

How Do Debt Collection Restrictions Affect Hospitals and Patients?

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Abstract

Although intended to curb predatory practices, tighter regulations on debt collectors may affect hospitals, which rely on collectors to recover delinquent unsecured consumer debt. Our paired-county stacked difference-in-differences design shows that these regulations increase hospital receivables and allowances for uncollectible debt while reducing receivables-collateralized borrowing and profitability. Although inpatient volume remains unchanged, hospitals reduce medical labor and care capacity, including critical care beds and critical-care days per inpatient, shift toward higher-charge procedures, while mortality rises. Nonprofit hospitals reduce charity care for uninsured patients. Overall, these consumer protection laws have consequences for hospitals, quality of care, and consumers' access to healthcare.

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Debt collection plays an essential role in unsecured consumer credit markets by recovering delinquent debts and returning funds to creditors. In 2020, debt collectors recovered approximately \$102 billion and returned nearly \$90 billion to creditors (ACA International (2020)). These recoveries limit creditor losses, support credit availability, and improve market efficiency. However, abusive and predatory collection practices have become an increasing concern, prompting a growing number of states to adopt stricter debt collection regulations. Such laws protect consumers but might limit recoveries on defaulted unsecured debts and affect industries that rely on debt collection. We examine these implications for the hospital sector, which accounts for the largest share of debt sold to collectors. We find that debt collection regulations adversely affect hospitals and, in turn, healthcare quality and access.

Prior evidence shows that stricter debt collection regulations lead financial lenders to reduce consumer credit because of lower recovery rates on unsecured delinquent debt (Fedaseyeu (2020), Fonseca (2023), Romeo and Sandler (2021)). These regulations may affect hospitals as well, given they account for 47.2% of debt sold to collectors, more than four times the 11.1% share of financial lenders (Fedaseyeu (2020)). The widespread prevalence of delinquent medical debt further highlights hospitals' exposure to debt recovery: it is the most common category of unpaid debt in collections on consumer credit reports, affecting between one-fifth and one-third of U.S. adults (CFPB (2014), CFPB (2023)). Moreover, hospitals, unlike lenders, have limited scope to screen patients' ability to pay before providing care and fewer mechanisms to manage credit risk or diversify the patient base. Also, patients' financial obligations are difficult to determine at admission because medical procedures, costs, and billing are often not fully known, while eventual payments depend on contractual arrangements and institutional payers. We therefore hypothesize that stricter debt collection regulations could have substantial effects on hospitals.

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 these laws across all 50 states from 2013 till 2022. For earlier years, we use data compiled by

Fedaseyeu (2020) and subsequently used in and updated by Fonseca (2023). Our sample period begins in 2010, the first year since when hospital cost report data became consistently available.¹ Between 2010 and 2022, we identify 31 regulatory changes across 18 states that increased restrictions on third-party debt collectors. These changes typically impose licensing and surety bond requirements, increase financial penalties, or criminalize certain collection practices.

To lend causal interpretation to our findings, we combine the methodology of Dube, Lester, and Reich (2010), which compares outcomes in contiguous counties straddling state borders where one state implements a stricter debt collection law and the other does not, with the stacked difference-in-differences (DD) approach for staggered treatments (Gormley and Matsa (2011), Cengiz et al. (2019)). 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 matching each treated county with all its neighboring counties from across the state border. We repeat this pairing for each of the regulatory changes and create a stacked panel aligned in calendar year with respect to the respective treatment years.² The event window spans three years before and after each adoption. 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 over a seven-year event window.

Combining contiguous-county comparisons with the stacked approach offers several advantages. Because treated and control counties are contiguous, they are less likely to differ systematically in local shocks, demographics, or socioeconomic trends. Moreover, by exploiting only within-event-window treatment variation, stacking flexibly accounts for systematic changes at the hospital, county, and state levels that

¹ The substantial redesign of the cost reports in 2010 complicates the merger of pre-2010 cost report data with data from later years to form a consistent longitudinal series (Locey and Stein (2023)).

² Note that the repeated inclusion of treated counties across pairs does not mechanically inflate estimated treatment effects, as county-pair fixed effects ensure that estimates are identified solely from within-pair variation and aggregated across pairs according to their relative contribution to overall variation (Kumar (2026)).

may occur across treatment events. It also avoids the negative-weighting problem associated with staggered settings (Cengiz et al. (2019)).

We begin our empirical analysis by examining whether stricter collection laws affect the debt collection industry. Using County Business Patterns data and state-level paired DD comparisons, we find that the growth rates of the number of establishments, total wages, average wages per employee, and average wages per establishment decline in the industry following the adoption of the laws, relative to bordering control states.

Our main analysis uses hospital-level Healthcare Provider Cost Reporting Information System (HCRIS) data from the RAND Corporation and the stacked paired-county specification. We find that, relative to control hospitals, treated hospitals experienced an almost 15% increase in accounts receivable and an 11% decline in cash holdings, both scaled by total assets, following the event. These declines are consistent with stricter laws reducing the recovery of delinquent medical bills.³ Moreover, in line with accounting principles requiring hospitals to recognize expected recoveries, the allowances for uncollectible receivables scaled by total revenues increased by 12%. This rise is particularly notable as it reflects hospitals' assessment of the impact of the stricter laws on their expected recoveries. Finally, we find no statistically significant evidence of diverging pre-trends between treated and control hospitals for these outcomes.

Are debt collectors economically significant for hospitals? A back-of-the-envelope calculation suggests so. The 12% increase in uncollectible debt allowances (scaled by revenue) implies an annual provision increase of \$2 million per hospital, or nearly 17% of average net income of sample hospitals. Although recovery rates from medical debt sales—ranging from under 1 cent to 5.5 cents per dollar (Kluender et al. (2025))—might appear low, they represent a meaningful source of liquidity. In the presence of financial frictions, even small changes in cash flows can exert material effects on firms through working capital multiplier effect (Barrot and Nanda (2020)). Debt collections

³ Note that these effects do not result from weaker creditor rights. While hospitals are (operational) creditors to patients, the effects arise from restrictions on third-party debt collectors with whom neither party has a contractual relationship when patients receive care. In a conventional credit contract, the parties could adjust credit terms ex ante in response to collection restrictions, but hospitals have limited scope to make such adjustments when providing care.

are important also because reduced recoveries can impose borrowing constraints by reducing the collateralizability of accounts receivable, as we show later.

Because these outcomes are central to establishing how the regulations affect hospitals, we implement several robustness tests motivated by the paired-county design literature. We first examine potential spillovers, which could arise if patients from control counties sought care in treated counties to benefit from stricter debt collection protections. Two institutional features limit this concern. First, because debt collection laws apply based on the debtor’s residence, hospitals in treated states can continue to use collectors from control states, where the laws remain unchanged. Second, insurance and referral-based access create barriers to switching healthcare providers across state lines.⁴ Accordingly, treated hospitals did not experience an increase in patient volume relative to controls.

We also directly test for spillovers using the normalized border-to-inner-county outcome spread, defined as the difference between the outcome of a hospital in treated (border) county and the mean outcome across hospitals in interior counties of the same state, scaled by the standard deviation of the latter. A statistically significant DD coefficient on this spread would indicate effects consistent with spillovers (Dube, Lester, and Reich (2010), Kumar (2026)). However, we find no evidence of such effects across these outcomes. Together with the absence of an increase in patient volume at treated hospitals, these findings alleviate concerns about spillovers and potential violations of the Stable Unit Treatment Value Assumption (SUTVA).

Several of the paired counties differ in their proximity to major cities and metropolitan areas and consequently in hospital counts, which may generate differential post-treatment trends unrelated to the event. We address this concern by re-estimating the effects in subsamples consisting of only the county pairs in which both the treated and control counties have more than n ($=2, 3$, or 4) hospitals. The estimated effects

⁴ For example, many insurance plans, including Medicaid and Medicare Advantage health maintenance organization (HMO) plans, limit access to out-of-state hospitals for non-emergency care. While out-of-state care may be available under preferred provider organization (PPO) plans, these are substantially more expensive. Insurers’ pre-certification requirements for planned treatments further limit switching to cross-state providers.

remain similar across all subsamples for all four outcomes, alleviating this concern. The baseline estimates are also robust to restricting the sample to pairs whose county population centroids are less than 75 kilometers (~46 miles) apart and to excluding the COVID-19 years (2020–2022). The effects are also robust in urban treated counties, but mixed in rural treated counties.

The stricter collection regulations also impose financing constraints on hospitals. Using Uniform Commercial Code (UCC) data covering nearly the universe of secured borrowing, we find that the probability of hospitals issuing new accounts-receivable-collateralized loans declined by almost 50%, while that of issuing equipment-collateralized loans remained unchanged. The differential response implies a decline in the collateralizability of accounts receivable after the event, likely due to the reduced recoverability, and demonstrates worsening financing constraints for hospitals. Moreover, matching hospital systems to DealScan borrowers using data from Aghamolla et al. (2024), we find that greater exposure to the regulations is associated with higher loan spreads and fees and smaller loan amounts, providing further evidence of financing constraints.

Three additional findings help isolate the decline in third-party debt collection as a source of the adverse effects of the stricter regulations on hospitals. First, the treatment effects for the baseline outcomes were stronger among hospitals in states with an above-median number of debt collectors (or debt collector firms) per capita. Second, hospitals increased the share of billing-and-collection-related job postings by almost 77%, whereas non-hospital firms did not, consistent with efforts to shift collection activities in-house in response to these regulations that restrict only third-party collectors but not creditors collecting their own debt. Finally, the state-level growth rate of debt-collection complaints related to non-healthcare firms remained unchanged, whereas those related to hospitals increased by 20 percentage points after the event, likely reflecting increased collection-related hiring by hospitals.

The regulations impacted hospital financial performance and prompted operational adjustments, with downstream implications for care quality and access. Profit margins

declined by about 23% relative to pre-event levels among treated hospitals. Hospitals reduced medically-relevant labor salaries and paid hours by about 8% and 10%, respectively. These led to declines in the relevant hours per inpatient and per inpatient-day by 1.3 and 0.34 hours respectively, indicating fewer labor resources devoted to inpatient care. Care capacity also declined, with beds decreasing by 1% and inpatient procedure coverage, measured by the number of unique Diagnosis-Related Groups (DRGs) performed, by 1.4%. Following the event, mortality rates from pneumonia (PN) and acute myocardial infarction (AMI) increased by 45 and 17 basis points (bps), respectively. A potential factor is critical care constraints: critical care beds, available bed-days, inpatient bed-days, and inpatient bed-days per inpatient declined by 4.7%, 6.5%, 5.7%, and 4.4%, respectively. State-level DD evidence of rising medical delivery errors, proxied by rising medical malpractice cases, may also contribute to rising mortality. Finally, nonprofit hospitals reduced spending on charity care for insured patients by 4%, consistent with reduced access to care for uninsured patients.

Regarding pricing, inpatient charges remained unchanged, likely due to existing contracts and institutional payer involvement. In contrast, outpatient charges rose by 4%, a burden borne fully by uninsured and out-of-network privately insured patients, unlike their insured and in-network counterparts. Average outpatient reimbursements rose by only 50 bps, yielding a net 70-basis-point decline in the payment-to-charge ratio.

Although inpatient charges remained unchanged, we find a quantity response by hospitals. The inpatient treatment mix shifted toward higher-charge procedures. Specifically, the number of inpatients billed in low-charge DRGs (below the 10th, 20th, and 25th percentiles) declined by 3.6% to 4.3%, while high-charge discharges (above the 75th, 80th, or 90th percentiles) increased by nearly double that magnitude. Event-study plots further suggest that both effects emerged sharply following the event. These diverging trends likely reflect revenue-maximizing adjustments by hospitals rather than changes in underlying population health needs, which are unlikely to shift across the treatment-charge distribution within a brief three-year window.

Contribution and Related Literature: To the best of our knowledge, this is the first study to examine how stricter third-party debt collection regulations affect hospitals, a nonfinancial sector with high reliance on debt collection industry to recover unpaid medical bills. We contribute to the healthcare finance literature, which has examined how financial shocks, including changes in bank credit, endowment losses, and investment returns, affect hospitals (Aghamolla et al. (2024), Adelino, Lewellen, and Sundaram (2015), Adelino, Lewellen, and McCartney (2022), Dranove, Garthwaite, and Ody (2017)).⁵ Our setting is distinct in that the shock originates from consumer protection regulation and operates through a widely used hospital revenue collection channel, reducing the recoverability of receivables and tightening borrowing constraints. This distinction is crucial because the nature of the shock can shape how hospitals respond. A striking example is that nonprofit hospitals selectively reduce charity care for uninsured patients, who are more likely to be low-income and to have delinquent medical debt, for which collection becomes more costly after regulatory protections take effect, but not for insured patients. Our key contribution is therefore to show that restrictions on debt collection affect not only hospital finances but also care capacity, quality, and access, emphasizing a trade-off between consumer financial protection and healthcare access.

This paper also builds on the recent literature examining consumer debt collection laws and access to credit (Fedaseyeu (2020), Fonseca (2023), Romeo and Sandler (2021)). We contribute by documenting that the effects of these financial protection laws extend beyond traditional financial institutions to hospitals. Finally, the trade-off between healthcare provision and consumer protection from debt collection connects to the growing literature studying the consumer finance consequences of medical debt and healthcare policies.⁶

⁵ Other studies on hospitals have examined private equity investment (Gao, Kim, and Sevilir (2025), Richards, Shi, and Whaley (2024), Zeller (2023)), ownership differences (Herpfer, Lin, and Maturana (2026), Gao et al. (2026)), and telehealth adoption (Cornaggia, Li, and Ye (2024)).

⁶ See, for example, Duarte et al. (2025), Kluender et al. (2025), Loutskina and Won (2026b), and Loutskina and Won (2026a).

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

I. Institutional Details

A. Debt Collection Industry Regulations

In the US, third-party debt collection practices are federally governed by the Fair Debt Collection Practices Act of 1977 (FDCPA), which establishes baseline consumer protections against unfair, deceptive, or abusive collection practices. States may enact stricter statutory protections. By 2022, 43 states have adopted legislation to regulate third-party debt collection at the state level. These typically include mandatory licensing, higher surety bond requirements, heightened statutory penalties, expanded disclosure requirements, and criminalization of particularly abusive collection practices.

