I Z A Institute
of Labor Economics
Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 16448

The Impact of Hospital Closures on Medical Debt in Collections: Analysis Using Consumer Credit Bureau Data

Jennifer Andre
Fredric Blavin
Breno Braga
Anuj Gangopadhyaya

SEPTEMBER 2023

I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 16448

The Impact of Hospital Closures on Medical Debt in Collections: Analysis Using Consumer Credit Bureau Data

Jennifer Andre
Urban Institute

Fredric Blavin
Urban Institute

Breno Braga
Urban Institute and IZA

Anuj Gangopadhyaya
Loyola University Chicago

SEPTEMBER 2023

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

The Impact of Hospital Closures on Medical Debt in Collections: Analysis Using Consumer Credit Bureau Data*

This study presents new evidence on the potential detrimental effects of hospital closures. We examine how hospital closures affect the likelihood of incurring medical debt. Hospital closures can increase market concentration by removing a competitor from the market. Closures can also have negative spillover effects on the local economy and affect the population's ability to pay their bills. We combine 2011-2020 consumer credit bureau data with information on hospital closures from 2014-2018 to assess the relationship between closures and medical debt. Using a stacked event study approach, we find that a closure that reduces hospital supply in a Hospital Referral Region (HRR) by 10 percent is associated with a 4 percent increase in the share of consumers with medical debt, with larger effects in HRRs that are urban and have higher rates of poverty. Moreover, we find that a hospital closure is associated with about a 6-8 percent increase in hospital market concentration. These findings suggest that the primary mechanism through which hospital closures affect medical debt is by reducing hospital competition in local markets.

JEL Classification: I11, I14, I18

Keywords: medical debt, hospital closures, hospital competition

Corresponding author:
Breno Braga
Urban Institute
500 L'Enfant Plaza SW
Washington, DC 20024
USA
E-mail: bbraga@urban.org

* This paper was funded by Arnold Ventures. We are grateful to Chris Whaley and the seminar participants of the American Society of Health Economist (ASHEcon) conference and the Urban Institute for their helpful comments.

1. Introduction

Medical debt is a critical challenge to Americans' financial stability and well-being. In 2022, about 4 in 10 US adults reported some form of medical debt, and 1 in 8 consumers had medical debt in collections on their credit reports (Lopes et al. 2022; Urban Institute 2022). Medical debt represents 58 percent of all debt in collections, resulting in damaged credit scores that affect a person's access to credit and their ability to rent or buy a home and find employment (CFPB 2022). Medical debt is also associated with a greater likelihood of forgoing needed health care, having difficulty meeting other basic needs, experiencing food and housing insecurity, and facing an increased risk of bankruptcy (Himmelstein et al. 2022; Rabin et al. 2020; Dobkin et al. 2018; Hamel et al. 2016).

On the consumer side, medical debt is most prevalent among people of color, people with disabilities or chronic health conditions, uninsured and underinsured adults, families with low incomes, and residents of states that did not expand Medicaid under the Affordable Care Act (ACA) (Lopes et al. 2022; Karpman et al. 2022; Bennett et al. 2021; Kluender et al. 2021). Although health insurance coverage and Medicaid expansion play an important role in reducing medical debt in collections, most medical debt is incurred by people who had insurance at the time the debt was incurred due to cost-sharing and limitations on covered services (Finkelstein et al. 2012; Caswell and Waidmann 2017; Karpman and Long 2015).

Medical debt may also reflect provider practices that increase the risk of unexpectedly high medical bills. For instance, the rate at which patients receive surprise bills for out-of-network care varies widely across states and hospitals (Pollitz et al. 2020; Sun et al. 2019). Some evidence shows that hospital systems are also becoming increasingly aggressive in collecting payments by filing lawsuits and garnishing wages. For example, hospital lawsuits against patients in Wisconsin increased 37 percent between 2001 and 2018, disproportionately affecting Black patients and patients in low-income communities (Cooper, Han, and Mahoney 2021). Researchers and journalists have also used court records data to highlight the frequency with which hospitals sue patients for unpaid medical bills, which can result in wage and bank account garnishments or liens placed on homes (Bruhn et al. 2019; Kliff 2019; McGhee and Chase 2023).

In this analysis, we examine how hospital closures affect the risk of consumers incurring medical debt. We combine 2011–2020 consumer credit bureau data with information on hospital closures from 2014–2018 to assess the relationship between hospital closures and medical debt in collections. Using a stacked event study approach, we compare medical debt in collections among residents of hospital referral regions (HRRs) that experienced a hospital closure with residents of HRRs that did not experience a hospital closure. We compare trends in medical debt between our treatment and comparison groups in the three years before and after a closure.

Hospital closures can affect medical debt through multiple pathways. Hospital closures can increase market concentration by removing a competitor from the market, which, in turn, can increase remaining providers' pricing power and lead to higher prices charged to commercial payers. Multiple studies find that market concentration is associated with higher hospital prices, with price increases often exceeding 20 percent when mergers occur in already concentrated markets (Gaynor 2020; Cooper et al. 2019; Gaynor, Ho, and Town 2015; Gaynor and Town 2012; Fulton 2017; Dafny 2009). Anecdotal evidence also suggests that a lack of hospital competition can make healthcare providers more aggressive in collecting unpaid bills and reduce the availability of financial assistance (e.g., charity care), which represents an additional potential mechanism through which increasingly concentrated market power may translate into greater medical debt (Hancock and Lucas 2019).

Other potential mechanisms through which hospital closures can affect medical debt may have ambiguous directions. For example, while rural hospital closures can have negative spillover effects on the local economy and affect the population's ability to pay their bills (Holmes et al. 2006; Vogler 2021; Alexander and Richards 2023), the loss of employer-sponsored health insurance following a closure can also lead to reductions in health care utilization, and in turn medical debt, especially if the closing hospital is a large employer relative to the size of the community. In addition, empirical evidence suggests rural hospital closures result in lower availability of nearby hospital services and short-term reductions in the use of hospital services, particularly for non-urgent care, which in turn could lower short-term medical debt (Carroll 2019). However, by reducing access to and use of hospital services, hospital closures are also associated with increasing the mortality risk for heart attacks, unintentional injuries, and time-sensitive conditions (Carroll 2019; Shen and Hsia 2012; Buchmueller, Jacobson, and Wold 2006; Gujral and Basu 2019; Wishner et al. 2016). This increase in health risk and intensive care can in turn lead to an increase in medical debt, as previous research has shown that poor local health status is a strong predictor of medical debt (Blavin, Braga, and Gangopadhyaya 2022).

Overall, we find that, compared to HRRs that experience no hospital closures over the same period, a hospital closure that reduces total hospital supply in an HRR by about 10 percent is associated with about a 4 percent increase in the share of consumers with medical debt in collections, with larger effects in HRRs that are urban, have higher rates of poverty, and, somewhat surprisingly, in states that expanded Medicaid under the ACA. We find that these effects do not persist beyond the first two years of a hospital closure. In terms of mechanisms, we find that a 10 percent reduction in hospital supply due to closures is associated with about a

7–8 percent reduction in the number of hospital entities and a 6–8 percent increase in hospital market concentration, as measured by the Herfindahl-Hirschman Index (HHI). These findings suggest that one of the primary mechanism through which hospital closures affect medical debt is by reducing hospital competition in local markets.

This analysis contributes to the growing literature on the determinants of medical debt. While past work has studied the importance of health insurance coverage and local health and socioeconomic outcomes (Caswell and Waidmann 2017; Blavin Braga, and Gangopadhyaya 2022), to our knowledge this is the first study to assess hospital closures as a potential driver of medical debt. In addition, this study adds to the extensive literature on the potential detrimental effects of hospital closures on patient distances and travel times, mortality rates for time-sensitive conditions, and quality of care (Shen and Hsia 2012; Bazzoli et al. 2012; McCarthy et al. 2021; Carroll 2019; Buchmueller, Jacobson, and Wold 2006; Gujral and Basu 2019). Findings from this study can also inform policymakers on the potential harm to consumers of hospital closures and other actions that can increase market concentration (i.e., mergers and acquisitions). This study is particularly pertinent as policymakers have increasingly focused on the role of hospital billing and collection practices in contributing to medical debt, as shown by the enactment of the No Surprises Act of 2020, which aims to provide federal protections to consumers against surprise out-of-network medical bills, along with various state laws.

