in a zip for dependent variables chapter 7, chapter 13 and total bankruptcy, mortgage application denial rate, total mortgage application, proportion of denials citing high debt-to-income ratio and proportion of applications for second-lien mortgages. The price $log(ZipPrice_{z,t})$ 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. I include time-varying controls for income, total population, medicaid and medicare enrollment. The medians of uninsured population are time-varying.

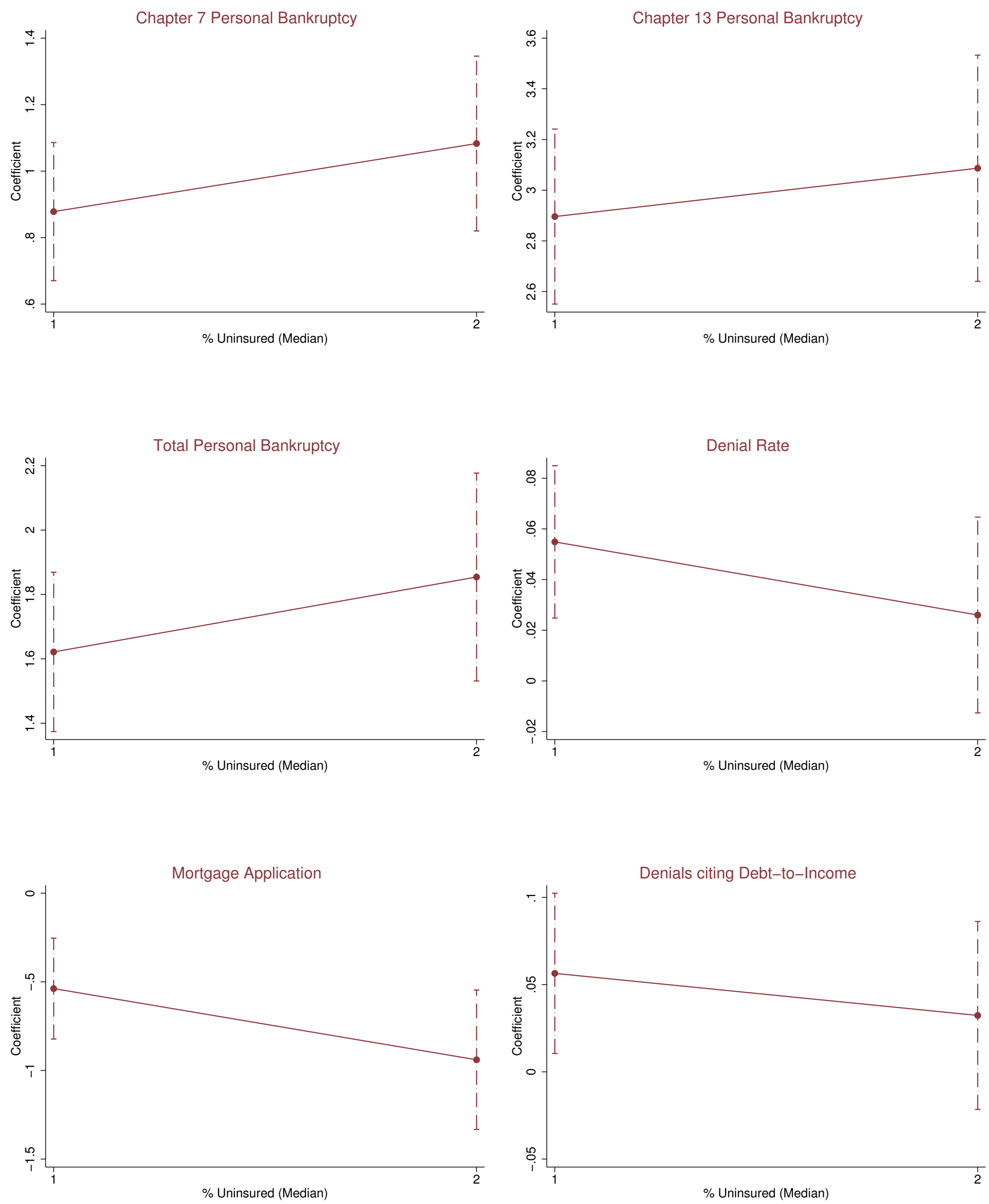

Figure 2: Heterogeneity Tests: Medicaid Enrollment

This figure provides coefficients for instrument prices interacted with an indicator for below and above the median of Medicaid enrollment in a zip for dependent variables chapter 7, chapter 13 and total bankruptcy, mortgage application denial rate, total mortgage application, proportion of denials citing high debt-to-income ratio and proportion of applications for second-lien mortgages. The price $log(ZipPrice_{z,t})$ 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. I include time-varying controls for income, total population, medicare enrollment and uninsured population. The medians of medicaid enrollment are time-varying.