To systematically collect information on these state laws, we followed a two-step procedure. First, we used the dataset compiled by Fedaseyeu (2020) to identify the statutory text of debt collection laws in each state from 2010 onward on the Justia platform, which serves as our source text. Starting from these laws, we manually examined changes in the statutory text over time through 2022. Whenever a change represented a substantive tightening of the law, we recorded the year of tightening as an event, excluding clerical updates and technical corrections. Second, we used the 2023 compilation of state debt collection laws by (LexisNexis (2023)) to identify laws in effect in 2023, located their statutory text on the Justia platform, and traced changes in the text backward to 2010, applying the same procedure to identify substantive changes. This two-step procedure allows us to identify both updates to laws active earlier in the sample period and new laws in effect in 2023 that may not have been captured in the earlier compilation.

We identified 31 instances of regulatory tightening across 18 states between 2010 and 2022. Panel A of Figure 1 maps these states across the contiguous US. Examples include Illinois increasing fines for unlicensed practices from \$5,000 to \$10,000 in 2013 and Iowa enacting the Debt Collection Practices Act in 2015, which codified prohibited

practices for debt collection agencies, established penalties, and granted state residents a private right of action.

B. Conceptual Framework: Debt Collection Market Efficiency vs Consumer Protection

Regulating third-party debt collection balances unsecured credit market efficiency against consumer protection. Third-party collection offers two main efficiency advantages. First, specialized agencies lower collection costs through economies of scale by pooling costs across large numbers of consumers and through specialized expertise in using communication and technology to generate information about consumers' ability and, particularly, willingness to pay. These benefits are especially valuable to non-financial creditors such as hospitals, whose core competency is patient care rather than debt recovery (Fedaseyeu and Hunt (2018)). Second, outsourcing can limit reputation damage and litigation exposure for original creditors arising from consumer disputes over aggressive collection practices.

On the other side of the trade-off is consumer protection against abusive collection practices. Such practices impose substantial nonpecuniary costs through repeated and excessive contacts, abusive language, and reputation harm when collectors contact employers or family members. They can also have serious financial consequences. One such practice is known as "rocket docketing." Delinquent consumers facing these proceedings typically lack the resources to secure legal representation, allowing collection agencies to exploit this disadvantage and enabling proceedings to move forward with limited judicial scrutiny or opportunity for contest.

II. Empirical Research Design

A. Empirical Strategy

We exploit variation in state-level regulations that tighten debt collection practices over time to estimate their effects on hospitals. A state-level staggered difference-in-differences (DD) design without stacking faces two key challenges. First, staggered treatment timing raises concerns about treatment-effect heterogeneity across events and bad comparisons (Goodman-Bacon (2021)). Second, because states are geograph-

ically large, state-level comparisons may pool hospitals operating in different local markets that may be experiencing differential economic trends.

We combine two empirical approaches to address these challenges. We implement a stacked DD strategy similar to Cengiz et al. (2019), which avoids problematic comparisons and the associated negative-weight issue. We augment it with a paired-bordering-county design popular in empirical labor studies, introduced in Card and Krueger (1994) and developed by Holmes (1998), Huang (2008), and Dube, Lester, and Reich (2010), among others, and used more recently in settings beyond labor markets (Fonseca (2023), Kumar (2026)). This design compares hospitals in contiguous counties on opposite sides of a state border, exploiting differences in debt collection laws across states while holding geographic proximity and broader local economic conditions relatively constant. The geographic proximity of counties within each pair makes it unlikely that the paired treated and control units face substantially different socioeconomic trends.

We first construct the paired-county stacked panel. We begin with the 31 instances of regulatory tightening across 18 states between 2010 and 2022. The calendar year in which a regulation is adopted defines the “event” year. For each event, counties along the border of the state enacting the regulation constitute the treated counties. Counties that share a border with a treated county but lie across the state border are potential controls. We retain as “clean” controls only counties located in states that did not enact a tighter debt collection regulation during the seven-year event window, defined as three years before and after the event year. For states with multiple treatment events, we exclude subsequent events occurring within six years of an earlier event. Applying these criteria yields 21 distinct law changes across 17 states.⁷

Having identified the treated and clean control counties, we pair each treated county with every neighboring clean control county across state lines. Thus, a treated county appears as many times as the number of its clean control counties. For example,

⁷ In 2013, California (CA) enacted a reform requiring debt collectors to obtain original debt agreements and granting consumers a private right of action. Its seven-year event window spans 2010–2016, so we omit CA’s 2015 policy change because it falls within this window.

San Bernardino County, CA, forms three distinct pairs with adjacent control counties: La Paz and Mohave in Arizona and Clark in Nevada. Crucially, the repetition of treated counties across pairs does not mechanically amplify treatment effects, because our specification employs pair fixed effects (as discussed below), which use only within-pair variation and aggregate effects as variance-weighted sums (Kumar (2026)).

For each event, we construct a seven-year panel around the corresponding treated-control pairs and stack the event-specific panels by aligning them to the event year, yielding the stacked panel of sample counties. We merge this panel with hospital-year data, assigning hospitals in treated counties to the treatment group and those in control counties to the control group. To focus on standard care delivery, our baseline sample retains the five most common hospital types, which account for 98% of providers (codes 1, 2, 4, 5, and 7). We exclude government-run hospitals because of their distinct safety-net mandates, governmental oversight, and incentive structures. We also exclude uncommon ownership forms (“proprietary, individual” and “proprietary, partnership”) which account for less than 2.4% of the hospitals. The resulting stacked-hospital panel contains 17,012 hospital-year observations from 589 unique treated hospitals and 672 control hospitals, located in 201 treated and 233 control counties. Panel A of Figure 1 maps the treated and control counties across the contiguous US. Panel B shows the mean number of hospitals in each county over the sample period.

B. Regression Specification

We use the following stacked DD regression specification for hospital-level analysis:

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

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 . Treat_{ickp} equals one if the hospital is located in a state that tightened its debt collection regulations during event k , and zero otherwise. $\text{Post}_{kp\tau}$ is defined separately for each event k and equals one for $0 \leq \tau \leq 3$, corresponding to the event year and the subsequent three years, and zero otherwise. 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 $\times$ county-pair $\times$ hospital and event $\times$ county-pair $\times$ relative year fixed effects, respectively. For outcomes measured at county and state levels, we adapt the above equation and discuss in Section IV, where we present the results.

III. Data and Summary Statistics

We use data from several sources. The primary data are hand-collected state-level debt collection regulation changes from 2010 to 2022, described earlier. Our second main source is the HCRIS maintained by CMS, which provides more than 16,000 items covering all Medicare-certified hospitals. We use the version processed and standardized by the RAND Corporation, which creates a consistent time series of approximately 2,000 variables from the raw HCRIS reports. These variables capture comprehensive annual information on hospital characteristics, ownership, wages, employment, financial conditions, including assets, liabilities, net income, charity care, and operations, including utilization, beds, and inpatient discharges. To evaluate hospital care quality, we use CMS Hospital Compare data on risk-standardized 30-day mortality for three core conditions: acute myocardial infarction, heart failure, and pneumonia.

We also use two CMS datasets to examine healthcare procedures performed by hospitals. The Medicare Inpatient Hospitals by Provider and Service dataset, available from 2013 onward, provides charges, reimbursements, and inpatient volume by DRG within each hospital. DRGs group clinically similar conditions and associated procedures, allowing us to consistently observe each hospital’s inpatient treatment mix across DRG groups. Its outpatient counterpart, Medicare Outpatient Hospitals by Provider and Service, available from 2015 onward, provides comparable information on outpatient procedures.

To identify hospital secured borrowing, we use Uniform Commercial Code (UCC) filings, which provide near-universal coverage of secured borrowing in the U.S. and

record information including the lender, loan, and underlying collateral.⁸ We isolate healthcare borrowers (NAICS 621 and 622) and link the filings to hospitals using text matching and manual verification. We then aggregate the filings to the hospital-year level, capturing new secured loans, collateral types, and the number of active loans. Because UCC filings do not capture loan terms such as loan amounts and interest rates, we additionally use syndicated loan data from DealScan. We link this data with hospitals using borrower-hospital crosswalk constructed by Aghamolla et al. (2024).

We also use job posting data from Lightcast to examine hospitals' demand for skills. The data provide standardized information on job postings, including employer, job title, location, posting date, occupation, and industry. Using text-matching algorithms and manual verification, we construct a hospital-year panel from 2010 to 2022 capturing the share of job postings in different occupation groups.

Finally, we supplement our analysis with county-level socioeconomic indicators from public sources, including population from Census Bureau estimates; establishments, payroll, and employment from County Business Patterns; GDP from the Bureau of Economic Analysis; and average household debt-to-income ratios from the Federal Reserve Board's Enhanced Financial Accounts.

Table I reports summary statistics for the key variables. Panel A presents hospital-level variables from HCRIS. Average net patient revenue, inpatient volume, salaries, paid hours, and beds are \$194 million, 7,114 patients, \$9.9 million, 165,451 hours, and 158, respectively. The table reports statistics, including means, computed from the natural logarithms of these variables rather than from their levels. Panel B summarizes four county-level control variables used in the regression specifications: average household debt-to-income, employment, GDP, and population.

[Insert Table I Here]

⁸ We obtain UCC filing data from mailinglists.com, a commercial vendor that processes the raw filings, including classifying the collateral into 40 types.

IV. Results

We organize the results in two stages. First we present evidence consistent with stricter third-party regulations reducing hospitals' collections and increasing receivables. We then examine the downstream effects on hospital financial performance, operational adjustments, patient care quality, and healthcare access.

A. Stricter Third-party Collection Regulations: First-Stage Impacts

A.1. Debt Collection Industry

To assess whether the stricter regulations affect collections, we begin by examining whether these laws constrain the debt collection industry. Using NAICS codes 561440 and 561491 in the County Business Patterns (CBP) data, we identify establishments operating in the debt collection industry and estimate the effects of these laws at the state level using the following equation:⁹

$$Y_{skp\tau} = \alpha + \beta \text{Treat}_{skp} \times \text{Post}_{kp\tau} + \text{Controls} + \gamma_{skp} + \eta_{kp\tau} + \epsilon_{skp\tau}. \quad (2)$$

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 s tightened its debt collection regulations during event k and zero otherwise. $\text{Post}_{kp\tau}$ is defined separately for each event k and equals one for $0 \leq \tau \leq 3$, corresponding to the treatment year and the subsequent three years, and zero otherwise. β is the coefficient of interest capturing 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 $\times$ state-pair and event $\times$ state-pair $\times$ relative year fixed effects, respectively. Controls are the natural logarithms of state-level employment, GDP, and population.

Table C.1 in the Online Appendix presents regressions of the growth rate of the number of establishments (column (1)), total annual state payroll (column (2)), average wages per employee (column (3)), and average wages per establishment

⁹ This regression is specified at the state level because debt collection establishments are sparse in counties along state borders, creating a measurement limitation that precludes county-level estimation. This limitation, however, does not affect identification and is consistent with the institutional setting: collection regulations operate at the state level, and collectors can serve consumers throughout a state without maintaining establishments in the counties where they collect debts.

(column (4)). Relative to the controls, treated states experienced declines in the growth rates of these four outcomes of 4, 28, 6, and 22 percentage points, respectively, consistent with the stricter regulations constraining the growth in the debt collection industry. Although the CBP data do not report revenues or other financial measures that would allow us to more directly assess changes in debt collection amounts, these outcomes provide evidence of a shrinking industry footprint, employment, and wages.

A.2. Hospital Receivable Outcomes

With the debt collection industry shrinking following stricter regulations, hospitals' ability to collect unpaid bills from patients is likely to be affected. Although collections themselves are not recorded in the cost report data, receivable measures are consistently reported and directly relate to collections.¹⁰ We examine these outcomes using regression equation (1). The controls include one-year lagged hospital-level $\ln(\text{Beds})$, Opri Inc/NFA , Cash/NFA , Medicare Mix , and county-level $\text{Avg Household Debt-to-Income}$, as well as the natural logarithms of contemporaneous county-level employment, GDP, and population.¹¹ Table II presents the results. Columns (1) and (2) show that accounts receivable scaled by total assets and accounts receivable days increased by 4.9 percentage points and 3.9 days, respectively, in treated hospitals relative to controls. These effects represent increases of 14.9% and 11%, respectively, relative to the pre-event-year ($\tau = -1$) average levels among treated hospitals. Changes in receivables can have material effects on firms, as Barrot and Nanda (2020) argue theoretically that even small changes in cash collection can substantially affect firms through the working-capital multiplier in the presence of financial frictions.

[Insert Table II Here]

Furthermore, consistent with rising receivables drawing down cash holdings, column (3) shows that hospitals' cash and temporary investments (consisting of

¹⁰ We do not have access to data on actual recovery amounts received by hospitals from debt collectors. As far as we know, no such systematic data exists.

¹¹ All hospital controls are lagged to avoid a bad-control problem arising from controlling for variables that may themselves be affected by the treatment consistent with the approach in the literature (Aghamolla et al. (2024)). For the same reason, the county-level average household debt-to-income ratio is lagged because local household indebtedness may respond to collection regulations (following Fonseca (2023)). Excluding the latter from controls does not affect the inference.

highly liquid short-term securities) scaled by total assets declined by 2.2 percentage points. Proportionally, this represents an 11% reduction relative to pre-event-year levels among treated hospitals. Finally, because accounting principles require hospitals to recognize expected losses on uncollectible receivables, allowances for uncollectible receivables provide a measure of expected recoveries as assessed by hospitals themselves. Column (4) shows that allowances scaled by total revenues increased by 60 bps, or about 12%, relative to the pre-event level of 5.03% among treated hospitals. This represents an increase of about \$2 million in provisions per hospital, or 17% of average net income among treated hospitals in the pre-event year.¹² Finally, Figure 2 presents event-study plots for the four outcomes and shows no evidence of diverging pre-trends. Restricting the sample to general short-term acute care hospitals, which account for 77% of all hospitals, yields similar results, with no evidence of differential pre-trends (Online Appendix Figure B.1).