2. Methodology

2.1 Data

Our primary outcome is an indicator for whether the consumer has medical debt in collections, meaning debt from a health care provider that was sent to a third-party collector or assigned to a creditor's internal collections department. Debt in collections is normally at least 180 days past due, where the creditor acted to collect the unpaid debt but was unsuccessful. To measure medical debt in collections, we use the Urban Institute longitudinal credit bureau data, which is a nationally representative sample of depersonalized consumer data from a major credit bureau and has been used in several prior analyses (Caswell and Goddeeris 2020; Caswell and Waidmamn 2017; Braga and Oglesby-Neal 2023; Andre et al. 2023). We use data collected from August 2011 through August 2020, including a two percent sample of consumers in each year from 2011 through 2019 (i.e., over 5 million consumers in each year) and a four percent sample in 2020 (i.e., over 10 million consumers). All records were stripped of personally identifiable information, and no data on race and ethnicity, gender, or income were included; however, we do use information on a consumer's age and their zip code of residence. Based on the consumer's residential zip code, we identify the consumer's HRR of residence using crosswalk files from the Dartmouth Atlas of Health Care. For computational feasibility, we estimate our models at the zip code level, weighting each observation by the number of consumers sampled in the zip code.

The credit bureau data have three important limitations. First, we observe only the stock (collection balance), and we do not observe flows of new collections. Second, a debt appears in the credit record data at the time it was reported to the credit bureau as being in collections, not at the time the debt was initially incurred. Finally, we do not observe demographic or socioeconomic characteristics such as income or health insurance status for individual consumers. Instead, we utilize the characteristics of their local communities defined by Zip Code Tabulation Areas, or ZCTAs.

We supplement the credit bureau data with the 2011–2020 American Hospital Association's Annual Survey Database (AHASD) to identify hospital closures and measure market concentration. We restrict our analysis to hospitals providing general acute care and exclude federal hospitals and hospitals providing specialty care. We use AHASD information on hospital additions and deletions each year and the recorded explanation for each addition or deletion (e.g., "hospital closed") to identify hospital closures. We obtain geographic information for each hospital and closing hospital, including the HRR in which they are located.

To assess potential mechanisms, we use each hospital's adjusted admissions and system affiliation to construct the HHI, a common measure of market concentration, for each HRR. The HHI is calculated by squaring the market share of each unique system and independent hospital competing in the HRR and then summing the resulting numbers. We also assess the effect of hospital closures on the number of hospitals in the HRR. In both instances, we log transform the number of hospitals and HHI to deal with the skewness of each outcome and for ease of interpretation.

To provide contextual information on zip codes of consumers' residence in the credit bureau data, we merge in data on average household income, share of families with incomes below the poverty line, share uninsured, and racial-ethnic composition using the Census Bureau 5-year American Community Survey. We use 5-year period estimates from years 2007–2011 through 2016–2020 and merge these with the credit data, matching the final year in the period with the year of the credit data extract. We also identify zip codes as urban or rural using 2010 Rural-Urban Commuting Area codes from the US Department of Agriculture and the WWAMI Rural Health Research Center. Finally, we include an indicator for Medicaid expansion status based on the credit bureau data extract year and the consumer's state of residence.

We also use these contextual factors to stratify the sample by poverty status, rurality, and Medicaid expansion status. To investigate heterogeneous effects by poverty status, we compare zip codes with a family poverty rate above the yearly median rate (for at least 50 percent of the years the zip code appears in the credit bureau data) with the remaining below-median zip codes. To investigate heterogeneous effects by rurality, we first construct an HRR-level measure of rurality by finding the share of HRR consumers (in 2011) living in a rural zip code, and then split the HRRs relative to the median HRR-level rurality value. Finally, for Medicaid expansion status, we categorize zip codes as being in states that (1) expanded Medicaid in 2014, (2) expanded Medicaid between 2015 and 2018, and (3) expanded Medicaid after 2018 or not at all.

2.2 Empirical Approach

Estimating the impact of hospital closures on medical debt in collections is challenging because hospital markets experiencing a closure may be distinct from markets that do not experience a closure in many other ways that could, in turn, be related to medical debt. To address this endogeneity problem, we use an event study analysis that compares changes in trends in medical debt in collections in HRRs that do and do not experience a closure (hereafter referred to as treatment and comparison HRRs, respectively). To address some of the well-documented methodological problems of using earlier-treated HRRs as comparison HRRs in later years (e.g., Callaway, Goodman-Bacon, and Sant'anna 2021; Goodman-Bacon 2020), we use a stacked regression approach to estimate our event study model. We construct year-specific analytic samples for closures that occurred for each individual year between 2014 and 2018—which we call panels. For each of these panels, we use information from 3 years pre- and 3 years post-closure date (including the year of closure), thus constructing a unique 6-year window for each hospital closure. We designate all HRRs that experience a hospital closure in that year as treated *for that panel*; all HRRs that do not experience a closure in the 6-year window for the panel are the comparison HRRs. We then pool, or stack, each of these 6-year panels in a single estimating equation, described below:

$$(1)\quad Y_{zhtc} = \sum_{k=-3}^{2} \alpha_k (RelativeYear_k) + \sum_{k=-3}^{2} \delta_k \, (RelativeYear_k * Treat_{hc}) + \beta(Treat_{hc}) + \theta_h + \lambda_c + \Gamma' X_{zt} + \epsilon_{zhtc}$$

Where Y measures the share of adults with medical debt in collections in zip code z, HRR h, time period t, which is a date centered around the closure year for each panel, and panel c, representing each of the distinct 6-year panels. The estimating equation includes indicators for the year relative to the closure year ($RelativeYear_k$), a treatment variable ($Treat_{hc}$), and interactions between the relative year and the treatment variable. We further include HRR fixed effects (θ_h) and indicators for each of the unique 6-year panels that have been stacked together (λ_c). Because HRRs that experience closures in later years can serve as comparison HRRs in earlier closure panels, treatment varies at the HRR by closure year level. Moreover, for this reason, HRR fixed effects are not collinear with the closure year indicators or the main effect. HRRs that experience closures in earlier years cannot serve as comparison HRRs in later closure panels.

To control for changes in secular trends in medical debt related to major national policies and macroeconomic shocks, all regressions include calendar year fixed effects. We also control for several zip code level contextual factors including the share of the population uninsured, the share of families in poverty, the log of the average household income, racial and ethnic composition, an indicator for the rurality of the zip code, an indicator for whether the state the zip code is in has expanded Medicaid under the ACA (X_{zt}), and the zip code–level age distribution of consumers with a credit record. All regressions are weighted for the number of consumers in each zip code in our credit bureau sample. In all models, standard errors are clustered by HRR, the level at which treatment varies in this analysis.

We express $Treat_{hc}$ as a dosage variable, defined as the proportion of hospitals in the HRR in the year before treatment that experience closure in the treatment year—this helps characterize the magnitude of a hospital closure based on the number of other hospitals available to patients. As a sensitivity test, we also define $Treat_{hc}$ as a binary indicator for whether an HRR experiences a hospital closure. We omit the year before closure and set this as the reference period. These interactions then produce two pre-closure coefficients (δ_{-3}, δ_{-2}) and three post-closure coefficients ($\delta_0, \delta_1, \delta_2$).

The basic identifying assumption of this methodological approach is that, in the absence of hospital closures, the trends in the share of adults with medical debt in collections would have been similar in treated and comparison HRRs. Observing distinct trends in this outcome before the closure occurs would suggest the parallel trends assumption does not hold. Thus, in estimating (1), the two pre-closure coefficients on the interaction terms (δ_{-3}, δ_{-2}) test for whether the parallel trends assumption holds before treatment. Beyond *t*-testing for the significance of these individual parameters, we also use an *F*-test to assess whether the two pre-closure coefficients are jointly significant. The three post-closure coefficients on the interaction terms ($\delta_0, \delta_1, \delta_2$) estimate whether hospital closures affected outcome trends in treated HRRs relative to comparison HRRs, and, specifically, whether the impact, if any, is persistent across multiple years.

