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ABSTRACT

This study examines the link between credit supply and hospital health outcomes. We use bank stress tests as exogenous shocks to credit access for hospitals that have lending relationships with tested banks. We find that affected hospitals shift their operations to increase resource utilization following a negative credit shock but reduce the quality of their care to patients across a variety of measures, including a significant increase in risk-adjusted readmission and mortality rates. The results indicate that access to credit can affect the quality of healthcare hospitals deliver, pointing to important spillover effects of credit market frictions on health outcomes.

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1 Introduction

Hospitals play an essential role in maintaining public health. Hospitals are also crucial to the economy, with healthcare spending in the U.S. accounting for 18–20% of GDP and the hospital sector accounting for one-third of this spending.[1] However, like other enterprises, hospitals must obtain financing for their operations and utilize credit markets for this financing. Indeed, the vast majority of U.S. hospitals carry leverage and often rely on debt for their financing needs. Moreover, due to low profit margins, hospitals carry considerable default risk, with healthcare defaults on municipal bonds comprising 20% of all bond defaults, second only to housing. Consequently, frictions in the credit market can exacerbate impediments to credit access for hospitals, straining hospital finances and potentially influencing real decisions and outcomes.

Given the prevalence of borrowing in the hospital sector (among all types of hospitals, including non-profit and rural hospitals), it is important to understand the role of credit access in shaping hospital operating decisions, as well as the potential spillover effects of such decisions on the hospital's quality of care. The questions we seek to address are thus: (*i*) How do shocks to credit markets transmit to hospital finances?; (*ii*) How do hospitals respond to negative shocks to credit access in terms of financing and operating decisions?; and finally, (*iii*) Do we observe indirect, negative effects on patient health outcomes following tightened credit constraints? Given their importance to public health, we would expect (or hope) that hospitals can maintain the same quality of care despite frictions in financial markets. This question highlights an important yet overlooked negative societal externality—health consequences—that can arise from credit shocks. Research on this topic may therefore have important social consequences and policy implications.

To help shed light on the above questions, we utilize the staggered pattern of stress tests on U.S. banks implemented by the 2010 Dodd-Frank Act to cleanly test the effects of shocks to the supply of credit. Stress tests are regulatory assessments by the Federal Reserve designed to gauge a bank's ability to withstand an impending economic crisis, the first of which were implemented in 2012. Following a stress test, banks often engage in risk management actions in order to improve their solvency and capital adequacy ratios. We

[1] U.S. healthcare spending was $4.1 trillion in 2020, constituting 19.7% of U.S. GDP. Furthermore, hospital employment in the U.S. exceeds 5.7 million, and hospitals are among the top employers across U.S. cities (Samuelson (2017)). See also Gaynor et al. (2015). Moreover, the economic decline following the 2020 pandemic is reported to be partly attributed to the large reduction in healthcare spending, leading to significant layoffs of hospital medical staff. See, e.g., "Plunge in health-care spending a big reason US economy sank in first quarter," *CNBC*, April 29, 2020. Healthcare spending in other OECD countries is similar, with an average of 8–9% of GDP.

use the fact that a given hospital's bank experiences a stress test as an exogenous negative shock to credit for the hospital. As noted by Gao et al. (2019), hospitals are particularly risky borrowers, with higher than average yields and default rates for municipal bonds. Consequently, to better manage their risk or improve their capital adequacy, stress-tested banks can lower the amount of credit provided or demand higher rates from these risky borrowers (Acharya et al. (2018), Cortés et al. (2020)).[2]

Using a staggered difference-in-differences specification over the period 2010–2016, we examine the change in operating decisions and performance, as measured by patient health outcomes, between hospitals subject to a credit supply shock—hospitals that had lending relationships with banks which were later stress-tested—relative to hospitals which did not experience a shock. This empirical strategy has the advantage that (*i*) the stress tests themselves are unrelated to the underlying health of a local population; (*ii*) the tests occurred in a staggered manner; (*iii*) the tests were applied to banks based on size thresholds rather than on bank performance; and (*iv*) it is unlikely that hospitals could anticipate the negative bank responses following a stress test.

We first establish that bank stress tests constitute a negative credit shock to their connected hospital borrowers. In particular, we find that loan spreads increase while loan amounts and maturity periods decrease for affected hospitals, and these hospitals are more likely to switch lenders to one for which they did not have a previous relationship with.[3] These results are consistent with bank stress tests increasing the cost of credit for an affected bank's hospitals and reinforce the findings of Acharya et al. (2018) and Cortés et al. (2020). The increases in debt servicing costs are economically significant for hospitals in our sample, due to low profit margins within the hospital industry. For example, the impact of the higher spread (interest rate over LIBOR) alone results in an additional $1.07 million in interest expense per year for an affected hospital in our sample, which amounts to an economically sizable 13.4% of net income. A decrease in net income heightens the likelihood of hospital insolvency and closure—an ever-present risk in the hospital industry (Bai et al. (2020))—and also leaves the hospital with fewer internally generated funds with which to finance future operations.

We then explore how hospital financial and operating outcomes change as a result. We

[2]As shown by Acharya et al. (2018) and Cortés et al. (2020), banks trim their loan portfolios and charge higher rates for riskier loans following a stress test, thus constituting a negative credit supply shock to firms that borrow from these tested banks.

[3]Changing lenders or acquiring loans from new banks also proves problematic for hospitals, as new lenders require a higher rate to compensate for the more severe information asymmetry due to the absence of a previous relationship.

find that, in response to the credit shock, affected hospitals improve profit margins on services and ramp up internally generated funds (i.e., net income). In particular, in response to tighter credit conditions, we find evidence that hospitals rely more on their existing resources by increasing bed utilization and discharge rates. In a given year, each bed in an affected hospital is occupied by eight more days per year, on average, relative to an unaffected hospital. Moreover, affected hospitals accommodate 2.4 more patients per bed each year, which amounts to 375 additional patients accommodated per year for the average affected hospital. These utilization effects are consistent with prior literature that has documented an increase in efficiency following stricter financial constraints (e.g., Hovakimian (2011)).