A.2.1 Robustness to identification concerns: As these outcomes are central to illustrating how stricter collection regulations propagate to hospitals, we conduct a series of robustness tests motivated by the paired-county design literature (Dube, Lester, and Reich (2010), Kumar (2026)). First, patient movement across state lines to seek healthcare could generate spillovers and bias the estimates. Although institutional features of healthcare delivery limit such movement (see footnote 4), we directly test for spillovers. Specifically, we examine the normalized difference between the outcome of a hospital in a bordering county and the mean outcome for same-state hospitals in inner counties, scaled by the standard deviation of the outcome across inner hospitals. If the event generates spillovers, this difference should change because bordering counties are more exposed to spillovers than inner counties. Table C.2 in the Online Appendix shows the estimates from regression equation (1) using the normalized differences for

¹² The 12% increase in allowances scaled by total revenue, together with a 3% reduction in revenues (Table V, column (1)), implies an 8.64% increase in allowances ($=1.12 \times 0.97\%$). With \$15.2 billion in aggregate allowances held by treated hospitals in the pre-event year, this implies an increase in aggregate provisions of about \$1.3 billion, or \$2 million per hospital, equivalent to nearly 17% of average net income. Increased provisions likely reflect a combination of intensive-margin responses, such as selling delinquent debt at larger discounts, and extensive-margin responses, such as reduced ability to sell some debts or longer delays.

the four outcomes. None of the four normalized differences are statistically significant, consistent with the absence of significant spillovers.

Second, even bordering counties may experience different local economic trends when they are geographically large, as their shared border might not imply geographic proximity between their population centers. We address this by restricting the sample to county pairs whose population centroids are within 75 kilometers (46 miles) of each other, following Dube, Lester, and Reich (2016) and Kumar (2026). Estimates for all baseline outcomes remain essentially unchanged (Online Appendix Table C.3).

Third, large differences in the number of hospitals operating in treated versus control counties in a pair could potentially generate differential trends. The absence of pre-trends in Figure 2 mitigates this concern. As an additional test, we re-estimate the effects for county pairs in which both counties have more than n hospitals, for $n = 2, 3, 4$. Online Appendix Table C.4 shows that the estimates remain largely similar despite substantial changes in sample size, corroborating the robustness of the baseline results. A related concern is that urban and rural counties may follow different trends. Using the 2013 urban-rural classification from the National Center for Health Statistics (NCHS), we estimate the effects separately for treated urban counties (codes 1 and 2) and treated rural counties (codes 3 to 6) relative to the control counties. Columns (1) to (4) and (5) to (8) of Online Appendix Table C.5 report the respective results. All four outcomes remain robust in the urban sample, while the receivable outcomes remain robust in the rural sample.

Finally, because the baseline sample includes the COVID-19 period, which was unusual for the healthcare sector, we re-estimate the effects in sample ending in 2019. Table C.6 in Online Appendix shows that the results remain robust.

A.2.2 Receivable outcomes heterogeneity by debt collector density: We conduct a heterogeneity test to isolate our proposed mechanism that stricter debt collection laws reduce the recoverability of unpaid medical bills, affecting hospitals' working capital and financial condition. If so, the effects should be stronger for hospitals more reliant on third-party debt collectors. Because direct measures of reliance are unavailable, we

proxy it using debt collector density. This proxy is motivated by healthcare being the largest debt-supplier to the collection industry, suggesting that higher local collector density may reflect greater reliance of healthcare providers on the collectors. To test this, we classify states by the number of establishments in debt collection industry per capita. For each event, hospitals in states above the sample median in the pre-event year ($\tau = -1$) are classified as more reliant on debt collectors than those below the median. This classification is held fixed within the event.

Table C.7 in Online Appendix reports the results for the same four outcomes estimated separately for high and low groups in columns (1) to (4) and (5) to (8) respectively. The effects on all four outcomes are consistently larger and statistically significant in the high-reliance group than in low-reliance group.¹³ We repeat the analysis using debt collection industry employees per capita and report the results in Online Appendix Table C.8. The results are similar.

A.2.3 Receivable outcomes heterogeneity by type of debt collection laws: Although the estimates thus far capture the average effect of the regulations, the laws differ in their specific provisions. Given the limited number of events (21) and overlap in provisions across laws, statistical power to detect heterogeneity is limited. Nonetheless, we classify the laws into two non-exclusive categories: (i) compliance-based provisions that raise licensing, bonding, and operational requirements, and (ii) rules that restrict specific abusive practices and increase contact transparency. Online Appendix Table C.9 presents the results. The effects are more pronounced for compliance-based provisions, which directly increase operating costs for debt collectors.

Overall, the baseline estimates, robustness tests, and heterogeneity analyses provide consistent evidence that adoption of third-party debt collection regulations adversely affected hospitals' receivable outcomes.

¹³The opposite treatment effects on cash holding and revenues in low-reliance group likely arise from successful cost-saving and revenue-maximizing measures taken by treated hospitals offsetting the adverse impacts of the laws, likely because these hospitals were not deeply reliant on debt collectors to begin with.

A.3. Borrowing Constraints

Beyond affecting receivable recoveries, the stricter regulations may constrain hospitals' ability to use receivables as collateral and limit access to secured credit. We test this mechanism using UCC data, which allows us to identify the near-universe of hospitals' secured borrowings and their underlying collateral. Table III reports the results. Columns (1) and (2) examine whether hospitals issue new loans collateralized by accounts receivable (AR) and equipment, respectively. The probability of issuing an AR-collateralized loan declined by 4.9 percentage points, while equipment-collateralized borrowing remained unchanged. Columns (3) and (4) scale these outcomes by the total number of secured loans, standardizing for any differences in secured borrowing across hospitals. The same pattern emerges: new AR-collateralized loans declined by 40 bps, while equipment-collateralized loans are unaffected. This differential response across collateral types is not only consistent with a decline in the collateralizability of receivables, but also isolates receivables as the underlying outcome through which these regulations affected hospitals, as medical equipment remained outside the scope of these laws.

[Insert Table III Here]

A limitation of the UCC data is that they do not contain intensive-margin information on borrowing, such as loan amounts or pricing. If regulations constrain hospitals' access to borrowing, these margins may also deteriorate. To examine this possibility, we use an alternative empirical approach based on hospital linkages to DealScan borrowers from Aghamolla et al. (2024). Because a DealScan borrower typically represents multiple hospitals operating across states, we construct annual DealScan-borrower-level exposure to debt collection restriction laws, *DCR Exposure*. It is defined as the asset-weighted average of the state-level debt collection restriction index across states in which the borrower operates. Our index follows the approach in Fedaseyeu (2020) and begins with our sample period. The regression equation is as follows:

$$Y_{lit} = \alpha + \beta \times \text{DCR Exposure}_{it} + \text{Controls} + \gamma_i + \eta_t + \epsilon_{lit}. \quad (3)$$

Here, the outcome is loan l of DealScan borrower i in calendar year t . γ_i and η_t denote borrower and calendar-year fixed effects, respectively. Controls include borrower i 's natural logarithm of net fixed assets, income-to-total-assets, total-liabilities-to-total-assets, and net-fixed-assets-to-total-assets.¹⁴ The sample period spans from 2010 to 2020, the last year for which loan data are available in the legacy DealScan dataset. Columns (5) and (6) of Table III show that a unit increase in the *DCR exposure* is associated with an 81.5-basis-point increase in spreads and fees and a 24% ($= e^{-0.28} - 1$) decline in outstanding loan amounts. In magnitude, the increase in the spreads is at least 10% larger than the 68–74 basis-point increase associated with bank stress testing, while the decline in loan amounts is 6 percentage points, or about 20%, smaller (Aghamolla et al. (2024)). Our estimates are robust to alternative aggregation weights based on total income, net fixed assets, or accounts receivable, as shown in Online Appendix Table C.10.

Overall, these results demonstrate that stricter collection laws affect hospitals beyond direct recoveries by also inducing borrowing constraints.

B. Hospitals' Response to Stricter Third-party Collection Regulations

In this section, we examine hospitals' responses to stricter collection regulations and their implications for care capacity, quality, and consumer access to healthcare.

B.1. In-House Debt Collection and Financial Management Efforts

While financial and operational hospital outcomes are helpful in determining the “end” effect of the underlying shocks, job postings data allow us to further study what hospitals seek to achieve in response. By measuring whom hospitals seek to employ, disaggregated by occupation, these data provide a revealed-preference measure of hospitals' demand for labor skills and are well suited to capture shifts in their efforts to hire workers with particular skills.

Since the regulations applied to third-party but not in-house collections, hospitals may respond by expanding efforts to improve patient collections, including more

¹⁴ Borrower-level controls are constructed by first aggregating the respective quantities across hospitals matched to each DealScan borrower and then calculating the ratios. This cross-sectional regression specification in 3 uses contemporaneous controls to account for variation across borrowers.

intensive first-party collection activities. Deteriorating receivables and cash holdings may lead hospitals to also strengthen internal budgeting and financial management. We therefore identify two groups of occupations: those related to patient billing, collections, and credit authorization, and those related to internal financial and budgetary management. Section A.1 in the Online Appendix describes these occupations. We then use text-matching algorithms and manual processing to identify job postings by individual hospitals and construct, for each hospital-year and each group, the share of total job postings accounted for by that group.¹⁵ We also construct these outcomes for firms in non-healthcare sectors and use them as placebo sample.

[Insert Table IV Here]

We follow the regression equation (1) and report results in Table IV. Column (1) shows that, relative to controls, treated hospitals increased hiring for patient billing and collection occupations by 0.92 percentage points, a 77% increase over the pre-event-year mean of 1.19%. Moreover, column (2) shows no corresponding increase among firms in other industries operating in the same counties and hence facing the same local economic conditions and collection regulations but lacking comparable exposure to debt collection. Columns (3) and (4) show the same pattern in hiring for occupations related to internal financial management, consistent with a rising need for improved budgeting and financial management among hospitals. These differential responses, together with earlier evidence of a contracting debt collection industry and rising hospital receivables and uncollectible allowances, demonstrate the relevance of the consumer debt collection channel through which stricter regulations affect hospitals.

The increased hiring of billing and collection employees may result in more-intense in-house collection efforts at hospitals, potentially offsetting the intended effects of stricter third-party collection regulations. We examine this possibility using CFPB consumer complaint narratives data, available from 2013 onward, which such a shift

¹⁵ 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.

would be reflected in the increased complaints about debt collection directed against hospitals. We classify narratives as hospital-related if they contain one or more of 53 hospital-care keywords and as non-hospital-related otherwise. Section A.2 in the Online Appendix lists these keywords. Because these data provide limited geographic variation within our sample counties and period, we conduct the analysis at the state level using equation (2) with the same controls. Columns (5) and (6) show that the growth rate of complaints directed against hospitals increased by 22% ($= e^{0.20} - 1$) following the stricter regulations, while that of complaints directed against non-hospital firms remained unchanged. This divergence, together with the hiring evidence, indicates that some collection activity and its associated consumer consequences may have shifted from third-party agencies toward hospitals.

B.2. Financial Performance

We examine whether stricter collection regulations affect hospitals' financial performance. We estimate equation (1) and report the results in Table V. We examine net patient revenue, defined as gross patient revenue adjusted for contractual allowances and discounts, and the number of inpatients. Columns (1) and (2) show that affected hospitals experienced a 3% decline in revenue relative to the control group, while the number of inpatients remained unchanged. The decline corresponds to an annual revenue decline of \$5.9 million per hospital, based on the pre-event-year average revenue of \$197 million among treated hospitals. These changes together are consistent with hospitals offering greater discounts to increase the likelihood of timely patient payments and limit the amount of billed charges that may otherwise become accounts receivable. The unchanged inpatient volume is also consistent with healthcare demand being largely unaffected by stricter collection regulations.

[Insert Table V Here]

Columns (3) and (4) show that both profit margin and fixed asset efficiency, measured as net income relative to net fixed assets, declined. The 0.95-percentage-point decline in profit margin represents nearly a 23% reduction relative to the pre-event-year mean of 4.12% among treated hospitals. Columns (5) and (6) respectively

show similar effects when net income is replaced with operating margin. Overall, these results indicate that stricter collection regulations have economically meaningful effects on hospitals' financial performance and asset efficiency.

B.3. Medically-Relevant Labor and Care Capacity Decisions

Facing borrowing constraints and deteriorating financial performance, hospitals may respond by adjusting medically relevant labor use and care capacity. We examine this response using cost report data. We identify medically relevant labor as labor providing direct medical care or devoted to managing the hospital's medical-care workforce. Section A.3 in the Online Appendix details the relevant cost report line items.

[Insert Table VI Here]

We estimate equation (1) and report the results in Table VI. Columns (1) and (2) show that treated hospitals reduced salaries paid to medically relevant employees by 7.8%, largely by curtailing paid hours, which declined by 9.8%. Columns (3) and (4) further show that hours per inpatient and per inpatient-day declined by 1.35 and 0.34 hours, respectively, equivalent to 7.2% and 9.0% of their respective pre-event-year averages among treated hospitals. These declines imply that patients received fewer hours of medically relevant labor, consistent with hospitals conserving labor resources. Columns (5) and (6) examine beds and treatment breadth, measured as the share of unique Diagnosis-Related Groups (DRGs) performed by a hospital relative to the total number performed by all sample hospitals in the same state-year. Beds declined by 1%, or 1.1 beds, while DRG coverage declined by 1.4 percentage points, or 5.5%, relative to their respective pre-event-year averages. Overall, these findings suggest that hospitals responded by curtailing both labor and care capacity in ways relevant to the quality of patient care.

B.4. Mortality And Critical Care

With care capacity and medically relevant labor shrinking at affected hospitals, we next test whether the effects of stricter regulations extend to patient mortality, a standard risk-adjusted measure of care quality, and explore potential underlying mechanisms.

Specifically, we study 30-day risk-standardized mortality rates for Pneumonia (PN), acute myocardial infarction (AMI), and heart failure (HF), the “core conditions” used for measuring hospital quality and patient outcomes (Gupta (2021), Aghamolla et al. (2024)). Because mortality rates are reported over 36-month rolling windows, using them directly would yield measures that overlap the pre- and post-event periods. To prevent this contamination, we drop overlapping hospital-year observations and retain only rates calculated exclusively from calendar years preceding the event for pre-event periods and from calendar years following the event for post-event periods.¹⁶

[Insert Table VII Here]

We use equation (1) for these outcomes and report the results in Table VI. Columns (1) through (3) show that mortality rates for pneumonia and AMI increased in treated hospitals by 0.45 and 0.16 percentage points, respectively, while heart failure mortality remained unchanged. These increases represent a relative rise of 3% for pneumonia and 1% for AMI, translating to roughly 594 and 80 additional deaths per year across treated hospitals attributable indirectly to the adoption of stricter collection regulations.

