How Do Debt Collection Restrictions Affect Hospitals and Patients?

Christine Zhuowei Huang Amit Kumar Lynn Linghuan Wang*

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Abstract

Tighter regulations on consumer debt collectors, although intended to curb predatory practices, may disrupt industries to which such debts are owed. Using a paired-county stacked difference-in-differences design, we show that these regulations adversely affect hospitals. While hospital patient volume remains unchanged, their account receivables, liabilities, and profitability deteriorate, with stronger effects for ex-ante higher financial liability and debt collector density. Consequently, hospitals reduce capacity, employment, and care quality, and steer patients to high-cost procedures. Additionally, non-profit hospitals reduce charity care for uninsured patients. Overall, ignoring spillovers of consumer financial protection laws on non-financial sectors may overstate their benefits.

JEL Classification: D18, G18, G51, I11, I18.

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*Huang is at Naveen Jindal School of Management, University of Texas at Dallas; email: zhuowei.huang@utdallas.edu. Kumar is at Lee Kong Chian School of Business, Singapore Management University; email: amitkumar@smu.edu.sg. Wang is at National University of Singapore Business School; email: lynn.wang@nus.edu.sg. We thank Ilona Babenko, Jessica Bai, Hendrik Bessembinder, Philip Bond, Francesco D'Acunto, Janet Gao, Christopher Hrdlicka, Justin Murfin, Maureen O'Hara, Mayank Kumar, Clemens Otto, Stephan Siegel, Denis Sosyura, Ana-Maria Tenekedjieva, Scott Yonker, Fernando Zapatero, Bart Yueshen Zhou, and the seminar participants at Arizona State University, Boston University, Cornell University, Georgetown University, Singapore Management University, University of Texas at Dallas, and University of Washington for valuable comments. All errors are our own.

Third-party debt collection industry in the U.S. specializes in recovering defaulted unsecured debt from consumers and plays an essential role in the consumer credit ecosystem. In 2020, it recovered approximately $102 billion in unsecured unpaid consumer debt and returned nearly $90 billion to creditors (ACA International (2020)). By helping creditors recover unpaid debt, this industry minimizes creditor losses and potentially allows them to expand credit availability, thereby enhancing efficiency of the consumer credit markets. At the same time, serious concerns have been raised about the prevalence of abusive and deceptive collection practices.[1] In an effort to protect consumers from such practices, states enact stricter debt collection laws that typically raise compliance costs and create entry barriers for the industry, for example by imposing mandatory licensing and bond requirements, raising financial penalties, or classifying certain collection practices as criminal offenses etc. While these laws are generally effective in containing the growth of the industry, they can also reduce recovery rates on defaulted unsecured debts, essentially trading off credit market efficiency against consumer protection. This paper emphasizes this trade-off by examining the implications of these stricter regulations for a specific creditor industry—hospitals, which are the largest users of the debt collection industry, accounting for nearly half of all volumes sold to collectors and significantly surpassing financial institutions, which represent only 11% (Fedaseyeu (2020)).

We focus on hospitals for two reasons. The first is their essential role in healthcare delivery, which is not only crucial for individual well-being and health outcomes but also makes a significant contribution to the economy. The healthcare sector is the largest employer and healthcare expenditure accounted for 17% of the national gross domestic product (BLS (2023), CMS (2023)). The second reason is their substantial usage of the debt collection industry, accounting for 47.2% of the volume sold to this sector in 2013, as noted previously. This dependence on collection

[1] For example, the debt collection industry accounts for the highest number of fraud cases filed with the Federal Trade Commission (FTC (n.d.)) and consistently ranks among the top sources of consumer complaints to the CFPB (CFPB (2015)). Reported abusive practices include attempts to collect debts not owed, threats of illegal actions, inappropriate contact with employers or family members, and repeated and harassing phone calls often involving abusive language.

industry is immediately evident in the widespread prevalence of medical debt, which consistently ranks as the most common category of unpaid debt in collections recorded on consumers' credit reports and affects between one-fifth to one-third of the entire American adult population (CFPB (2014), CFPB (2023)).[2]

The key to our empirical strategy is the staggered adoption of stricter third-party debt collection regulations by states. We hand-collected data on changes in state debt collection laws across all 50 states from 2013 till 2022. For earlier years, we supplemented our data with information originally compiled by Fedaseyeu (2020), which was subsequently used by Fonseca (2023) with some modifications. Our sample period begins in 2010—the first year since when hospital-level variables of interest became consistently available in hospital cost report data.[3] Within our sample period spanning 2010 and 2022, we identify 28 instances of regulatory changes that increased restrictions on third-party collection industries.

For causal estimates of the third-party debt collection restriction regulations on hospitals, we combine the approach of Dube, Lester, and Reich (2010) to compare the outcomes in contiguous (neighboring) counties straddling state borders—where one state adopts a tighter debt collection law while the other does not—with the stacking approach of Cengiz et al. (2019) in a stacked difference-in-differences (DiD) setting. Specifically, we classify the counties located along the borders of the states adopting the regulation as treated counties. We then create treated-control county pairs by repeatedly matching each of the treated counties with all its neighboring counties from across the state border. We perform this pairing for each of the 28 regulatory changes and create a stacked panel aligned with respect to the respective treatment years, with an event window spanning three years before and after each adoption. We include only clean controls in the stacked panel by dropping the years in which control states (and

[2] The high incidence of unpaid medical bills (accounts receivable) and bad debt in the hospital industry are commonly attributed to several factors, including limited ex ante price transparency, uncertainty regarding the cost of care at the time of patients' admission, the complexity and opacity of medical billing, and reliance on reimbursements from insurers and third-party payers that could be subject to delays, disputes, and denial risks after the care has been rendered.

[3] Constructing a consistent time series for earlier years is infeasible due to the substantial redesign of the cost reports by Centers for Medicare & Medicaid Services (CMS) in 2010.

counties) are within their respective post-treatment window, if any. In essence, we compare outcomes in hospitals at the border of states enacting tighter debt collection regulations with those from neighboring counties across state border where there was no change in such laws using two-way fixed effects estimators (TWFE).

Combining contiguous county comparison with stacked approach offers several key advantages. First, since the treated and control counties are contiguous, they are unlikely to experience broadly different local shocks. Second, stacking the events allows us to inclusion event×county-pair×hospital fixed effects (FE), which flexibly account for any time-varying changes across events experienced by the hospitals, counties, and states. This implies that we exploit only the variations within hospitals located within a pair of contiguous counties over a single six-year event window, making our estimates immune to the alternative explanations, such as changes in state laws, demographics, or socio-economic changes. Third, the stacked panel also permits inclusion of event×county-pair×relative-year FE, which flexibly eliminates the effects of geographically varying year-specific shocks by allowing a separate time trend for each county pair across each event. Finally, the stacking approach avoids the negative weighting issue of TWFE (Cengiz et al. (2019)).

We examine our DiD design for two essential features. First, regarding the parallel trends assumption, we find no evidence of diverging pre-trends between treated and control group across a range of county characteristics including employment, population, and GDP, and hospitals characteristics, such as size, operating margins, account receivables, and liability. Second, regarding the relevance of the treatment event, we find using county-level regressions that growth rate of number of establishments and wages in debt collection industry declined after the adoption of the stricter laws. These reductions were also accompanied by a decline in county-aggregate establishment size, wages, and employment in healthcare industry. Overall, these findings broadly emphasize the reliance of healthcare industry on debt-collection industry.

We also consider the issue of spillovers inherent in geographic DiD designs such as ours, which uses counties neighboring the treated counties as controls. Negative

spillovers from treatment counties to the control may induce upward bias in the estimated treatment effects. In our context, this would imply that adverse outcomes for hospitals—discussed in detail later—are driven by an increased inflow of out-of-state patients seeking care in treated states with stricter debt collection laws, potentially with the intention of avoiding payments and strategically defaulting on it. We argue that such spillovers are likely to be very limited, if present at all, for several reasons. First, insurance plans often restrict patients from using out-of-state hospitals for planned care.[4] Second, since the state debt collection laws apply to the place of collection (defaulted debtor's residence), hospitals in the treated states can simply employ debt collectors operating in the patient's home state (the control), where debt collection laws did not change, by design. Third, planned healthcare access at hospitals is intricately tied to referrals, medical history, and continuity of care, making switching of providers across state lines both uncommon and impractical. Fourth, there was no increase in number of patients in treated hospitals relative to control after the event.

We begin our main empirical analysis by examining the changes in financial health of hospitals using Healthcare Provider Cost Reporting Information System (HCRIS) data made available by Rand Corporation. Hospital-level DiD regressions suggest that treated hospitals experienced an increase in account receivables and unreimbursed cost of care relative to control hospitals following the adoption of stricter debt collection regulations by the state. These findings are consistent with reduced recovery from patients defaulting on medical bills.[5] Additionally, in line with hospitals anticipating declines in the recovery of unpaid medical bills, they increased the amount set aside

[4] For example, both Medicaid and Medicare Advantage health maintenance organizations (HMOs) plans restrict patients to in-state hospitals for planned care. Moreover, while preferred provider organization (PPO) insurance plans may allow out-of-state access, they are substantially more expensive than HMO plans. Thus, the population which subscribes to PPO plans is unlikely to engage in switching to an out-of-state hospital to receive planned care with the intention to strategically default on the medical bills. Insurer's pre-certification requirements for planned treatment also act as a barrier to accessing planned care from out-of-state hospitals.

[5] Note that this reduction does not stem from weaker creditor rights. It arises from restrictions on informal predatory collection practices employed by the collection industry, with whom neither patients nor hospitals have a credit contract prior to the provision of care. Had such a contractual relationship existed, the laws would likely have exerted little impact on hospitals, since the contracting parties could have negotiated the terms to account for stricter collection restrictions—though such adjustments would still have faced limits of incomplete contracting.

for allowance for uncollectible receivables as the ratio of total revenues. With declining recoverability of unpaid bills, unsurprisingly their financial liability—measured by both the ratio of interest expense to revenues and that of total liability to total assets—increased as well relative to control hospitals.

Two sets of results reaffirm that the reason behind these adverse changes is the enactment of stricter third-party debt collection restriction laws. First, we examine hospital job postings and find that the share of job postings for "collection representatives" in relation to all job postings increased by 1.8 percentage points or by almost 28% over the pre-event-year mean in treated hospitals relative to the control group. Second, we examine state-level consumer complaints about debt collectors using CFPB complaint data. We find that while the growth rate of total complaints against debt collectors declined by 10 percentage points, complaints related to healthcare firms increased by 23 percentage points, whereas those related to non-healthcare firms declined by 11 percentage points. This marked shift in complaint patterns, coupled with the increased hospital demand for in-house collection representatives, indicates that hospitals responded to stricter third-party debt collection laws by adopting more aggressive in-house collection practices.

We next investigate the effect of the tighter restrictions on hospital financial performance. We find that while patient volume remained unchanged at treated hospitals compared to control group, their net patient revenues declined by 2 percent. This suggests that, anticipating lower recovery rates on unpaid bills, hospitals likely offered lower charges to patients to increase the probability of payment. As a result of reduced patient revenue, along with the previously discussed increases in accounts receivable and financial liabilities, treated hospitals experienced declines in both profit and operating margins by 0.9 to 1 percentage points. They also curtailed overall employment by two percent, wages by four percent, and core medical professionals (physicians and registered nurses) by a striking seven percent, ultimately leading to a seven-percentage-point decline in the number of core medical professionals per bed-day.

We observe similar cuts in care capacity. They reduced overall beds and ICU beds by 1 and 4 percent, respectively; reduced the number of healthcare sub-facilities by 4 percent; and lowered investments in information technology (as a share of net fixed assets) by 0.84 percentage points. Finally, using hospital by Diagnosis Related Group (DRG) data from CMS, we document a decline in the availability of medical treatment procedures. Specifically, within the universe of procedures provided by the sample hospitals, the share offered by a typical treated hospital declined by 0.8 percentage points relative to the control group, implying that debt collection restrictions also result in lost access to healthcare treatment procedures.

We also find evidence consistent with hospitals steering patients to high-cost procedures after the adoption of tighter debt collection restriction laws. We find that while total number of inpatients remained unchanged between treated and control hospitals, the treated hospitals show a 2.7 percent reduction in inpatients treated with low-cost treatment procedures but 3.2 percent increase in inpatients treated with high-cost procedures. Given that it is unlikely that debt collection restrictions would influence the healthcare needs toward high-cost procedures, these patterns suggest patient steering by affected hospitals in response to the adverse effects of the restriction laws.

We further probe the patient-steering phenomenon by examining differential trends in inpatient care across hospitals specializing in high- versus low-cost DRG procedures. We find that within the sample hospitals specializing in high-cost procedures (that is, those whose share of revenue from high-cost procedures is above the sample median), treated hospitals increased inpatient days by 2 percent while maintaining the same levels of bed utilization. In contrast, within the sample hospitals specializing in low-cost procedures, treated hospitals decreased inpatient days and bed utilization by 9 and 4 percent, respectively. These contrasting patterns strongly indicate patient steering to high-cost procedures by hospitals specialized in high-cost procedures.