While the previous results suggest that hospitals work to improve their financial efficiency through expanding their profitable operations in response to tightening credit, we find that this comes at the expense of healthcare quality for patients. More specifically, affected hospitals experience a significant *decline* in quality of care and patient health outcomes. We examine patient health outcomes following treatment using risk-adjusted, unplanned 30-day hospital readmission rates for various health conditions, a widely used measure by both government agencies and academic researchers for quality of care that assesses the effectiveness of treatment.[4] We also gather data on 30-day risk-adjusted mortality rates for similar conditions. Finally, as a direct measure of patient satisfaction with the quality of care and attentiveness, we utilize patient survey data. This data includes patient satisfaction following discharge regarding hospital quality, communication with physicians and nurses, efficacy of pain control, and other items relevant to the treatment and hospital stay.

Across all sets of measures, the results show that hospital performance declines following credit supply shocks. We find that patients discharged from affected hospitals are significantly more likely to be readmitted within 30 days from discharge. This result is strikingly consistent across the three diagnostic groups for which we have detailed data (heart failure, acute myocardial infraction, and pneumonia) and also holds for a wider set of medical conditions. The magnitude of the effect is sizable; restrictions to the access of credit for hospitals indirectly leads to an additional 1,570 patients readmitted per year in aggregate across affected hospitals. Similarly, with respect to patient mortality from pneumonia—a

[4]For example, the Centers for Medicare and Medicaid Services, under the Hospital Readmissions Reduction Program, uses unplanned readmission rates as the central performance criteria when determining Medicare payment reductions. Moreover, rehospitalization accounts for more than $17 billion in avoidable Medicare expenditures and is associated with poor outcomes (Jencks et al. (2009)). A substantial portion of readmissions are estimated to be preventable (MedPAC (2007)). See also https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/AcuteInpatientPPS/Readmissions-Reduction-Program.

common hospital-acquired condition (Rothberg et al. (2014))—the results show an increase of 718 patient deaths a year across affected hospitals.

With respect to patient experiences, patient evaluations regarding efficacy of treatment and attentiveness of the medical staff are consistently lower for affected hospitals. Across *all* eight rating dimensions, recently discharged patients from affected hospitals are significantly less satisfied, including with regard to lower overall care quality, less communication with doctors and nurses, and worse pain control. Collectively, these results suggest that patient health outcomes and quality of care are adversely affected for hospitals which experience a shock to credit access.

We further utilize patient-level data for several states to better understand the mechanisms underlying the above-mentioned results. We find that affected hospitals increase their income and profit margins through increased resource utilization and cost efficiency. Specifically, affected hospitals increase admissions per diagnosis-related group (DRG) by 4.6%, in line with our earlier results that discharges and bed utilization increase for affected hospitals. Moreover, the increase in admissions is driven by greater inpatient admissions from patients who arrive at the emergency department (ED) and through an increase in scheduled non-emergency (i.e., elective) procedures which require an inpatient stay (such as hip replacements). Interestingly, inpatient admissions for DRGs with *lower* relative weights (which reflect lower complexity or severity of the patient's condition) see a *larger* increase. These findings are consistent with hospitals lowering the threshold for inpatient admission and admitting more patients with less severe conditions. These results also comport with anecdotal evidence and Department of Justice cases whereby hospitals use higher inpatient admissions to increase revenues (Pomorski (2021)).

In terms of cost efficiency, affected hospitals significantly reduce the number of procedures provided for admitted inpatients across all insurance types and also reduce inpatient length of stays (for privately insured patients). Such actions lower costs for hospitals while maintaining similar payments for inpatient admissions reimbursed on a fixed payment scheme. Collectively, these responses illustrate how hospitals increase revenues while also lowering costs to improve profitability.

To shed light on the decrease in care quality, we examine hospital staffing using the patient-level data mentioned above. We find that physicians are on average providing care for a greater number of patients per DRG and that the unique number of physicians providing care per DRG remains the same at affected hospitals. These results suggest that physicians face greater strains on their time and attention following the shock. We additionally utilize data on hospitals' use of timely and effective treatment and procedures by medical staff for certain medical conditions to measure attentiveness and care quality. As an example, this includes the frequency with which patients suffering from a heart attack received a percutaneous coronary intervention (PCI) within 90 minutes of arrival. The results show that affected hospitals exhibit increased delay in providing critical treatment and a lower propensity in performing requisite medical procedures for the specific medical conditions. For affected hospitals, the likelihood of failing to provide proper treatment for five out of six quality metrics increases by 0.5–1.4%, which represents a 14–22% increase relative to the sample mean of 3.2–6.5%, depending on the treatment or procedure. This decline in the process of care scores is consistent with medical staff being less attentive to patients in affected hospitals, which helps to explain the increase in readmission rates reported above.

Taken together, the above findings imply that affected hospitals adjust for the increased cost of debt or the decline in external financing by increasing cost efficiency and internally generated funds from patients. This includes greater admission of patients with less severe conditions and of privately-insured patients. The increase in inpatient admissions, however, is not met with a contemporaneous increase in hospital physicians, resulting in physicians providing care for a larger number of patients. Consequently, the heavier inpatient volume comes at the cost of worse performance: medical staff appear to be less attentive to patients, as evidenced by a decrease in the quality and timeliness of care, and patient health outcomes decline, as unplanned readmissions rise. In sum, hospitals attempt to "make up the difference" through higher resource utilization, but sacrifice quality of care in the process, which in turn results in worse health outcomes.