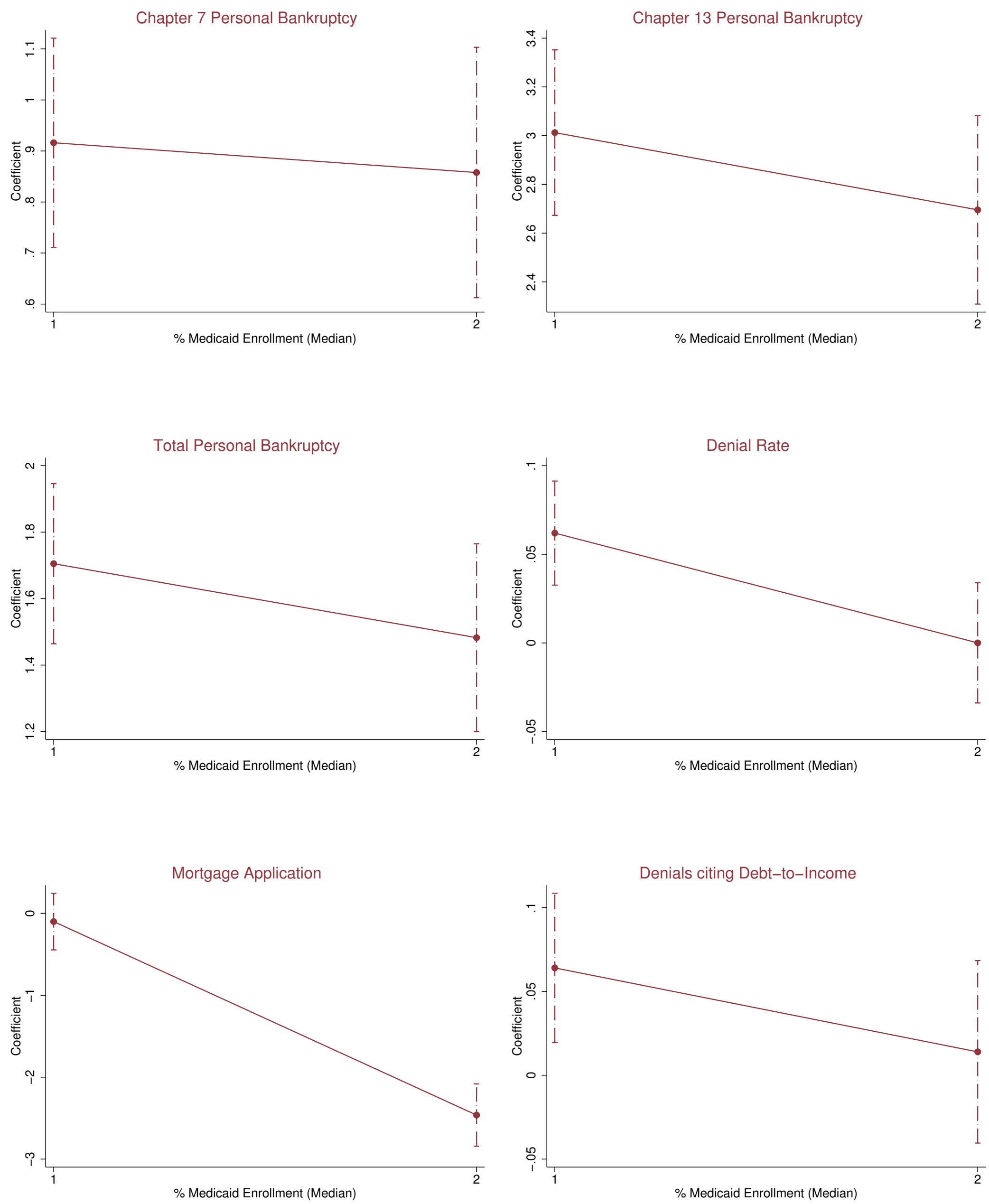

Figure 3: Heterogeneity Tests: Medicare Enrollment

This figure provides coefficients for instrument prices interacted with an indicator for below and above the median of Medicare enrollment in a zip for dependent variables chapter 7, chapter 13 and total bankruptcy, mortgage application denial rate, total mortgage application, proportion of denials citing high debt-to-income ratio and proportion of applications for second-lien mortgages. The price $log(ZipPrice_{z,t})$ 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. I include time-varying controls for income, total population, medicaid enrollment and uninsured population. The medians of Medicare enrollment are time-varying.

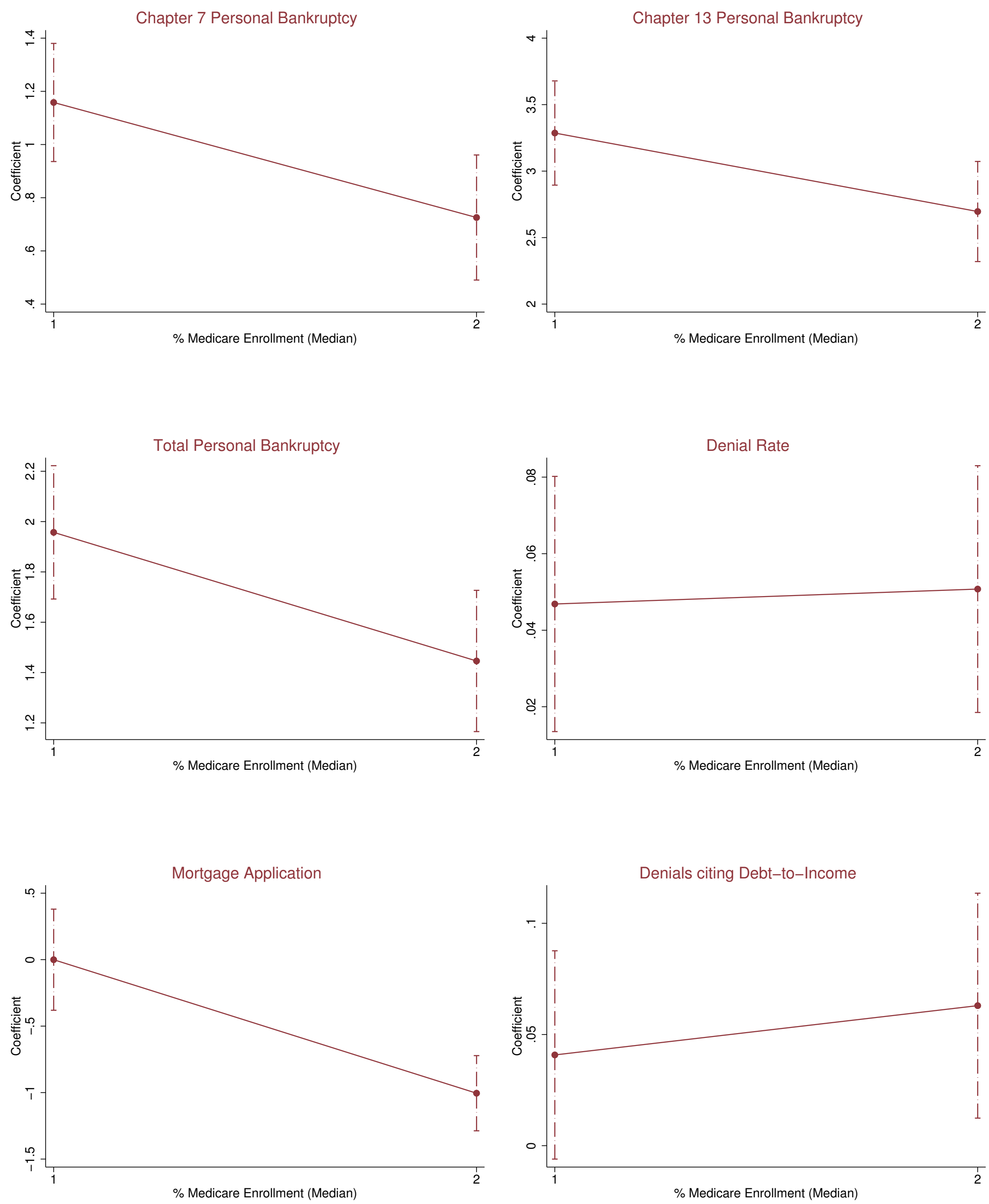

Figure 4: Heterogeneity Tests: % People of Color Population

This figure provides coefficients for instrument prices interacted with an indicator for below and above the median of people of color population in a zip for dependent variables chapter 7, chapter 13 and total bankruptcy, mortgage application denial rate, total mortgage application, proportion of denials citing high debt-to-income ratio and proportion of applications for second-lien mortgages. The price $log(ZipPrice_{z,t})$ 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. I include time-varying controls for income, total population, medicaid and medicare enrollment and uninsured population. The medians of people of color population are constructed for the zip z in year 2000.