Standard mortality-based quality of care metrics also deteriorated at treated hospitals after the law changes. Specifically, using Hospital Compare data, we find that

mortality rate due to both pneumonia and acute myocardial infarction increased in treated hospitals compared to the control. In addition, treated hospitals significantly reduced the level of charity care provided to uninsured patients. Service charges, cost of care, and uncompensated costs associated with charity care all declined relative to control hospitals. At the same time, there was no corresponding decline in charity care for insured patients. Together, these findings strongly suggest that hospitals responded to debt collection restrictions by reducing the provision of charity care, particularly for the uninsured population.

Contribution and Related Literature: To the best of our knowledge, this is the first study to examine the impact of debt collection restriction on hospitals—a sector that is central to healthcare delivery. Hospitals have unique characteristics that set them apart: the cost of services is often uncertain at the time of admission, they cannot geographically diversify their patient base, and as discussed previously, they rely heavily on third-party debt collection agencies for recovery of unpaid unsecured medical debt.

Our findings highlight that consumer financial protection laws can have significant effects on non-financial sectors. Specifically, we show that stricter third-party debt collection regulations affect hospitals through the informal supply chain of defaulted consumer debt. We argue that these regulations reduce the recoverability of hospitals earned revenues, representing a persistent financial shock to which hospitals respond in ways that deteriorate employment, care capacity and quality, investment, the availability of treatment procedures, and access to healthcare for uninsured populations.

Through these findings, we contribute to the emerging literature at the intersection of healthcare and finance. Prior research in this area has typically examined the effects of shocks originating from financial markets—that tend to be non-permanent—on hospitals, with the focus in many cases on specific organizational forms, such as non-profit institutions, or on narrow quality-of-care outcomes. For example, Adelino, Lewellen, and Sundaram (2015) examine how returns on financial securities influence investment decisions of nonprofit hospitals; Aghamolla et al. (2024) study the effects

of attenuated bank credit—caused by supervisory stress testing at 26 banks—to 505 borrower hospitals; and Adelino, Lewellen, and McCartney (2022) analyze the impact of hospitals' lost endowment during the financial crisis on treatment quality for heart attack and C-section patients.[6] Building on these studies, we focus on a regulatory change that directly and permanently reshapes the financial relationship between hospitals and their patients by reducing the recoverability of their earned revenues. Through this unique context, we highlight a trade-off between consumer financial protection laws and access to healthcare arising from the informal supply chain that links defaulted consumers to hospitals through third-party debt collection agencies. Our results on the reduction in availability of treatment procedures and the decline in charity care for uninsured patients highlight the unintended implications of stricter debt collection laws for access to healthcare.

This paper also speaks to a nascent but growing literature on consumer debt collection laws. Prior literature has highlighted their implications on access to credit (Fedaseyeu (2020), Fonseca (2023), Romeo and Sandler (2021)). Relative to these studies, we make two distinct contributions. First, we are the first to show that the effect of these consumer financial protection laws is not limited to financial institutions but rather extends to hospitals—a non-financial industry—due to the informal supply chain of defaulted consumer credit. This is however not surprising, since the share of non-financial industry is significantly larger than financial industry, as discussed previously. Second, we also contribute a hand-collected dataset on state-level debt collection restriction laws from 2010 to 2022, extending previous academic efforts that compiled this data until 2015.

The rest of this paper is organized as follows. Section I provides institutional information, and Section II describes research design and data. Section IV discusses results and Section VI concludes.

[6] Other notable studies on hospitals unrelated to financial shocks include: the differential effects of telehealth adoption on urban and rural hospitals (Cornaggia, Li, and Ye (2024)); the impact of private equity investments on hospital operations (Gao, Kim, and Sevilir (2025), Richards, Shi, and Whaley (2024), Zeller (2023)); and the effects of financial liquidity disclosure mandates (Bourveau et al. (2024)).

I. Institutional Details

A. Debt Collection Industry Regulations

Debt collection practices in the US are regulated federally under the Fair Debt Collection Practices Act of 1977 (FDCPA). While FDCPA sets a baseline for consumer protection against unfair, deceptive, or abusive actions by third-party debt collectors, it allows states the flexibility to enact their own laws to provide more stringent protection to state residents. By 2022, forty-three states had adopted legislation to further regulate third-party debt collection. These restrictions include mandatory licensing requirements, increased penalties for violations, and classification of certain offenses as criminal.

To systematically collect information on state laws governing third-party debt collection, we followed a two-step procedure. First, we relied on the dataset compiled by Fedaseyeu (2020), which covers the laws through 2015. For each state, we verified whether a debt collection law was in effect from 2010 onward, then manually examined the statutory text available on the Justia platform for each year through 2022. Whenever we observed a textual change, we assessed whether it represented a substantive tightening of the law and recorded the year of tightening as an event. Through this manual examination, we ensured to exclude clerical updates and technical corrections to the statutory text. Second, we drew on the 2023 compilation of state debt collection laws by (LexisNexis (2023)) and manually back-traced all laws active in 2023 to 2010, applying the same procedure to identify law changes.

Through this forward- and backward-tracing strategy we identified 28 instances of regulatory tightening across 17 states between 2010 and 2022. The changes identified through this process include Illinois increasing fines for unlicensed practices from $5000 to $10,000 in 2015; Iowa enacting Debt Collection Practices Act in the same year, which codified the list of prohibited practices for debt collection agencies, defined penalties and granted state residents the private right of action; and Oregon introducing additional licensing, pleading, and substantive requirements for debt buyers in 2018.

B. Conceptual Framework: Credit Market Efficiency vs Consumer Protection

As discussed in the introduction, regulating the third-party debt collection industry involves balancing a trade-off between efficiency in unsecured credit markets and consumer protection against abusive collection practices. The efficiency rationale for third-party debt collection rests on several benefits. First, outsourcing collections to specialized firms often provides cost advantages to creditors relative to in-house collection. These advantages arise from economies of scale, as such firms pool collection costs across large number of consumers, and from their specialized expertise—such as generating new information on consumers' ability and willingness to pay through communication and technology (Fedaseyeu and Hunt (2018)). These benefits are especially valuable for non-financial creditors, such as hospitals, whose core competency lies in healthcare provision rather than debt recovery. Second, outsourcing collections shields hospitals from reputational harm, particularly when recovery efforts are not conducted in their own name. Third, using these agencies allows hospitals to hedge potential litigation risks that could arise if excessively aggressive practices are employed against consumers.

On the other side of the trade-off lies the protection of consumers from abusive collection practices. Such practices impose significant non-pecuniary disutility in the form of harassment through repeated and excessive contacts, the use of abusive language, and reputational damage caused by these agencies contacting employers and family members. More importantly, the abusive collection practices could also have serious financial consequences, most notably through the practice known as the "rocket docket." In these proceedings, collection agencies obtain default judgments in "judgeless courtrooms" against thousands of consumers, thereby gaining the legal authority to garnish wages and bank accounts (Stifler (2017)). Collectors exploit the fact that defaulted consumers typically lack the resources to secure legal representation, allowing these proceedings to move forward with minimal judicial scrutiny, if any.

Overall, our results indicate that stricter third-party debt collection laws impose adverse consequences on hospitals. In response, hospitals engage in more aggressive in-house collection practices, steer patients toward higher-cost procedures, curtail employment and a range of healthcare procedures, and reduce charity care for uninsured patients. By documenting these unintended consequences of stricter debt collection policies, our findings contribute to a broader understanding of how such regulations affect healthcare providers and the delivery of care and can inform design of policy interventions.

II. Empirical Research Design

A. Empirical Strategy

We exploit the variation in state-level regulations that tightens debt collection practices over time to estimate its effect on hospitals. Estimating a state-level staggered difference-in-differences (DiD) design comparing outcomes before and after such law changes across states faces two key identification challenges. First, the staggered timing of restrictions raises concerns about treatment-effect heterogeneity across events and issues of bad comparisons (Goodman-Bacon (2021)). Second, hospitals in states tightening debt collection laws may systematically differ from those in states without such changes.

In an effort to address these concerns, we combine two complementary empirical approaches. Specifically, we implement a stacked DiD strategy following Cengiz et al. (2019) and augment it with the paired-bordering county comparison design widely used in empirical labor studies, which is motivated by the approach first used in Card and Krueger (1994) and developed later by Huang (2008) and Dube, Lester, and Reich (2010), among others. First, while stacked designs do not perfectly weight and sum event-specific treatment effects, they ensure that there are no problematic comparisons and thus avoid the associated issues such as negative weights in TWFE (Goodman-Bacon (2021)).

Second, our identification strategy compares hospitals located in contiguous counties on either side of a state border, leveraging only the variation in debt collection laws

of one state while holding local geography and broader economic conditions relatively constant. The geographic proximity of the border counties ensures that the treated and control units being compared are not subject to vastly different state policies or local socioeconomic trends. Moreover, in Section IV, we show that the treated and control groups exhibit no diverging pre-trends in a range of hospital outcomes and county characteristics, alleviating concerns about potential violations of the parallel trends assumption.

As mentioned previously, we identify 28 events of regulation tightening across 17 states between 2010 and 2022. The calendar year in which a given regulation is adopted is an "event" year. The counties located along the border of a state enacting the law constitute the treated counties for a given event. All counties that share border with the treated counties but are located across the state lines are potential control counties. From these, we select the "clean" control counties—those located in such states that itself did not enact a tighter debt collection regulation over a seven-year event window (three years before and after the event year). For states with multiple treatment events during the sample period, we exclude subsequent events that occur within six years of the initial one. Applying these criteria gives us 20 distinct law changes across 16 states over the sample period.

Having identified the treated and clean control counties, we pair each treated counties repeatedly with control counties, allowing each treated county to appear as many times in the sample as the number of neighboring clean control counties.[7] We then create a seven-year panel around the treated-control pairs corresponding to each event and stack these event-specific datasets by aligning them with respect to the event year. This gives us the stacked panel of paired treated and control counties.

[7] In 2013, California introduced a policy requiring debt collectors to obtain the original debt agreement before attempting collection and granted consumers a private right of action. The corresponding event window is from 2010 to 2016. As an example, the treated county of San Bernardino borders three adjacent control counties across state lines: La Paz and Mohave in Arizona, and Clark in Nevada, resulting in three county pairs. To avoid overlap between closely timed events, we exclude California's 2015 regulatory change from the analysis, as it falls within the event window of the 2013 policy and cannot be separately identified.

We merge the county panel with hospital data. Naturally, all hospitals located in treated counties comprise the treatment group, and those in control counties comprise the control group. We exclude government-owned hospitals, as their operations are directly supported by government financial assistance and are subject to different incentive structures than non-governmental hospitals. The baseline sample covers 16,230 hospital-year observations from 574 treated hospitals and 655 control hospitals, located in 178 treated and 205 control counties, respectively. Panel A of Figure 1 shows all treated and control counties on the map of contiguous US. Panel B indicates the mean number of hospitals over the sample period in these counties.

For our main specification, we utilize the following hospital-level stacked DiD regression to explore the effect of debt collection restrictions on hospital outcomes:

$$Y_{ickp\tau} = \alpha + \beta \times \text{Treat}_{ickp} \times \text{Post}_{kp\tau} + \text{Controls} + \gamma_{ickp} + \eta_{kp\tau} + \epsilon_{ickp\tau}, \tag{1}$$

where $Y_{ickp\tau}$ is the outcome variable of hospital i, located in county c within county-pair p, in relative year τ with respect to event k. Outcomes include measures of hospital financial, operational, and care quality information. $Treat_{ickp}$ equals one if the hospital is located in a state that tightened its debt collection regulations during event k, and zero otherwise. $Post_{kp\tau}$ is one for $\tau \geq 0$—i.e., the year of treatment and the subsequent three years—in event k and zero otherwise. This definition implies that $\tau = 0$ represents the year of the regulation change, and $\tau = -1$ is the year prior to treatment. β is the coefficient of interest capturing the average change in outcomes of hospitals before and after the event in the treated counties relative to the control. *Controls* vary across specifications and consist of a host of hospital and county-level socioeconomic characteristics. γ_{ickp} and $\eta_{kp\tau}$ denote event×county-pair×hospital and event×county-pair×relative year fixed effects, respectively.

To analyze outcomes measured at county and state levels, we adapt the above equation and discuss in Section IV, where we present the results.