Additionally, using a continuous treatment variable requires making additional assumptions about the paths of outcomes among treated HRRs (Callaway, Goodman-Bacon, Sant'Anna 2021); we are not only drawing comparisons between HRRs that did and did not experience closures but also between HRRs that experienced closures that affected hospital markets to varying degrees. Thus, an additional assumption we make throughout this analysis is that outcomes in higher-dosage HRRs (i.e., HRRs in which hospital closures in the treatment year represent a large share of the available hospitals in the area) would have evolved similarly as HRRs with lower treatment dosage *at the lower treatment level*. We cannot explicitly test this assumption with our research design. To address this limitation, we supplement our main specification with a binary $Treat_{hc}$ indicator (a 0–1 indicator for any closure in the HRR) that solely depends on the basic parallel trends assumptions between treated and untreated HRRs discussed above.

3. Results

3.1 Summary Statistics

Table 1 summarizes the 2011 baseline characteristics of our analytical sample separately for HRRs that experienced a hospital closure and those that did not experience a closure between 2014 and 2018. The sample includes 75 treated HRRs that experienced at least one hospital closure, representing approximately 2 million consumers in the credit bureau data, and 231 comparison HRRs, representing approximately 3.2 million consumers.

Average credit scores were slightly lower for consumers living in treatment HRRs than for consumers in comparison HRRs (656 vs. 667, respectively). However, treatment HRRs had a higher percentage of uninsured adults (18 percent) and families below the poverty line (12 percent) compared to comparison HRRs (15 and 10 percent, respectively) at baseline. Moreover, the average 2011 household income in treated HRRs was $4,300 (6 percent) lower than in all other HRRs. Approximately 15 percent of consumers in both groups reside in rural zip codes, and the age compositions were similar in both groups. HRRs that experienced closures had a smaller share of non-Hispanic white adults (8 percentage points lower) and a higher share of Hispanic adults (5 percentage points higher). The geographic distribution of consumers in comparison HRRs was even across the four Census regions, whereas more than half of consumers in treated HRRs (51percent) were in the South, 26 percent were in the West, 16 percent were in the Midwest, and less than 10 percent were in the Northeast.

3.2 Hospital Closures and the Incidence of Medical Debt in Collections

During the year of closure (year 0) and the subsequent year, the incidence of medical debt in collections increased in treatment HRRs compared to HRRs that did not experience closures during the same period (Figure 1; point estimates are reported in Appendix Table 1). The closure of approximately 10 percent of hospitals within an HRR was associated with a 0.70 percentage point increase in medical debt in collections during the closure year and a 0.76 percentage point increase in the following year, and both estimates were statistically significant. These effects represent about a 4 percent increase in the share of adults with medical debt relative to the baseline average. The difference in trends in medical debt in collections following closures becomes small and insignificant two years after a hospital closure occurs, suggesting that the impact of hospital closures on medical debt in collections is not persistent over longer periods.

Figure 1 also supports our parallel trends assumption. Before a hospital closure, trends in medical debt in collections were comparable between the treatment HRRs and comparison HRRs, with estimates being small and statistically insignificant relative to the reference year (the year before closure). Appendix Table 1 further shows that these pre-closure coefficients are jointly insignificant. Together, these findings support the assumption that HRRs that do not experience closures serve as an appropriate counterfactual to those that do.

In Appendix Tables 2 through 4 we estimate additional supplementary specifications to our main analysis. In Appendix Table 2 we evaluate the impacts of hospital closures when specifying our treatment variable as a binary, rather than continuous, measure. This analysis *solely* depends on the parallel trends assumption between treated and untreated HRRs (i.e. rather than an additional assumption about parallel outcome paths for treated HRRs that experienced larger/smaller shares of hospitals closing in the treatment year). Appendix Table 2 finds that a hospital closure is associated with a 0.46 and 0.52 percentage point increase in the likelihood of having any medical debt in collections in the year of the hospital closure and the following year. This represents a 2.5 to 2.9 percent increase in medical debt relative to the sample mean, which is slightly smaller but qualitatively similar to the results from our main analysis. Appendix Table 3 shows that our main analysis is not sensitive to the exclusion of 2020, which is both the only pandemic year in the analysis and the year in which the sampling frame is larger relative to other years (see discussion in data section). In Appendix Table 4, we evaluate *how much* additional medical debt is incurred following hospital closures. We evaluate this in both levels and as a log-dependent variable—both analyses yield similar results and indicate that, following the closure of about 10 percent of hospitals in an HRR, the amount of medical debt in collections increases by about 0.8 to 0.9 percent.

3.3 Investigating Heterogeneity by Poverty, Rurality, Medicare Eligibility, and Medicaid Expansion

In Tables 2 and 3, we evaluate the heterogeneity of the main effects, focusing on differential effects by economic, geographic, and policy characteristics. The effects of hospital closures on the share of adults with medical debt in collections were more pronounced in areas with higher poverty rates. Specifically, a 10 percent reduction in the number of hospitals in areas with above-median poverty rates is associated with a statistically significant increase of 0.95 percentage points (4.1 percent increase) in the share of adults with medical debt in collections in both the year of the closure and the year following the closure. However, the impact of hospital closures on medical debt in collections did not persist two years after the closure occurred. In contrast, we find smaller effects—0.35 and 0.54 in the year of the closure and the year following the closure, respectively—of hospital closures on the share of adults with medical debt in areas with poverty rates below the median.

Next, we assess the differential effects of hospital closures based on the rurality of the area (Table 2). We do not find significant effects of closures on medical debt in rural areas, as indicated by small and statistically insignificant post-closure coefficients. In contrast, we find that the effects of hospital closures are concentrated among the residents of urban zip codes. In those areas, the closure of 10 percent of hospitals is associated with 0.89 and 1.2 percentage point increases in the share of adults with medical debt in the year of the closures and subsequent year, respectively.

Table 3 investigates the impact of hospital closures on medical debt in collections separately for adults below and at or above age 65. At 65, adults become age-eligible for Medicare, which, for many, provides significant protection from out-of-pocket expenditures. We find that for adults age 65 or older, the closure of 10 percent of hospitals is associated with a 3.0–3.2 percentage point increase in the share of elderly adults with medical debt in collections, representing about a 3.6–3.8 percent effect. This effect is only concentrated in the year of closure. For adults under age 65, the closure of 10 percent of hospitals is associated with a 6.3–6.6 percentage points increase in the share of nonelderly adults with medical debt in collections. In relative terms, these effect sizes are similar to the elderly population, representing 2.8–3.0 percent effects relative to the average share of non-elderly adults with medical debt in collections. Effect sizes for the non-elderly population are similar in the year after closure, although they are no longer statistically significant. We observe no persistence in effects after two years after closure.

The final set of columns in Table 3 evaluates the impact of hospital closures on medical debt in collections by state Medicaid expansion status under the ACA. We divide the sample into three categories—zip codes in states that expanded Medicaid in 2014, zip codes in states that expanded in 2015–2018, and zip codes in states that never expanded Medicaid during our analysis period. We find that the effects of closures on medical debt are more pronounced among the states that expanded Medicaid (ranging from about 0.93 to 1.4 percentage points in the post-closure period). Effects in the five states that expanded between 2015 and 2018 are slightly larger but estimated with less precision. We find no statistically significant relationship between hospital closures and the share of adults with medical debt in non-expansion states. We further discuss the potential drivers behind these heterogeneity results in the conclusion.

3.4 Investigating Mechanisms

One primary mechanism through which hospital closures may affect the likelihood of incurring medical debt in collections is through changes in the number of available hospitals and, relatedly, changes in the market concentration of hospitals in an HRR. Descriptively, HHRs which experienced an increase in market concentration in the period of analysis, also observed a relative increase in medical debt (Figure 2).

In Table 4, we formally test whether hospital closures led to fewer available hospitals and greater hospital market concentration. We first assess whether hospital closures are associated with clear and persistent reductions in the number of hospitals in an area. While closures are expected to mechanically reduce the number of entities in an HRR, the relationship is not necessarily straightforward because a closure could be associated with the entry of other hospitals. We find that a 10 percent reduction in hospitals due to closure reduced the number of hospitals by approximately 7.9 percent in the year of the closure, with comparable reductions remaining throughout the post-closure period (Table 3). This finding implies a persistent decline in the supply of hospitals after the closure. Consistently, we also observe a 6–8 percent significant increase in market concentration, as measured by the HHI, following hospital closures, which also persists throughout the post-closure period. This increase in market concentration, a proxy for competitiveness, suggests a decrease in hospital competitiveness after closures.