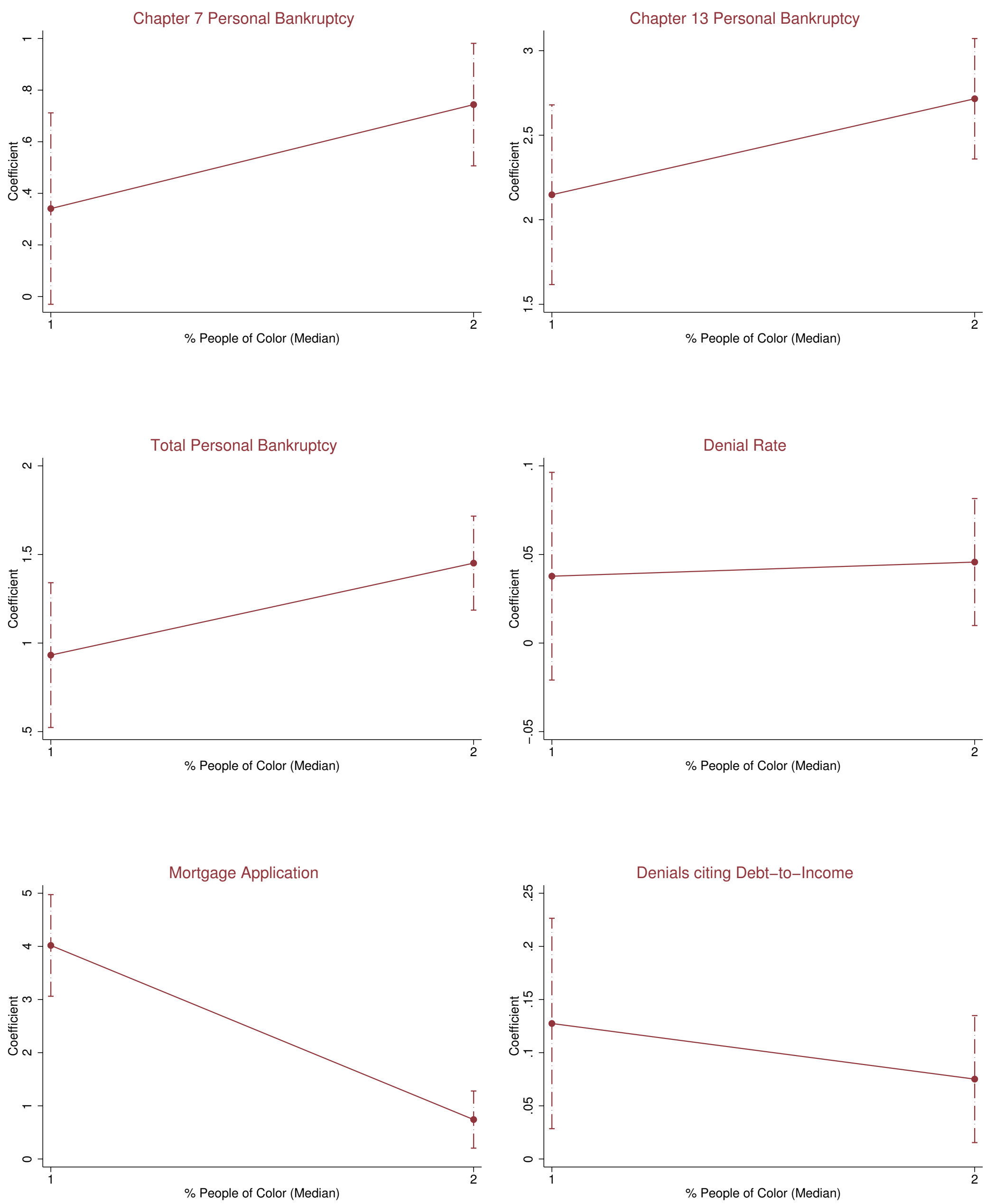

Figure 5: Heterogeneity Tests: Median Household Income

This figure provides coefficients for instrument prices interacted with an indicator for below and above the median of median household income in a zip for dependent variables chapter 7, chapter 13 and total bankruptcy, mortgage application denial rate, total mortgage application, proportion of denials citing high debt-to-income ratio and proportion of applications for second-lien mortgages. The price $log(ZipPrice_{z,t})$ 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. I include time-varying controls for income, total population, medicaid and medicare enrollment and uninsured population. The medians of median household income are constructed for the zip z in year 2000.