B. Examining Pre-Trends

To examine pre-trends in the hospital outcomes discussed above, we estimate the following the dynamic version of equation (1) as follows:

$$Y_{ickp\tau} = \alpha + \sum_{\tau=-3,\ \tau\neq-1}^{3} \beta_\tau \text{Treat}_{ickp} \times \mathbb{1}(\text{R.Year} = \tau) + \text{Controls} + \gamma_{ickp} + \eta_{kp\tau} + \epsilon_{ickp\tau}, \quad (2)$$

where $\mathbb{1}(\text{R.Year} = \tau)$ is equal to one when the relative year to the event year is τ. Panels A to H of Figure 2 plot β_τs and the corresponding 95% confidence intervals based on standard errors clustered by state for eight hospital-level variables: allowance for uncollectible receivables to revenues, accounts receivable (in days), total liability to total assets, operating margin, and the natural logarithm of net patient revenues, employment, wages, and number of ICU beds. We do not observe any statistical difference or diverging trends between the treated and control group prior to the event for these key hospital outcomes, indicating an absence of pre-trends.

We also examine the pre-trends in county-level control variables. Panels A to D of Figure 3 plot the coefficients β_τ and the corresponding 95% confidence intervals from a dynamic regression specification similar to equation 2, estimated at the county level for four county-level variables: the unemployment rate, and the natural logarithm of aggregate employment, gross domestic product, and population.[8] We do not observe diverging trends in any of these variables.

Overall, the absence of diverging trends in the key hospital and county characteristics does not raise concerns about a violation of parallel-tends assumption in our DiD design.

III. Data and Summary Statistics

We utilize data from a variety of sources. The primary data is the state-level debt collection regulation changes from 2010 to 2022, which we described earlier. Our second main data is about hospitals. We source the data from the Healthcare Cost Report Information System (HCRIS) maintained by CMS, which contains detailed information on Medicare-certified hospitals. We use the version processed and

[8] The equation is: $Y_{ckp\tau} = \alpha + \sum_{\tau=-3,\ \tau\neq-1}^{3} \beta_\tau \text{Treat}_{ckp} \times \mathbb{1}(\text{R.Year} = \tau) + + \gamma_{ckp} + \eta_{kp\tau} + \epsilon_{ckp\tau}$

standardized by the RAND Corporation, which consolidates approximately 2,000 variables from over 16,000 raw items in the original HCRIS reports. The Rand hospital data offer a consistent time series of variables capturing comprehensive information on hospital characteristics, utilization, costs, charges, wages, employment, ownership type (for-profit vs. non-profit), operational information such as total occupied bed days, inpatient discharges, and financial information such as detailed assets, liabilities, net income, and costs of charity care.

To measure hospital care quality, we use risk-standardized 30-day mortality data from the CMS Hospital Compare program. Mortality is defined as patient death within 30 days of discharge from a hospital admission, including deaths occurring during hospitalization. We focus on mortality rates for three key acute conditions—acute myocardial infarction (AMI or heart attack), heart failure, and pneumonia.

For diagnosis-related analyses, we use the Medicare Inpatient Hospitals by Provider and Service dataset from CMS. Available from 2013 onward, this dataset reports service utilization, total and Medicare-specific payments, and submitted charges at the hospital–MS-DRG level. MS-DRGs are a classification system that groups clinically similar conditions and the associated procedures performed during a hospital stay. Each hospital discharge is assigned to one MS-DRG. This dataset aggregates the patient-level data in a given year to hospital-by-MS-DRG level. This dataset is particularly well suited for our analysis because it consistently captures the actual services and treatment procedures performed by hospitals, allowing us to assess the changes in the scope and menu of available treatment procedures.

Finally, we complement our analysis with a range of county-level socio-economic indicators drawn from publicly available sources. Population counts come from the Census Bureau's annual county resident population estimates. Information on establishments and payroll at the county–industry level is drawn from the County Business Patterns dataset. To capture local labor market conditions, we use the number of active employment and rate of unemployment from the Bureau of Labor Statistics'

Local Area Unemployment Statistics (LAUS). In addition, we incorporate county-level gross domestic product (GDP) data from the Bureau of Economic Analysis.

Table I shows the summary statistics for the key variables. Panel A shows the hospital level variables from HCRIS data. The mean profit margin and operating margin are 3.26% and 0.76%, respectively. On average, the natural logarithm of the number of inpatients is 7.62, and the natural logarithm of hospital beds is 4.39. A typical hospital in our sample takes approximately 42 days to collect payments. Panel B presents county-level data on healthcare establishment size, unemployment rate, employment, GDP, and population.

[Insert Table I Here]

IV. Results

A. Debt Collection Restrictions Laws and the Collection Industry

Before turning to the effects of debt collection regulations on hospitals, we first assess whether these laws were effective in constraining the debt collection industry. Establishing this link allows us to validate the underlying mechanism: stricter regulations constrain the collection industry, limiting hospitals' ability to recover unpaid bills and ultimately shaping their financial and operations decisions. We obtain data on debt collection industry from county business patterns (CBP) data by focusing on NAICS codes 561440 and 561491. We estimate the effect of the restriction laws on the industry at state-level using the following equation:[9]

$$Y_{skp\tau} = \alpha + \beta\, \text{Treat}_{skp} \times \text{Post}_{kp\tau} + \text{Controls} + \gamma_{skp} + \eta_{kp\tau} + \epsilon_{skp\tau}. \tag{3}$$

Here $Y_{skp\tau}$ denotes a state-aggregate measure of debt collection industry in state s, within state-pair p, in relative year τ of event k. $Treat_{skp}$ equals one if a state tightened its debt collection regulations during event k and zero otherwise. $Post_{kp\tau}$ is defined for each treatment event as one for $0 \leq \tau \leq 3$—that is, for the year of treatment and the subsequent three years—and zero otherwise. β is the coefficient of interest capturing

[9] We conduct this analysis at the state level because the industry is regulated at that level, and while collectors may operate statewide, many border counties do not have any registered establishments in this industry.

the average change in outcome variable before and after the event in the treated states relative to the control. γ_{skp} and $\eta_{kp\tau}$ denote event×state-pair and event×state-pair×relative year fixed effects, respectively. Controls are state-level unemployment rate and the natural logarithms of employment, GDP, and population.

Table B.1 in Online Appendix presents the regression results from the above equation for the growth rate of the number of establishments in column (1), state-aggregated wages in column (2), average wages per employee in column (3), and average wages per establishment in column (4). All these variables declined in treated states relative to the control, indicating that the restriction laws were effective in constraining the growth of the industry.

B. Debt Collection Restriction Laws and the Healthcare Industry

We structure our analysis of the effects of the restriction laws on hospitals in two steps. First, we analyze the impact of the laws on the broader healthcare industry at the county-aggregated level. We then narrow the focus to hospital-level effects using more stringent specifications. We do so because the aggregate analysis provides context for the hospital-level results and offers broader insights into the overall impact of the laws on the healthcare sector.

We obtain county-level data on establishments and wages in the healthcare industry from CBP data by focusing on 3-digit NAICS codes 621 and 622, and use the following regression equation:

$$Y_{ckp\tau} = \alpha + \beta\, \text{Treat}_{ckp} \times \text{Post}_{kp\tau} + \text{Controls} + \gamma_{ckp} + \eta_{kp\tau} + \epsilon_{ckp\tau}, \tag{4}$$

where $Y_{ckp\tau}$ denotes the healthcare industry outcome in county c, within county-pair p, in relative year τ of event k. $Treat_{ckp}$, $Post_{kp\tau}$, and *Controls* are the county-level analogues of the corresponding state-level definitions in equation (3). The coefficient β captures the average change in county-level healthcare industry outcomes in treated counties relative to controls, before and after the event. γ_{ckp} and $\eta_{kp\tau}$ denote event×county-pair×county and event×county-pair×relative year fixed effects, respectively.

[Insert Table II Here]

Table II reports the results. In column (1), we see that the average establishment size in healthcare industry, defined as the ratio of number of establishments to number of employees in a county, declined by 6% in treated counties relative to the control. Regarding wages, we find in columns (2) to (4) that aggregate wages, average wages per employee, and average wages per establishment declined by eight, three, and ten percent, respectively. Collectively, these findings indicate that the stricter debt collection regulations had negatively impacted the broader healthcare industry.

C. Hospital-Level Outcomes

Building on the previous results, which suggest that tighter debt collection laws constrained the growth of the collection industry and negatively affected the broader healthcare sector at the county level, we now examine their effects on hospitals in greater detail and explore the underlying mechanisms.

C.1. Rising Bad-Debt Concerns and Financial Obligations of Hospitals

The first outcome we examine is hospitals' ability to collect unpaid bills from patients. Using regression equation (1), we regress the ratio of accounts receivable to total assets and accounts receivable collection periods (in days) and present the results in columns (1) and (2) of Table III. Following the adoption of stricter debt collection laws, the accounts receivable-to-total assets ratio for affected hospitals increased by 3.54 percentage points, and the accounts receivable period increased by 3.6 days, relative to the control hospitals in neighboring counties. The increase in the ratio is equivalent to an 11.4% rise relative to the pre-event-year ($\tau = -1$) mean across treated hospitals of 31.3%. Similarly, the increase in collection period represents a 9.4% rise over the pre-event-year treated sample mean of 38 days.

[Insert Table III Here]

Although an increase in receivables indicates that hospitals' ability to recover unpaid bills has weakened, the extent to which this affects them depends on whether they can offset the shortfalls by securing higher reimbursements from insurance programs. We therefore next examine the changes in hospitals' unreimbursed costs, which represent the portion of expenses incurred for providing care to patients covered

by public insurance programs that are not reimbursed. Using Rand Hospital data, we obtain total unreimbursed costs for Medicaid, the State Children's Health Insurance Program (SCHIP), and state and local indigent care programs.[10] We regress the ratio of total unreimbursed costs to gross patient revenues and present the result in column (3). The coefficient suggests that the affected hospitals experienced an increase of 0.15 percentage points in unreimbursed costs-to-total assets ratio relative to the control hospitals, equivalent to an 8.6% increase over pre-event-year mean of 1.74 for the treated hospitals. This implies that the hospitals did not experience an increase in reimbursements from public insurance programs that could cover the increase in receivables they faced following the stricter debt collection laws.

Facing rising receivables and unreimbursed costs following the adoption of stricter collection laws, hospitals are expected under standard accounting practices to adjust their allowances for uncollectible receivables upward. We assess this prediction by regressing the ratio of allowances for uncollectible receivables to gross patient revenues using equation (1) and present the result in column (4). The coefficient implies that the ratio increased by 0.69 prcentage points for affected hospitals relative to the control, equivalent to an increase of about 12% relative to the pre-event-year mean of 5.75 for treated hospitals. This increase suggests that hospitals anticipated that the share of patient and payer receivables they would be able to collect will decline after the regulation. The idea is that their ability to sell receivables to third-party debt collectors would decline, resulting in both intensive margin effects of higher discounts and inability to sell the debts in extensive margin.

In light of the deterioration in hospitals' operational metrics noted above, we now examine changes in interest expenses and financial liabilities following the adoption of stricter collection laws, which serve as indicators of credit risk and borrowing costs. The coefficient in column (5) shows that, relative to control hospitals, the affected

[10] Unreimbursed cost is distinct from charity care, which refers to free or discounted healthcare to people who cannot afford to pay for their medical bills, regardless of insurance status. Unreimbursed cost pertains to insured patients for whom payments and reimbursements from public insurance programs are inadequate. It is calculated as the difference between the total cost of providing care to patients in these programs and the total payments and reimbursements received. Note that our data does not cover information on unreimbursed costs from private insurance programs.

hospitals' ratio of interest expenses to total revenues increased by 7 basis points (bps), a substantial 18.9% increase over pre-event-year mean of 0.37 for treated hospitals. Similarly, column (6) further shows that total liability to total assets increased by 4.4 percentage points, equivalent to an increase of 8.8% over pre-event-year mean of 50.07 percent across treated hospitals.

To further corroborate the evidence on the cost and amount of borrowing, we focus on hospital-related borrowers in Dealscan loan data, following Aghamolla et al. (2024), and conduct a loan-level analysis. We link CMS hospital data to Dealscan hospital borrowers using data from Aghamolla et al. (2024). Given that a Dealscan hospital borrower often represents multiple hospitals which may operate across several states, we calculate a borrower-level exposure to debt collection restriction laws, *DCR Exposure*, as the sum of the state-level debt collection restriction index, weighted by the net fixed assets of the CMS hospital operating in each respective state.[11] We then use the following regression equation:

$$Y_{lit} = \alpha + \beta \times \text{DCR Exposure}_{it} + \text{Controls} + \gamma_i + \eta_t + \theta_s + \epsilon_{lit}. \tag{5}$$

Here the outcome is loan l of a Dealscan hospital borrower i in calendar year t. γ_i, η_t, and θ_s respectively denote fixed effects for Dealscan hospital borrower, calendar year, and the state of the borrower as recorded in Dealscan. The sample period for this regression spans from 2010 to 2020, the last year for which loan data are available in the legacy Dealscan dataset.