What drives these mortality increases? We examine deteriorating critical care provision, one of most expensive resource, as the potential driver. Specifically, we leverage HCRIS data to calculate critical care capacity and length of stay decisions, defined as intensive care and coronary care. Columns (4) and (5) show that critical care beds and available bed-days declined by 5.2% and 6.8%, respectively. The larger drop in bed-days implies that hospitals not only reduced physical critical care capacity, but also operated the remaining capacity for shorter durations. This pattern is consistent with resource constraints, such as insufficient nursing staff or operational inputs, preventing them from keeping critical care units continuously open. These reductions translate to 505 fewer critical care beds and 167,363 fewer bed-days, aggregated across treated hospitals. Columns (6) and (7) further show that total

¹⁶Specifically, for a given pre-event year t , we use the 36-month window ending in t (e.g., July 2010 to June 2013 for $t = 2013$). For a post-event year t , we use the window beginning in t (e.g., July 2013 to June 2016 for $t = 2013$), ensuring complete separation between the pre- and post-treatment information.

critical care inpatient days and critical care days per admission declined by 6.1% and 4.6%, respectively. This implies that critical care patients experienced shorter lengths of stay, both in aggregate and on a per-patient basis, consistent with hospitals discharging or transferring patients out of critical care more rapidly under resource pressures.

We next assess the robustness of these findings. First, because our sample period includes the COVID-19 pandemic, a period marked by extreme mortality rates and severe capacity strains, we re-estimate our models on a subsample ending in 2019. The results, reported in Table C.11 of Online Appendix, remain essentially the same. Second, because mortality and critical care utilization depend on patient severity, we additionally control for the hospital's Medicare casemix index and find similar results in Table C.12 of Online Appendix. Finally, while intensive and coronary care units are common critical care units, reporting practices vary across hospitals, with many sub-classifying critical beds under "Other specialty care", burn intensive care, and surgical intensive care. When defining critical care alternatively to include these units, we observe comparable reductions in critical care provision (Table C.13 of Online Appendix).

How might shrinking critical care provision contribute to rising mortality? We examine healthcare delivery errors as a potential channel, using medical malpractice activity from the National Practitioner Data Bank (NPDB) as a proxy. The NPDB records malpractice cases resulting in payments made on behalf of healthcare practitioners or entities to injured claimants or their surviving families. Importantly, nearly 80% of these cases involve errors in medical diagnosis, treatment, or surgery, making malpractice activity particularly relevant to healthcare delivery errors. Because the data lack hospital- or county-level identifiers, we conduct the analysis at the state level using equation (2). Columns (1) to (3) of Online Appendix Table C.14 show that treated states experienced significant increases in malpractice activity: 4.05 additional practitioners involved in malpractice per million, 2.3 malpractice cases per million, and \$840 in total payout amounts per 1,000 population, respectively.

Taken together, these results indicate that mortality rose at treated hospitals, driven by contractions in critical care capacity and, potentially, an increase in medical errors.

B.5. Charity Care by Non-profit Hospitals

We next examine whether hospitals' responses extend to the provision of charity care—a policy-relevant dimension of healthcare access for low-income, underinsured, and uninsured patients. To maintain their tax-exempt status, nonprofit hospitals are required to provide free or reduced-cost care to vulnerable populations. However, the precise volume of charity care is not strictly mandated by IRS regulations and remains largely at the hospital's discretion, making inadequate charity care provision a longstanding policy concern (Zare, Eisenberg, and Anderson (2022)).

[Insert Table VIII Here]

We estimate equation (1) and report the results in Table VIII. Columns (1) through (3) examine charity care provided to uninsured patients at nonprofit hospitals, scaled by net fixed assets. Compared to control nonprofits, the affected nonprofits devoted 1.57 percentage points less of their gross chargemaster charges to charity care, and curtailed estimated and incurred uncompensated costs by 0.47 and 0.42 percentage points, respectively. These cuts correspond to a 20.4% reduction in gross charity care charges, a 23% reduction in estimated costs to provide the care, and a 21.8% reduction in actual uncompensated care costs relative to pre-event means among treated nonprofit hospitals. Conversely, columns (4) through (6) reveal that charity care provided to insured patients remained unchanged. These findings indicate that hospitals disproportionately reduced charity care for uninsured patients in response to stricter debt collection laws. This response has important implications for healthcare access among uninsured patients, who are particularly vulnerable to unpaid medical debt (CFPB (2022), p.10) and represent a core population the stricter collection regulations originally sought to protect.

B.6. Treatment Charges (Prices) of Healthcare Services

Our analysis thus far has focused on non-price margins. A critical remaining question is whether hospitals responded to stricter debt collection laws by adjusting prices.

While raising prices could offset revenue losses, hospitals may face considerable rigidity because of existing contracts and the substantial share of revenues tied to Medicare and contracted insurers. On the other hand, hospitals might lower prices, such as through prompt-payment discounts, to accelerate collections and curb bad debt accumulation among self-pay patients.

Ultimately, whether hospitals raised or lowered prices becomes an empirical question, which we examine next using procedure-level pricing for all inpatient and outpatient services from CMS data. Inpatient procedures are categorized by DRGs (677 unique categories, with 577 in our merged sample) and start from 2013, whereas outpatient procedures are enumerated by Ambulatory Payment Classifications (APCs; 71 unique categories, with 70 in our sample) and start from 2015. We expand our hospital-level stacked panel to a hospital-by-service stacked panel and estimate price effects using the following equation:

$$Y_{isckp\tau} = \alpha + \beta \text{Treat}_{isckp} \times \text{Post}_{kp\tau} + \text{Controls} + \gamma_{isckp} + \eta_{kp\tau} + \epsilon_{isckp\tau}. \quad (4)$$

Here $Y_{isckp\tau}$ represents the price outcome for healthcare procedure s (DRG or APC) conducted by hospital i located in county c of county pair p in relative year τ of event k . Controls follow equation (1). Fixed effects γ_{isckp} (event $\times$ county-pair $\times$ hospital $\times$ service) and $\eta_{kp\tau}$ (event $\times$ county-pair $\times$ relative year) absorb unobserved heterogeneity. Specifically, γ_{isckp} limits comparisons to within hospital-by-healthcare procedure pairs, mitigating concerns related to hospital specialization differences, the outlier frequent services, or treatment-mix substitution toward higher-cost procedures.

[Insert Table IX Here]

We examine four key price metrics of healthcare inpatient and outpatient procedures: average chargemaster charge (often inflated), average payment received from all payers, average payment received from Medicare, and the payment-to-charge ratio. Table IX presents the results. Columns (1) to (4) show that the four metrics remained unchanged for inpatient services. For outpatient service, hospitals raised charges by about 4% (column 5), but realized payments rose by only 50 bps overall (column 6) and 60 bps from Medicare (column 7), leading to a 70

bps decline in the payment-to-charge ratio (column 8). Though small, outpatient price increases disproportionately burden uninsured patients, out-of-network insured individuals, and workers' compensation payers, who directly face full chargemaster rates, whereas insured populations experience indirect effects through premium adjustments (Zander et al. (2024)).

B.7. Shift Toward Higher-Charge Inpatient Treatments

Although inpatient charges remained unchanged, likely reflecting hospitals' limited ability to raise prices, hospitals may respond to deteriorating financial performance through the quantity margin by shifting their inpatient treatment mix toward higher-charge procedures to increase revenues. Such a quantity response is plausible for high-charge DRGs billed to Medicare because patients have limited influence over assignment of specific diagnosis, treatment, and billing codes, while the payments from Medicare for complex covered inpatient procedures remain largely guaranteed.¹⁷ Moreover, population health needs are unlikely to shift systematically toward higher-charge DRGs over a brief three-year post-treatment window.

[Insert Table X Here]

We test for such a response using CMS Inpatient dataset. For each year and DRG, we calculate the median of hospital-reported submitted charges, which are reported for each hospital×DRG cell as averages across patients, rank DRGs by this median charge, and assign them to charge percentiles. We then merge these annual percentiles and inpatient counts into a hospital×DRG panel and merge it further with our hospital-level stacked panel. We estimate equation (4) and presents the results in Table X. The number of discharges in DRGs below the 10th, 20th, and 25th charge percentiles declined by 3.6% to 4.3% (columns (1) to (3)), whereas those above the 75th, 80th, and 90th percentiles increased by 2.2% to 7% (columns (4) to (6)).¹⁸ Crucially, event

¹⁷ In 2026, the Original Medicare Part A deductible is \$1,736 per benefit period, with a copayment of \$0 for the first 60 days of inpatient care.

¹⁸ Examples of high-charge DRGs include advanced immunotherapies such as CAR T-cell therapy, while low-charge DRGs include routine otolaryngology care and childbirth. Changes in inpatient volume across these groups do not imply direct clinical substitution, such as replacing an ear-related procedure with immunotherapy, but rather a compositional shift toward higher-complexity, higher-

study plots for the 10th and 90th percentiles in Figure 3 indicate that these changes emerge sharply after the policy adoption. Taken together, these patterns are consistent with hospitals shifting their treatment mix toward higher-charge inpatient procedures, with potential implications for patient welfare.

V. Additional Results

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

A. Population Healthcare Utilization Across Hospital vs Non-Hospital Providers

Our findings so far indicate that affected hospitals experienced adverse financial and quality shocks. We next ask whether debt collection regulations affected population-level aggregate healthcare utilization or shifted some care from hospitals to non-hospital providers. Using county-level data from the CMS Geographic Variation files and the Dartmouth Atlas, we examine the impact on healthcare utilization across provider types using the following county-level regression equation:

$$Y_{ckp\tau} = \alpha + \beta \text{Treat}_{ckp} \times \text{Post}_{kp\tau} + \text{Controls} + \gamma_{ckp} + \eta_{kp\tau} + \epsilon_{ckp\tau}, \quad (5)$$

where $Y_{ckp\tau}$ is the county-level outcome in county c , county pair p , and relative year τ of event k . Variables Treat_{ckp} , $\text{Post}_{kp\tau}$, controls, and β mirror their state-level counterparts in equation (2). Fixed effects γ_{ckp} (event $\times$ county pair $\times$ county) and $\eta_{kp\tau}$ (event $\times$ county pair $\times$ relative year) absorb unobserved local heterogeneity and common annual shocks.

Table C.15 in the Online Appendix reports the results. Column (1) shows that county-aggregated outpatient visits to hospitals declined by 2% in treated counties, whereas emergency department (ED) visits and inpatient stays remained unchanged (columns 2 and 3). Conversely, utilization at non-hospital providers—including primary care physicians, ambulatory surgery centers, and home health agencies—saw no significant changes (columns (4) and (6)). The contraction in hospital outpatient care likely reflects the rising charges as well as the availability of comparable services

charge diagnoses and billings. Moreover, such a shift may be related to the increase in medical malpractice cases discussed in Section IV.B.4 and reported in Table C.14 of Online Appendix.

from non-hospital-based providers. In contrast, the null effects on inpatient care and ED visits are consistent with exclusivity of hospitals in delivering these services as opposed to non-hospital type healthcare providers.

B. Effect on Broader Healthcare Industry: County-level Evidence

We next examine impacts across the broader healthcare sector, comprising both hospitals and other care establishments. It generalizes our main hospital-level findings and allows us to also conduct placebo checks on non-healthcare industries and reinforces the causal interpretation of our hospital-based findings. Using regression equation (5), Table C.16 in the Online Appendix reports results for total annual payroll, average annual payroll per employee, and average annual payroll per establishment using CBP data. Columns (1) to (3) present results for the healthcare industry, identified in the CBP data via 3-digit NAICS codes 621 and 622. Column (1) shows that total wages declined by 10% in treated counties relative to the control group. Furthermore, columns (2) and (3) indicate that average wages per employee and average wages per establishment fell by 3% and 10%, respectively. Columns (4)–(6) present results for the grocery, restaurant, and fitness industries; columns (7)–(9) cover all non-tradable industries excluding healthcare; and columns (10)–(12) encompass all industries excluding healthcare.¹⁹ We observe no significant effects for any of these industries, which operate in the same counties and thus face the same regulatory and local economic conditions. Non-tradable industries provide a particularly informative placebo because, like hospitals, their production and consumption are primarily local. These placebo results strengthen the causal interpretation of our hospital-level evidence: unlike hospitals, these industries do not rely on debt collection and show no response despite facing the same regulatory environment. They also alleviate the concern that the hospital effects were driven by contemporaneous shocks specific to the local economy, which would be expected to affect these industries as well.

¹⁹ Non-tradable industries follow classification 1 of Mian and Sufi (2014).

VI. Conclusion

Consumer financial protection policies can have unintended consequences for non-financial sectors. We examine this possibility in the context of third-party debt collection laws, which states enact to protect consumers from predatory collection practices. We hand-collect state-level data on debt collection regulations through 2022, supplementing them with data compiled by Fedaseyeu (2020) and further updated and used by Fonseca (2023). Using these data in a stacked difference-in-differences design based on contiguous county pairs, we estimate the causal effects of these laws on hospitals. We find that stricter collection laws negatively affect hospitals, which rely heavily on the debt collection industry to recover unpaid, unsecured medical debt. Specifically, these regulations increase uncollected receivables and tighten borrowing constraints by reducing receivables-collateralized borrowing and raising borrowing costs. In response, hospitals expand in-house collection efforts while reducing medically relevant labor and critical care capacity. Risk-adjusted mortality rises for core conditions. Nonprofit hospitals also curtail charity care for uninsured patients.

Overall, these laws have unintended consequences for healthcare delivery, as well as healthcare access among a core population they aim to protect: uninsured patients, who are more likely to incur medical debt and may face reduced access to charity care following their enactment. Greater specificity and precision in the design of these laws could help limit their unintended effects on hospitals and healthcare access while preserving consumer protection objectives. Failing to account for these effects may overstate the benefits of such policies.