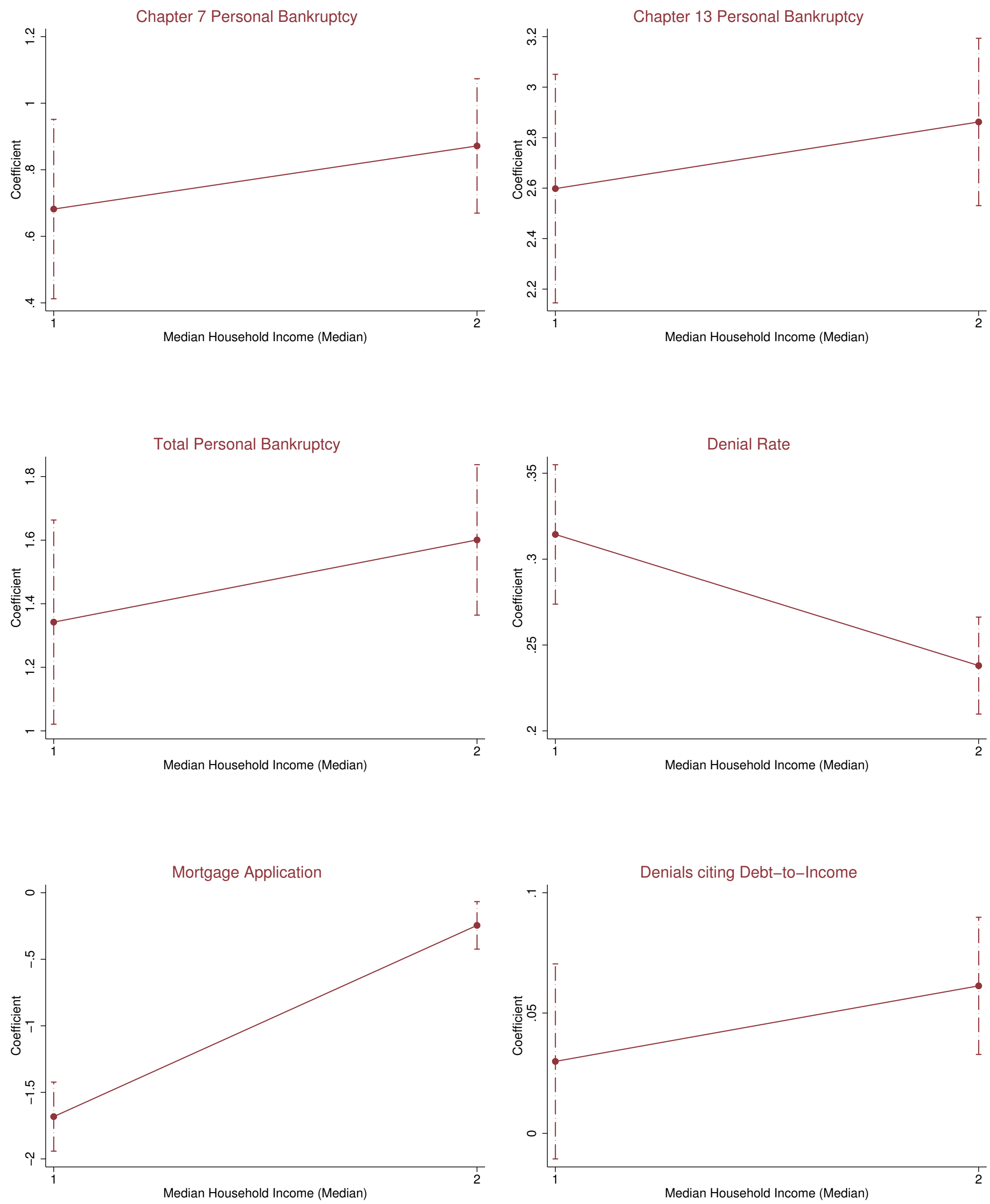

Figure 6: Supply Elasticity and Home Values

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 $MLR_{z,t-1,t-3}$ 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. I include time-varying controls for income, total population, medicaid and medicare enrollment and uninsured population.

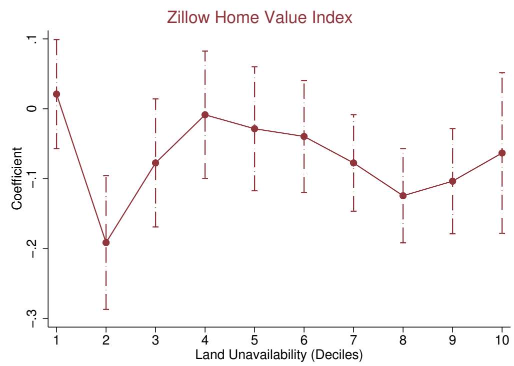

Figure 7: Home Equity Channel

This figure provides coefficients for instrument prices interacted with an indicator for the decile of land unavailability in a zip for dependent variables chapter 7, chapter 13 and total bankruptcy, mortgage application denial rate, total mortgage application and proportion of denials citing high debt-to-income ratio. The price $log(ZipPrice_{z,t})$ 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. I include time-varying controls for income, total population, medicaid and medicare enrollment and uninsured population.