Table B.2 in online appendix presents the results of regressing loan spread and fees in column (1) and the natural logarithm of outstanding loan amounts in column (2). We find that a unit increase in exposure to these regulations is associated with an increase in spreads and fees of about 85 bps and a decline in outstanding loan amounts of about 20% ($e^{-0.22} - 1$). The estimated effect on loan spreads is at least 15% larger than the effect induced by bank stress testing (68–74 bps) in Aghamolla et al. (2024), while the decline in loan amounts due to the restriction laws is 33% smaller. These

[11] Our debt collection index is a continuation of that in Fedaseyeu (2020) for our sample period.

suggest that credit risk of hospitals increased after the adoption of the debt collection restriction laws.

To summarize, our findings in this section strongly indicate that the restriction laws on third-party debt collection resulted in reduced ability of hospitals to recover receivables from patients and also increased their credit risk and financial obligations.

C.2. Hospital In-House Debt-Collection Efforts

We now turn to evidence on the underlying mechanism driving the adverse effects on hospitals. Specifically, we aim to demonstrate that these effects were caused by restrictions on third-party debt collection rather than by other contemporaneous factors. If the laws constrained third-party collectors and thereby negatively affected hospitals, one would expect hospitals to respond by expanding their own in-house collection efforts, as the restrictions did not apply to creditors collecting on their own behalf. Consistent with this idea, we examine whether hospitals increased hiring of collection specialists and intensified in-house collection practices following the law changes.

To analyze changes in hospital hiring practices, we first merge CMS hospital provider numbers with Lightcast company data using text-matching. We then identify 30 unique 5-digit Standard Occupational Classification (SOC) codes associated with debt collection, detailed in Section A.1 in Online Appendix. Using these codes, we classify hospital job postings into collection-related and non-collection-related positions.[12] We calculate the ratio of collection-related job postings to total job postings at hospital-year level and estimate regression equation (1). Column (1) of Table IV shows that the affected hospitals significantly increased their efforts to hire collection specialist relative to the control group, with the ratio rising by 1.78 percentage points—a sizable 28.5% increase over the pre-event-year mean of 6.25 across treated hospitals.

[Insert Table IV Here]

[12] Here are two examples of debt-collection–related hospital job postings identified using our method. Ascension Health, part of Amita Health, posted a full-time job in Arlington Heights, IL, whose description included: "Locates and notifies responsible parties of delinquent accounts to collect payment." Similarly, Temecula Valley Hospital posted a Patient Access Coordinator position with responsibilities that included payment processing and adherence to cash collection practices.

To gauge changes in aggressiveness of in-house collection efforts of hospitals, we draw on CFPB's consumer complaint narrative data, available from 2013 onward. The idea is that, because hospitals faced greater difficulty recovering payments through third-party collection agencies due to the restriction laws, they may respond by increasing the aggressiveness of in-house collection efforts, which in turn would generate more consumer complaints related to hospital debt collection. We test this by first classify consumer complaints as related to hospital care if they contain one or more of 53 keywords associated with hospital care and as related to non-hospital firms otherwise. The keywords are listed in Section A.2 in Online Appendix. Due to limited geographic variation in the complaints data within our sample counties, we examine this at the state level using regression equation (3), with the same set of controls. Columns (2) to (4) of Table IV report the results. We find that while the growth rate of total consumer complaints regarding debt collection declined by 10% after the adoption of third-party debt collection restrictions (Column (1)), complaints against hospitals increased by 23%, whereas those against non-hospital firms declined by 11%. These diverging patterns strongly suggest that, although the restriction laws improved the overall debt collection environment by reducing consumer complaints overall, they likely shifted the abusive practices from third-party agencies to in-house collectors—at least for hospitals, the largest users of third-party collection services.

C.3. Financial Performance

We continue our analysis by now focusing specifically on the effects of the stricter collection laws on financial performance of hospitals. We continue to use regression equation (1). The first outcome of interest is net patient revenues, measured as the natural logarithm of patient charges minus contractual allowances and discounts. Column (1) of Table V shows that affected hospitals experienced a 2% revenue decline relative to the control group, equivalent to an annual revenue loss of $3.72 million based on the pre-event-year average of $186.52 million for treated hospitals.

This revenue decline could arise either from lower inpatient volume or from higher discounts offered by hospitals in an effort to increase the likelihood of timely payments

from patients and to prevent billed revenues from being converted into accounts receivable. To disentangle these channels, we regress the natural logarithm of the number of inpatients and find statistically insignificant coefficient, as reported in column (2). This suggests that the revenue decline was not driven by a reduction in inpatient volume, but likely by larger discounts on patient charges.

The absence of change in inpatient volume has two important implications. One, because the restriction laws do not alter the underlying healthcare needs of the population, patient volume is expected to remain unchanged. Two, it helps rule out the concern that patients in adjacent control counties might have strategically switched to treated states to receive care, default on medical debt, and benefit from stricter protections against debt collection practices. Three factors support this. First, such switching would have increased the patient volume at treated hospitals, which we do not evidence. Second, institutional provisions in the healthcare industry make strategic changes of providers highly unlikely, as noted in the introduction and footnote 4. Third, debt collection laws apply based on the defaulter's state of residence rather than the state where the debt originated, so collection practices of treated hospitals for out-of-state patients remain unaffected from the tightening of collection laws of their state of operation.

[Insert Table V Here]

Finally, we investigate hospital profitability. In column (3), we find that affected hospitals' profit margin decreased by 0.95 percentage points, equivalent to a stark decline of almost 48% over pre-event-year mean value of 1.97 for treated hospitals. Similarly, column (4) indicates that operating margin declined by 1 percentage point, while column (5) and (6) show that the declines are robust when net income and operating income are scaled by net fixed assets, instead of revenues.

C.4. Employment Decisions

We next test whether employment decisions of hospitals were impacted amid deteriorating operational and financial performance following states' adoption of the stricter collection laws. We assess a series of employment-related outcomes using

regression equation 1, and report the results in Table VI. Columns (1) and (2) show that the affected hospitals reduced overall employment and core medical workers by 2% and 7% respectively relative to the control group.[13] These percentages correspond to declines of 27 total jobs and 7.3 core medical jobs, based on the respective pre-event-year sample means. Columns (3) and (4) further suggest that both hospital-aggregated wage and average wage per employee declined by 4% and 1% respectively. Given that the number of inpatients did not decline, the cuts in employment indicate a reduction in medical professionals per patient. We confirm this interpretation in column (5), which shows that the ratio of core workers to inpatient bed-days declined by 7%. The decline in this ratio indicates a deterioration in patient care quality. Overall, these findings suggest that hospitals scaled back their core physician workforce more than the patient occupancy. Given the crucial role these employees play in healthcare delivery, administrating treatment procedures, and managing medication and other care, these cuts in employment and wages have serious adverse implications for quality of patient care.

[Insert Table VI Here]

C.5. Care Capacity and Asset Divestitures

We now show that hospitals also curtailed back care capacity and engaged in asset divestitures as cost-saving measures following the adoption of stricter laws. We use regression equation (1) and report the results in Table VII. Columns (1) and (2) show that, relative to the control group, affected hospitals reduced the total number of beds by 1% and functioning ICU beds by 4%, whereas column (3) suggests that the number of non-ICU beds remained unchanged. Taken together, these findings are consistent with hospitals curtailing ICU beds to achieve cost savings, since maintaining ICU capacity entails substantially higher per-day costs due to the need for adequate critical care and medical staff—which, as shown in our previous results, declined—and essential equipment. Along the same lines, we see in column (4) that they reduced investment in information technology infrastructure by 0.84 percentage points

[13] These variables are defined in Section A.3 of Online Appendix.

relative to control group. Investment in health IT, particularly electronic medical records, not only generates productivity gains through complementary investments by other healthcare providers (Dranove et al. (2014)) but is also highly elastic, making it sensitive to market fluctuations (Richards, Shi, and Whaley (2025)). Consequently, these reductions may limit hospitals' ability to coordinate care delivery and, ultimately, affect care quality.

[Insert Table VII Here]

For asset divestitures, we estimate changes in the number of hospital sub-providers or sub-units, which are distinct functional divisions located within hospital providing specialized medical and operational services.[14] The coefficient in column (5) suggests that affected hospitals reduced the number of sub-units by 4% relative to control group, indicating a potential narrowing of scope of healthcare delivery.

Lastly, we directly examine changes in scope of care by using data on Diagnosis-Related Group (DRG) procedures performed by hospitals. A DRG classifies patients based on diagnosis similarity, severity of the illness, complications, procedures performed etc. For each hospital, we calculate its unique number of DRGs relative to the total number of unique DRGs performed by all sample hospitals in the same state-year. This measure captures the breadth of treatment options or procedural coverage at a hospital relative to its state peers in the same year. The coefficient in column (6) indicates that affected hospitals' DRG share declined by 0.8 percentage points relative to the control group, corresponding to a 3.5% reduction in coverage. Since debt collection restriction laws are unlikely to directly influence patients' medical needs, the reduction in coverage likely reflects hospitals' decision to eliminate treatment procedures—potentially due to the loss of specialized core medical workers, which we documented previously—thereby limiting patients' access to specialized care.

[14] Hospitals sub-units include specialty certified ambulatory surgical centers, renal dialysis providers, inpatient rehabilitation and psychiatric facilities, hospice providers, skilled nursing facilities etc.

C.6. *Pricing Markups on Healthcare Services*

Our analysis thus far has examined the effects of stricter collection laws on hospitals' non-price responses. An important policy-relevant question that follows is whether hospitals increased charges (prices) and markups on their services in response to worsening financial performance. Since a substantial share of hospital revenues come from insurers, who may offset the higher charges through reimbursement adjustments and negotiated prices, the effectiveness of raising prices is inherently limited.[15] At the same time, hospitals may have incentives to reduce prices (by offering larger discounts) in an effort to increase the likelihood of timely payments and limit the accumulation of receivables and bad debt. Whether hospitals ultimately raised or lowered prices is therefore an empirical question, which we address by examining the changes in their cost-to-charge ratio (CCR). It is a standard measure of pricing markups of hospital services calculated as the ratio of total Medicare-allowable costs for the hospital and the corresponding total charges and represents the inverse of markup rate (Pickens, Liang, and Roemer (2021)).[16]

[Insert Table VIII Here]

CCR is available at both hospital level and division levels, such as ICU and emergency rooms, allowing us to conduct a granular analysis of changes in pricing markups. We regress various CCRs using equation (1) and report the results in Table VIII. The coefficients in columns (1) to (5) suggest that markups at treated hospitals did not change relative to the control group, either at overall hospital level or within specific departments such as ICU, adult and pediatric room, operating room, and

[15] Patients are nonetheless adversely affected by rising prices, though the impact varies across patient groups. For those covered by public insurance or in-network private insurance, the effect is largely indirect, through higher premiums and deductibles. In contrast, privately insured out-of-network patients, uninsured patients, and workers' compensation insurers bear the full burden of price increases (Zander et al. (2024)).

[16] CCR has several attractive properties. First, while it depends on direct and indirect operational costs of providing service, it is independent of the direct effects of worsening revenue cycles and financing conditions such as rising receivables and bad debt, making it a clean measure of pricing markups. Second, the underlying cost and charge data are vetted and unlikely to be manipulated, as they are drawn from cost reports that CMS collects for reimbursement purposes under Social Security Amendments Act of 1983's Medicare prospective payment system. Third, it is standardized and not influenced by hospital-specific accounting practices.

emergency room. In contrast, columns (6) and (7) show that CCRs increased for clinics and drugs at treated hospitals relative to control group, implying that they effectively reduced charges for these services. This is consistent with the outpatient-facing nature of these departments, where hospitals may offer lower charges (prices) to increase the likelihood of receiving full and timely payments. Recall that we observed a similar pattern in the first two columns of Table (V) regarding net patient revenues. Taken together, these results indicate that hospitals did not raise charges for their services following the adoption of the stricter collection laws.

C.7. Patient Steering to High-Cost Procedures

Building on the previous analysis of care capacity and asset divestiture, we now turn to an important non-health based proxy for quality of care: patient steering. Specifically, we investigate whether hospitals steer patients toward high-cost treatment procedures (or, DRGs) following the adoption of stricter debt collection laws in an effort to maximize revenues. Using the Medicare Inpatient Hospitals by Provider and Service data, available beginning in 2014, we collect all DRGs conducted by sample hospitals. Each year, we classify DRGs into low- and high-cost groups based on submitted charges by these hospitals. Specifically, DRGs below the 25^{th} percentile of submitted charges are categorized as low-cost, while those above the 75^{th} percentile are categorized as high-cost.[17] Naturally, high-cost DRGs generate higher revenues per patient because they involve more complex, resource-intensive procedures. They potentially create distorted incentives for financially constrained hospitals to steer patients toward such treatments. We expand the previous hospital-level stacked panel to hospital-by-DRG-level stacked panel and use the following regression equation (6):

$$Y_{idckp\tau} = \alpha + \beta \text{Treat}_{idckp} \times \text{Post}_{kp\tau} + \text{Controls} + \gamma_{idckp} + \eta_{kp\tau} + \epsilon_{idckp\tau}, \tag{6}$$

where $Y_{idckp\tau}$ denotes the natural logarithm of the number of inpatients discharged and billed for DRG d in relative year τ with respect to event k by hospital i, where hospital i is located in county c that belongs to county pair p. The controls are the same

[17] Examples of high-cost DRGs include chimeric antigen receptor (CAR) T-cell therapy and other immunotherapies, while low-cost DRGs include childbirth and ear, nose, and throat diagnosis.

as in equation (1). γ_{idckp} and $\eta_{kp\tau}$ respectively denote fixed effects for event×county-pair×hospital×DRG and event×county-pair×relative year. Since the former fixed effects restrict comparisons within hospital–DRG combinations, the estimates address concerns that some DRGs may have a disproportionately large share in the sample, that hospitals may differ in their specialization, or that a shift toward high-cost DRG procedures could simply reflect substitution of older procedures with newer costlier procedures.