A question which arises from these results is whether the change in hospital operations implies that affected hospitals were operating suboptimally prior to the credit shock. Hospitals aim to maximize profitability, but, unlike other firms, hospitals also have a health provision objective (i.e., concerns for patient utility) that can run counter to profitability. Consequently, hospitals optimize between profits and health provision in their objective function. Our results imply that the tightening of financial constraints can lead hospitals to re-optimize and shift their decisions more towards profitability and away from healthcare quality.[5]

In additional analyses, we explore differential responses based on hospital characteristics as well as heterogeneous exposure to the treatment. As discussed above, we predict that the primary channel by which hospital performance declines is through frictions in credit access.

[5]Hospitals may also need to increase internally generated funds to prevent closure, a prevalent concern among many U.S. hospitals (see, e.g., Capps et al. (2010), Bai et al. (2020), Pomorski (2021)).

Accordingly, under the hypothesized channel, hospital borrowers that are more affected by tightened credit constraints should experience a more pronounced effect in outcomes and performance. We find that the effects are stronger for hospitals that have a greater reliance on bank loan financing and smaller cash holdings prior to the stress tests. In terms of heterogeneous exposure to the treatment, we build from the observation that banks whose stress test outcomes are closer to the regulatory minimum have a stronger incentive to manage risk relative to banks whose projected outcomes are farther from the threshold (Cortés et al. (2020)). This shorter distance from the threshold translates to a more severe credit supply shock for a bank's corresponding hospital borrowers (e.g., through a greater reduction in lending or higher interest rates). We find that hospitals that borrow from banks whose outcomes are closer to the regulatory minimum exhibit stronger responses to the tightened credit constraints.

Finally, we consider a variety of robustness tests. These include running our results on a propensity score-matched sample and controlling for time-varying geographical differences. In addition, we explore robustness related to our sample composition, including samples restricted to hospitals that are in small hospital systems, have for-profit status, or have borrowed from commercial banks. We also examine a placebo test centered on non-exposed rival hospitals.

This study relates to several different areas. Our paper contributes to the literature that examines the impact of financial frictions. This includes studies that document a negative impact on investment in the presence of constraints to credit access (see, e.g., Chava and Roberts (2008), Campello et al. (2010), Duchin et al. (2010), Lemmon and Roberts (2010)). The current study shows that shocks to credit supply can influence distinct firm decisions aside from investment, such as more granular firm operating activities. Moreover, our results indicate that such decisions can (indirectly) have real effects on health outcomes. As such, our paper ties into the strand of literature that studies the real effects of credit supply shocks (e.g., Gan (2007), Hombert and Matray (2017)). Our study identifies a novel and important real effect—health consequences—arising from frictions in financial markets. Relatedly, our results show unintended downstream consequences of public policy decisions regarding the financial sector. This contributes to our understanding of how changes in public policy can affect bank lending activities and the potential spillover effects (see, e.g., Bernanke and Gertler (1995)). The current study is also related to the large literature that studies relationship lending (e.g., Petersen and Rajan (1994), Boot (2000), Detragiache et al. (2008)). We contribute to this literature by showing that a negative shock to relationship lending which reduces credit supply in turn reduces the *quality* of service of an important public good (healthcare). As a result, we provide novel evidence of how credit markets can indirectly affect health outcomes.

Our analysis is also related to the literature at the intersection of healthcare and finance. Adelino et al. (2015) use non-profit hospitals to test the investment cash-flow sensitivity of non-profit firms and find that these hospitals respond to increases in their cash flows (due to financial investments) by increasing their investments, in a similar way as public firms. Dranove et al. (2017) and Adelino et al. (2019) examine hospital responses following a drop in investments due to the 2008 financial crisis. Dranove et al. (2017) find that the average non-profit hospital did not respond to the crisis with price increases, but reduced unprofitable service offerings (with the reverse holding for non-profit hospitals with greater bargaining power). Adelino et al. (2019) find no aggregate evidence of a shift towards more profitable procedures due to the financial crisis, except by the most severely affected hospitals.[6] Gupta et al. (2021) examine the effect of private equity investments in the quality of care delivered by nursing homes. Another stream of research investigates the impact of government healthcare reforms, such as the Affordable Care Act (ACA), on equity and debt prices. Koijen et al. (2016) consider medical innovation and R&D, and document a premium in the equity returns of healthcare firms (including drug and biologic companies) due to the risk of government reforms. Gao et al. (2022) examine the effect of the ACA on non-profit hospital municipal bond spreads. Our paper contributes to the finance and healthcare literature by documenting a link between hospitals and credit markets and shows how credit markets may indirectly affect healthcare. To the best of our knowledge, the present study is the first to document the impact of credit access on patient health outcomes, quality of care, and patient satisfaction as indirectly arising from frictions in the credit market.