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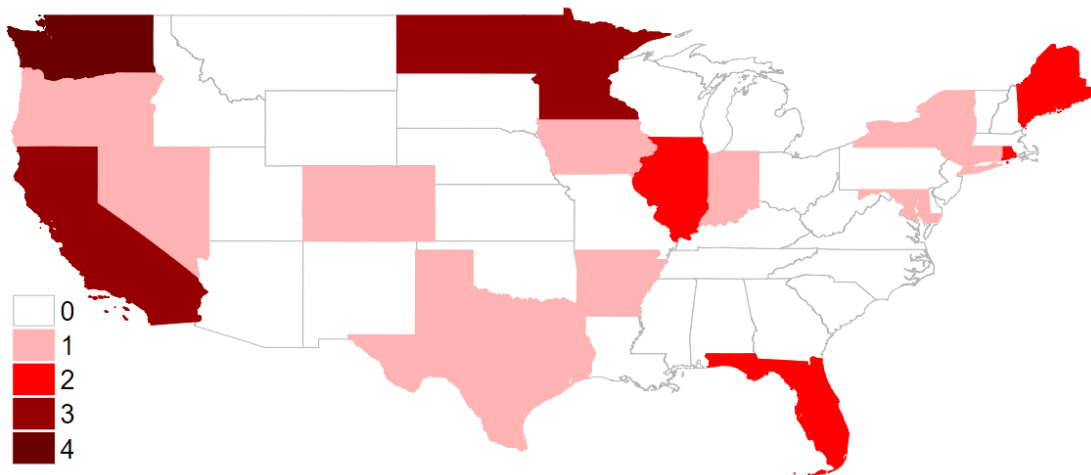
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(A) # Debt Collection Restriction Changes 2010 to 2022



(B) Mean Hospital Counts in Sample Counties

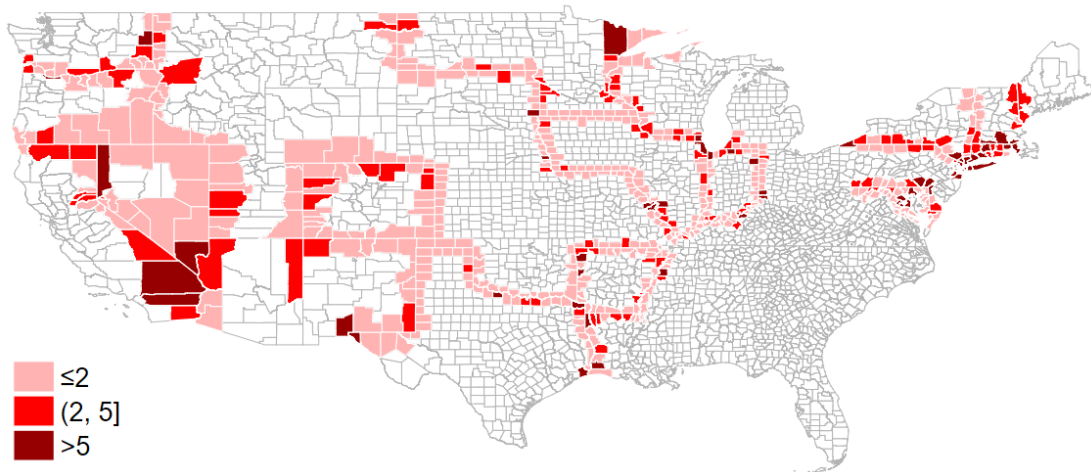


Figure 1. Debt Collection Policy Changes and Hospital Distribution. Panel A maps the 31 state-level changes in debt collection restrictions identified between 2010 and 2022 across 18 states. Panel B maps the treatment and control counties in the estimation sample across the contiguous U.S. and reports the average number of hospitals in each county over 2010–2022. Treated counties in Panel B correspond to 21 events across 17 states.

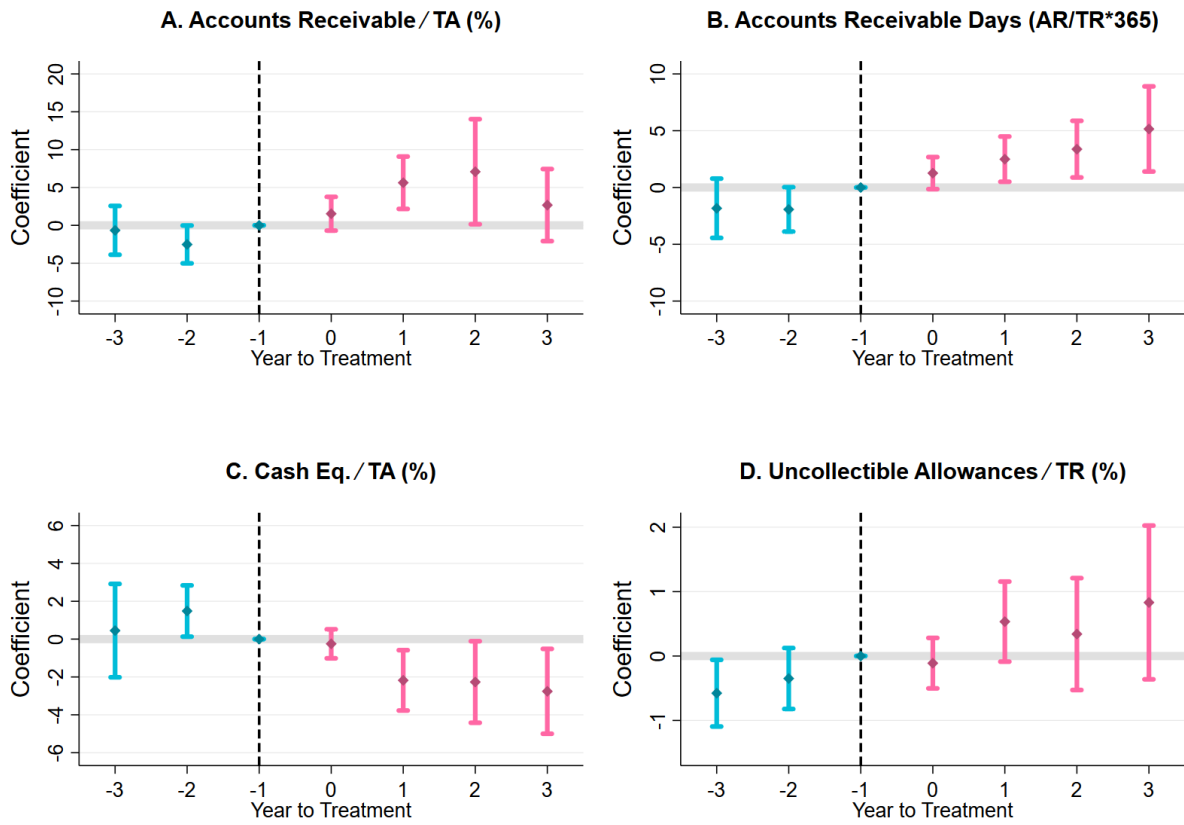


Figure 2. Event Study Plots for Hospital-level Receivable Outcomes. This figure plots the coefficients β_τ and 95% confidence intervals for the four hospital-level outcomes indicated in the respective panels. The horizontal axis shows years relative to the event year, with $\tau = 0$ indicating the year the state adopted the stricter collection law.

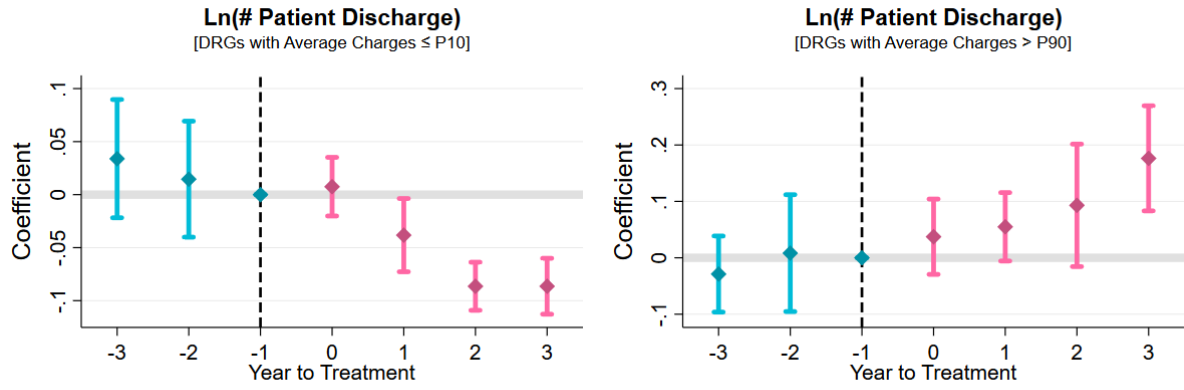


Figure 3. Event Study Plots for Patients across DRG Groups. This figure shows coefficients β_τ and 95% confidence intervals for the natural logarithm of patient discharges in DRG groups classified by charges. DRGs are first ranked annually based on the median submitted charge across sample hospitals, where submitted charges represent hospital $\times$ DRG annual averages across inpatients, and then classified into percentile groups according to this ranking. The left and right panels report results for DRGs at or below the 10th percentile and above the 90th percentile, respectively. The horizontal axis shows years relative to the event year, with $\tau = 0$ indicating the year the state adopted the stricter collection law.

Table I
Summary Statistics

This table reports summary statistics. $\ln(\text{Net Pat Rev})$ is the natural logarithm of net patient revenue (in million \$). $\ln(\# \text{ Inpat})$ is the natural logarithm of the number of inpatients. *Profit Margin* is profit margin, defined as net income over total income. *AR/TA* is the ratio of accounts receivable to total assets. *AllowUncoll/Rev* is the ratio of allowances for uncollectible notes and accounts receivable to gross patient revenue. $\ln(\text{Salaries})$ is the natural logarithm of adjusted salaries (in \$) of employed medically-relevant labor, which are defined in Appendix A.3. $\ln(\text{Paid Hours})$ is the natural logarithm of paid hours related to salaries of employed medically-relevant labor. $\ln(\text{Beds})$ is the natural logarithm of the total number of hospital beds. *Opert Inc/NFA* is the ratio of operating income to net fixed assets. *Cash/NFA* is the ratio of cash to net fixed assets. *Medicare Mix* is the ratio of Medicare inpatient days to all inpatient days. *Avg Household Debt-to-Income* is the average household debt-to-income at the county level. *Employment*, *GDP*, and *Population* denote county-level measures. *Controls* include one-year-lagged hospital-level $\ln(\text{Beds})$, *Opert Inc/NFA*, *Cash/NFA*, and *Medicare Mix*, and four county-level measures: *Avg Household Debt-to-Income* and the natural logarithms of contemporaneous *Employment*, *GDP*, and *Population*.

	N	Mean	P25	Median	P75	SD
	(1)	(2)	(3)	(4)	(5)	(6)
<i>A. Hospital×Year-Level Variables</i>						
$\ln(\text{Net Pat Rev (\$mn)})$	7,781	4.43	3.33	4.49	5.53	1.37
$\ln(\# \text{ Inpat})$	7,812	7.91	6.67	8.19	9.24	1.60
<i>Profit Margin (%)</i>	7,781	4.26	-0.53	4.60	10.35	13.24
<i>AR/TA (%)</i>	7,725	36.94	12.11	22.52	44.83	42.52
<i>AllowUncoll/Rev (%)</i>	5,383	6.58	1.64	4.66	8.73	8.35
$\ln(\text{Salaries})$	5,510	15.55	14.65	15.62	16.55	1.50
$\ln(\text{Paid Hours})$	5,399	11.50	10.66	11.56	12.37	1.42
$\ln(\text{Beds})$	7,818	4.51	3.47	4.64	5.34	1.07
<i>Opert Inc/NFA (%)</i>	7,756	17.49	-1.40	4.62	14.98	124.99
<i>Cash/NFA (%)</i>	7,573	17.14	0.04	3.73	13.19	78.93
<i>Medicare Mix (%)</i>	7,768	42.24	29.18	40.72	53.64	19.12
<i>B. County×Year-Level Variables</i>						
<i>Avg Household Debt-to-Income</i>	2,855	1.76	1.14	1.64	2.28	0.81
$\ln(\text{Employment})$	2,848	9.13	7.68	9.07	10.62	2.17
$\ln(\text{GDP})$	2,841	7.92	6.72	7.72	8.91	1.67
$\ln(\text{Population})$	2,841	10.99	9.94	10.80	12.04	1.55

Table II
Hospital Receivable Outcomes

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, defined as accounts receivable divided by gross patient revenue, multiplied by 365. $CashEq/TA$ is the ratio of cash and temporary investments to total assets, expressed as a percentage. $AllowUncoll/Rev$ is the ratio of allowances for uncollectible notes and accounts receivable to gross patient revenue, 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 eight hospital- and county-level variables mentioned and defined in the notes to Table I. One-year-lagged $Cash/NFA$ is excluded from controls in column (3). Fixed effects for each specification are noted in the table. Standard errors are clustered by state and reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

	(1)	(2)	(3)	(4)
Outcome:	$\frac{AR}{TA}$	AR Days	$\frac{CashEq}{TA}$	$\frac{AllowUncoll}{Rev}$
Treat×Post	4.88** (1.87)	3.89*** (0.79)	-2.21*** (0.78)	0.60** (0.27)
FE: Event×Pair×R.Year	Y	Y	Y	Y
FE: Event×Pair×Hosp	Y	Y	Y	Y
FE: Hospital Type	Y	Y	Y	Y
Adjusted R ²	0.66	0.79	0.83	0.72
Observations	14,630	14,760	15,103	9,509