Altogether, our mechanisms analysis indicates that closures lead to a reduction in the number of available hospital entities for consumers to choose from, resulting in increased market concentration. These findings suggest a potential association between the rise in medical debt collections and the decrease in hospital competitiveness in the HRR, which may result in increased prices for hospital services as well as increased efforts from standing hospitals to collect on debts.

4. Discussion

Overall, we estimate that the closure of 10 percent of hospitals within an HRR is associated with a 4 percent increase in the share of adults with medical debt in the year of the closure and the following year. This estimated magnitude is similar to the intent-to-treat effect of expanding Medicaid broadly to non-disabled, low-income adults. The Oregon Health Insurance Experiment, which used a randomized lottery to assign Medicaid eligibility to non-disabled adults, found that gaining Medicaid eligibility was associated with about a 5.7 percent reduction in the probability of having any medical debt in collections (Finkelstein et al. 2012). Similarly, others found a 3.3 percent reduction in the probability of medical collection during the last 6 months in states that expanded Medicaid under the ACA (Caswell and Waidmann 2017). In contrast, another study found much larger effects (i.e., 20–25 percent) associated with Medicare, of which most of the population is eligible for and receives at age 65, and therefore this estimate is best interpreted as an average treatment effect rather than an intent-to-treat effect (Caswell and Goddeeris 2020).

Our findings also suggest that hospital closures increased market concentration, which in turn led to greater medical debt. We found that hospital closures were associated with an approximate 6–8 percent increase in market concentration throughout the post-closure period. A prior analysis of hospital closures between 1993 and 1998 found that closures led to a one-time, permanent 4 percent increase in prices (Wu 2008). This finding, along with the plethora of evidence in the market concentration literature, suggests that hospital closures increased remaining hospitals' pricing power and, subsequently, medical debt among consumers. However, one limitation of this analysis is that we are unable to disentangle this likely price effect from other potential mechanisms—for example, changes in aggressive behavior from hospitals in response to the decline in competition, changes in consumer use of services and health risk, and spillover effects on the local economy.

Results from our subgroup analysis indicate that the effects of hospital closures on medical debt were more pronounced in urban zip codes and those with higher poverty rates, and states that expanded Medicaid under the ACA. The concentrated effects in higher-poverty-rate areas are consistent with the empirical evidence of medical debt being most prevalent among low-income families and the hypothesis that lower-income households have a harder time finding affordable health services after hospital closures.

The lack of effects of hospital closures on medical debt in rural areas, and concentrated effects in urban areas, is somewhat surprising given that people residing in rural areas face more limited hospital options, making them more susceptible to reduced access to hospital services and increased exposure to high out-of-pocket expenses (Carroll 2020). However, the rural market results are consistent with past work showing very limited effects of rural hospital closure on the financial health of residents (Alexander and Richards 2023), while the urban market findings corroborate past work showing that hospital closures also have adverse effects on residents of urban areas (Buchmueller, Jacobson, and Wold, 2006). Our findings are also consistent with prior evidence of a negative relationship between market concentration and costs in urban areas, but not in rural areas (Vogel and Miller 1995). Differences in the organizational culture between urban and rural hospitals may also contribute to our findings— for example, remaining hospitals in rural areas may focus more on their communities and might be less likely to pursue medical debt following a closure, whereas urban hospitals may have the means and desire to more aggressively collect medical debt after a closure.

We also found comparable relative effects of hospital closures on medical debt among populations above and below age 65. This finding is consistent with the fact that Medicare does not provide complete protection from medical bills; in the absence of supplementary coverage (e.g., Medigap, Medicaid, or employee or retiree plans), patients still face separate deductibles for hospital care, outpatient care, and prescription medicines, as well as a 20 percent cost-share for outpatient or other physicians' services, among other out-of-pocket expenses.

Finally, while the pronounced effects in Medicaid expansion states are somewhat counterintuitive, given that Medicaid expansion served to primarily increase rates of insurance among low-income adults, this result is consistent with evidence that most medical debt is incurred by people who had insurance at the time the debt was incurred or are more subject to the increase of commercial price increases. The expansion versus non-expansion findings can also be closely related to the findings in urban versus rural areas—for example, there could be stronger community support in non-expansion states following closures because hospitals in these areas know that there is a weaker safety net in place without the ACA Medicaid coverage.

This study provides new and pertinent information to policymakers on the potential detrimental effects associated with hospital closures. While past work has documented how hospital closures have worsened healthcare quality and health outcomes, findings from this study provide insights into how hospital closures, and other actions that can increase market concentration (i.e., mergers and acquisitions), can financially harm consumers. Medical debt among consumers will continue to be a policy priority, despite recent report changes from credit reporting agencies; on April 11, 2023, the three credit bureaus announced the removal of all unpaid medical collections tradelines (i.e., specific items) under $500 from consumer credit reports. However, even though nearly three-quarters of consumers with medical debt nationally will have at least some of this debt removed from their credit reports, about half will continue to have medical debt appear on their credit reports (Consumer Financial Protection Bureau 2023). In addition, the change in credit reporting practices does not alter the underlying debt that consumers owe to healthcare providers. These providers and the third-party collection agencies with which they contract can still file civil lawsuits against patients and take other actions to collect payment for past-due medical bills.

5. References

Alexander, Diane, and Michael R. Richards. "Economic Consequences of Hospital Closures." *Journal of Public Economics* 221 (May 1, 2023): 104821. https://doi.org/10.1016/j.jpubeco.2023.104821.

Andre, Jennifer, Breno Braga, Kassandra Martinchek, and Signe-Mary McKernan. "The Effects of State Consumer Protection Policies During the Pandemic on the Use of Alternative Financial Services Loans." SSRN Scholarly Paper. Rochester, NY, February 1, 2023. https://doi.org/10.2139/ssrn.4345180.

Bazzoli, Gloria J, Woolton Lee, Hui-Min Hsieh, and Lee Rivers Mobley. "The Effects of Safety Net Hospital Closures and Conversions on Patient Travel Distance to Hospital Services." *Health Services Research* 47, no. 1 Pt 1 (February 2012): 129–50. https://doi.org/10.1111/j.1475-6773.2011.01318.x.

Neil Bennett, Jonathan Eggleston, Laryssa Mykyta, and Briana Sullivan. 2021. "19% of U.S. Households Could Not Afford to Pay for Medical Care Right Away." America Counts: Stories (blog). April 2021. https://www.census.gov/library/stories/2021/04/who-had-medical-debt-in-united-states.html.

Blavin, Fredric, Breno Braga, and Anuj Gangopadhyaya. "Which County Characteristics Predict Medical Debt?," June 15, 2022. https://policycommons.net/artifacts/2473381/which-county-characteristics-predict-medical-debt/3495427/.

Braga, Breno, and Ashlin Oglesby-Neal. "The Effects of Price Caps on Open-End Loans: Evidence from the 2015 Expansion of the Military Lending Act." SSRN Scholarly Paper. Rochester, NY, January 12, 2023. https://doi.org/10.2139/ssrn.4322925.

Bruhn, William E., Lainie Rutkow, Peiqi Wang, Stephen E. Tinker, Christine Fahim, Heidi N. Overton, and Martin A. Makary. "Prevalence and Characteristics of Virginia Hospitals Suing Patients and Garnishing Wages for Unpaid Medical Bills." *JAMA* 322, no. 7 (August 20, 2019): 691–92. https://doi.org/10.1001/jama.2019.9144.

Buchmueller, Thomas C., Mireille Jacobson, and Cheryl Wold. "How Far to the Hospital? The Effect of Hospital Closures on Access to Care." *Journal of Health Economics* 25, no. 4 (July 2006): 740–61. https://doi.org/10.1016/j.jhealeco.2005.10.006.