Panel A of Table IX reports the results. Columns (1) to (3) indicate that, relative to the control group, the affected hospitals did not experience a change in overall inpatient volume (in line with previous result in Table V), but the number of inpatients billed in low-cost DRGs declined by 2.7%, while those in high-cost DRGs increased by 3.2% following the law change. These differential patterns are strongly consistent with hospitals steering patients toward high-cost DRGs, since the debt collection restriction laws themselves are unlikely to influence the healthcare needs of the underlying population in the short run.[18] While our data cannot disentangle whether these patterns arise from shifts in actual diagnoses, changes in billing practices, or a combination of both, each carry important consequences for patient welfare and quality of care.

We further probe this patient-steering behavior using an alternative empirical strategy by classifying hospitals based on the share of revenues derived from high-cost DRGs. This measure proxies for their ability to alleviate financial constraints through patient steering. Hospitals whose menu of treatment procedures is concentrated in low-cost DRGs do not have the scope of benefiting from steering patients to high-cost DRGs, whereas those specialized in complex procedures derive a substantial share of revenues from high-cost DRGs have significantly greater potential to benefit from doing so. We classify hospitals into high- and low-DRG intensity groups based on

[18] Note that these patterns does not suggest a crude substitution of diagnosis for the same patient from low- to high-cost DRGs—for example, a patient with an ear condition receiving immunotherapy. Rather, it reflects a shift in the distribution, with a greater proportion of patients being assigned diagnoses that are billed at higher rates.

whether their annual ratio falls above or below the sample median in the pre-event-year of the respective event and hold this classification fixed over the event.

[Insert Table IX Here]

We regress inpatient days (in natural logarithm) for all hospitals and separately for the two DRG intensity groups using equation (1) and report the results in columns (1) to (3) of Panel B in Table IX. While we observe a 4% overall decline in inpatient days among affected hospitals relative to the control group, the decline is more than twice at 9% among low-DRG intensity hospitals, whereas high-DRG intensity hospitals exhibit a 2% increase in inpatient days. These diverging trends suggest that high-DRG-intensity hospitals began prescribing longer inpatient stays following the adoption of the laws, again consistent with patient steering. In columns (4) to (6), we observe a similar pattern for bed utilization, with overall decline of 2% driven entirely by low-DRG intensity hospitals.

Overall, we conclude that debt collection laws led to changes in allocation of patient to treatment procedures consistent with hospitals steering patients to high-cost procedures.

C.8. Quality of Care: Patient Mortality

We now turn to analyzing the effects of the restriction laws on standard health-based mortality measures of quality of care. Using data from CMS Hospital Compare, we investigate whether mortality associated with the following three common conditions deteriorated at the treated hospitals: pneumonia (PN), acute myocardial infarction (AMI), and heart failure (HF). A practical issue in using these data is that mortality rates are reported using a 36-month rolling window. For example, the rate reported on June 30, 2013, reflects data from July 1, 2010, to June 30, 2013, making a clean separation of pre- and post-event outcomes infeasible in our DiD setting, which spans six years. To address this issue, we construct annual mortality rates as follows: for each pre-period year t, we use the rate based on data ending in year t; for each post-period year t, we use the rate based on data beginning in year t. For instance, the pre-period 2013 rate is based on data from July 1, 2010, to June 30, 2013, while the post-period 2013 rate uses

data from July 1, 2013, to June 30, 2016. This scheme ensures that pre-period mortality rates rely solely on pre-event data, while post-period rates rely solely on post-event data.

[Insert Table X Here]

We regress these mortality rates using equation (1) and present the results in Table X. Columns (1) and (2) show that mortality rates for pneumonia and heart failure increased in affected hospitals relative to the control group. We do not detect an increase in AMI-related mortality, which may be because deterioration in care quality for AMI does not readily translate into higher mortality rates due to high autocorrelation in outcomes (Aghamolla et al. (2024)). In economic terms, the increases imply additional 136 pneumonia-related deaths and 21 HF-related deaths per year among the 716 affected hospitals in our sample. Taken together, these results reaffirm that care quality at affected hospitals deteriorated following the adoption of stricter debt collection laws.

V. Additional Results

In this section, we provide additional results that supplement the main results.

A. Charity Care by Non-profit Hospitals

A crucial dimension of the quality of healthcare delivery at non-profit hospitals is charity care. To maintain their tax exemption status, non-profit hospitals are required to provide free or reduced-cost care to patients who cannot afford to pay for healthcare services. This ensures that low income, underinsured, and uninsured individuals have access to essential medical services regardless of their ability to pay. We test the effect of the stricter collection laws on charity care at non-profit hospitals. We continue using equation (1) and report results in Table XI. Columns (1) to (3) report results for charity care at non-profit hospitals provided to uninsured patients, scaled by their net fixed assets. Compared to control non-profit hospitals, the affected non-profits devoted 1.07 percentage points less of their total charges (service revenues) to charity care and curtailed their estimated and incurred uncompensated costs of providing charity care

by 0.36 and 0.32 percentage points, respectively. These cuts are economically large and non-trivial, as these correspond to a 16.8% reduction in total charity care charges, a 19.3% reduction in estimated cost, and a 17.8% reduction in uncompensated cost, relative to respective pre-event year means across treated non-profit hospitals. In a stark contrast, we do not find any decline in any of these charity care measures for insured patients, as indicated by the coefficients in column (4) to (6).

[Insert Table XI Here]

These findings strongly suggest that hospitals selectively reduced charity care for uninsured patients as a cost-saving strategy following the adoption of stricter debt collection laws. This has important policy and public health implications, as the laws appear to have reduced access to healthcare for the uninsured—ironically, the group vulnerable to incurring unpaid medical debt (CFPB (2022), p.10) and central to the motivation behind the stricter debt collection laws.

B. Heterogeneity

In this section, we conduct two sets of heterogeneity tests that further offer insights into the proposed mechanism: that stricter debt collection laws affect hospitals by reducing the recoverability of unpaid medical bills, thereby impacting their financial positions. If this mechanism is correct, the effects should be more pronounced for ex ante financially weaker hospitals and for those with greater reliance on third-party collectors. We therefore first examine whether hospitals with weaker ex ante financial positions experienced stronger effects, reflecting their limited ability to absorb losses from unpaid medical bills. Second, we assess whether hospitals located in areas with higher debt collector density were more affected, reflecting their greater dependence on external collection agencies, which likely arises from the weaker financial and socio-economic profile of the local population that make collection activities more prevalent locally.

B.1. Heterogeneity by Hospital's Characteristics

To assess whether the effects of the stricter laws were stronger for hospitals with weaker ex ante financial position, we classify hospitals based on their ratio of total liabilities to

total assets (TL/TA) in the pre-event-year of the respective event. Hospitals above the sample median are categorized as having high financial liability, while those below the median are classified as having low financial liability. This classification is held fixed for each respective event. We then examine changes in three outcome variables: (i) the ratio of accounts receivable to total assets, (ii) the ratio of interest expense to revenues, and (iii) operating margin (in percentage).

[Insert Table XII Here]

We estimate regression equation (1) separately for the two groups and report the results in Panel A of Table XII. Coefficients in columns (1), (3), and (5) indicate that, among hospitals with high ex ante liability, the laws increased accounts receivable and interest expenses by 6.78 and 0.13 percentage points, respectively, while reducing operating margins relative to the control group by 1.4 percentage points. By contrast, the effects were not statistically significant for any of the three outcome variables among hospitals with stronger ex ante financial health, as indicated by coefficients in columns (2), (4), and (6). Taken together, these findings suggest that the shocks originating from the policy changes propagated to the hospitals through the financial-constraint channel, disproportionately affecting the financially vulnerable hospitals.

B.2. Heterogeneity by Debt Collector Density

To assess whether hospitals in areas with a higher density of debt collectors experienced more severe impacts of the restriction laws, we classify states based on the number of debt collectors per million population in the state. Hospitals located in states above the sample median in the pre-event-year of the respective event are classified as operating in environments with more intense debt collection activity, while those below the median are considered to face less intensive collection practices. This classification is held fix for each respective event. Panel B of Table XII reports the results of the same three outcome variables estimated separately for high and low group.

Coefficients in columns (1), (3), and (5) indicate that, among hospitals in states with high ex ante debt collector density, the laws increased accounts receivable and interest expenses by 3.13 and 0.14 percentage points, respectively, while reducing

operating margins relative to the control group by 2.3 percentage points. By contrast, for hospitals in states with lower ex ante collector density, the laws resulted in lower receivables (columns (2)), had no impact on interest expenses (column (4)), and higher operating margin by 3.4 percentage points (column (6)).[19] The stronger adverse effects for hospitals in higher collector density reaffirm our proposed mechanism that the laws impact the hospital outcomes through their dependence on the collection industry.

VI. Conclusion

Consumer financial protection policies may have unintended consequences even for non-financial sectors. In this paper, we show that stricter third-party debt collection laws—designed to protect consumers from predatory and abusive collection practices—have significant negative implications for hospitals, a non-financial sector that relies more heavily on the debt collection industry than even the financial industry to recover unpaid, unsecured medical debt. We employ the contiguous-county-pair comparisons combined with stacked difference-in-differences approach around the staggered adoption of stricter debt collection laws by states to draw causal conclusions. We hand-collected data on state-level regulations on debt collection restrictions until 2022 and supplement it with similar data previously compiled by Fedaseyeu (2020) until 2014 and used in Fonseca (2023).

We show that tighter debt collection regulations substantially increase hospitals' accounts receivable, unreimbursed costs, and financial liabilities, while reducing profitability and raising borrowing costs. In response, hospitals scale back on human capital and fixed asset investments, reduce the provision of charity care—especially for the uninsured—and narrow the menu of available medical treatment procedures. Importantly, health-based quality of care measures using mortality rates for major acute conditions also declined. Finally, while pricing markups for hospital services

[19] The surprising positive effects of the collection laws on receivables and operating margins for hospitals in the lower collector-density group may reflect cost-saving and revenue-maximizing measures that offset the laws' adverse impacts. These hospitals were likely less reliant on third-party debt collectors to begin with, which may have further mitigated the negative effects.

did not increase, we find evidence consistent with hospitals steering patients toward more complex, high-cost procedures, likely in a bid to offset the increased financial strain. We note that stricter third-party debt collection laws may inadvertently harm the very population they are intended to protect: uninsured patients—a group especially vulnerable to unpaid medical debt—experienced significant reductions in access to charity care following the enactment of these laws.

In summary, we emphasize that consumer financial protection policies can have unintended adverse consequences even for non-financial sectors, ignoring which may overstate the net benefits of those policies.