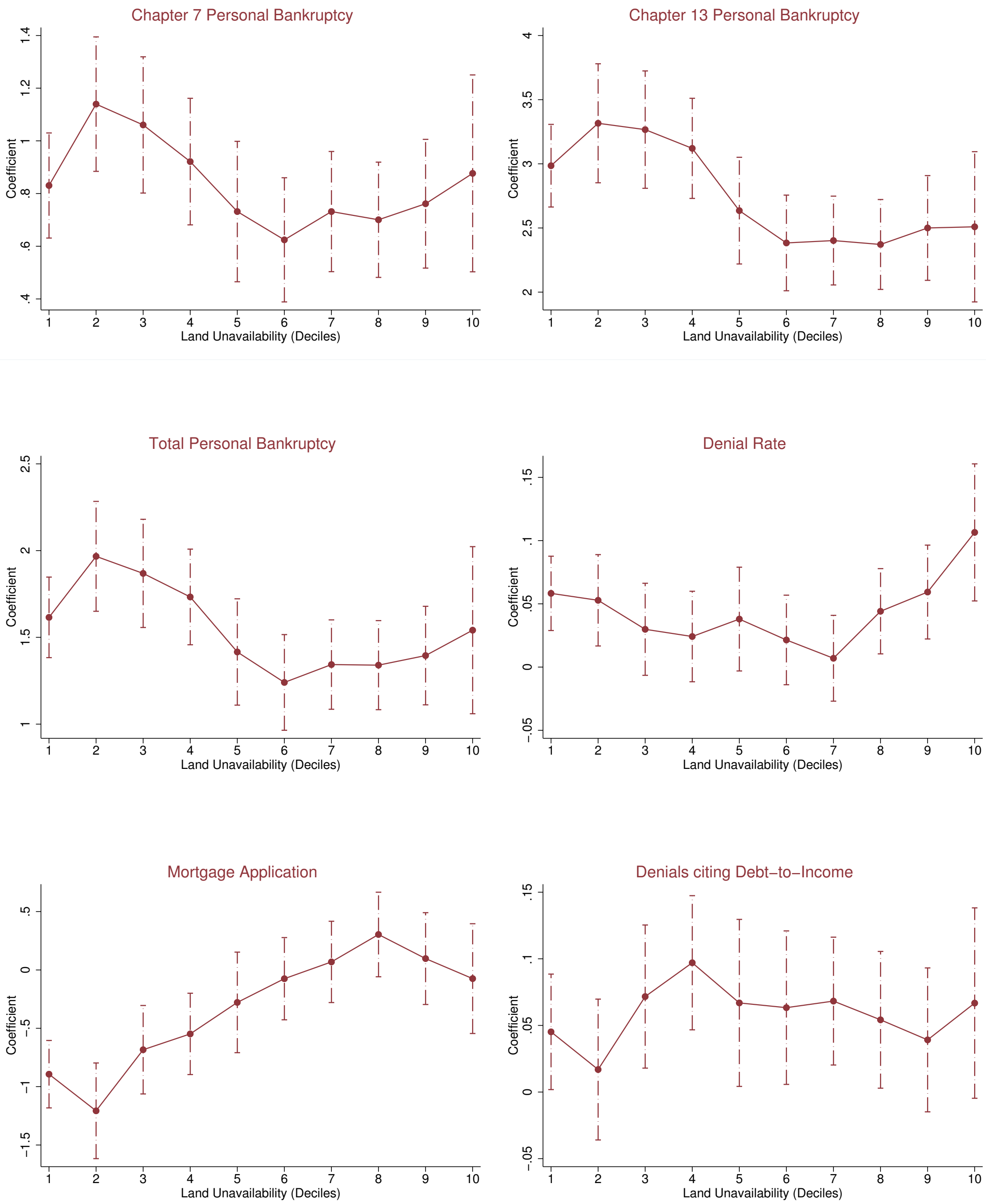

Table 1: Summary Statistics

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

	N	Mean	SD	p10	p25	Median	p75	p90
Panel A: Hospital Prices								
$ZipPrice_{z,t}$	80836	10695.76	3901.61	6271.83	7919.58	10082.83	12955.68	15958.83
$MLR_{z,t-1,t-3}$	78203	0.86	0.02	0.83	0.85	0.86	0.88	0.89
$OmittedZipPrice_{z,t}$	80669	9891.53	2821.54	6414.38	7413.98	9887.71	11754.92	13547.56
Panel B: FJCID								
Ch7 Bankruptcy	74580	20.52	36.94	0.00	1.00	5.00	24.00	61.00
Ch13 Bankruptcy	74580	7.57	16.22	0.00	0.00	1.00	7.00	22.00
Total Bankruptcy	74580	28.09	50.67	0.00	1.00	7.00	33.00	84.00
Bankruptcy w prior filing	74580	3.28	8.80	0.00	0.00	0.00	3.00	9.00
Debt-to-Income Ratio	1772188	7.21	11.57	0.82	1.66	3.72	7.31	15.30
Non-Priority Unsec/Liability	1945986	0.52	0.37	0.07	0.17	0.44	0.97	1.00
Secured/Liability	1947025	0.46	0.38	0.00	0.00	0.54	0.82	0.93
Total Debt	1925180	212542.35	222006.75	24671.10	48627.36	139744.00	300368.00	491199.84
Average Monthly Income	1951313	3483.84	2591.50	360.00	1600.00	3056.40	4866.66	6979.00
Average Monthly Expense	1962011	3262.32	1845.02	1283.40	1972.00	2918.00	4206.27	5697.00
Panel C: HMDA Database								
Mortgage Application	80836	236.44	420.23	0.00	10.00	68.00	295.00	661.00
Mortgage Origination	80836	172.85	312.08	0.00	6.00	46.00	209.00	492.00
Mortgage Application Denial	80836	63.58	123.04	0.00	3.00	18.00	79.00	168.00
Denial Rate	68208	0.29	0.14	0.14	0.20	0.27	0.36	0.48
% Second Lien Application	68208	0.09	0.08	0.00	0.03	0.06	0.13	0.21
Denial DTI	66467	0.19	0.12	0.00	0.11	0.18	0.25	0.33
Denial CRH	66467	0.19	0.13	0.00	0.11	0.17	0.25	0.33
Denial Collateral	66467	0.16	0.11	0.00	0.09	0.15	0.21	0.28
Denial Employment	66467	0.01	0.02	0.00	0.00	0.00	0.01	0.02
Denial Insufficient	66467	0.01	0.02	0.00	0.00	0.00	0.02	0.03
Panel D: SPCIQ Credit								
Credit Card HHs	29522	7467.49	8594.82	435.00	1123.00	3929.00	11503.00	19362.00
Avg Credit Card Balance	29474	3812.90	1301.39	2600.83	2924.96	3451.55	4344.35	5503.77
Bank Credit Card HHs	29522	4022.63	4602.62	239.00	624.00	2121.50	6232.00	10480.00
Avg Bank Card Balance	29522	6778.71	2443.34	4527.74	5129.57	6077.93	7793.38	10011.05
HELOC HHs	29522	400.49	441.09	26.00	68.00	230.00	604.00	1029.00
Avg HELOC balance	29522	27609.79	6957.91	18957.42	23196.90	26750.81	31569.50	36386.31

Table 2: Insurance Market Competition and Medical Loss Ratio

This table presents regression result from the OLS specification on Medical Loss Ratio. Observations are at the zip-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 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 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 result from the OLS specification on bankruptcy outcomes. 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 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.

	log(Ch7)	log(Ch13)	log(Total)	log(Prior)
	(1)	(2)	(3)	(4)
$log(ZipPrice_{z,t})$	0.039***	0.041***	0.045***	0.081***
	(0.010)	(0.011)	(0.010)	(0.009)
Zip-Code FE	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y
N	74524	74524	74524	74524
adj. R^2	0.938	0.889	0.946	0.833

Table 4: IV Specification: Bankruptcy Filings

This table presents regression result from the IV specification on bankruptcy 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 (2)-(5) reports 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 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					
$MLR_{z,t-1,t-3}$	1.631***				
	(0.114)				
$log(\widehat{ZipPrice}_{z,t})$		0.716***	2.371***	1.393***	2.292***
		(0.112)	(0.187)	(0.137)	(0.181)
Zip-Code FE	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y
N	68463	68463	68463	68463	68463
KP rk Wald F-stat	204.208				