Bureau, US Census. "19% of U.S. Households Could Not Afford to Pay for Medical Care Right Away." Census.gov. Accessed July 6, 2023. https://www.census.gov/library/stories/2021/04/who-had-medical-debt-in-united-states.html.

Callaway, Brantly, Andrew Goodman-Bacon, and Pedro H. C. Sant'Anna. 2021. "Difference-in-Differences with a Continuous Treatment." arXiv. https://doi.org/10.48550/arXiv.2107.02637.

Carroll, C. "Impeding Access or Promoting Efficiency? Effects of Rural Hospital Closure on the Cost and Quality of Care," 2019. https://www.semanticscholar.org/paper/Impeding-Access-or-Promoting-Efficiency-Effects-of-Carroll/27800f7217e237f8b13828527bff73562212760c.

Caswell, Kyle J., and John H. Goddeeris. "Does Medicare Reduce Medical Debt?" *American Journal of Health Economics* 6, no. 1 (January 2020): 72–103. https://doi.org/10.1086/706623.

Caswell, Kyle J., and Timothy A. Waidmann. "The Affordable Care Act Medicaid Expansions and Personal Finance." *Medical Care Research and Review* 76, no. 5 (October 1, 2017: 538–71. https://doi.org/10.1177/1077558717725164.

Consumer Financial Protection Bureau. "Consumer Credit and the Removal of Medical Collections from Credit Reports," April 26, 2023. https://www.consumerfinance.gov/data-research/research-reports/consumer-credit-and-the-removal-of-medical-collections-from-credit-reports/.

Consumer Financial Protection Bureau. "Medical Debt Burden in the United States," March 1, 2022. https://www.consumerfinance.gov/data-research/research-reports/medical-debt-burden-in-the-united-states/.

Cooper, Zack, Stuart V. Craig, Martin Gaynor, and John Van Reenen. "The Price Ain't Right? Hospital Prices and Health Spendig on the Privately Insured." *The Quarterly Journal of Economics* 134, no. 1 (February 2019): 51–107. https://doi.org/10.1093/qje/qjy020.

Cooper, Zack, James Han, and Neale Mahoney. "Hospital Lawsuits Over Unpaid Bills Increased By 37 Percent In Wisconsin From 2001 To 2018." *Health Affairs* 40, no. 12 (December 2021): 1830–35. https://doi.org/10.1377/hlthaff.2021.01130.

Dafny, Leemore. "Estimation and Identification of Merger Effects: An Application to Hospital Mergers." *The Journal of Law and Economics* 52, no. 3 (August 2009): 523–50. https://doi.org/10.1086/600079.

Dobkin, Carlos, Amy Finkelstein, Raymond Kluender, and Matthew J. Notowidigdo. "The Economic Consequences of Hospital Admissions." *American Economic Review* 108, no. 2 (February 2018): 308–52. https://doi.org/10.1257/aer.20161038.

Finkelstein, Amy, Sarah Taubman, Bill Wright, Mira Bernstein, Jonathan Gruber, Joseph P. Newhouse, Heidi Allen, Katherine Baicker, and Oregon Health Study Group. "The Oregon Health Insurance Experiment: Evidence from the First Year*." *The Quarterly Journal of Economics* 127, no. 3 (August 1, 2012): 1057–1106. https://doi.org/10.1093/qje/qjs020.

Fulton, Brent D. "Health Care Market Concentration Trends In The United States: Evidence And Policy Responses." *Health Affairs* 36, no. 9 (September 2017): 1530–38. https://doi.org/10.1377/hlthaff.2017.0556.

Gaynor, Martin. "What to Do about Health-Care Markets? Policies to Make Health-Care Markets Work," 2020. The Hamilton Project.

Gaynor, Martin, Kate Ho, and Robert J. Town. "The Industrial Organization of Health-Care Markets." *Journal of Economic Literature* 53, no. 2 (June 2015): 235–84. https://doi.org/10.1257/jel.53.2.235.

Gaynor, Martin, and Robert Town. n.d. "The Impact of Hospital Consolidation —Update." The Synthesis Project. Robert Wood Johnson Foundation.

Goodman-Bacon, Andrew. 2021. "Difference-in-Differences with Variation in Treatment Timing." *Journal of Econometrics* 225 (2): 254–77. https://doi.org/10.1016/j.jeconom.2021.03.014.

Gujral, Kritee, and Anirban Basu. "Impact of Rural and Urban Hospital Closures on Inpatient Mortality." Working Paper. Working Paper Series. National Bureau of Economic Research, August 2019. https://doi.org/10.3386/w26182.

Hamel, Liz, Mira Norton, Karen Pollitz, Larry Levitt, Gary Claxton, and Mollyann Brodie. 2016. "The Burden of Medical Debt: Results from the Kaiser Family Foundation/New York Times Medical Bills Survey." Kaiser Family Foundation. https://www.kff.org/wp-content/uploads/2016/01/8806-the-burden-of-medical-debt-results-from-the-kaiser-family-foundation-new-york-times-medical-bills-survey.pdf.

Himmelstein, David U., Samuel L. Dickman, Danny McCormick, David H. Bor, Adam Gaffney, and Steffie Woolhandler. "Prevalence and Risk Factors for Medical Debt and Subsequent Changes in Social Determinants of Health in the US." *JAMA Network Open* 5, no. 9 (September 16, 2022): e2231898. https://doi.org/10.1001/jamanetworkopen.2022.31898.

Holmes, George M., Rebecca T. Slifkin, Randy K. Randolph, and Stephanie Poley. "The Effect of Rural Hospital Closures on Community Economic Health." *Health Services Research* 41, no. 2 (April 2006): 467–85. https://doi.org/10.1111/j.1475-6773.2005.00497.x.

Karpman, Michael and Sharon Long. "Most Adults with Medical Debt Had Health Insurance at the Time the Debt Was Incurred," May 21, 2015. https://www.urban.org/research/publication/most-adults-medical-debt-had-health-insurance-time-debt-was-incurred.

Karpman, Michael, Kassandra Martinchek, and Breno Braga. "Medical Debt Fell during the Pandemic. How Can the Decline Be Sustained?," n.d.

Kliff, Sarah. "With Medical Bills Skyrocketing, More Hospitals Are Suing for Payment." *The New York Times*, November 8, 2019. https://www.nytimes.com/2019/11/08/us/hospitals-lawsuits-medical-debt.html.

Kluender, Raymond, Neale Mahoney, Francis Wong, and Wesley Yin. "Medical Debt in the US, 2009-2020." *JAMA* 326, no. 3 (July 20, 2021): 250–56. https://doi.org/10.1001/jama.2021.8694.

Lopes, Lunna, Alex Montero, and 2022. "Health Care Debt In The U.S.: The Broad Consequences Of Medical And Dental Bills - Main Findings." *KFF* (blog), June 16, 2022. https://www.kff.org/report-section/kff-health-care-debt-survey-main-findings/.

Lucas, Jay, and Elizabeth Hancock. "'UVA Has Ruined Us': Health System Sues Thousands Of Patients, Seizing Paychecks And Claiming Homes." *KFF Health News* (blog), September 10, 2019. https://kffhealthnews.org/news/uva-health-system-sues-patients-virginia-courts-garnishment-liens-bankruptcy/.

McCarthy, Sean, Dylana Moore, W. Andrew Smedley, Brandon M. Crowley, Shannon W. Stephens, Russell L. Griffin, Lauren C. Tanner, and Jan O. Jansen. "Impact of Rural Hospital Closures on Health-Care Access." *The Journal of Surgical Research* 258 (February 2021): 170–78. https://doi.org/10.1016/j.jss.2020.08.055.

McGhee, Michelle, and Will Chase. "How America's Top Hospitals Send Patient Costs Soaring." Accessed July 6, 2023. https://www.axios.com/hospital-billing.

Norton, Mira, Karen Pollitz, Gary Claxton, and 2016. "The Burden of Medical Debt: Results from the Kaiser Family Foundation/New York Times Medical Bills Survey." *KFF* (blog), January 5, 2016. https://www.kff.org/health-costs/report/the-burden-of-medical-debt-results-from-the-kaiser-family-foundationnew-york-times-medical-bills-survey/.