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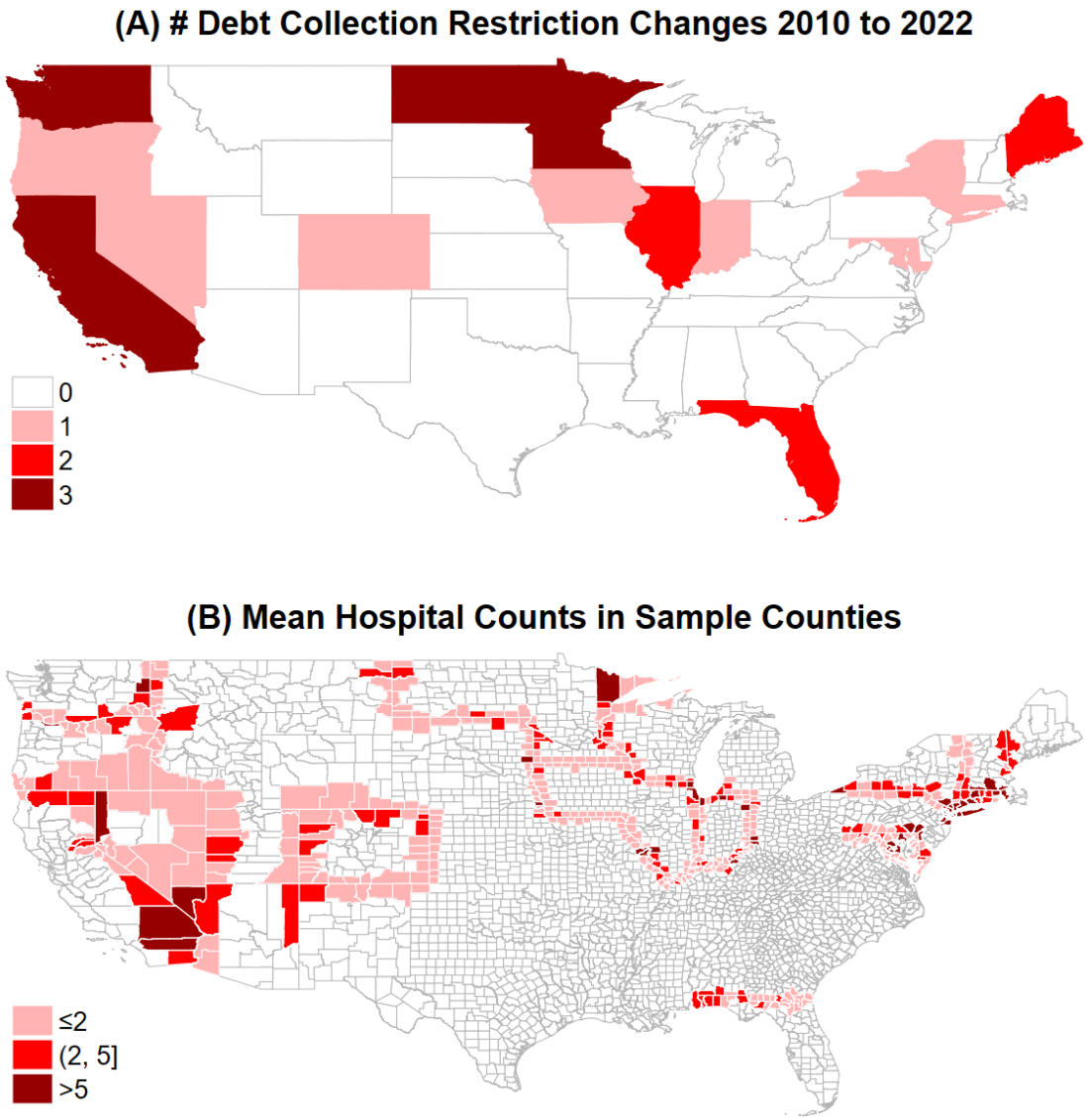


Figure 1. Debt Collection Policy Changes and Hospital Distribution. Panel A shows the number of state-level changes in debt collection restrictions between 2010 and 2022. Panel B shows the treatment and control counties plotted on the map of the contiguous U.S., along with the average number of hospitals located within them. These counties are located at the border between the treatment states and their neighboring control states.

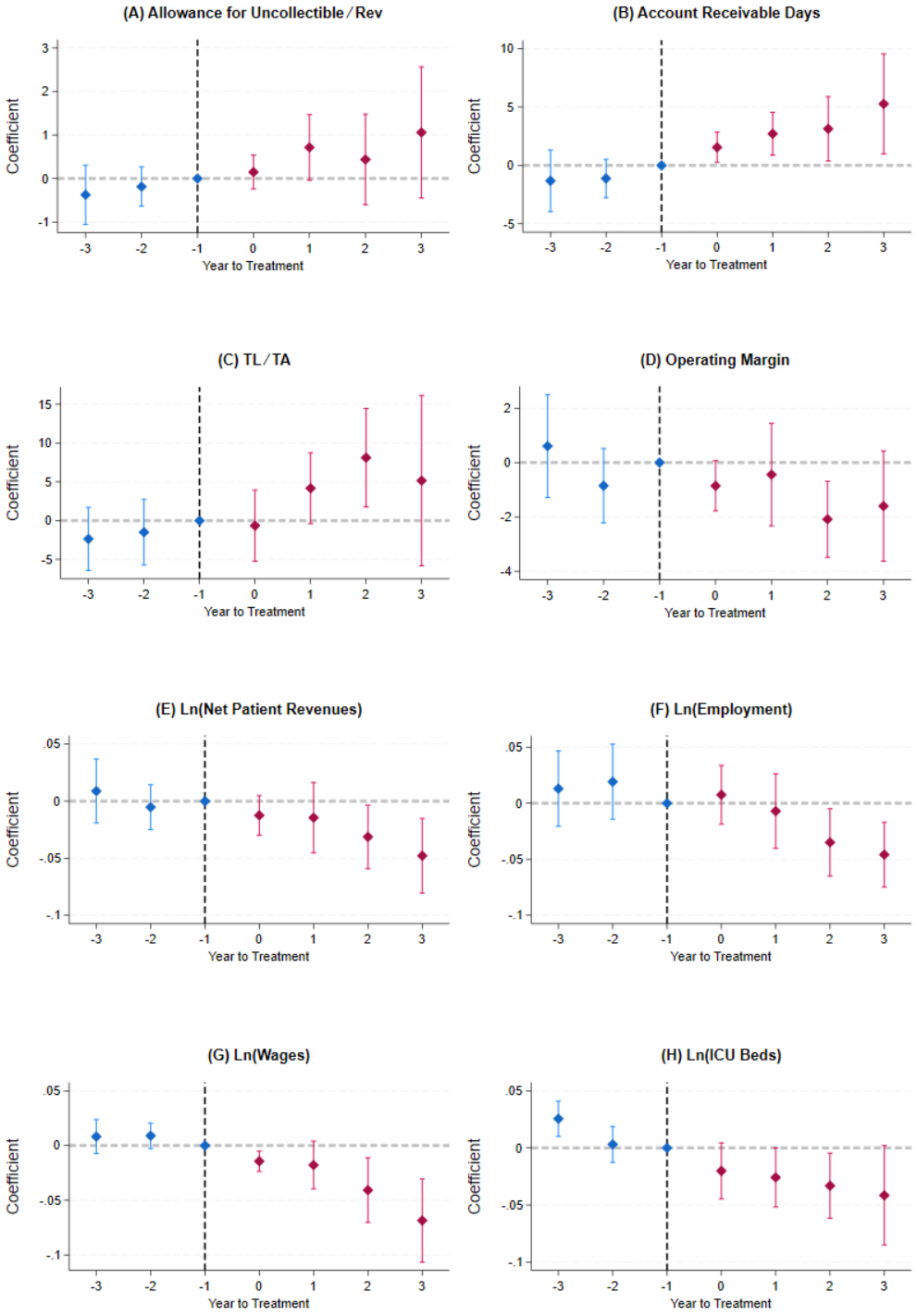


Figure 2. Pre-Trends for Hospital-level Variables. This figure shows the coefficients β_τs and 95% confidence intervals obtained from regression equation (2) for eight hospital-level variables, which are indicated in the respective panels. The horizontal axis shows years relative to the event year, with $\tau = 0$ indicating the first treated year.

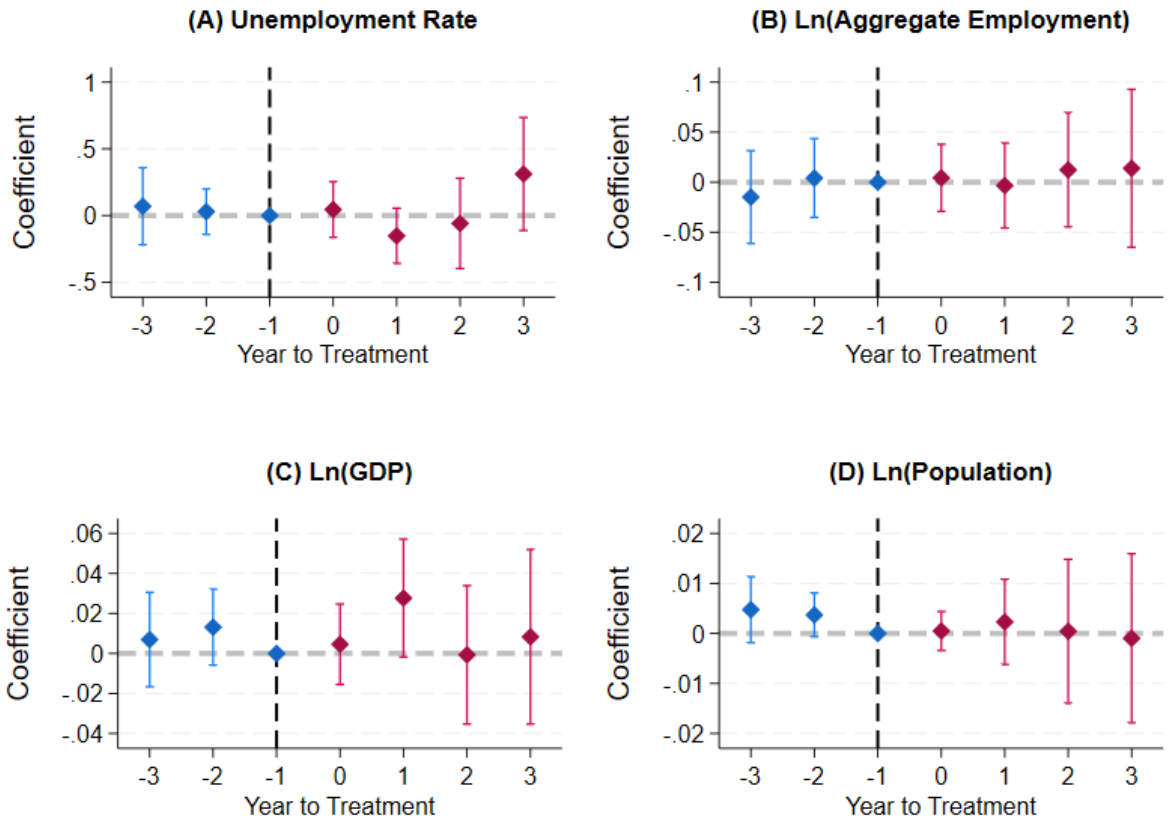


Figure 3. Pre-Trends for County-Level Control Variables. This figure shows the coefficients β_τ and 95% confidence intervals from the county-level version of the regression equation (2), as specified in footnote 8. The horizontal axis shows years relative to the event year, with $\tau = 0$ indicating the first treated year.

Table I
Summary Statistics

This table reports summary statistics. *Ln*(*Net Pat Rev*) is the natural logarithm of net patient revenue. *Profit Margin* is profit margin, defined as net income over total income. *Oprt Margin* is operating margin, defined as operating earnings over operating income. *Ln*(*# Inpat*) is the natural logarithm of the number of inpatients. *Ln*(*Beds*) is the natural logarithm of the total number of hospital beds. *Ln*(*Wages*) is the natural logarithm of annualized total salaries and employee benefits. *Ln*(*Emp*) is the natural logarithm of total employees. *AR Days* is days in gross accounts receivable. *Allowance Uncollectible/Rev* is the ratio of allowances for uncollectible notes and accounts receivable to gross patient revenue. *Oprt Inc/NFA* is the ratio of operating income to net fixed assets. *Cash/NFA* is the ratio of cash to net fixed assets. *Ln*(*HC Est Size*) is the natural logarithm of establishment size of the healthcare industry (3-digit NAICS codes 621 and 622), calculated as the number of employees divided by the number of establishments. *Ln*(*HC Agg Wage*) is the natural logarithm of total annual payroll in the healthcare industry. *Controls* in regressions include one-year lagged hospital-level *Ln*(*Beds*), *Oprt Inc/NFA*, and *Cash/NFA*, as well as county-level unemployment rate and the natural logarithms of employment, GDP, and population.