Our study is also related to the literature which considers potential inefficiencies in the healthcare sector. Prior studies have documented variation in treatment rates across

[6]Both Dranove et al. (2017) and Adelino et al. (2019) consider a shock to hospital endowments (i.e., a wealth shock), while the present study examines a shock to operating profitability (i.e., an income shock) and access to external financing. The nature of the shock (wealth versus income) can play a critical role in how hospitals respond, as changes in endowment values may not translate to changes in distributions or income from the endowment. In particular, as we show, a direct shock to operating profitability in the form of higher interest expenses results in a more immediate response, as hospitals must cut costs and boost revenues to mitigate the cost increase, while sacrificing the delivery of healthcare quality in return. Additionally, there are several reasons why hospitals may not respond to financial shocks with price increases, as documented in Dranove et al. (2017). For example, renegotiating prices with insurers may not be possible in the short-run if contracted prices with insurers have been set well in advance. Moreover, the hospital's ability to renegotiate prices depends on a number of factors that can be outside of the hospital's control, such as the market power of the hospital and insurer. Consequently, it can be more difficult for hospitals to adjust prices than to engage in other operational adjustments for which hospitals have more control over.

providers (e.g., Fisher et al. (2003), Abaluck et al. (2016), Chandra and Staiger (2020), Einav et al. (2021); see Chandra et al. (2011) for a review). We document an important substitution effect that may contribute to the observed heterogeneity: in the presence of (heterogeneous) financing constraints, hospitals turn to generating greater revenues through inpatient admissions, while reducing the number of procedures and average length of stay for inpatients. Furthermore, our paper is related to the literature on hospital cost-shifting, which considers potential increases in prices for private payers following reductions in public payments (e.g., Dranove (1988), Zwanziger and Bamezai (2006); see Frakt (2011) for a review). However, few studies in this literature consider *cost-cutting* by hospitals (exceptions include Cutler (1998) and Dranove et al. (2017)). We contribute to this literature by examining specific cost-cutting and revenue-increasing decisions, such as inpatient admissions and number of procedures, which, to the best of our knowledge, have not been considered in the extant literature. Moreover, we show that quality of care and patient health outcomes decline following the observed shift in utilization. Finally, our setting permits a research design with tight identification, allowing for a causal analysis.

The remainder of this paper is organized as follows. In Section 2, we describe our institutional setting and conceptual framework in detail. In Section 3, we discuss our empirical strategy and data. Section 4 presents the main results, while Section 5 explores mechanisms underlying the main results. We discuss heterogeneity and robustness tests in Section 6, and the final section concludes. Additional analysis is provided in the Online Appendix.

2 Institutional setting and conceptual framework

Stress tests

Following the 2008 financial crisis, sweeping reforms regarding the regulation and monitoring of financial institutions were enacted through the Dodd-Frank Wall Street and Consumer Protection Act (DFA) of 2010. Among the reforms, Section 165(i)(2) of the DFA requires large bank holding companies (hereafter "banks") to undergo annual stress tests generated by the Federal Reserve under each of three scenarios (baseline, adverse, and severely adverse).[7]

[7]The Federal Reserve uses current economic conditions to determine potential negative trajectories for the U.S. economy. For example, with respect to the 2020 stress tests, the Federal Reserve announced: "The DFAST 2020 supervisory scenarios include trajectories for 28 variables. These include 16 variables that capture economic activity, asset prices, and interest rates in the U.S. economy and financial markets, and 12 variables made up of 3 variables (real gross domestic product (GDP) growth, inflation, and the U.S./foreign currency exchange rate) for each of 4 countries/country blocks. [...] The severely adverse scenario is characterized by a severe global recession accompanied by a period of heightened stress in com-

The stress tests are intended to provide information about an individual bank company's ability to withstand potential economic crises and the resilience of the overall financial system. The first set of stress tests as mandated by the DFA were required for banks with assets of at least $50 billion and had to be completed by September 30, 2012. However, the Final Rule of the DFA required stress tests for all banks with assets of at least $10 billion beginning in the following year (Federal Register (2012)). Summary results of the stress tests are publicly disclosed and are closely watched by market participants.

The Dodd-Frank Act stress tests (hereafter DFAST) are designed to gauge bank capital adequacy following potential economic downturns and to assess bank risk taking. The Federal Reserve determines the scenarios to reflect the possible paths of aggregate economic variables, given current economic conditions. Moreover, the Federal Reserve develops a model to analyze each bank's capital adequacy and loan portfolio risk in light of the hypothetical situations. Both the Federal Reserve's model and their hypothetical scenarios for the stress tests are revised annually to reflect changes in economic conditions, as well as in response to richer data or other modeling enhancements that the Federal Reserve sees fit.[8] As such, banks cannot easily predict their outcomes to the stress tests, and the results are likely informative for banks regarding their ability to withstand plausible declines in economic conditions. The results of the stress tests include projections of capital ratios, loan losses across several loan types, risk-weighted assets, revenues, losses, and net income.

Following the stress tests, projected declines in capital or increases in loan losses (and the corresponding pressure from regulators) can incentivize banks to engage in risk management measures. (We exploit heterogeneity in stress test outcomes in some of our analyses.) These include reducing their current loan portfolio risks or improving their capital adequacy ratios to ensure that they have enough capital on hand in case of adverse economic events. To this end, banks can lower the amount of credit provided or demand higher rates from riskier borrowers. Consistent with this argument, Acharya et al. (2018) and Cortés et al. (2020) document that credit supply was negatively impacted among stress-tested banks. In particular, stress-tested banks significantly increased loan spreads (defined as the interest rate over LIBOR) and reduced lending to risky borrowers, and also maintained higher capital

mercial real estate and corporate debt markets" (Board Gov. Fed. Reserve Syst. (2020)). For more details, see https://www.federalreserve.gov/publications/june-2020-supervisory-scenarios.htm.

[8] As noted in the recent 2021 DFAST report by the Federal Reserve, "Each year, the Federal Reserve refines both the substance and process of the supervisory stress test, including its development and enhancement of independent supervisory models" (p. 19). As an example to changes in the hypothetical scenarios, in 2021 the Federal Reserve made several adjustments due to the COVID-19 event, which include revisions on the default probability or losses associated with auto and credit card loans, commercial real estate, and first-lien mortgages (Board Gov. Fed. Reserve Syst. (2021)).

ratios in response to the stress tests.