Pollitz, Karen, Lunna Lopes, Audrey Kearney, Matthew Rae, Cynthia Cox, Rachel Fehr, David Rousseau, and for the Kaiser Family Foundation. "US Statistics on Surprise Medical Billing." *JAMA* 323, no. 6 (February 11, 2020): 498. https://doi.org/10.1001/jama.2020.0065.

"Project MUSE - Under the ACA Higher Deductibles and Medical Debt Cause Those Most Vulnerable to Defer Needed Care." Accessed July 6, 2023. https://muse.jhu.edu/article/747797.

Rabin, David L, Anuradha Jetty, Stephen Petterson, and Allison Froehlich. 2020. "Under the ACA Higher Deductibles and Medical Debt Cause Those Most Vulnerable to Defer Needed Care." Journal of Health Care for the Poor and Underserved 31 (1): 424–40. https://doi.org/10.1353/hpu.2020.0031.

Shen, Yu-Chu, and Renee Y. Hsia. "Does Decreased Access to Emergency Departments Affect Patient Outcomes? Analysis of Acute Myocardial Infarction Population 1996-2005." *Health Services Research* 47, no. 1 Pt 1 (February 2012): 188–210. https://doi.org/10.1111/j.1475-6773.2011.01319.x.

"State Balance-Billing Protections," February 5, 2021. https://doi.org/10.26099/0x7j-7731.

Sun, Eric C., Michelle M. Mello, Jasmin Moshfegh, and Laurence C. Baker. "Assessment of Out-of-Network Billing for Privately Insured Patients Receiving Care in In-Network Hospitals." *JAMA Internal Medicine* 179, no. 11 (November 1, 2019): 1543–50. https://doi.org/10.1001/jamainternmed.2019.3451.

"The Burden of Medical Debt: Results from the Kaiser Family Foundation/New York Times Medical Bills Survey," n.d.

Urban Institute. 2022. "Debt in America: An Interactive Map." Accessed July 6, 2023. http://urbn.is/2AnVzHa.

Vogel, W. Bruce, and Michael K. Miller. "Variations in Rural Hospital Costs: Effects of Market Concentration and Location." *Health Care Financing Review* 17, no. 1 (1995): 69–83.

Vogler, Jacob. "Rural Hospital Closures and Local Economic Decline." SSRN Scholarly Paper. Rochester, NY, December 16, 2020. https://doi.org/10.2139/ssrn.3750200.

Wishner, Jane, Patricia Solleveld, Julia Paradise, Larisa Antonisse Published: Jul 07, and 2016. "A Look at Rural Hospital Closures and Implications for Access to Care: Three Case Studies." *KFF* (blog), July 7, 2016. https://www.kff.org/medicaid/issue-brief/a-look-at-rural-hospital-closures-and-implications-for-access-to-care/.

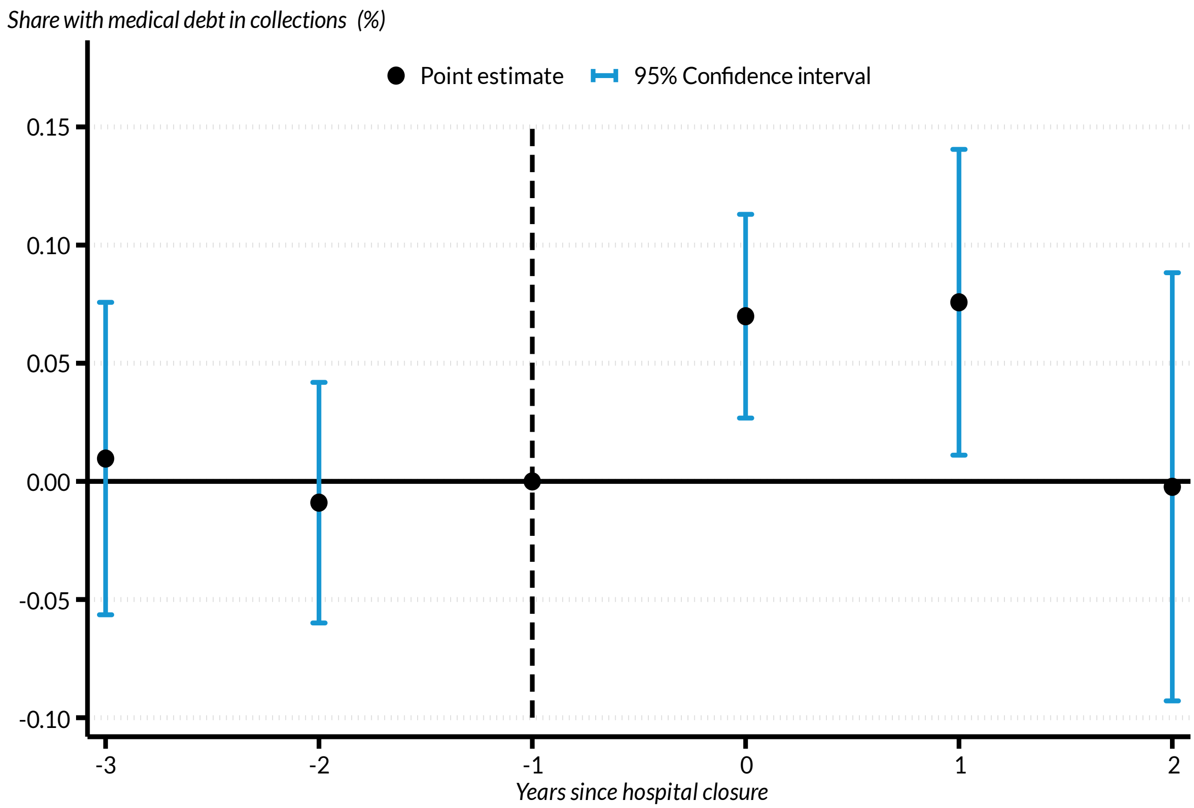
Wu, Vivian Y. "The Price Effect of Hospital Closures." *Inquiry: A Journal of Medical Care Organization, Provision and Financing* 45, no. 3 (2008): 280–92. https://doi.org/10.5034/inquiryjrnl_45.03.280.

Table 1. Baseline Descriptive Statistics

	HRRs that experienced a closure between 2014-2018	HRRs that did not experience a closure between 2014-2018
Individual Level		
Mean credit score	656	667
Age range shares		
18–26	12%	12%
27–44	28%	27%
45–64	30%	31%
65+	13%	14%
missing age	16%	16%
ZCTA Level		
Share rural	15%	15%
Share uninsured	18%	15%
Mean household income (nominal dollars)	$70,251	$74,544
Share of families below poverty line	12%	10%
Race and ethnicity shares		
White, non-Hispanic	59%	67%
Hispanic	19%	14%
Black, non-Hispanic	14%	12%
Asian, non-Hispanic	5%	5%
Native Hawaiian & Pacific Islander, non-Hispanic	0%	0%
American Indian & Alaska Native, non-Hispanic	1%	1%
Other race, non-Hispanic	0%	0%
Multiple races, non-Hispanic	2%	2%
Region of HRR of residence		
Midwest	16%	24%
Northeast	8%	24%
South	51%	29%
West	26%	22%
Number of HRRs	75	231
Number of consumers	2,003,592	3,210,972

Source: Individual-level credit information from Urban Institute analysis of credit bureau data from August 2011 to August 2020. Zip code-level characteristics from Census Bureau's 5-year American Community Survey files (2007–2011). Urban and rural indicators based on 2010 Rural-Urban Commuting Area codes from the US Department of Agriculture and the WWAMI Rural Health Research Center.
Notes: "ZCTA" = Zip code tabulation area. "HRR" = Hospital Referral Region.

Figure 1. Impact of Closure on Share with Medical Debt in Collections



Source: Individual-level credit information from Urban Institute analysis of credit bureau data from August 2011 to August 2020. Zip code-level characteristics from Census Bureau's 5-year American Community Survey files (2007–2011).
Notes: Results plot coefficients on interactions between a year relative to a hospital closure and an indicator for whether an HRR experiences a hospital closure from a stacked event study regression model (see Equation 1). These regressions include HRR fixed effects, indicators for each of the unique 6-year panels that have been stacked, year fixed effects, zip code level contextual factors (reported in Table 1), an indicator for whether the state the zip code in has expanded Medicaid under the Affordable Care Act, and a zip code–level age distribution of consumers with a credit record. Regressions are weighted for the number of consumers in each zip code in the credit bureau sample. Standard errors are clustered at the HRR level.