	N	Mean	P25	Median	P75	SD
	(1)	(2)	(3)	(4)	(5)	(6)
A. Hospital×Year-Level Variables						
Ln(Net Pat Rev)	8,791	4.30	3.20	4.28	5.45	1.42
Profit Margin (%)	8,782	3.26	-1.05	4.05	9.73	15.31
Oprt Margin (%)	8,727	0.76	-2.93	2.65	8.59	19.82
Ln(# Inpat)	9,102	7.62	6.29	7.80	9.11	1.75
Ln(Beds)	9,108	4.39	3.22	4.49	5.28	1.12
Ln(Wages)	9,059	3.59	2.54	3.54	4.61	1.32
Ln(Emp)	5,975	6.61	5.91	6.70	7.38	1.14
AR Days	8,790	41.80	19.39	33.67	53.52	36.08
Allowance Uncollectible/Rev (%)	6,087	7.16	1.83	5.12	9.13	9.25
Oprt Inc/NFA (%)	8,724	8.78	-2.81	3.38	12.49	107.74
Cash/NFA (%)	8,517	16.67	0.24	5.02	15.88	68.13
B. County×Year-Level Variables						
Ln(HC Est Size)	2,890	2.05	1.55	2.12	2.64	0.85
Ln(HC Agg Wage)	2,985	10.27	8.20	10.18	12.11	2.51
Unemployment Rate (%)	3,908	5.67	3.50	5.00	7.20	3.00
Ln(Employment)	3,842	8.22	6.62	8.18	9.97	2.48
Ln(GDP)	3,894	7.27	5.98	7.07	8.40	1.79
Ln(Population)	3,894	10.37	9.18	10.26	11.54	1.70

Table II
Effect on Healthcare Industry

All columns report estimates from the regression model in equation (4). All outcome variables are in natural logarithm, and observations are at the county-year level. *Est Size* is the number of employees divided by the number of establishments in healthcare industry (identified using 3-digit NAICS codes 621 and 622 in CBP data). *Agg Wage* is total annual payroll in the healthcare industry. *Avg Emp Wage* is average annual payroll per employee in the healthcare industry. *Avg Est Wage* is average annual payroll per establishment in the healthcare industry. *Treat* equals one if the county is located in a state that tightened its debt collection regulations during event k, and zero otherwise. *Post* is one for the year of treatment and the subsequent three years in event k and zero otherwise. Controls are county-level unemployment rate and the natural logarithms of employment, GDP, and population listed and defined in Table I. All models include event×county-pair×county and event×county-pair×relative year fixed effects. Standard errors are clustered by state and reported in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

	(1)	(2)	(3)	(4)
Outcome (in Ln):	Est Size	Agg Wage	Avg Emp Wage	Avg Est Wage
Treat×Post	-0.06*	-0.08**	-0.03**	-0.10***
	(0.03)	(0.03)	(0.02)	(0.03)
Event×Pair×R.Year FE	Y	Y	Y	Y
Event×Pair×County FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Adjusted R^2	0.88	0.98	0.59	0.90
Observations	4,748	5,000	4,748	5,000

Table III
Bad Debt Concerns and Financial Obligations of Hospitals

All columns report estimates from the regression model in equation (1). *AR/TA* is the ratio of accounts receivable to total assets, expressed as a percentage. *AR Days* is days in gross accounts receivable. *Unreimb/Rev* is the ratio of total unreimbursed cost for Medicaid, SCHIP and state and local indigent care programs to gross patient revenue, expressed as a percentage. *Allowance Uncollectible/Rev* is the ratio of allowances for uncollectible notes and accounts receivable to gross patient revenue, expressed as a percentage. *Int Exp/Rev* is the ratio of total interest expenses to gross patient revenues, expressed as a percentage. *TL/TA* is the debt-to-assets ratio, defined as total liability over total assets and expressed as a percentage. *Treat* equals one if the hospital is located in a state that tightened its debt collection regulations during event k, and zero otherwise. *Post* is one for the year of treatment and the subsequent three years in event k and zero otherwise. Controls are the seven hospital- and county-level variables listed and defined in Table I. All models include event×county-pair×hospital and event×county-pair×relative year fixed effects. Standard errors are clustered by state and reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Bad Debt Concerns				Financial Obligations	
	(1)	(2)	(3)	(4)	(5)	(6)
	$\frac{\text{AR}}{\text{TA}}$ %	AR Days	$\frac{\text{Unreimb}}{\text{Rev}}$ %	$\frac{\text{Allowance Uncollectible}}{\text{Rev}}$ %	$\frac{\text{Int Exp}}{\text{Rev}}$ %	$\frac{\text{TL}}{\text{TA}}$ %
Treat×Post	3.54*	3.57***	0.15*	0.69**	0.07***	4.40*
	(1.76)	(0.88)	(0.09)	(0.33)	(0.02)	(2.50)
FE: Event×Pair×R.Year	Y	Y	Y	Y	Y	Y
FE: Event×Pair×Hospital	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.63	0.81	0.68	0.71	0.82	0.78
Observations	13,989	14,106	8,691	9,160	14,109	14,105

Table IV
Aggressive Hospital Debt Collection Activities

Column (1) report estimates from regression model in equation (1), and the remaining use that in equation (3). *Job Postings %* is the percentage of a hospital's job postings related to debt collection. Δ *Debt Collection Complaints* is the growth rate of the number of debt collection-related consumer complaints reported to CFPB. The complaint categories corresponding to columns (2) to (4) are: all firms, hospitals, and non-hospitals, respectively. In column (1), *Treat* equals one if the hospital is located in a state that tightened its debt collection regulations during event k, and zero otherwise. In columns (2) to (4), *Treat* equals one if the state tightened its debt collection regulations during event k, and zero otherwise. *Post* is one for the year of treatment and the subsequent three years in event k and zero otherwise. Column (1) includes the seven hospital- and county-level control variables listed and defined in Table I, and columns (2) to (4) include state-level counterparts for four control variables—the unemployment rate and the natural logarithms of employment, GDP, and population. Column (1) includes event×county-pair×hospital and event×county-pair×relative year fixed effects. Columns (2) to (4) include event×state-pair×state and event×state-pair×relative year fixed effects. State pairs are constructed similarly to the county pairs described in Section II, pairing each treated state with appropriate control states. Standard errors are clustered by state and reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Outcome:	Job Postings %	Δ Debt Collection Complaints		
	(1)	(2)	(3)	(4)
	Collection Rep.	All Firms	Hospitals	Non-Hospitals
Treat×Post	1.78**	-0.10**	0.23**	-0.11**
	(0.86)	(0.04)	(0.11)	(0.04)
Panel	Hosp	State	State	State
Event×State Pair×R.Year FE	N	Y	Y	Y
Event×State Pair×State FE	N	Y	Y	Y
Event×Pair×R.Year FE	Y	N	N	N
Event×Pair×Hospital FE	Y	N	N	N
Adjusted R^2	0.03	0.89	-0.67	0.89
Observations	5,734	522	398	522

Table V
Financial Performance

All columns report estimates from the regression model in equation (1). *Ln(Net Pat Rev)* is the natural logarithm of net patient revenue. *Ln(# Inpat)* is the natural logarithm of the number of inpatients. *Profit Margin* is profit margin, defined as net income over total income. *Oprt Margin* is operating margin, defined as operating earnings over operating income. *NI/NFA* is the ratio of net income to net fixed assets, expressed as a percentage. *Oprt Inc/NFA* is the ratio of operating income to net fixed assets, expressed as a percentage. *Treat* equals one if the hospital is located in a state that tightened its debt collection regulations during event k, and zero otherwise. *Post* is one for the year of treatment and the subsequent three years in event k and zero otherwise. Controls are the seven hospital- and county-level variables listed and defined in Table I. All models include event×county-pair×hospital and event×county-pair×relative year fixed effects. Standard errors are clustered by state and reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln(Net Pat Rev)	Ln(# Inpat)	Profit Margin %	Oprt Margin %	$\frac{\text{NI}}{\text{NFA}}$ %	$\frac{\text{Oprt Inc}}{\text{NFA}}$ %
Treat×Post	-0.02**	-0.01	-0.95**	-1.02**	-10.51**	-9.66**
	(0.01)	(0.01)	(0.46)	(0.46)	(5.10)	(4.57)
FE: Event×Pair×R.Year	Y	Y	Y	Y	Y	Y
FE: Event×Pair×Hospital	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.98	0.99	0.57	0.61	0.33	0.35
Observations	14,109	14,120	14,102	14,076	14,081	14,088

Table VI
Employment Decisions

All columns report estimates from the regression model in equation (1). *Ln*(*Emp*) is the natural logarithm of total employees. *Ln*(*# Core*) is the natural logarithm of the number of physicians, nurses, and pharmacists, as defined in Gao, Kim, and Sevilir (2025). *Ln*(*Wages*) is the natural logarithm of annualized total salaries and employee benefits. *Ln*(*Avg Wages*) is the natural logarithm of average salary and employee benefits per employee. *# Core/Bed-Days* is the ratio of the number of nurses, physicians, and pharmacists to bed-days available (in '000s). *Treat* equals one if the hospital is located in a state that tightened its debt collection regulations during event *k*, and zero otherwise. *Post* is one for the year of treatment and the subsequent three years in event *k* and zero otherwise. Controls are the seven hospital- and county-level variables listed and defined in Table I. All models include event×county-pair×hospital and event×county-pair×relative year fixed effects. Standard errors are clustered by state and reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)	(5)
	Ln(Emp)	Ln(# Core)	Ln(Wages)	Ln(Avg Wages)	$\frac{\text{\# Core}}{\text{Bed-Days}}$
Treat×Post	-0.02*	-0.07**	-0.04***	-0.01*	-0.07*
	(0.01)	(0.03)	(0.01)	(0.01)	(0.04)
FE: Event×Pair×R.Year	Y	Y	Y	Y	Y
FE: Event×Pair×Hospital	Y	Y	Y	Y	Y
Adjusted R^2	0.97	0.94	0.99	0.86	0.92
Observations	9,933	9,863	14,084	14,073	14,118

Table VII
Investments

All columns report estimates from the regression model in equation (1). *Ln*(*Beds*) is the natural logarithm of the total number of hospital beds. *Ln*(*ICU Beds*) is the natural logarithm of the number of intensive care unit beds. *Ln*(*Non-ICU Beds*) is the natural logarithm of the number of non-intensive care unit beds, calculated as the difference between total beds and ICU beds. *IT*/*NFA* is the ratio of a hospital's investments in health information technology to its net fixed assets, expressed as a percentage. *Ln*(*# Sub-Units*) is the natural logarithm of the number of unique sub-providers for each hospital. *DRG Share* is the ratio of the number of unique DRGs a hospital handles to the total number of unique DRGs performed by all sample hospitals from the same state-year, expressed as a percentage. *Treat* equals one if the hospital is located in a state that tightened its debt collection regulations during event k, and zero otherwise. *Post* is one for the year of treatment and the subsequent three years in event k and zero otherwise. Controls are the seven hospital- and county-level variables listed and defined in Table I. All models include event×county-pair×hospital and event×county-pair×relative year fixed effects. Standard errors are clustered by state and reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln(Beds)	Ln(ICU Beds)	Ln(Non-ICU Beds)	$\frac{\text{IT}}{\text{NFA}}$ %	Ln(# Sub-Units)	DRG Share %
Treat×Post	-0.01**	-0.04**	-0.01	-0.84**	-0.04**	-0.80**
	(0.00)	(0.02)	(0.01)	(0.32)	(0.02)	(0.33)
FE: Event×Pair×R.Year	Y	Y	Y	Y	Y	Y
FE: Event×Pair×Hospital	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.99	0.97	0.99	0.17	0.92	0.99
Observations	14,118	8,428	14,118	1,125	8,593	5,268

Table VIII
Pricing Markups

All columns report estimates from the regression model in equation (1). The outcome variables are the respective cost-to-charge ratios for hospital services, as indicated in the bottom row of the column header. *Treat* equals one if the hospital is located in a state that tightened its debt collection regulations during event k, and zero otherwise. *Post* is one for the year of treatment and the subsequent three years in event k and zero otherwise. Controls are the seven hospital- and county-level variables listed and defined in Table I. All models include event×county-pair×hospital and event×county-pair×relative year fixed effects. Standard errors are clustered by state and reported in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Cost-to-Charge Ratio:	Overall	ICU	Adults & Peds	Oprt Room	Emergency	Clinic	Drugs
Treat×Post	0.01	-0.01	0.02	0.08	0.02	0.49**	0.03*
	(0.00)	(0.02)	(0.01)	(0.08)	(0.01)	(0.21)	(0.02)
FE: Event×Pair×R.Year	Y	Y	Y	Y	Y	Y	Y
FE: Event×Pair×Hospital	Y	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.90	0.87	0.85	0.15	0.52	0.44	0.78
Observations	12,042	8,175	12,040	9,915	9,344	7,484	11,599

Table IX
Steering Patients To High-Cost Procedures

Panel A reports estimates from the regression model in equation (6), while Panel B reports estimates from the regression model in equation (1). *Ln*(*# Inpat*) is the natural logarithm of the number of inpatients. *Ln*(*Inpat-Days*) is the natural logarithm of inpatient days. *Bed Utilization* is the average daily fraction of hospital beds that are occupied, defined as inpatient days over bed-days available. In Panel A, the bottom row in the column header denotes the sample by DRG type. *Low-Cost* DRGs are those with average submitted charges to Medicare below the annual median value for all sample hospitals. *High-Cost* DRGs are those with the average charges above this median. In Panel B, the bottom row in the column header denotes the sample by Hospital DRG Intensity. *Hospital DRG Intensity* is defined as the share of a hospital's total submitted charges to Medicare that originate from high-cost DRGs. *Low Hospital DRG Intensity* hospitals are those with an intensity value below the annual samle median in the pre-event-year of the respective event, while *High Hospital DRG Intensity* hospitals are those above the median. We hold this classification fixed over the respective event. *Treat* equals one if the hospital is located in a state that tightened its debt collection regulations during event k, and zero otherwise. *Post* is one for the year of treatment and the subsequent three years in event k and zero otherwise. Controls are the seven hospital- and county-level variables listed and defined in Table I. Panel A includes event×county-pair×hospital×DRG and event×county-pair×relative year fixed effects. Panel B includes event×county-pair×hospital and event×county-pair×relative year fixed effects. Standard errors are clustered by state and reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

A: Steering Patients to High-Cost Procedures (*Hospital×DRG Panel*)