Table 5: IV Specification: Bankruptcy Filer Characteristics

This table presents regression result 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 $MLR_{z,t-1,t-3}$ 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)-(6) reports 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, $P - Unsecured/Liability$ is the proportion of total priority unsecured liability in total liability, $Secured/Liability$ is the proportion of total secured liability in total liability, $Income$ is the average monthly income and $Expense$ is the average monthly expense of the bankruptcy filers in zip z in year t. For columns (1)-(3), 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	log(Total Debt)	log(Income)	log(Expense)
	(1)	(2)	(3)	(4)	(5)	(6)
Medical Loss Ratio IV						
$log(\widehat{ZipPrice}_{z,t})$	1.597^{*}	0.119^{***}	-0.028^{***}	0.264^{***}	-0.012	0.064
	(0.843)	(0.029)	(0.009)	(0.100)	(0.152)	(0.086)
Zip-Code FE	Y	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y	Y
N	1757301	1930675	1895447	1908988	1935002	1945620
KP rk Wald F-stat	52.104	45.974	45.859	47.189	47.418	46.644

Table 6: IV Specification: Mortgage Applications and Denials

This table presents regression result 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 (2)-(5) reports 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 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(Mort App)	log(Mort Org)	% Second Lien App	Denial Rate
	(1)	(2)	(3)	(4)	(5)
Medical Loss Ratio IV					
$MLR_{z,t-1,t-3}$	2.352***				
	(0.133)				
$log(\widehat{ZipPrice}_{z,t})$		−0.703***	−0.836***	0.030***	0.216***
		(0.139)	(0.131)	(0.009)	(0.019)
Zip-Code FE	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y
N	78148	78148	78148	66050	66050
KP rk Wald F-stat	312.197				

Table 7: IV Specification: Reasons for Mortgage Application Denials

This table presents regression result 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 $MLR_{z,t-1,t-3}$ 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)-(5) reports 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					
$log(\widehat{ZipPrice}_{z,t})$	0.079***	−0.079***	−0.055***	−0.005*	0.009**
	(0.017)	(0.020)	(0.016)	(0.003)	(0.003)
Zip-Code FE	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y
N	64394	64394	64394	64394	64394
KP rk Wald F-stat	274.451	274.451	274.451	274.451	274.451

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

This table presents regression result 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 $MLR_{z,t-1,t-3}$ 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)-(5) reports the results for the second stage instrumental variable regressions. $Income\,Qi$ is the denial rate for applications where the applicant income falls in quintile i, 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.

	Application Denials				
	Income Q1	Income Q2	Income Q3	Income Q4	Income Q5
	(1)	(2)	(3)	(4)	(5)
Medical Loss Ratio IV					
$log(\widehat{ZipPrice}_{z,t})$	0.427***	0.294***	0.168***	0.109***	0.043
	(0.036)	(0.031)	(0.029)	(0.029)	(0.038)
Zip-Code FE	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y
N	63096	63025	62677	61747	58439
KP rk Wald F-stat	262.818	264.227	256.408	252.175	224.586

Table 9: IV Specification: Additional Credit Outcomes

This table presents regression result from the IV specification on additional credit outcomes. 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)-(6) reports the results for the second stage instrumental variable regressions. $HH\,Credit\,Card$ is the number of households with Discover, AMEX, Mastercard or VISA credit cards, $Avg\,Credit\,Balance$ is the average reported balance of these credit cards, $HH\,Bank\,Cr\,Card$ is the number of households with bank credit card, $Bank\,Cr\,Card\,Amt$ is the average reported balance of these credit cards, $HH\,HELOC$ is the number of households with home equity line of credit (HELOC) and $Avg\,HELOC\,Balance$ is the average reported HELOC balance 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					
	log(HH Credit Card)	log(Avg Credit Balance)	log(HH Bank Cr Card)	log(Bank Cr Card Amt)	log(HH HELOC)	log(Avg HELOC Balance)
	(1)	(2)	(3)	(4)	(5)	(6)
Medical Loss Ratio IV						
$log(\widehat{ZipPrice}_{z,t})$	0.027	0.390^{**}	0.112	0.400^{**}	0.362^{**}	-1.680^{***}
	(0.143)	(0.173)	(0.129)	(0.193)	(0.142)	(0.481)
Zip-Code FE	Y	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y	Y
N	27127	27127	27127	27127	27127	27127
KP rk Wald F-stat	29.208	29.208	29.208	29.208	29.208	29.208

Table 10: Heterogeneity Test: % Uninsured Population

This table presents regression result 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 $MLR_{z,t-1,t-3}$ 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. The price has been interacted with an indicator variable $\mathbf{1}[X_{z,t} > Median]$ which takes value 1 if the zip z has uninsured rate above the median value in year t, and 0 otherwise. Columns (1)-(6) reports 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 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$_{z,t}$					
	log(Ch7)	log(Ch13)	log(Total)	Denial Rate	log(Mort App)	Denial DTI
	(1)	(2)	(3)	(4)	(5)	(6)
Medical Loss Ratio IV						
$\mathbf{1}[X_{z,t} < Median]log(\widehat{ZipPrice}_{z,t})$	0.878***	2.896***	1.622***	0.055***	−0.538***	0.056**
	(0.126)	(0.210)	(0.150)	(0.018)	(0.173)	(0.028)
$\mathbf{1}[X_{z,t} > Median]log(\widehat{ZipPrice}_{z,t})$	1.083***	3.087***	1.854***	0.026	−0.940***	0.032
	(0.160)	(0.271)	(0.196)	(0.023)	(0.239)	(0.033)
Zip-Code FE	Y	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y	Y
N	47397	47397	47397	47160	47420	46887
KP rk Wald F-stat	85.874	85.874	85.874	84.993	85.812	85.019

Table 11: Heterogeneity Test: % Medicaid Enrollment

This table presents regression result 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 $MLR_{z,t-1,t-3}$ 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. The price has been interacted with an indicator variable $\mathbf{1}[X_{z,t} > Median]$ which takes value 1 if the zip z has medicaid enrollment above the median value in year t, and 0 otherwise. Columns (1)-(6) reports 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 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$_{z,t}$					
	log(Ch7)	log(Ch13)	log(Total)	Denial Rate	log(Mort App)	Denial DTI
	(1)	(2)	(3)	(4)	(5)	(6)
Medical Loss Ratio IV						
$\mathbf{1}[X_{z,t} < Median]log(\widehat{ZipPrice}_{z,t})$	0.916***	3.013***	1.705***	0.062***	−0.100	0.064**
	(0.125)	(0.206)	(0.147)	(0.018)	(0.210)	(0.027)
$\mathbf{1}[X_{z,t} > Median]log(\widehat{ZipPrice}_{z,t})$	0.858***	2.696***	1.483***	0.000	−2.462***	0.014
	(0.149)	(0.235)	(0.172)	(0.021)	(0.231)	(0.033)
Zip-Code FE	Y	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y	Y
N	47397	47397	47397	47160	47420	46887
KP rk Wald F-stat	76.998	76.998	76.998	76.009	76.778	75.415