We note that the Federal Reserve implemented other policies related to stress tests around this time. We discuss these other programs further and examine their potential effects in Appendix A.2.

Hospital borrowing

Hospitals of all types rely partially on debt to finance their operations. Indeed, borrowing represents one of the sole avenues of external financing for hospitals, as few hospitals have access to public equity markets. Accordingly, almost all of the hospitals in our sample (93%) have debt financing, and the amount of debt that hospitals utilize is substantial.[9] Moreover, hospitals are particularly risky borrowers. For example, healthcare bonds have significantly higher yields and lower ratings than non-healthcare bonds (Gao et al. (2022)). Furthermore, healthcare bonds accounted for 20% of all municipal bond defaults from 1999 to 2010 (Gao et al. (2019)).[10] Bank loan maturity periods are also substantially lower for hospitals relative to other industries, which is consistent with evidence that banks tend to provide shorter-maturity loans to riskier borrowers (e.g., Strahan (1999)). Therefore, in line with the evidence that banks tend to reduce credit supply to risky borrowers following heightened risk-management incentives induced by stress tests (Acharya et al. (2018), Cortés et al. (2020)), banks may be inclined to reduce credit to risky hospital borrowers or to raise interest rates following stress tests.

Due to their reliance on debt as a source of operational financing, hospitals regularly take out new loans even prior to the maturity of existing debt. Thus, credit may be curtailed or more expensive from a hospital's existing lender. Hospitals may alternatively react to this credit shock by seeking credit from other lenders. However, as has been well established in the banking literature, long-term lending relationships help to lower asymmetric information between borrowers and lenders, thus reducing the cost of credit for borrowers.[11] New lenders without an established relationship would thus require higher interest rates or provide less credit as a result of greater information asymmetry. Indeed, in line with this argument,

[9]Debt comprises 33% of total hospital assets and 58% of total liabilities for the average hospital with debt in our sample.

[10]Non-profit hospitals may borrow through tax-free municipal bonds to finance construction for specific infrastructure projects, however this option is not available for most for-profit hospitals. Healthcare municipal bonds have an average yield of 3.22%, while the average for non-healthcare municipal bonds is 2.39% (Gao et al. (2022)).

[11]For example, see Rajan (1992), Petersen and Rajan (1994), Boot and Thakor (2000), Degryse and Ongena (2005), Bharath et al. (2007), and Botsch and Vanasco (2019), among many others. Boot (2000) and Elyasiani and Goldberg (2004) provide surveys.

we show that after a bank is stress-tested, the hospitals that borrowed from it experience a significant increase in loan spreads, a decrease in loan amounts, and are more likely to borrow from a new lender.[12] These results reinforce the findings of Acharya et al. (2018) and Cortés et al. (2020) and are consistent with the argument that hospital borrowers experienced a shock to credit supply subsequent to a lender's stress test.

Consequently, following a shock to credit supply, hospitals may be faced with less external financing or a higher cost of debt. Hospitals operate on thin profit margins and thus the tighter credit constraints are likely to strain hospital finances. As a result, hospitals can respond with revenue-increasing or cost-saving measures.[13] Since patients are the primary source of revenue, hospitals may be inclined to increase revenues through higher resource utilization, such as increased inpatient admissions or more intensive use of outpatient hospital services.[14] Anecdotal evidence of such actions to increase hospital revenues has been noted in recent media coverage. For example, executives of a major Philadelphia hospital attempted to increase revenue "based in part on the assumption that increasing in-patient admissions through the E.R. would yield greater reimbursements from insurance companies" (*The New Yorker*, June 7, 2021). Moreover, the U.S. Department of Justice has successfully pursued cases involving unnecessary or excessive hospital admissions, including a case where hospitals implemented inpatient admission targets from the hospital emergency department (ED) and even tied admission percentages to physician compensation as a way to increase revenues through greater admissions.[15] Indeed, hospitals have considerable discretion on whether to

[12] In untabulated tests, we also show that the increased cost of credit that hospitals face is not mitigated over time for affected hospitals that take out new loans in the years after their bank is stress-tested. This suggests that the stress test-induced risk management incentives that push banks to restrict credit supply to hospitals is not a short-lived phenomenon.

[13] It is possible that hospitals could simply postpone financing given the higher cost of credit. However, a hospital that is in need of financing would then have to find an alternative (and potentially more expensive) source for such financing or rely more on their own internally generated funds. We would therefore expect a similar response by hospitals that postponed financing in light of the tighter credit constraints (e.g., increasing revenues to cover the higher cost of external financing or the greater reliance on internal funds). Moreover, we find that new loans initiated by affected hospitals following the shock have higher rates and worse terms and that the majority (79%) of affected hospitals take out new loans following the shock, suggesting that hospitals cannot afford to substantially delay access to credit and have few alternatives for external financing.

[14] Medicare payments to hospitals are based on the inpatient/outpatient prospective payment system. Specifically, inpatient revenues are determined by the diagnosis-related group (DRG) that the patient is assigned to when admitted, with riskier or more complicated groups corresponding to higher payment rates. Hence, increased admissions or assigning patients to higher-paying DRGs can generate higher revenues. Similarly, outpatient service payments are set prospectively based on ambulatory payment groups. A new procedure gets paid for the ambulatory group it is assigned. As a result, unlike inpatient services, additional procedures for outpatient services can generate more revenue for the hospital.

[15] See, for example, "Hospital Chain Will Pay Over $260 Million to Resolve False Billing and Kickback Allegations; One Subsidiary Agrees to Plead Guilty," U.S. Department of Justice Office of Public Affairs, September 25, 2018. As noted by the Department of Justice: "According to admissions made in the reso-

admit patients who arrive at the ED or have them discharged without an inpatient stay.