Outcomes:	Ln(# Inpat)		
	(1)	(2)	(3)
DRG Type:	All	Low-Cost	High-Cost
Treat×Post	-0.011	-0.027*	0.032***
	(0.012)	(0.015)	(0.011)
FE: Event×Pair×R.Year	Y	Y	Y
FE: Event×Pair×Hospital×DRG	Y	Y	Y
Adjusted R^2	0.85	0.85	0.79
Observations	386,880	160,004	45,417

B: Patient Steering and Hospital DRG Intensity (*Hospital Panel*)

Outcomes:	Ln(Inpat-Days)			Bed Utilization		
	(1)	(2)	(3)	(4)	(5)	(6)
Hospital DRG Intensity:	All	Low	High	All	Low	High
Treat×Post	-0.04**	-0.09***	0.02**	-0.02*	-0.04***	0.00
	(0.02)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)
FE: Event×Pair×R.Year	Y	Y	Y	Y	Y	Y
FE: Event×Pair×Hospital	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.97	0.95	0.97	0.92	0.91	0.91
Observations	5,802	2,736	2,516	5,802	2,736	2,516

Table X
Patient Mortality

All columns report estimates from the regression model in equation (1). The outcome variable is the 30-day mortality rate, expressed as a percentage. A mortality is defined as a patient death within 30 days of discharge from a hospital admission. Column header denotes the diagnostic groups: pneumonia, AMI, and heart failure. *Treat* equals one if the hospital is located in a state that tightened its debt collection regulations during event k, and zero otherwise. *Post* is one for the year of treatment and the subsequent three years in event k and zero otherwise. Controls are the seven hospital- and county-level variables listed and defined in Table I. All models include event×county-pair×hospital and event×county-pair×relative year fixed effects. Standard errors are clustered by state and reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	(1)	(2)	(3)
Mortality Rate %:	Pneumonia	AMI	Heart Failure
Treat×Post	0.38**	0.14*	-0.16
	(0.17)	(0.07)	(0.16)
FE: Event×Pair×R.Year	Y	Y	Y
FE: Event×Pair×Hospital	Y	Y	Y
Adjusted R^2	0.77	0.64	0.62
Observations	7,703	5,613	7,166

Table XI
Charity Care at Non-Profit Hospitals

All columns report estimates from the regression model in equation (1). The outcome variables, *Chrg Apv*, *Cost Est*, and *Cost Uncomp*, are all scaled by net fixed assets and expressed as a percentage. *Chrg Apv* is the gross charges for services provided to patients approved for a discount under the hospital's charity care policy, *Cost Est* is the estimated cost to the hospital of providing these services, and *Cost Uncomp* is the net cost to the hospital of providing these services, defined as the difference between the estimated cost and the partial payments made by the patients. Columns (1) to (3) present results for uninsured patients, and columns (4) to (6) present results for insured patients. *Treat* equals one if the hospital is located in a state that tightened its debt collection regulations during event k, and zero otherwise. *Post* is one for the year of treatment and the subsequent three years in event k and zero otherwise. Controls are the seven hospital- and county-level variables listed and defined in Table I. All models include event×county-pair×hospital and event×county-pair×relative year fixed effects. Standard errors are clustered by state and reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Patient Type:	Uninsured			Insured		
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome (%): scaled by NFA	Chrg Apv	Cost Est	Cost Uncomp	Chrg Apv	Cost Est	Cost Uncomp
Treat×Post	-1.07*	-0.36**	-0.32**	-0.05	-0.02	-0.05
	(0.54)	(0.16)	(0.16)	(0.14)	(0.08)	(0.08)
FE: Event×Pair×R.Year	Y	Y	Y	Y	Y	Y
FE: Event×Pair×Hospital	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.58	0.56	0.56	0.58	0.58	0.56
Observations	8,889	8,889	8,843	7,278	7,286	7,257

Table XII
Effect Heterogeneity

All columns report estimates from the regression model in equation (1). All outcome variables are expressed as a percentage. *AR/TA* is the ratio of accounts receivable to total assets. *Int Exp/Rev* is the ratio of total interest expenses to gross patient revenues. *Oprt Margin* is operating margin, defined as operating earnings over operating income. The binary variable $\mathbb{K}$ equals one in Panel A for *High Ex-Ante Financial Liability*, defined as total liability over total assets, and *High Ex-Ante # Debt Collectors Per Mil. Population* in Panel B. Each indicator is based on whether its value exceeds the respective event-specific pre-event-year median. We hold classification fixed over the sample period. *Treat* equals one if the hospital is located in a state that tightened its debt collection regulations during event k, and zero otherwise. *Post* is one for the year of treatment and the subsequent three years in event k and zero otherwise. Controls are the seven hospital- and county-level variables listed and defined in Table I. All models include event×county-pair×hospital and event×county-pair×relative year fixed effects. Standard errors are clustered by state and reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

A: Effect Heterogeneity by Ex-Ante Financial Liability

Outcome:	$\frac{\text{AR}}{\text{TA}}$ %		$\frac{\text{Int Exp}}{\text{Rev}}$ %		Oprt Margin %	
	(1)	(2)	(3)	(4)	(5)	(6)
Sample Cut by $\frac{\text{TL}}{\text{TA}}$:	High	Low	High	Low	High	Low
Treat×Post	6.78**	1.23	0.13**	0.02	-1.42*	-1.02
	(3.33)	(2.21)	(0.06)	(0.01)	(0.75)	(0.94)
FE: Event×Pair×R.Year	Y	Y	Y	Y	Y	Y
FE: Event×Pair×Hospital	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.62	0.68	0.83	0.69	0.56	0.60
Observations	6,488	6,049	6,574	6,078	6,551	6,072

B: Effect Heterogeneity by Ex-Ante Per Capita Debt Collectors

Outcome:	$\frac{\text{AR}}{\text{TA}}$ %		$\frac{\text{Int Exp}}{\text{Rev}}$ %		Oprt Margin %	
	(1)	(2)	(3)	(4)	(5)	(6)
Sample Cut by $\frac{\text{\# Debt Collector}}{\text{Population}}$:	High	Low	High	Low	High	Low
Treat×Post	3.13**	-10.84***	0.14**	0.01	-2.30*	3.39**
	(1.51)	(1.70)	(0.05)	(0.08)	(1.14)	(1.55)
FE: Event×Pair×R.Year	Y	Y	Y	Y	Y	Y
FE: Event×Pair×Hospital	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.60	0.69	0.82	0.79	0.63	0.64
Observations	8,773	4,062	8,866	4,084	8,843	4,080

Internet Appendix to

"Do Debt Collection Restrictions Hurt Hospitals?"

Christine Zhuowei Huang* Amit Kumar† Lynn Linghuan Wang‡

* Naveen Jindal School of Management, University of Texas at Dallas; email: zhuowei.huang@utdallas.edu

† Lee Kong Chian School of Business, Singapore Management University; email: amitkumar@smu.edu.sg

‡ National University of Singapore Business School; email: lynn.wang@nus.edu.sg

A. Data Appendix

1. SOC Codes associated with debt collection activities

SOC Code	Occupation	SOC Code	Occupation
11-1021	General and Operations Managers	15-2011	Actuaries
11-3012	Administrative Services Managers	23-1011	Lawyers
11-3031	Financial Managers	23-2093	Title Examiners, Abstractors, and Searchers
13-1031	Claims Adjusters, Examiners, and Investigators	23-2099	Legal Support Workers, All Other
13-1051	Cost Estimators	31-9092	Medical Assistants
13-2011	Accountants and Auditors	43-3011	Bill and Account Collectors
13-2031	Budget Analysts	43-3021	Billing and Posting Clerks
13-2041	Credit Analysts	43-3031	Bookkeeping, Accounting, and Auditing Clerks
13-2051	Financial and Investment Analysts	43-4021	Correspondence Clerks
13-2052	Personal Financial Advisors	43-4041	Credit Authorizers, Checkers, and Clerks
13-2053	Insurance Underwriters	43-4131	Loan Interviewers and Clerks
13-2061	Financial Examiners	43-4141	New Accounts Clerks
13-2071	Credit Counselors	43-6012	Legal Secretaries and Administrative Assistants
13-2072	Loan Officers	43-6013	Medical Secretaries and Administrative Assistants
13-2099	Financial Specialists, All Other	43-9061	Office Clerks, General

2. Keywords to identify debt collection complaints related to hospitals

ER, ICU, hospital, medical, doctor, clinic, emergency room, emergencies, abortion, health center, obgyn, ob-gyn, ob gyn, orthopedic, pediatric, cardiology, oncology, neurology, dermatology, radiology, anesthesiology, urology, pharmacy, pharmacies, pharmacist, drugstore, gastroenterology, endocrinology, psychiatry, dental, dentist, optometry, primary care, urgent care, healthcare, surgery, surgical center, nursing home, prescription, prescriptions, drug, drugs, physician, lab test, therapy, ambulance, ambulatory care, in network, in-network, out-of-network, out of network, co-pay, copay, co pay, no surprises act

3. Constructing Employment and Wage Variables from Rand Hospital Data and HCRIS

- $Ln(Emp)$: The natural logarithm of total employees, measured in full-time equivalent employees based on paid hours. This information is sourced from HCRIS Worksheet S-3, Part II, Line 1.

- *Ln*(# *Core*): The natural logarithm of the number of nurses, physicians, and pharmacists, measured in full-time equivalent employees based on paid hours. This information is sourced from HCRIS Worksheet S-3, Part II. Core workers include Non-physician anesthethist Part A (Line 2), Non-physician anesthethist Part B (Line 3), Physician - Part A - Administrative (Line 4), Physician - Part A - Teaching (Line 4.01), Physician and Non Physician-Part B (Line 5), Interns & residents (in an approved program) (Line 7), Contracted interns & residents (in an approved program) (Line 7.01), Contract labor: Direct Patient Care (Line 11), Contract labor: Physician - Part A - Administrative (Line 13), Home office: Physician Part A - Administrative (Line 15), Home office & Contract Physician Part A - Teaching (Line 16), Nursing Administration (Line 38), and Pharmacy (Line 40). This definition is based on Gao, Kim, and Sevilir (2025).

- *Ln*(*Wages*): The natural logarithm of annualized total salaries and employee benefits. Total salaries and employee benefits are sourced from HCRIS Worksheet A, Line 4 and 200. This variable is normalized to an annualized basis by the RAND Corporation.

- *Ln*(*Avg Wages*): The natural logarithm of average salary and employee benefits per employee. This variable is calculated by RAND Corporation as total annualized salaries and employee benefits divided by the number of full-time equivalent employees.

B. Additional Regression Results

Table B.1
Effect on Debt Collection Industry

All columns report estimates from the regression model in equation (3). All outcome variables are in natural logarithm, and observations are at the state-year level. # *Est* is the number of establishments in the debt collection industry (NAICS codes 561440 and 561491). *Agg Wage* is total annual payroll in the debt collection industry. *Avg Emp Wage* is average annual payroll per employee in the debt collection industry. *Avg Est Wage* is average annual payroll per establishment in the debt collection industry. *Treat* equals one if the state tightened its debt collection regulations during event k, and zero otherwise. *Post* is one for the year of treatment and the subsequent three years in event k and zero otherwise. Controls are state-level counterparts for four county-level control variables listed and defined in Table I—the unemployment rate and the natural logarithms of employment, GDP, and population. All models event×state-pair×state and event×state-pair×relative year fixed effects. State pairs are constructed similarly to the county pairs described in Section II, pairing each treated state with appropriate control states. Standard errors are clustered by state and reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)
Outcome: Growth Rate	# Est	Agg Wage	Avg Emp Wage	Avg Est Wage
Treat×Post	-0.03*	-0.15***	-0.08***	-0.12**
	(0.02)	(0.05)	(0.02)	(0.06)
Event×State Pair×R.Year FE	Y	Y	Y	Y
Event×State Pair×State FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Adjusted R^2	0.20	-0.26	-0.38	0.11
Observations	702	670	644	670

Table B.2
Effect on Hospital Loans

All columns report estimates from the regression model in equation (5). The unit of observation is a loan facility *l*, borrowed by hospital borrower *i* in year *t*. *DCR Exposure* is the net fixed asset-weighted exposure to the debt collection restriction tightening. *Spread & Fee* is the interest rate spread (in basis points) over LIBOR, plus fees on the drawn portion of the loan. *Ln*(*Loan Amt*) is the natural logarithm of the loan facility amount. Controls are borrower *i*'s natural logarithm of net fixed assets, operating income over net fixed assets, total liabilities over total assets, and cash over net fixed assets. All models include hospital borrower, year, and state fixed effects. Standard errors are clustered by hospital borrower and reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Loan facility level regression:

	(1)	(2)
	Spread&Fee	Ln(Loan Amt)
DCR Exposure	85.39*	-0.22*
	(42.29)	(0.13)
FE: Hosp, Loan Year, State	Y	Y
Adjusted R^2	0.54	0.78
Observations	258	359