Table 12: Heterogeneity Test: % Medicare Enrollment

This table presents regression result 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 $MLR_{z,t-1,t-3}$ 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. The price has been interacted with an indicator variable $\mathbf{1}[X_{z,t} > Median]$ which takes value 1 if the zip z has medicare enrollment above the median value in year t, and 0 otherwise. Columns (1)-(6) reports 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 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$_{z,t}$					
	log(Ch7)	log(Ch13)	log(Total)	Denial Rate	log(Mort App)	Denial DTI
	(1)	(2)	(3)	(4)	(5)	(6)
Medical Loss Ratio IV						
$\mathbf{1}[X_{z,t} < Median]log(\widehat{ZipPrice}_{z,t})$	1.158***	3.287***	1.957***	0.047**	−0.000	0.041
	(0.135)	(0.238)	(0.161)	(0.020)	(0.231)	(0.028)
$\mathbf{1}[X_{z,t} > Median]log(\widehat{ZipPrice}_{z,t})$	0.726***	2.696***	1.446***	0.051***	−1.004***	0.063**
	(0.143)	(0.229)	(0.171)	(0.020)	(0.172)	(0.031)
Zip-Code FE	Y	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y	Y
N	47397	47397	47397	47160	47420	46887
KP rk Wald F-stat	92.905	92.905	92.905	91.165	92.727	90.531

Table 13: Heterogeneity Test: % People of Color

This table presents regression result 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 $MLR_{z,t-1,t-3}$ 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. The price has been interacted with an indicator variable $\mathbf{1}[X_z > Median]$ which takes value 1 if the zip z has people of color population above the median value in the year 2000, and 0 otherwise. Columns (1)-(6) reports 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 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 = % People of Color$_{2000}$					
	log(Ch7)	log(Ch13)	log(Total)	Denial Rate	log(Mort App)	Denial DTI
	(1)	(2)	(3)	(4)	(5)	(6)
Medical Loss Ratio IV						
$\mathbf{1}[X_z < Median]log(\widehat{ZipPrice}_{z,t})$	0.341	2.148***	0.932***	0.038	4.017***	0.127**
	(0.226)	(0.323)	(0.248)	(0.036)	(0.581)	(0.060)
$\mathbf{1}[X_z > Median]log(\widehat{ZipPrice}_{z,t})$	0.744***	2.716***	1.451***	0.046**	0.742**	0.075**
	(0.144)	(0.217)	(0.161)	(0.022)	(0.327)	(0.036)
Zip-Code FE	Y	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y	Y
N	47397	47397	47397	47160	47420	46887
KP rk Wald F-stat	39.873	39.873	39.873	36.951	39.560	36.346

Table 14: Heterogeneity Test: Median Household Income

This table presents regression result 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 $MLR_{z,t-1,t-3}$ 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. The price has been interacted with an indicator variable $\mathbf{1}[X_z > Median]$ which takes value 1 if the zip z has median household income above the median value in the year 2000, and 0 otherwise. Columns (1)-(6) reports 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 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 = Median Household Income_{2000}					
	log(Ch7)	log(Ch13)	log(Total)	Denial Rate	log(Mort App)	Denial DTI
	(1)	(2)	(3)	(4)	(5)	(6)
Medical Loss Ratio IV						
$\mathbf{1}[X_z < Median]log(\widehat{ZipPrice}_{z,t})$	0.682***	2.598***	1.342***	0.314***	−1.682***	0.030
	(0.164)	(0.275)	(0.195)	(0.025)	(0.158)	(0.025)
$\mathbf{1}[X_{z,t} > Median]log(\widehat{ZipPrice}_{z,t})$	0.872***	2.862***	1.601***	0.238***	−0.245**	0.061***
	(0.123)	(0.202)	(0.144)	(0.017)	(0.108)	(0.017)
Zip-Code FE	Y	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y	Y
N	47993	47993	47993	53970	55468	53458
KP rk Wald F-stat	64.291	64.291	64.291	118.981	123.387	118.688

Table 15: IV Specification: Zillow Home Value Index

This table presents regression result 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 (2) reports the results for the second stage instrumental variable regressions. $ZHVI$ is the log value of Zillow House Price Index 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.

	First Stage	Second Stage
	$log(ZipPrice_{z,t})$	log(ZHVI)
	(1)	(2)
Medical Loss Ratio IV		
$MLR_{z,t-1,t-3}$	2.410^{***}	
	(0.128)	
$log(\widehat{ZipPrice}_{z,t})$		-0.190^{***}
		(0.033)
Zip-Code FE	Y	Y
State-Year FE	Y	Y
N	55965	55965
KP rk Wald F-stat	351.920	351.920

Appendix

A.1 Alternative Identification Strategy

Figure A1.1: Omitted Peer of a Hospital

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

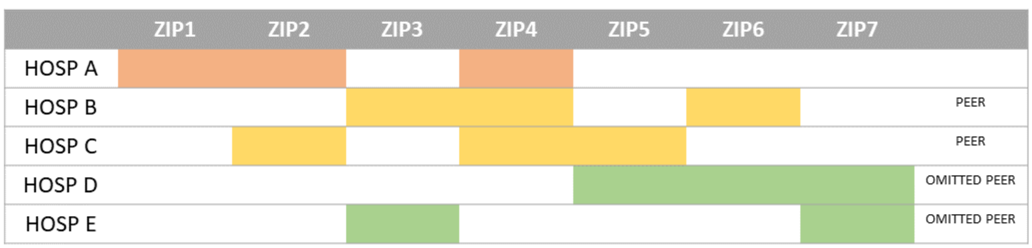

Table A1.1: IV Specification: Bankruptcy Filings

This table presents regression result from the IV specification on bankruptcy 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) reports 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 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					
$log(OmittedZipPrice_{z,t})$	0.102***				
	(0.009)				
$log(\widehat{ZipPrice}_{z,t})$		0.456***	1.488***	1.010***	1.371***
		(0.155)	(0.205)	(0.171)	(0.189)
Zip-Code FE	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y
N	74408	74408	74408	74408	74408
KP rk Wald F-stat	131.442				