Table III
Borrowing Constraints

Columns (1) to (4) report estimates from regression model in equation (1), and the remaining use that in equation (3). *AR-Backed Loan?* is an indicator taking the value of 100 if a hospital has at least one new loan backed by accounts receivable as collateral during the year, and zero otherwise. *Eqp-Backed Loan?* is an indicator taking the value of one if a hospital has at least one new loan backed by equipment as collateral during the year, and zero otherwise. *# AR-Backed Loan/# Loans (%)* is the ratio of newly originated loans backed by accounts receivable as collateral to the total number of loans held by a hospital during the year. *# Eqp-Backed Loan/# Loans (%)* is the ratio of newly originated loans backed by equipment as collateral to the total number of loans held by a hospital during the year. The unit of observation of equation (3) is a loan facility l , borrowed by hospital borrower i in year t . *DCR Exposure* is the exposure to debt collection restriction tightening, weighted by total assets. *Spread & Fee* is the interest rate spread (in basis points) over LIBOR, plus fees on the drawn portion of the loan. $\ln(\text{Loan Amt})$ is the natural logarithm of the loan facility amount. Controls in columns (1) to (4) include the eight hospital- and county-level control variables mentioned and defined in the notes to Table I. Controls in columns (5) and (6) include DealScan borrower i 's natural logarithm of net fixed assets, income over total assets, total liabilities over total assets, and net fixed assets over total assets. Fixed effects for each specification are noted in the table. Standard errors are clustered by state in Columns (1) to (4) and by DealScan hospital borrower in columns (5) and (6), and are reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)
	AR-backed Loan? [=100]	Eqp-backed Loan? [=100]	$\frac{\# \text{ AR-backed Loans}}{\# \text{ Loans}} \%$	$\frac{\# \text{ Eqp-backed Loans}}{\# \text{ Loans}} \%$	Spread&Fee	$\ln(\text{Amt})$
Treat×Post	-4.93* (2.60)	2.37 (3.18)	-0.40** (0.19)	-0.74 (0.98)		
DCR Exposure					81.59** (36.83)	-0.28*** (0.10)
Panel	Hosp	Hosp	Hosp	Hosp	Loan	Loan
FE: Event×Pair×R.Year	Y	Y	Y	Y	N	N
FE: Event×Pair×Hosp	Y	Y	Y	Y	N	N
FE: Hospital Type	Y	Y	Y	Y	N	N
FE: Hosp, Year of Loan	N	N	N	N	Y	Y
Adjusted R ²	0.15	0.46	0.02	0.03	0.58	0.78
Observations	9,592	9,592	8,141	8,141	249	347

Table IV
In-house Debt Collection and Financial Management Efforts

Columns (1) to (4) report estimates from regression model in equation (1), and columns (5) and (6) use that in equation (2). *Billing/Collection Job Posts %* is the percentage of job postings related to billing and collection activities, and *Fin Mgmt Job Postings %* is the percentage of job postings related to internal financial management activities. Δ *Debt Collection Complaints* is the growth rate of the number of debt collection-related consumer complaints reported to CFPB. Columns (1), (3), and (5) report estimates for hospitals, while columns (2), (4), and (6) report estimates for non-hospitals. In columns (1) to (4), *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 (5) and (6), *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. Columns (1) and (3) include the eight hospital- and county-level control variables listed and defined in Table I; columns (2) and (4) include only the county-level controls, and columns (5) and (6) include state-level counterparts for three control variables—the natural logarithms of employment, GDP, and population. Fixed effects for each specification are noted in the table. 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:	Billing/Collection Job Posts %		Fin Mgmt Job Posts %		Δ Debt Collection Complaints	
	(1)	(2)	(3)	(4)	(5)	(6)
	Hospitals	Non-Hospitals	Hospitals	Non-Hospitals	Hospitals	Non-Hospitals
Treat $\times$ Post	0.92** (0.40)	-0.01 (0.01)	0.79** (0.39)	-0.05** (0.03)	0.20** (0.09)	0.00 (0.09)
Panel	Firm	Firm	Firm	Firm	State	State
(F)irm/(A)rea Controls	A, F	A	A, F	A	A	A
Event $\times$ Pair $\times$ R.Year FE	Y	Y	Y	Y	N	N
Event $\times$ Pair $\times$ Firm FE	Y	Y	Y	Y	N	N
Hospital Type FE	Y	N	Y	N	N	N
Event $\times$ State Pair $\times$ R.Year FE	N	N	N	N	Y	Y
Event $\times$ State Pair $\times$ State FE	N	N	N	N	Y	Y
Adjusted R ²	0.06	0.32	-0.09	0.33	-0.65	0.87
Observations	5,765	2,532,712	5,765	2,532,712	462	602

Table V
Financial Performance

All columns report estimates from the regression model in equation (1). $\ln(\text{Net Pat Rev})$ is the natural logarithm of net patient revenue. $\ln(\# \text{ Inpat})$ is the natural logarithm of the number of inpatients. *Profit Margin* is net income over total income. NI/NFA is the ratio of net income to net fixed assets, expressed as a percentage. *Opert Margin* is operating margin, defined as operating earnings over operating income. $\text{Opert Inc}/\text{NFA}$ 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 eight hospital- and county-level variables mentioned and defined in the notes to Table I. One-year-lagged $\text{Opert Inc}/\text{NFA}$ is excluded from controls in columns (5) and (6). Fixed effects for each specification are noted in the table. 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)
Outcome:	$\ln(\text{Net Pat Rev})$	$\ln(\# \text{ Inpat})$	Profit Margin %	$\frac{\text{NI}}{\text{NFA}} \%$	Opert Margin %	$\frac{\text{Opert Inc}}{\text{NFA}} \%$
Treat $\times$ Post	-0.03** (0.01)	-0.01 (0.02)	-0.97** (0.47)	-12.17** (5.94)	-0.97** (0.47)	-11.60** (5.53)
FE: Event $\times$ Pair $\times$ R.Year	Y	Y	Y	Y	Y	Y
FE: Event $\times$ Pair $\times$ Hosp	Y	Y	Y	Y	Y	Y
FE: Hospital Type	Y	Y	Y	Y	Y	Y
Adjusted R ²	0.98	0.99	0.54	0.45	0.50	0.47
Observations	14,763	14,771	14,701	14,732	14,701	14,741

Table VI
Medically-Relevant Labor and Care Capacity Decisions

All columns report estimates from the regression model in equation (1). $\ln(\text{Salaries})$ is the natural logarithm of adjusted salaries of employed medically-relevant staff, as defined in Appendix A.3. $\ln(\text{Paid Hours})$ is the natural logarithm of paid hours of these staff. $\text{Paid Hours}/\text{Inpat}$ is the total employed medically-relevant staff paid hours per inpatient. $\text{Paid Hours}/\text{Inpat Days}$ is the total employed medically-relevant staff paid hours per inpatient day. $\ln(\text{Beds})$ is the natural logarithm of the total number of hospital beds (HCRIS CMS-2552-10 Worksheet S-3, Part I, Column 2, Line 14). $\text{DRG Coverage\%}$ 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 eight hospital- and county-level variables listed and defined in Table I. The number of observations in column (6) is lower because the CMS inpatient data begin in 2013. Fixed effects for each specification are noted in the table. 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)
Outcome:	$\ln(\text{Salaries})$	$\ln(\text{Paid Hours})$	$\frac{\text{Paid Hours}}{\text{Inpat}}$	$\frac{\text{Paid Hours}}{\text{Inpat-days}}$	$\ln(\text{Beds})$	$\text{DRG Coverage\%}$
Treat×Post	-0.078* (0.042)	-0.098*** (0.034)	-1.351** (0.612)	-0.342** (0.158)	-0.011** (0.005)	-1.379*** (0.401)
FE: Event×Pair×R.Year	Y	Y	Y	Y	Y	Y
FE: Event×Pair×Hosp	Y	Y	Y	Y	Y	Y
FE: Hospital Type	Y	Y	Y	Y	Y	Y
Adjusted R ²	0.93	0.94	0.86	0.89	0.99	0.98
Observations	10,376	10,117	14,771	14,771	14,772	5,684

Table VII
Mortality and Critical Care Provision

All columns report estimates from the regression model in equation (1). *Mortality Rate (MR)%* 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. Columns (1) to (3) report mortality rates for pneumonia, acute myocardial infarction (AMI), and heart failure, respectively. *Critical Care (CC)* comprises intensive care and coronary care. For columns (4) to (7), the dependent variables are the natural logarithms of critical care beds, critical care bed-days available, critical care inpatient-days, and critical care inpatient-days per inpatient, respectively. *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 eight hospital- and county-level variables listed and defined in Table I. Fixed effects for each specification are noted in the table. Standard errors are clustered by state and reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Outcome Category:	Mortality Rate (MR)%			Critical Care (CC): Intensive Care + Coronary Care			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ln, except mortality rates:	MR _{PN}	MR _{AMI}	MR _{HF}	CC Beds	CC Bed-days	CC Inpat-days	$\frac{\text{CC Inpat-days}}{\text{\# Inpat}}$
Treat×Post	0.454** (0.18)	0.165** (0.08)	-0.133 (0.15)	-0.052*** (0.02)	-0.068*** (0.02)	-0.061*** (0.02)	-0.046** (0.02)
FE: Event×Pair×R.Year	Y	Y	Y	Y	Y	Y	Y
FE: Event×Pair×Hosp	Y	Y	Y	Y	Y	Y	Y
FE: Hospital Type	Y	Y	Y	Y	Y	Y	Y
Adjusted R ²	0.77	0.66	0.64	0.97	0.95	0.95	0.87
Observations	8,957	6,412	8,274	8,945	8,934	8,925	8,925

Table VIII
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 eight hospital- and county-level variables listed and defined in Table I. Fixed effects for each specification are noted in the table. 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	-1.57** (0.63)	-0.47** (0.18)	-0.42** (0.18)	-0.02 (0.13)	-0.03 (0.08)	-0.05 (0.08)
FE: Event×Pair×R.Year	Y	Y	Y	Y	Y	Y
FE: Event×Pair×Hosp	Y	Y	Y	Y	Y	Y
FE: Hospital Type	Y	Y	Y	Y	Y	Y
Adjusted R ²	0.64	0.66	0.66	0.62	0.59	0.57
Observations	9,035	9,035	8,989	7,353	7,361	7,332

Table IX
Treatment Charges

All columns report estimates from the regression model in equation (1). The outcome variables are the natural logarithm of the average charge (*Avg Chrg*), average payment received from all sources (*Avg pmt [All Src]*), average payment received from Medicare (*Avg pmt [Mdcr]*), and the payment-to-charge ratio (*Pmt/Chrg*), with the average calculated across patients of a given hospital for a given procedure. Columns (1) to (4) show results for inpatient healthcare services, and (5) to (8) for outpatient services. *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 eight hospital- and county-level variables listed and defined in Table I. Sample sizes in columns (5) through (8) are lower due to data availability—CMS outpatient reporting begins two years after the inpatient data—and because the count of unique outpatient APC codes is one-tenth that of inpatient DRGs. Fixed effects for each specification are noted in the table. Standard errors are clustered by state and reported in parentheses. **p* < 0.1; ***p* < 0.05; ****p* < 0.01.

Procedure Type:	Inpatient Procedures				Outpatient Procedures			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome in Ln, except ratio:	Avg Chrg	Avg Pmt [All Src]	Avg Pmt [Mdcr]	Pmt/Chrg	Avg Chrg	Avg Pmt [All Src]	Avg Pmt [Mdcr]	Pmt/Chrg
Treat×Post	-0.012 (0.02)	0.010 (0.01)	0.013 (0.01)	0.008 (0.01)	0.040*** (0.01)	0.005* (0.00)	0.006* (0.00)	-0.007** (0.00)
FE: Event×Pair×R.Year	Y	Y	Y	Y	Y	Y	Y	Y
FE: Event×Pair×Hosp×DRG	Y	Y	Y	Y	N	N	N	N
FE: Event×Pair×Hosp×APC	N	N	N	N	Y	Y	Y	Y
FE: Hospital Type	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R ²	0.97	0.98	0.98	0.96	0.97	0.99	0.99	0.90
Observations	548,757	548,757	548,757	548,757	101,455	101,455	101,455	101,455

Table X
Inpatient Volume By Treatment Charges

This table reports estimates from the regression model in equation (4). $\ln(\# \text{ Patient Discharge})$ is the natural logarithm of the number of patient discharges. DRGs are ranked annually based on the median of average submitted charges across all hospitals in the sample and classified into percentile groups according to this ranking. Specifically, $\leq P10$, $\leq P20$, $\leq P25$, $> P75$, $> P80$, and $> P90$ denote DRGs at or below the 10th, 20th, and 25th percentiles and above the 75th, 80th, and 90th percentiles, respectively. $Treat$ 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 hospital- and county-level variables listed and defined in Table I, as well as the Medicare casemix index (CMI) from CMS hospital impact files. Fixed effects for each specification are noted in the table. Standard errors are clustered by state and reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Outcome:	Ln (# Patient Discharge)					
	(1)	(2)	(3)	(4)	(5)	(6)
Percentile of DRG Charge:	$\leq P10$	$\leq P20$	$\leq P25$	$> P75$	$> P80$	$> P90$
Treat $\times$ Post	-0.043** (0.020)	-0.043** (0.017)	-0.036** (0.014)	0.022** (0.010)	0.043*** (0.015)	0.069** (0.027)
FE: Event $\times$ Pair $\times$ R.Year	Y	Y	Y	Y	Y	Y
FE: Event $\times$ Pair $\times$ Hosp $\times$ DRG	Y	Y	Y	Y	Y	Y
FE: Hospital Type	Y	Y	Y	Y	Y	Y
Adjusted R ²	0.87	0.86	0.86	0.79	0.80	0.77
Observations	53,852	126,276	153,676	45,018	34,595	10,847

Internet Appendix to
“How Do Debt Collection Restrictions Affect Hospitals
and Patients?”

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A. Data Appendix

1. SOC Codes for Relevant Job Postings

SOC	Occupation	Typical Role
<i>Panel A: Customer (Patient) Billing and Collection Related Occupations</i>		
13-2071	Credit Counselors	Advise individuals on managing debt and credit and may help develop debt-management or repayment plans.
43-3011	Bill and Account Collectors	Contact customers with delinquent accounts to solicit payment, receive and post payments, and maintain records on collection activity and account status.
43-3021	Billing and Posting Clerks	Compile and record billing and accounting information and prepare invoices for services rendered.
43-4041	Credit Authorizers, Checkers, and Clerks	Review customers' credit information, investigate credit standing, process credit applications, and authorize credit charges.
43-4141	New Accounts Clerks	Assist customers in establishing new accounts, explain available account services, and process account applications.
43-6013	Medical Secretaries and Administrative Assistants	Perform administrative duties using knowledge of medical and hospital procedures, including patient billing, scheduling, and maintaining medical records and correspondence.
<i>Panel B: Financial Management Related Occupations</i>		
11-3031	Financial Managers	Plan, direct, or coordinate an organization's accounting and other financial activities.
13-2011	Accountants and Auditors	Examine and interpret accounting records, prepare or evaluate financial statements, and advise on systems for recording costs and other financial data.
43-3031	Bookkeeping, Accounting, and Auditing Clerks	Compute, classify, post, and verify financial data to maintain complete and accurate accounting records.
13-2051	Financial and Investment Analysts	Conduct quantitative analyses of financial data and evaluate financial performance, investments, and the value of organizations or projects.
13-2099	Financial Specialists, All Other	Perform financial-specialist functions not classified in another specific financial occupation.