Table 2. Impact of Hospital Closures on Share with Medical Debt in Collections, by Poverty and Rural Status

	Poverty Share		Rural Share	
	Above Median (1)	Below Median (2)	Above Median (1)	Below Median (2)
Closure Year -3	0.0059	0.0114	0.0165	0.001
	(0.0384)	(0.0308)	(0.0424)	(0.0476)
Closure Year -2	-0.0229	0.01	-0.0432	0.0057
	(0.0297)	(0.0229)	(0.0305)	(0.0367)
Closure Year 0	0.0946**	0.0345**	0.0265	0.089**
	(0.0317)	(0.0152)	(0.0313)	(0.0284)
Closure Year +1	0.095**	0.0542**	0.0021	0.1164**
	(0.0434)	(0.0262)	(0.0569)	(0.0398)
Closure Year +2	0.0093	0.0039	-0.0324	0.0154
	(0.0523)	(0.0433)	(0.077)	(0.0593)
Observations	292,027	393,654	398,937	286,744
Mean of Dependent Variable	23.23	14.31	18.24	17.93
Prob > F	0.346	0.909	0.0993	0.955

Source: Individual-level credit information from Urban Institute analysis of credit bureau data from August 2011 to August 2020. Zip code-level characteristics from Census Bureau's 5-year American Community Survey files (2007–2011). Urban and rural indicators based on 2010 Rural-Urban Commuting Area codes from the US.

Notes: Results report coefficients on interactions between a year relative to a hospital closure and a measure for the share of hospitals closed (if any) in an HRR during the treatment year in each panel from a stacked event study regression model (see Equation 1). These regressions include HRR fixed effects, indicators for each of the unique 6-year panels that have been stacked, year fixed effects, zip code level contextual factors (reported in Table 1), an indicator for whether the state the zip code in has expanded Medicaid under the Affordable Care Act, and a zip code-level age distribution of consumers with a credit record. Regressions are weighted for the number of consumers in each zip code in the credit bureau sample. Standard errors are clustered at the HRR level. ** $p < 0.05$, * $p < 0.1$

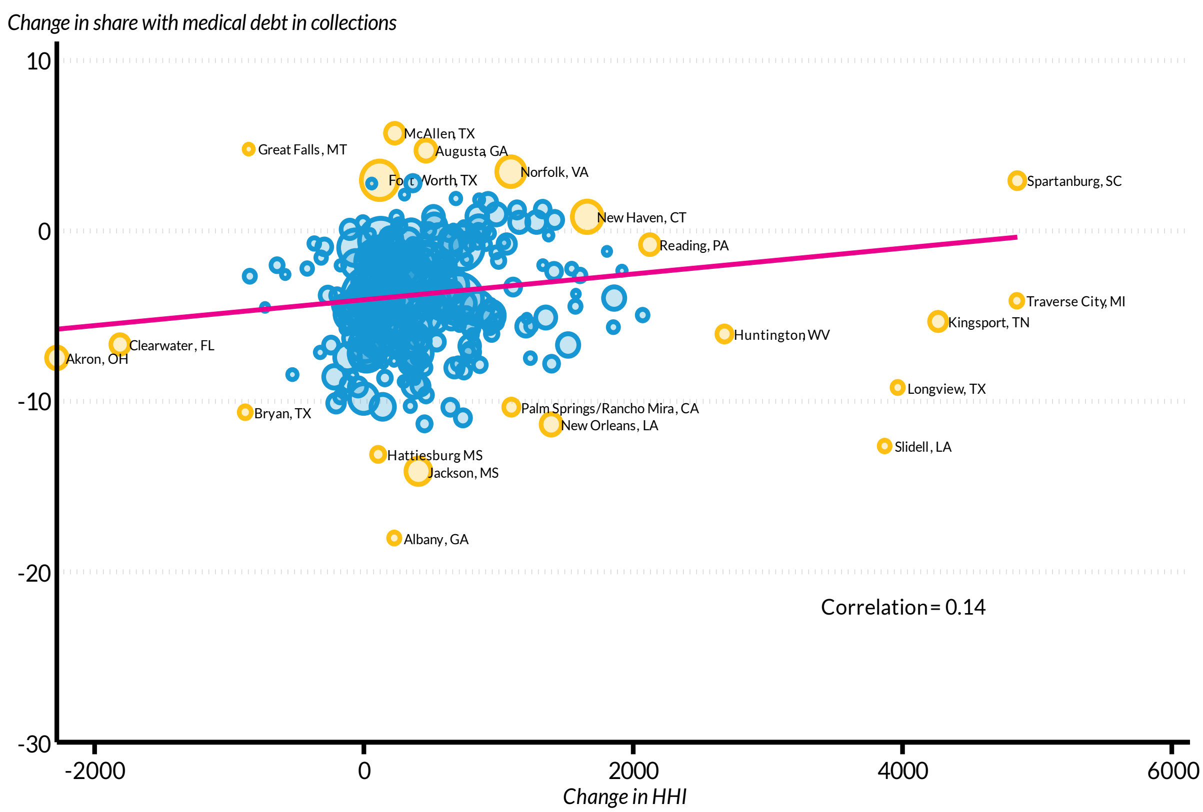
Table 3. Impact of Hospital Closures on Share with Medical Debt in Collections, by Age Group and Medicaid Expansion Status

	Age Group		Medicaid Expansion Status		
	Consumers <65 (1)	Consumers 65+ (2)	Expanded in 2014 (1)	Expanded 2015–2018 (2)	Never expanded (3)
Closure Year -3	0.0055	-0.0078	0.0394	0.0286	-0.0135
	(0.035)	(0.0199)	(0.0433)	(0.0511)	(0.0533)
Closure Year -2	-0.0112	-0.0239*	0.0134	0.027	-0.0338
	(0.0269)	(0.0144)	(0.035)	(0.0309)	(0.039)
Closure Year 0	0.0659**	0.0316**	0.093**	0.1126*	0.0316
	(0.0222)	(0.0138)	(0.0335)	(0.0663)	(0.0251)
Closure Year +1	0.0669*	0.0208	0.1441*	0.1774	-0.0093
	(0.0355)	(0.0172)	(0.0334)	(0.1126)	(0.0581)
Closure Year +2	-0.0291	0.0042	0.1088**	0.1026	-0.1195
	(0.0516)	(0.0292)	(0.0433)	(0.1073)	(0.0841)
Observations	666,894	603,505	373,191	78,862	233,628
Mean of Dependent Variable	22.02	8.27	16.06	18.98	21.09
Prob > F	0.690	0.135	0.374	0.685	0.582

Source: Individual-level credit information from Urban Institute analysis of credit bureau data from August 2011 to August 2020. Zip code-level characteristics from Census Bureau's 5-year American Community Survey files (2007–2011).

Notes: Results report coefficients on interactions between a year relative to a hospital closure and an indicator for whether an HRR experiences a hospital closure from a stacked event study regression model (see Equation 1). These regressions include HRR fixed effects, indicators for each of the unique 6-year panels that have been stacked, year fixed effects, zip code level contextual factors (reported in Table 1), an indicator for whether the state the zip code in has expanded Medicaid under the Affordable Care Act, and a zip code-level age distribution of consumers with a credit record. Regressions are weighted for the number of consumers in each zip code in the credit bureau sample. Standard errors are clustered at the HRR level. ** $p < 0.05$, * $p < 0.1$

Figure 2. Correlation Between Change in Medical Debt and Change in HHI from 2011–2013 to 2018–2020



Source: Individual-level credit information from Urban Institute analysis of credit bureau data from August 2011 to August 2020. Zip code-level characteristics from Census Bureau's 5-year American Community Survey files (2007–2011). HHI calculated based on adjusted admissions and system affiliations reported in the American Hospital Association's Annual Survey Database.

Note: "HHI" = Herfindahl-Hirschman Index.