Hospitals can also increase admissions by strengthening ties with physician offices, thereby increasing physician referrals for inpatient or outpatient elective procedures. Indeed, numerous hospitals have been penalized for providing remuneration to physician offices for patient referrals.[16,17]

Other revenue-increasing actions include properly documenting the severity of patient conditions to increase reimbursement from insurers, such as hiring nurse-consultants to oversee diagnoses or employing doctors with greater familiarity in medical coding (as noted in Pomorski (2021)). Such actions may be considered "upcoding" if patient conditions are exaggerated in insurance claims (see, e.g., Silverman and Skinner (2004), Geruso and Layton (2020)). Furthermore, recent anecdotal evidence indicates that hospitals can turn to converting pediatric beds to adult units to increase profitability, as adult admissions typically generate higher reimbursement rates than pediatric admissions. As noted in recent media coverage: "Hospitals around the country, from regional medical centers to smaller local facilities are closing down pediatric units. The reason is stark economics: Institutions make more money from adult patients" (*The New York Times*, October 11, 2022).

Hospitals can also take cost-saving measures, such as delaying new equipment purchases and capital investment, more aggressively pursuing unpaid invoices, or reducing hospital staff.[18] Likewise, for inpatient admissions with reimbursements based on a prospective, fixed payment structure, hospitals can improve cost efficiency by scaling back on services provided during inpatient stays or reducing the length of inpatient stays. Such hospital responses do

lution documents, HMA instituted a formal and aggressive plan to improperly increase overall emergency department inpatient admissions at all HMA hospitals, including at Carlisle Regional Medical Center. As part of the plan, HMA set mandatory company-wide admission rate benchmarks for patients presenting to HMA hospital emergency departments—a range of 15 to 20 percent for all patients presenting to the emergency department, depending on the HMA hospital, and 50 percent for patients 65 and older (i.e. Medicare beneficiaries)—solely to increase HMA revenue. HMA executives and HMA hospital administrators executed the scheme by pressuring, coercing and inducing physicians and medical directors to meet the mandatory admission rate benchmarks and admit patients who did not need impatient admission through a variety of means, including by threatening to fire physicians and medical directors if they did not increase the number of patients admitted" (U.S. Department of Justice (2018)). We note that Health Management Associates (HMA) is not a treated hospital system in our sample and that the practices described took place prior to our treatment period. Our results are also unaffected if we exclude HMA from the sample.

[16]Examples include "Hospital Chain Will Pay over $513 Million for Defrauding the United States and Making Illegal Payments in Exchange for Patient Referrals; Two Subsidiaries Agree to Plead Guilty" (U.S. Department of Justice (2016)), and "West Virginia Hospital Agrees To Pay $50 Million To Settle Allegations Concerning Improper Compensation To Referring Physicians" (U.S. Department of Justice (2020)).

[17]Hospitals can also directly acquire physician practices or community hospitals to increase referrals (see, e.g., Nakamura et al. (2007)).

[18]For anecdotal evidence of hospitals increasing collections from unpaid patient invoices to boost profits, see "They Were Entitled to Free Care. Hospitals Hounded Them to Pay," *The New York Times*, September 24, 2022.

not suggest a clear prediction on actual patient health outcomes. In particular, greater admitted volume may lead to less attention and thus worse quality of care (e.g., Silver (2021)). On the other hand, if inpatient and outpatient services of elective, non-emergency procedures (such as hip and knee replacements) are increased to compensate for the decreased funds, then patient health may be unaffected (e.g., Clemens and Gottlieb (2014), Einav et al. (2018)) or even improved if such measures imply greater attention and care.

3 Research Design

3.1 Data and Summary Statistics

We utilize data on hospital characteristics and outcomes from a variety of sources. Medicare-certified hospitals (providers), which include almost all hospitals in the U.S., are required to submit an annual cost report to a Medicare Administrative Contractor, in which they provide complete information on facility characteristics. The U.S. Centers for Medicare & Medicaid Services (CMS), a federal agency within the Department of Health and Human Services, maintains the cost report data in the Healthcare Provider Cost Reporting Information System (HCRIS). We obtain all available reported information on hospitals from the HCRIS database. For each provider, this covers common financial statement items such as total assets (TA), total liabilities, and net income, among others. In addition, the data include hospital utilization information, including total inpatient discharges, total occupied bed days, and total available bed days.[19]

Our sample includes yearly hospital observations from 2010 to 2016. Our sample begins in 2010 because it is from this date that our key variables are consistently defined; prior to this, a number of our key variables are missing or defined in an inconsistent way in data reporting.[20] Financial information is complete in the database for most hospitals up to calendar year 2016. We restrict the sample to include only short-term acute care hospitals (the most common type of hospitals), though our results are robust to including other types of hospitals, as well as controlling for hospital-type fixed effects. We further exclude government-owned hospitals (such as Veterans Affairs hospitals and clinics), as they typically directly receive

[19] An occupied bed day is a day during which a person is confined to a bed and in which the patient stays overnight in a hospital. An available bed day is a day in which a bed is in the facility and can possibly be occupied. This includes all types of beds (general and special care).

[20] One major change is due to the American Recovery and Reinvestment Act of 2009, which motivated hospitals to adopt a healthcare information technology (HIT) system. After 2010, total assets include accumulated HIT investment net of depreciation.

government financial assistance and have different incentive structures than other hospitals (Duggan (2000)). Our final sample includes 3,658 unique hospitals.