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. *Medically-Relevant Labor Salaries and Paid Hours in HCRIS and Rand Hospital Data*

- *Ln(Salaries)*: The natural logarithm of adjusted salaries for employed medically relevant staff. This information is sourced from HCRIS Worksheet S-3, Part II. Medically relevant staff include Non-physician anesthetist Part B (Line 3), Physician - Part A - Administrative (Line 4), 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), and Nursing Administration (Line 38).
- *Ln(Paid Hours)*: The natural logarithm of paid hours for employed medically relevant staff, as defined above. This information is sourced from HCRIS Worksheet S-3, Part II.
- *Paid Hours/Inpat*: Total paid hours for employed medically relevant staff divided by the number of inpatients.
- *Paid Hours/Inpat-Days*: Total paid hours for employed medically relevant staff divided by the number of inpatient days.

B. Additional Figures

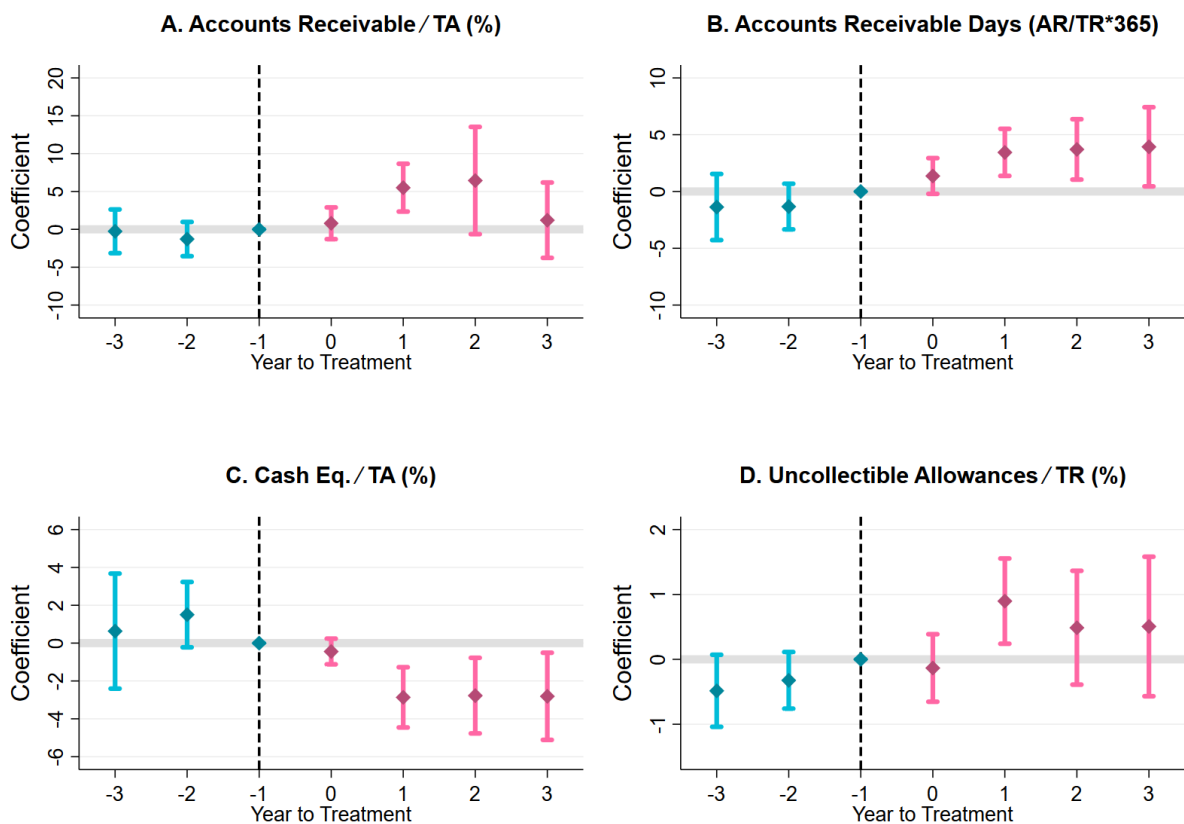


Figure B.1. Event Study Plots for Hospital-level Receivable Outcomes for Short-Term Acute Care Hospitals. This figure plots the coefficients β_τ and 95% confidence intervals for general short-term acute care hospitals for the four hospital-level outcomes shown in the respective panels. The horizontal axis shows years relative to the event year, with $\tau = 0$ denoting the first treated year.

C. Additional Regression Results

Table C.1
Effect on Debt Collection Industry

All columns report estimates from the regression model in equation (2). The outcome variables are expressed as year-on-year growth rate, and observations are at the state-year level. *# Est* is the number of establishments in the debt collection industry (NAICS codes 561440 and 561491). *Tot 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 three county-level control variables listed and defined in Table I—the natural logarithms of employment, GDP, and population. Fixed effects for each specification are noted in the table. 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	Tot Wage	Avg Emp Wage	Avg Est Wage
Treat×Post	-0.04** (0.02)	-0.28*** (0.10)	-0.06** (0.03)	-0.22* (0.11)
FE: Event×State Pair×R.Year	Y	Y	Y	Y
FE: Event×State Pair×State	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Adjusted R ²	0.26	-0.26	-0.38	-0.04
Observations	794	762	736	762

Table C.2
Hospital Receivable Outcomes: Cross-Border Spillover Effects

All columns report estimates from the regression model in equation (1). All outcomes are measured as normalized difference, defined as the difference in the outcome of a hospital in a bordering county and the mean outcome for same-state hospitals in inner counties, scaled by the standard deviation of the outcome across inner hospitals. *AR/TA* is the ratio of accounts receivable to total assets, expressed as a percentage. *AR Days* is days in gross accounts receivable. *CashEq/TA* is the ratio of cash and temporary investments to total assets, expressed as a percentage. *AllowUncoll/Rev* is the ratio of allowances for uncollectible notes and accounts receivable to gross patient revenue, 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 eight hospital- and county-level variables mentioned and defined in the notes to Table I. One-year-lagged *Cash/NFA* is excluded from controls in column (3). Fixed effects for each specification are noted in the table. 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 normalized differences):	$\frac{AR}{TA}$	AR Days	$\frac{CashEq}{TA}$	$\frac{AllowUncoll}{Rev}$
Treat×Post	0.04 (0.09)	-0.01 (0.04)	17.71 (14.83)	-0.03 (0.08)
FE: Event×Pair×R.Year	Y	Y	Y	Y
FE: Event×Pair×Hosp	Y	Y	Y	Y
FE: Hospital Type	Y	Y	Y	Y
Adjusted R ²	0.53	0.70	0.16	0.69
Observations	12,637	12,761	12,095	8,045

Table C.3
Hospital Receivable Outcomes: County Pairs with Population Centroid ≤ 75 km Apart

All columns report estimates from the regression model in equation (1). The sample includes only the county pairs where the population centroids of the two counties are less than 75 kilometers (46 miles) apart, following Dube, Lester, and Reich (2016). *AR/TA* is the ratio of accounts receivable to total assets, expressed as a percentage. *AR Days* is days in gross accounts receivable. *CashEq/TA* is the ratio of cash and temporary investments to total assets, expressed as a percentage. *AllowUncoll/Rev* is the ratio of allowances for uncollectible notes and accounts receivable to gross patient revenue, 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 eight hospital- and county-level variables mentioned and defined in the notes to Table I. One-year-lagged *Cash/NFA* is excluded from controls in column (3). Fixed effects for each specification are noted in the table. Standard errors are clustered by state and reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

	(1)	(2)	(3)	(4)
Outcome:	$\frac{AR}{TA}$	AR Days	$\frac{CashEq}{TA}$	$\frac{AllowUncoll}{Rev}$
Treat×Post	6.39*** (2.07)	4.62*** (0.90)	-2.48** (0.93)	1.05*** (0.28)
FE: Event×Pair×R.Year	Y	Y	Y	Y
FE: Event×Pair×Hosp	Y	Y	Y	Y
FE: Hospital Type	Y	Y	Y	Y
Adjusted R ²	0.63	0.77	0.82	0.69
Observations	10,937	11,008	11,304	6,750

Table C.4
Hospital Receivable Outcomes: Estimates by County Hospital Count

The columns report coefficient β associated with $Treat_{ickp} \times Post_{kpt}$ and the number of observations N from the regression model in equation (1) for the subsamples of county pairs where the number of hospitals in both treated and control counties exceeds $n(n = 2, 3, 4)$. The outcomes variables are noted in rows. AR/TA is the ratio of accounts receivable to total assets, expressed as a percentage. $AR\ Days$ is days in gross accounts receivable. $CashEq/TA$ is the ratio of cash and temporary investments to total assets, expressed as a percentage. $AllowUncoll/Rev$ is the ratio of allowances for uncollectible notes and accounts receivable to gross patient revenue, 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 eight hospital- and county-level variables mentioned and defined in the notes to Table I. One-year-lagged $Cash/NFA$ is excluded from controls in column (3). All models include event $\times$ county-pair $\times$ hospital, event $\times$ county-pair $\times$ relative year, and hospital type fixed effects. Standard errors are clustered by state and reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

# Hosp in each county of a pair:	# Hosp ≥ 2		# Hosp ≥ 3		# Hosp ≥ 4	
Statistics:	β	Obs.	β	Obs.	β	Obs.
<i>Outcome Variable</i>						
$\frac{AR}{TA}$	5.38**	11,100	7.21***	7,261	7.50**	5,394
AR Days	3.20***	11,201	4.65***	7,329	4.90***	5,451
$\frac{CashEq}{TA}$	-2.59***	11,452	-3.20***	7,504	-3.76***	5,609
$\frac{AllowUncoll}{Rev}$	0.55**	7,521	1.15***	5,035	1.50***	3,696

Table C.5
Hospital Receivable Outcomes: Urban vs Rural Counties

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. *CashEq/TA* is the ratio of cash and temporary investments to total assets, expressed as a percentage. *AllowUncoll/Rev* is the ratio of allowances for uncollectible notes and accounts receivable to gross patient revenue, expressed as a percentage. *County Rurality* is based on NCHS Urban–Rural Classification Scheme. Counties classified as large central metro or large fringe metro are categorized as *Urban*, while those classified as medium metro, small metro, micropolitan, or noncore are categorized as *Rural*. *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 eight hospital- and county-level variables mentioned and defined in the notes to Table I. One-year-lagged *Cash/NFA* is excluded from controls in column (3). Fixed effects for each specification are noted in the table. Standard errors are clustered by state and reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

County Rurality:	Urban				Rural			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome:	$\frac{AR}{TA}$	AR Days	$\frac{CashEq}{TA}$	$\frac{AllowUncoll}{Rev}$	$\frac{AR}{TA}$	AR Days	$\frac{CashEq}{TA}$	$\frac{AllowUncoll}{Rev}$
Treat×Post	6.61** (2.82)	5.06*** (1.07)	-3.09*** (0.74)	0.72* (0.39)	2.79** (1.31)	2.55** (0.97)	-0.96 (0.89)	0.43 (0.36)
FE: Event×Pair×R.Year	Y	Y	Y	Y	Y	Y	Y	Y
FE: Event×Pair×Hosp	Y	Y	Y	Y	Y	Y	Y	Y
FE: Hospital Type	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R ²	0.66	0.81	0.84	0.72	0.69	0.80	0.83	0.73
Observations	10,439	10,545	10,781	6,857	10,660	10,722	11,020	6,971

Table C.6
Hospital Receivable Outcomes: Excluding Covid Years 2020–2022

All columns report estimates from the regression model in equation (1). The sample excludes observations from the COVID-19 period (2020–2022). *AR/TA* is the ratio of accounts receivable to total assets, expressed as a percentage. *AR Days* is days in gross accounts receivable. *CashEq/TA* is the ratio of cash and temporary investments to total assets, expressed as a percentage. *AllowUncoll/Rev* is the ratio of allowances for uncollectible notes and accounts receivable to gross patient revenue, 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 eight hospital- and county-level variables mentioned and defined in the notes to Table I. One-year-lagged *Cash/NFA* is excluded from controls in column (3). Fixed effects for each specification are noted in the table. Standard errors are clustered by state and reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

	(1)	(2)	(3)	(4)
Outcome:	$\frac{AR}{TA}$	AR Days	$\frac{CashEq}{TA}$	$\frac{AllowUncoll}{Rev}$
Treat×Post	5.53** (2.23)	4.38*** (1.08)	-2.15*** (0.79)	0.58** (0.27)
FE: Event×Pair×R.Year	Y	Y	Y	Y
FE: Event×Pair×Hosp	Y	Y	Y	Y
FE: Hospital Type	Y	Y	Y	Y
Adjusted R ²	0.67	0.78	0.83	0.69
Observations	10,790	10,861	11,061	7,213

Table C.7

Hospital Receivable Outcomes: Heterogeneity By Debt Collector Firm Density

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. $CashEq/TA$ is the ratio of cash and temporary investments to total assets, expressed as a percentage. $AllowUncoll/Rev$ is the ratio of allowances for uncollectible notes and accounts receivable to gross patient revenue, expressed as a percentage. $\# Debt Collector Firms Per Capita$ is the number of debt collection firms in a state per capita. It is *High* if this value exceeds the respective event-specific pre-event-year median, and *Low* otherwise, with the classification held fixed over the 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 eight hospital- and county-level variables mentioned and defined in the notes to Table I. One-year-lagged $Cash/NFA$ is excluded from controls in column (3). Fixed effects for each specification are noted in the table. Standard errors are clustered by state and reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