Table 4. Impact of Closures on Number of Hospitals and HHI, Mechanism Analysis

	Number of Hospitals, log transformed	HHI, log transformed
Closure Year -3	0.0013	-0.0017
	(0.0013)	(0.0024)
Closure Year -2	0.0011	-0.0013
	(0.0007)	(0.0014)
Closure Year 0	-0.0079**	0.0056**
	(0.0015)	(0.0022)
Closure Year +1	-0.0074**	0.0062**
	(0.0016)	(0.0026)
Closure Year +2	-0.0066**	0.0076**
	(0.0022)	(0.0027)
Observations	6,450	6,450
Mean of Dependent Variable	2.193	8.046
Prob > F	0.248	0.676

Source: Individual-level credit information from Urban Institute analysis of credit bureau data from August 2011 to August 2020. Zip code–level characteristics from Census Bureau's 5-year American Community Survey files (2007–2011). HHI is calculated based on adjusted admissions and system affiliations reported in the American Hospital Association's Annual Survey Database.

Notes: "HHI" = Herfindahl-Hirschman Index. Results report coefficients on interactions between a year relative to a hospital closure and a measure for the share of hospitals closed (if any) in an HRR during the treatment year in each panel from a stacked event study regression model (see Equation 1). These regressions include HRR fixed effects, indicators for each of the unique 6-year panels that have been stacked, year fixed effects, zip code level contextual factors (reported in Table 1), an indicator for whether the state the zip code in has expanded Medicaid under the Affordable Care Act, and a zip code–level age distribution of consumers with a credit record. Regressions are weighted for the number of consumers in each zip code in the credit bureau sample. Standard errors are clustered at the HRR level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix Table 1. Impact of Hospital Closure on Share with Medical Debt in Collections

	(1)	(2)
Closure Year -3	0.0138	0.0097
	(0.0332)	(0.0336)
Closure Year -2	-0.005	-0.009
	(0.0256)	(0.0259)
Closure Year 0	0.0679**	0.0699**
	(0.0205)	(0.0219)
Closure Year +1	0.0703**	0.0758**
	(0.0317)	(0.0329)
Closure Year +2	-0.0114	-0.0023
	(0.0474)	(0.046)
Fixed Effects	Year, Experiment, HRR	
Controls	No	Yes
Observations	685,681	685,681
Mean of Dependent Variable	18.11	18.11
Prob > F	0.619	0.567

Source: Individual-level credit information from Urban Institute analysis of credit bureau data from August 2011 to August 2020. Zip code–level characteristics from Census Bureau's 5-year American Community Survey files (2007–2011). HHI calculated based on adjusted admissions and system affiliations reported in the American Hospital Association's Annual Survey Database.

Notes: "HHI" = Herfindahl-Hirschman Index. Results report coefficients on interactions between a year relative to a hospital closure and a measure for the share of hospitals closed (if any) in an HRR during the treatment year in each panel from a stacked event study regression model (see Equation 1). These regressions include HRR fixed effects, indicators for each of the unique 6-year panels that have been stacked, year fixed effects, zip code level contextual factors (reported in Table 1), an indicator for whether the state the zip code in has expanded Medicaid under the Affordable Care Act, and a zip code–level age distribution of consumers with a credit record. Regressions are weighted for the number of consumers in each zip code in the credit bureau sample. Standard errors are clustered at the HRR level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix Table 2. Estimating the Impact of Closure on Share with Medical Debt in Collections using a Binary Treatment Variable

	(1)	(2)
Closure Year -3	-0.0089	0.0288
	(0.2497)	(0.2501)
Closure Year -2	-0.0101	0.0116
	(0.1758)	(0.174)
Closure Year 0	0.4466**	0.4565**
	(0.1206)	(0.1236)
Closure Year +1	0.5075**	0.5154*
	(0.2564)	(0.2631)
Closure Year +2	0.1811	0.2047
	(0.3934)	(0.3811)
Fixed Effects	Year, Experiment, HRR	
Controls	No	Yes
Observations	685,681	685,681
Mean of Dependent Variable	18.11	18.11
Prob > F	0.998	0.992

Source: Individual-level credit information from Urban Institute analysis of credit bureau data from August 2011 to August 2020. Zip code–level characteristics from Census Bureau's 5-year American Community Survey files (2007–2011). HHI calculated based on adjusted admissions and system affiliations reported in the American Hospital Association's Annual Survey Database.

Notes: "HHI" = Herfindahl-Hirschman Index. Results report coefficients on interactions between a year relative to a hospital closure and an indicator for whether an HRR experiences a hospital closure from a stacked event study regression model (see Equation 1). These regressions include HRR fixed effects, indicators for each of the unique 6-year panels that have been stacked, year fixed effects, zip code level contextual factors (reported in Table 1), an indicator for whether the state the zip code in has expanded Medicaid under the Affordable Care Act, and a zip code–level age distribution of consumers with a credit record. Regressions are weighted for the number of consumers in each zip code in the credit bureau sample. Standard errors are clustered at the HRR level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix Table 3. Investigating Sensitivity of Main Analysis to Excluding 2020 Analysis Year

	(1)	(2)
Closure Year -3	0.0155	0.0156
	(0.0359)	(0.0364)
Closure Year -2	0.0118	0.0105
	(0.0256)	(0.0257)
Closure Year 0	0.0729**	0.0771**
	(0.0236)	(0.0254)
Closure Year +1	0.0729**	0.0809**
	(0.0354)	(0.0373)
Closure Year +2	-0.0284	-0.011
	(0.0575)	(0.0569)
Fixed Effects	Year, Experiment, HRR	
Controls	No	Yes
Observations	568,376	568,376
Mean of Dependent Variable	18.42	18.42
Prob > F	0.894	0.908

Source: Individual-level credit information from Urban Institute analysis of credit bureau data from August 2011 to August 2020. Zip code–level characteristics from Census Bureau's 5-year American Community Survey files (2007–2011). HHI calculated based on adjusted admissions and system affiliations reported in the American Hospital Association's Annual Survey Database.

Notes: "HHI" = Herfindahl-Hirschman Index. Results report coefficients on interactions between a year relative to a hospital closure and an indicator for whether an HRR experiences a hospital closure from a stacked event study regression model (see Equation 1). These regressions include HRR fixed effects, indicators for each of the unique 6-year panels that have been stacked, year fixed effects, zip code level contextual factors (reported in Table 1), an indicator for whether the state the zip code in has expanded Medicaid under the Affordable Care Act, and a zip code–level age distribution of consumers with a credit record. Regressions are weighted for the number of consumers in each zip code in the credit bureau sample. Standard errors are clustered at the HRR level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix Table 4. Impact of Hospital Closures on the Amount of Medical Debt in Collections

	Average Medical Debt in Collections	Log of Average Medical Debt in Collections
Closure Year -3	-0.8092	-0.0025
	(3.4987)	(0.0059)
Closure Year -2	0.3583	-0.0006
	(2.6596)	(0.0036)
Closure Year 0	4.6856**	0.0084**
	(1.4741)	(0.0026)
Closure Year +1	5.6655*	0.0095**
	(3.1213)	(0.0037)
Closure Year +2	-0.8445	0.0025
	(2.9938)	(0.005)
Fixed Effects	Year, Experiment, HRR	
Controls	Yes	Yes
Observations	685,681	569,235
Mean of Dependent Variable	482.2	5.426
Prob > F	0.726	0.875

Source: Individual-level credit information from Urban Institute analysis of credit bureau data from August 2011 to August 2020. Zip code–level characteristics from Census Bureau's 5-year American Community Survey files (2007–2011). HHI calculated based on adjusted admissions and system affiliations reported in the American Hospital Association's Annual Survey Database.

Notes: "HHI" = Herfindahl-Hirschman Index. Results report coefficients on interactions between a year relative to a hospital closure and an indicator for whether an HRR experiences a hospital closure from a stacked event study regression model (see Equation 1). These regressions include HRR fixed effects, indicators for each of the unique 6-year panels that have been stacked, year fixed effects, zip code level contextual factors (reported in Table 1), an indicator for whether the state the zip code in has expanded Medicaid under the Affordable Care Act, and a zip code–level age distribution of consumers with a credit record. Regressions are weighted for the number of consumers in each zip code in the credit bureau sample. Standard errors are clustered at the HRR level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$