Table A1.2: IV Specification: Bankruptcy Filer Characteristics

This table presents regression result 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, $P-Unsecured/Liability$ is the proportion of total priority unsecured liability in total liability, $Secured/Liability$ is the proportion of total secured liability in total liability, $Income$ is the average monthly income and $Expense$ is the average monthly expense of the bankruptcy filers in zip z in year t. For columns (1)-(3), 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	log(Total Debt)	log(Income)	log(Expense)
	(1)	(2)	(3)	(4)	(5)	(6)
Omitted Peer Price IV						
$log(\widehat{ZipPrice}_{z,t})$	10.582**	0.472**	−0.183**	2.936**	1.792*	2.995**
	(5.276)	(0.201)	(0.081)	(1.256)	(0.950)	(1.277)
Zip-Code FE	Y	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y	Y
N	1769575	1944242	1908905	1922412	1948559	1959222
KP rk Wald F-stat	5.185	6.088	5.561	5.493	5.856	5.969

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

This table presents regression result 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) reports 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 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(Mort App)	log(Mort Org)	% Second Lien App	Denial Rate
	(1)	(2)	(3)	(4)	(5)
Omitted Peer Price IV					
$log(OmittedZipPrice_{z,t})$	0.153***				
	(0.009)				
$log(\widehat{ZipPrice}_{z,t})$		−0.316	−0.646***	−0.015	0.309***
		(0.265)	(0.247)	(0.013)	(0.028)
Zip-Code FE	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y
N	80631	80631	80631	68009	68009
KP rk Wald F-stat	292.664				

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

This table presents regression result 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) reports 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					
$log(\widehat{ZipPrice}_{z,t})$	0.064**	−0.142***	−0.122***	−0.008**	−0.004
	(0.025)	(0.028)	(0.024)	(0.004)	(0.006)
Zip-Code FE	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y
N	66262	66262	66262	66262	66262
KP rk Wald F-stat	287.775	287.775	287.775	287.775	287.775

A.2 Robustness Tests

Table A2.1: Robustness: Population Scaled Count Variables

This table presents regression result from the IV specification on bankruptcy 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 (2)-(5) reports 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 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						
$log(\widehat{ZipPrice}_{z,t})$	1.371***	2.430***	3.801***	0.981***	−11.088***	−14.014***
	(0.332)	(0.246)	(0.464)	(0.141)	(2.523)	(1.868)
Zip-Code FE	Y	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y	Y
N	53743	53743	53743	53743	63190	63190
KP rk Wald F-stat	171.231	171.231	171.231	171.231	242.955	242.955

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

This table presents regression result from the IV specification on bankruptcy 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) reports 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 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			
	log(Ch7)	log(Ch13)	log(Total)	log(Prior)
	(1)	(2)	(3)	(4)
Medical Loss Ratio IV				
$log(\widehat{ZipPrice}_{z,t})$	0.901***	2.953***	1.659***	2.667***
	(0.127)	(0.213)	(0.152)	(0.203)
Controls	Y	Y	Y	Y
Zip-Code FE	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y
N	47382	47382	47382	47382
KP rk Wald F-stat	183.243	183.243	183.243	183.243

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

This table presents regression result 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 (2)-(5) reports 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 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									
$log(\widehat{ZipPrice}_{z,t})$	-0.587^{***}	-0.589^{***}	0.052^{***}	0.170^{***}	0.054^{*}	-0.010	-0.187^{***}	-0.001	0.008
	(0.176)	(0.172)	(0.019)	(0.016)	(0.028)	(0.031)	(0.028)	(0.006)	(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	47403	47403	47149	47149	46877	46877	46877	46877	46877
KP rk Wald F-stat	182.916	182.916	179.967	179.967	178.608	178.608	178.608	178.608	178.608

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

This table presents regression result from the IV specification on bankruptcy 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) reports 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 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			
	log(Ch7)	log(Ch13)	log(Total)	log(Prior)
	(1)	(2)	(3)	(4)
Medical Loss Ratio IV				
$log(\widehat{ZipPrice}_{z,t})$	0.731***	2.515***	1.466***	2.448***
	(0.119)	(0.192)	(0.144)	(0.185)
Zip-Code FE	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y
N	69750	69750	69750	69750
KP rk Wald F-stat	235.002	235.002	235.002	235.002

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

This table presents regression result 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 (2)-(5) reports 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 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									
$log(\widehat{ZipPrice}_{z,t})$	-0.831^{***}	-0.976^{***}	0.257^{***}	0.037^{***}	0.095^{***}	-0.092^{***}	-0.068^{***}	-0.006^{*}	0.010^{**}
	(0.165)	(0.156)	(0.024)	(0.010)	(0.021)	(0.024)	(0.019)	(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	79717	79717	67088	67088	65348	65348	65348	65348	65348
KP rk Wald F-stat	285.320	285.320	271.496	271.496	268.974	268.974	268.974	268.974	268.974

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

This table presents regression result from the IV specification on bankruptcy 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) reports 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 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			
	log(Ch7)	log(Ch13)	log(Total)	log(Prior)
	(1)	(2)	(3)	(4)
Medical Loss Ratio IV				
$log(\widehat{ZipPrice}_{z,t})$	0.695***	2.710***	1.496***	2.757***
	(0.144)	(0.268)	(0.185)	(0.268)
Zip-Code FE	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y
N	56990	56990	56990	56990
KP rk Wald F-stat	122.740	122.740	122.740	122.740

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

This table presents regression result 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 (2)-(5) reports 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 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									
$log(\widehat{ZipPrice}_{z,t})$	−0.075	−0.315***	0.241***	0.023***	0.093***	−0.093***	−0.021	−0.006*	0.008**
	(0.120)	(0.112)	(0.020)	(0.009)	(0.018)	(0.021)	(0.017)	(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	66594	66594	56826	56826	55416	55416	55416	55416	55416
KP rk Wald F-stat	276.441	276.441	244.387	244.387	242.239	242.239	242.239	242.239	242.239