# Debt Collector Firms Per Capita:	High				Low			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome:	$\frac{AR}{TA}$	$AR\ Days$	$\frac{CashEq}{TA}$	$\frac{AllowUncoll}{Rev}$	$\frac{AR}{TA}$	$AR\ Days$	$\frac{CashEq}{TA}$	$\frac{AllowUncoll}{Rev}$
Treat×Post	6.29** (2.67)	6.90*** (1.48)	-3.03* (1.50)	1.54*** (0.36)	-1.32 (1.44)	0.25 (0.96)	3.42*** (1.08)	-1.07*** (0.26)
FE: Event×Pair×R.Year	Y	Y	Y	Y	Y	Y	Y	Y
FE: Event×Pair×Hosp	Y	Y	Y	Y	Y	Y	Y	Y
FE: Hospital Type	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R ²	0.64	0.83	0.83	0.71	0.65	0.71	0.82	0.74
Observations	9,485	9,575	9,828	5,685	3,653	3,669	3,748	2,757

Table C.8
Hospital Receivable Outcomes: Heterogeneity by Debt Collector Employee Density

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. *CashEq/TA* is the ratio of cash and temporary investments to total assets, expressed as a percentage. *AllowUncoll/Rev* is the ratio of allowances for uncollectible notes and accounts receivable to gross patient revenue, expressed as a percentage. *# Debt Collectors Per Capita* is the number of debt collectors in a state per capita. It is *High* if this value exceeds the respective event-specific pre-event-year median, and *Low* otherwise, with the classification held fixed over the 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 eight hospital- and county-level variables mentioned and defined in the notes to Table I. One-year-lagged *Cash/NFA* is excluded from controls in column (3). Fixed effects for each specification are noted in the table. Standard errors are clustered by state and reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

# Debt Collectors Per Capita:	High				Low			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome:	$\frac{AR}{TA}$	AR Days	$\frac{CashEq}{TA}$	$\frac{AllowUncoll}{Rev}$	$\frac{AR}{TA}$	AR Days	$\frac{CashEq}{TA}$	$\frac{AllowUncoll}{Rev}$
Treat×Post	5.53*	6.09***	-4.64*	-0.01	-3.01	-1.72	1.26	0.85**
	(3.05)	(1.86)	(2.27)	(1.02)	(2.87)	(2.28)	(1.22)	(0.30)
FE: Event×Pair×R.Year	Y	Y	Y	Y	Y	Y	Y	Y
FE: Event×Pair×Hosp	Y	Y	Y	Y	Y	Y	Y	Y
FE: Hospital Type	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R ²	0.64	0.80	0.83	0.71	0.68	0.80	0.81	0.75
Observations	8,917	9,018	9,200	5,563	4,430	4,444	4,602	2,945

Table C.9

Hospital Receivable Outcomes: Heterogeneity Across Legislation Characteristics

All columns present results from equation (1) estimated separately by regulatory focus: laws governing licensing, bonding, and penalties versus those targeting practice restrictions and transparency. The categories are not mutually exclusive. *AR/TA* is the ratio of accounts receivable to total assets, expressed as a percentage. *AR Days* is days in gross accounts receivable. *CashEq/TA* is the ratio of cash and temporary investments to total assets, expressed as a percentage. *AllowUncoll/Rev* is the ratio of allowances for uncollectible notes and accounts receivable to gross patient revenue, 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 eight hospital- and county-level variables mentioned and defined in the notes to Table I. One-year-lagged *Cash/NFA* is excluded from controls in column (3). Fixed effects for each specification are noted in the table. Standard errors are clustered by state and reported in parentheses. **p* < 0.1; ***p* < 0.05; ****p* < 0.01.

Law Type:	Lic/Bond/Penalty				Restrict Praticce/Increase Transparency			
[# Events:]	[16]				[14]			
Outcome:	(1) $\frac{AR}{TA}$	(2) AR Days	(3) $\frac{CashEq}{TA}$	(4) $\frac{AllowUncoll}{Rev}$	(5) $\frac{AR}{TA}$	(6) AR Days	(7) $\frac{CashEq}{TA}$	(8) $\frac{AllowUncoll}{Rev}$
Treat×Post	4.08* (2.22)	3.42*** (1.09)	-1.68* (0.84)	0.62* (0.33)	0.72 (1.88)	2.11 (1.30)	-2.37*** (0.83)	-0.31 (0.34)
FE: Event×Pair×R.Year	Y	Y	Y	Y	Y	Y	Y	Y
FE: Event×Pair×Hosp	Y	Y	Y	Y	Y	Y	Y	Y
FE: Hospital Type	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R ²	0.65	0.80	0.82	0.70	0.67	0.83	0.84	0.71
Observations	9,792	9,879	10,097	6,168	5,978	6,054	6,158	4,028

Table C.10
Hospital Dealscan Loans: Alternative Exposure Weights

All columns report estimates from the regression model in equation (3). The unit of observation is a loan facility l , borrowed by hospital borrower i in year t . *DCR Exposure* is the exposure to debt collection restriction tightening, weighted by the variables indicated in the top row of the column header. *Spread & Fee* is the interest rate spread (in basis points) over LIBOR, plus fees on the drawn portion of the loan. $\ln(Amt)$ is the natural logarithm of the loan facility amount. Controls are borrower i 's natural logarithm of net fixed assets, income over total assets, total liabilities over total assets, and net fixed assets over total assets. Fixed effects for each specification are noted in the table. Standard errors are clustered by hospital borrower and reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Exposure Weight:	Total Income		NFA		AR	
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome:	Spread&Fee	Ln(Amt)	Spread&Fee	Ln(Amt)	Spread&Fee	Ln(Amt)
DCR Exposure	89.87** (36.80)	-0.25** (0.12)	87.52** (34.43)	-0.23** (0.10)	72.70** (31.62)	-0.24** (0.10)
FE: Hosp, Loan Year	Y	Y	Y	Y	Y	Y
Adjusted R ²	0.58	0.78	0.58	0.78	0.58	0.78
Observations	249	347	249	347	249	347

Table C.11

Effects on Mortality and Critical Care Provision: Excluding Covid Years 2020–2022

All columns report estimates from the regression model in equation (1). The sample excludes observations from the COVID-19 period (2020–2022). *Mortality Rate (MR)%* 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. Columns (1) to (3) report mortality rates for pneumonia, acute myocardial infarction (AMI), and heart failure, respectively. *Critical Care (CC)* comprises intensive care and coronary care. For columns (4) to (7), the dependent variables are the natural logarithms of critical care beds, critical care bed-days, critical care inpatient-days, and critical care inpatient-days per inpatient, respectively. *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 eight hospital- and county-level variables listed and defined in Table I. Fixed effects for each specification are noted in the table. Standard errors are clustered by state and reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Outcome Category:	Mortality Rate (MR)%			Critical Care (CC): Intensive Care + Coronary Care			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ln, except mortality rates:	MR _{PN}	MR _{AMI}	MR _{HF}	CC Beds	CC Bed-days	CC Inpat-days	CC Inpat-days # Inpat
Treat×Post	0.452** (0.18)	0.162** (0.08)	-0.133 (0.15)	-0.047** (0.02)	-0.065*** (0.02)	-0.057*** (0.02)	-0.044*** (0.01)
FE: Event×Pair×R.Year	Y	Y	Y	Y	Y	Y	Y
FE: Event×Pair×Hosp	Y	Y	Y	Y	Y	Y	Y
FE: Hospital Type	Y	Y	Y	Y	Y	Y	Y
Adjusted R ²	0.77	0.64	0.60	0.97	0.95	0.95	0.88
Observations	7,677	5,443	7,052	6,522	6,507	6,507	6,507

Table C.12

Effects on Mortality and Critical Care Provision: Controlling for Case-Mix Index

All columns report estimates from the regression model in equation (1). *Mortality Rate (MR)%* 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. Columns (1) to (3) report mortality rates for pneumonia, acute myocardial infarction (AMI), and heart failure, respectively. *Critical Care (CC)* comprises intensive care and coronary care. For columns (4) to (7), the dependent variables are the natural logarithms of critical care beds, critical care bed-days, critical care inpatient-days, and critical care inpatient-days per inpatient, respectively. *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 eight hospital- and county-level variables listed and defined in Table I, as well as the Medicare casemix index (CMI) from CMS hospital impact files. Fixed effects for each specification are noted in the table. Standard errors are clustered by state and reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Outcome Category:	Mortality Rate (MR)%			Critical Care (CC): Intensive Care + Coronary Care			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ln, except mortality rates:	MR _{PN}	MR _{AMI}	MR _{HF}	CC Beds	CC Bed-days	CC Inpat-days	CC Inpat-days # Inpat
Treat×Post	0.529** (0.23)	0.155* (0.08)	-0.069 (0.16)	-0.047*** (0.02)	-0.063*** (0.02)	-0.055*** (0.02)	-0.033** (0.02)
FE: Event×Pair×R.Year	Y	Y	Y	Y	Y	Y	Y
FE: Event×Pair×Hosp	Y	Y	Y	Y	Y	Y	Y
FE: Hospital Type	Y	Y	Y	Y	Y	Y	Y
Adjusted R ²	0.79	0.66	0.65	0.97	0.94	0.94	0.85
Observations	7,385	6,384	7,312	8,202	8,202	8,193	8,193

Table C.13
Critical Care Provision: Alternative Definitions

All columns report estimates from the regression model in equation (1). *Critical Care* (CC) is alternatively defined as intensive care, coronary care, and other special care in columns (1) to (4), and as all critical care units, including intensive care, coronary care, other special care, burn intensive care, and surgical intensive care, in columns (5) to (8). The dependent variables are the natural logarithms of critical care beds, critical care bed-days, critical care inpatient-days, and critical care inpatient-days per inpatient, respectively. *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 eight hospital- and county-level variables listed and defined in Table I. Fixed effects for each specification are noted in the table. Standard errors are clustered by state and reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Critical Care Units (CC):	Intensive / Coronary / Other Speciality Care				All Critical Care Units			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln:	CC Beds	CC Bed-days	CC Inpat-days	$\frac{\text{CC Inpat-days}}{\# \text{ Inpat}}$	CC Beds	CC Bed-days	CC Inpat-days	$\frac{\text{CC Inpat-days}}{\# \text{ Inpat}}$
Treat×Post	-0.051*** (0.02)	-0.065*** (0.02)	-0.063*** (0.02)	-0.049** (0.02)	-0.035** (0.01)	-0.032** (0.02)	-0.057*** (0.02)	-0.043* (0.02)
FE: Event×Pair×R.Year	Y	Y	Y	Y	Y	Y	Y	Y
FE: Event×Pair×Hosp	Y	Y	Y	Y	Y	Y	Y	Y
FE: Hospital Type	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R ²	0.98	0.96	0.96	0.89	0.98	0.96	0.96	0.90
Observations	9,084	9,073	9,064	9,064	9,191	9,192	9,171	9,171

Table C.14
Medical Malpractice Instances

All columns report estimates from the regression model in equation (2). All outcome variables are measured per capita, and observations are at the state-year level. # *Practitioners* is the number of practitioners involved in malpractice payment cases per million population. # *Cases* is the total number of malpractice payment cases per million population. *Payment Amt* is the total amount of malpractice payments per 1000 population. *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. Fixed effects for each specification are noted in the table. 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)
Outcome (per population):	# Practitioner (per mn)	# Case (per mn)	Amt (per 1000)
Treat×Post	4.05*** (1.43)	2.30** (0.93)	844.68* (499.40)
FE: Event×State Pair×R.Year	Y	Y	Y
FE: Event×State Pair×State	Y	Y	Y
Controls	Y	Y	Y
Adjusted R ²	0.72	0.83	0.69
Observations	820	820	820

Table C.15
Healthcare Utilization

All columns report estimates from the regression model in equation (5). All outcome variables are in natural logarithm, with observations at the county-year level. The outcomes are respectively the natural logarithm of the number of hospital outpatient visits, hospital emergency department visits, hospital inpatient stays, physician visits, ambulatory surgery center events, and home health visits. *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 one-year lagged average household debt-to-income and the natural logarithms of employment, GDP, and population listed and defined in Table I. Fixed effects for each specification are noted in the table. Standard errors are clustered by state and reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Healthcare Provider Type:	Hospital			Non-Hospital		
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome (in Ln):	# OP Visits	# ED Visits	# IP Stays	# PC Visits	# ASC Events	# HH Visits
Treat×Post	-0.02** (0.01)	0.01 (0.01)	-0.01 (0.01)	-0.02 (0.01)	0.02 (0.02)	-0.02 (0.03)
FE: Event×Pair×R.Year	Y	Y	Y	Y	Y	Y
FE: Event×Pair×County	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Adjusted R ²	1.00	1.00	1.00	0.99	0.99	0.99
Observations	4,524	4,524	4,524	5,358	4,486	4,392

Table C.16
Aggregate Effects: Healthcare vs Placebo Industries

Industry:	Hosp, Physician, & Outpat Care Cntr			Grocery, Restaurant, & Fitness			Non-Tradable Excl. Healthcare			All Industries Excl. Healthcare		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Outcome (in Ln):	Tot Wage	Avg Emp Wage	Avg Est Wage	Tot Wage	Avg Emp Wage	Avg Est Wage	Tot Wage	Avg Emp Wage	Avg Est Wage	Tot Wage	Avg Emp Wage	Avg Est Wage
Treat×Post	-0.10* (0.06)	-0.03*** (0.01)	-0.10* (0.06)	0.03 (0.02)	0.01 (0.01)	0.02 (0.01)	0.01 (0.01)	0.00 (0.01)	0.00 (0.02)	0.02 (0.01)	0.01 (0.01)	0.00 (0.02)
FE: Event×Pair×R×Year	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
FE: Event×Pair×County	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R ²	0.97	0.76	0.87	0.99	0.78	0.91	0.99	0.75	0.89	1.00	0.82	0.96
Observations	4,536	4,390	4,536	8,356	8,254	8,356	8,248	8,078	8,248	9,118	9,118	9,118

All columns report estimates from the regression model in equation (5). All outcome variables are in natural logarithm, and observations are at the county-year level. Columns (1) to (3) show results for hospital, physician, and outpatient care center, whose 4-digit NAICS codes are 6211, 6214, 6221, 6222, and 6223; (4) to (6) for grocery, restaurants, and fitness; (7) to (9) for all non-tradable industries excluding healthcare (2-digit NAICS code 62); and (10) to (12) for all industries excluding healthcare. *Tot Wage* is total annual payroll. *Avg Emp Wage* is average annual payroll per employee. *Avg Est Wage* is average annual payroll per establishment. *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 one-year lagged average household debt-to-income and the natural logarithms of employment, GDP, and population listed and defined in Table I. Fixed effects for each specification are noted in the table. Standard errors are clustered by state and reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.