To measure hospital care quality, we merge the above information with two other datasets from CMS that provide measures of health outcomes and quality of care. The first measure is the risk-adjusted rate of unplanned readmissions, obtained from the CMS Hospital Compare program. A readmission is defined as an admission to an acute care hospital within 30 days of discharge from a previous hospital stay. Readmission rates are informative about the efficacy of treatment upon hospitalization and are widely-used measures for quality of care by both government agencies and researchers (e.g., Chandra et al. (2016), Beaulieu et al. (2020)). A relatively high readmission rate, for example, may imply that the hospital is more likely to have provided inadequate care or misdiagnoses during inpatient stays, resulting in more patients unexpectedly requiring rehospitalization. Readmission rates are provided for all diseases combined and are also separately documented for three key acute conditions: acute myocardial infarction (i.e., AMI or heart attack), heart failure, and pneumonia. We additionally collect risk-standardized 30-day mortality data for patients treated for these conditions, also provided by CMS.[21]

We also utilize patient evaluations to measure quality of care from the patient's perspective. In particular, we use the Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) data, which is a patient satisfaction survey required by CMS and is administered to a random sample of adult patients across various medical conditions between 48 hours and six weeks after discharge. The core questions cover the critical aspects of patients' hospital experiences, such as the overall rating of the hospital, efficacy of pain control, whether they would recommend the hospital, communication with nurses and doctors, the cleanliness and quietness of the hospital environment, and discharge information. Because rating scales differ across categories, we calculate the proportion of patients that give the highest rating instead of using average scores.[22] All variable definitions are also included in Appendix Table A.1.

To further explore mechanisms, we supplement the above hospital data with two additional datasets. The first is the State Inpatient Databases (SID) developed for the Healthcare Cost and Utilization Project (HCUP). We identify fifteen states that provide data both be-

[21]We provide details regarding the risk adjustment performed by CMS in Section A.3 of the Online Appendix.

[22]For example, the survey question for the variable *Recovery Information* is whether the patient was given information about what to do during their recovery at home, where the answer choices are "Yes" or "No." The question for the variable *Overall Rating* is a star-rating system from 1 (worst) to 3 (best). We define "highest rating" as answering "Yes" in the former and "3" in the latter.

fore and after the stress tests.[23] Each unit of observation in the SID is an inpatient encounter that records various treatment and demographic information. We discuss the variables in more detail and how we aggregate these in Section 5. The second supplemental dataset is the process of care scores from the CMS Hospital Compare program. CMS requires hospitals to submit information on timely and effective treatment which have been linked to improve patient outcomes for certain medical conditions. We examine six measures related to our conditions of focus—acute myocardial infarction, heart failure, and pneumonia—from 2010 to 2014.[24] We provide more detail on the measures in Section 5.

Lastly, we combine our hospital data with Dealscan loan data in order to identify treated and control hospitals. We keep all loan agreements (facilities) which have (*i*) a borrower 3-digit SIC code equal to 806 (Hospitals); (*ii*) a facility start date after January 1, 2007; and (*iii*) loan types that are either term loans or revolver. Following Ivashina (2009), we identify and keep the lead bank in a syndicate deal.[25] This results in 2,432 facility-lender combinations. The hospital-related borrowers in Dealscan are either individual providers (e.g., Houston Methodist Hospital) or hospital organizations and systems (e.g., HCA Healthcare). We then manually match borrowers to the HCRIS sample. For each individual hospital, HCRIS reports whether it belongs to a hospital chain and the organization name if it does. When we identify a borrower that is a hospital system, we assign each of the individual hospitals that are part of the system as being exposed to the loan deal. There are 1,447 facility-lender combinations in which we identify that the borrower is a Medicare-certified hospital.[26]

Panel A of Table 1 shows the yearly number of first-time stress-tested banks along with the exposed hospital borrowers in our sample. From 2012 to 2016, 26 stress-tested banks were lending to at least one hospital in our sample when tested for the first time. In total, this leads to 505 hospitals (out of 3,658) being exposed to the Dodd-Frank Act stress tests (DFAST). Banks with consolidated assets of $50 billion or above were required to conduct

[23]We access the SID through the National Bureau of Economic Research. The fifteen states with coverage during the sample period through our access include Arizona, Colorado, Florida, Kentucky, Maryland, Massachusetts, Nevada, New Jersey, New York, North Carolina, Rhode Island, Utah, Vermont, Washington, and Wisconsin.

[24]While the CMS data has other measures, we focus on these six measures because they are the most continuously-tracked and non-missing over our sample period. In 2005, the first set of ten "core" process of care measures were created for acute heart infarction, heart failure, pneumonia, and surgical care. Over the years, the program has terminated existing measures and medical conditions and has added new measures. This makes the other measures infeasible to use for our purposes.

[25]In our sample, this includes the Dealscan lender roles "Admin agent," "Arranger," "Documentation agent," "Senior managing agent," or "Syndications agent."

[26]The major borrowers that we do not match include psychiatric hospitals, specialty hospitals, non-Medicare hospitals, and telehealth service platforms.

their first annual stress tests using financial data as of September 30, 2012. Given their size, these banks jointly held a significant market share for hospital lending. In our sample, 15 banks (58% of the stress-tested banks) and 416 hospitals (82% of the affected hospitals) are exposed to the first DFAST that occurred in 2012. Banks with total consolidated assets of more than \$10 billion but less than \$50 billion were required to implement stress tests under the Dodd-Frank Act in the following years.

Panel B of Table 1 provides summary statistics for the loan characteristics in our sample. Bank loans are an important source of external financing for hospitals. The size of a bank loan for an individual lending agreement averages to \$78.4 million. Hospitals typically have multiple bank loans outstanding contemporaneously; the average amount of new bank lending taken out in a given year is \$144.3 million for hospitals that utilize bank lending in our sample. Loan maturity periods average just under five years, with an average annual interest rate of 3.88% over LIBOR. This amounts to an average of \$7.0 million in interest expenses per year for a given hospital in our sample that utilizes bank lending, indicative of the high cost of servicing debt for hospitals.

Summary statistics for all of our other variables are provided in Appendix Table A.1. We also provide summary statistics for our full sample as well as separately for our treatment and control groups in the year before DFAST implementation in Table 2. We additionally show that all of our main results hold for a sample that is tightly matched on observable characteristics; summary statistics for this matched sample are provided in Table A.2.[27]

3.2 Empirical Specification

For our main specification, we examine a staggered difference-in-differences (DID) regression to explore the effect of bank stress tests on hospital outcomes:

$$Y_{i,t} = \alpha + \beta STExposed_{i,t-1} + \gamma' Controls_{i,t-1} + \eta_t + \mu_i + \varepsilon_{i,t}. \tag{1}$$

In equation (1), $STExposed_{i,t-1}$ is an indicator variable that takes a value of one if at least one of hospital i's relationship banks experienced a stress test in year $t-1$ or earlier,

[27] Specifically, we construct our treatment and control groups by matching based on the year 2011 values of cash over total assets, logarithm of bed days, patient revenues over total assets, and pneumonia mortality rate based on the nearest two neighbors for each treatment hospital. We restrict our matched sample to a precision difference cutoff of 0.003. Summary statistics for the variable differences between the treatment and control samples in 2011 are provided in Table A.2, and show that our constructed treatment groups are tightly matched in terms of observable characteristics—there is no statistically significant difference between the treated hospitals (hospitals that have lending relationships with stress-tested banks) and control hospitals (those without loans from stress-tested banks).

and zero otherwise. Hospital i's relationship bank is defined as a lending bank that has non-matured loans with hospital i in year t. $Y_{i,t}$ is the outcome variable, which includes measures of hospital financial, operational, and care quality information. The parameters η_t and μ_i denote year and hospital fixed effects, respectively.

In equation (1), we include a vector of lagged control variables, $Controls_{i,t-1}$, in order to account for hospital-level characteristics that have the potential to drive differences between hospitals with respect to financing and operating decisions. For example, larger hospitals may experience relatively smaller percentage changes year-to-year in profitability or resources, and thus not controlling for size may induce omitted variable bias when examining responses to the credit supply shock. As such, we include $Log(Bed\,Days_{i,t-1})$, which is the logarithm of one plus available bed days,[28] to control for size based on physical hospital capacity. Likewise, cash holdings scaled by total assets ($Cash/TA_{i,t-1}$) controls for the ability of a hospital to utilize internal financing (accounting for its size), as a large literature in corporate finance has highlighted that this can influence investment and operating decisions by firms (see, e.g., Opler et al. (1999), Bates et al. (2009)). We lag all control variables in order to avoid using information not known at the time of the operating decision we examine as the dependent variable.[29]

The coefficient of interest in equation (1) is β, which captures the effect of bank stress-tests on hospital outcomes. Put differently, β represents the change in hospital outcomes after a stress test exposure in a year relative to the corresponding change for hospital-year observations with no stress test exposure. Our variation in treatment comes from (i) whether the hospital relies on loan financing from a bank that was subject to the DFAST requirements, and (ii) the staggered implementation of stress tests for different banks.[30] A recent econometrics literature has noted issues related to interpreting staggered DID specifications with two-way fixed effects; we discuss this in Section 4.4 and show that our results are robust

[28] A bed means an adult bed or other beds maintained in a patient care area for lodging patients in the hospital, including pediatric beds. Bed days are computed by the number of available beds multiplied by the number of days in the reporting period.

[29] The results are qualitatively similar if we exclude control variables from the analysis, as shown in Appendix Table B.1. We also present parallel trend graphs estimated without control variables in Appendix Figure B.1. Our results are also very similar when including additional control variables (available upon request). As is standard in the corporate finance literature, we winsorize all financial variables scaled by total assets at the 1% level to account for extreme outliers.

[30] As previously noted, the majority of treated hospitals (82%) are first exposed to DFAST in 2012, and thus the former source of variation is more predominant. Our results are robust to specifying our DID tests through a non-staggered specification by defining a dummy variable that takes a value of one if the year is 2013 or later (and zero otherwise), and interacting this with a treatment variable at the hospital level that takes a value of one if a hospital had a relationship loan prior to DFAST implementation (and zero otherwise).

to methods which explicitly account for these issues.

The identifying assumption is that a stress test to an affected bank is exogenous to the performance of the hospital which has a relationship with that specific bank. Reverse causality is not likely to hold in this setting, since the DFAST did not select a participating bank based on the hospitals which borrowed from the bank. In particular, banks were selected to be stress-tested based on whether their total assets exceeded a $10 billion threshold, which is exogenous to the hospitals which borrowed from the banks.

Self-selection by hospitals is also not likely to happen. Although the Dodd-Frank Act was enacted on July 21, 2010, the FDIC issued a notice of proposed rulemaking (NPR) on January 23, 2012. This NPR solicited public comment to finalize the implementation of the Act, and the effective date and public disclosure policy of results were changed due to major concerns. Thus, the actual timing of DFAST implementation was uncertain and therefore exogenous to the loan initiation. A hospital also had no incentive to borrow from a particular bank based on the fact that this bank would be stress-tested soon; indeed, as the relationship lending literature has shown, relationship borrowers tend to choose lenders based on factors such as whether the bank operates in the same geographical area (e.g., Petersen and Rajan (1995), Cantillo and Wright (2000), Degryse and Ongena (2005)).[31] Most stress-tested banks operate nationally with branches located across different states. Our discussions with senior hospital executives confirm this notion and provide anecdotal evidence that bank branch proximity is a major factor for hospitals when determining lending relationships. In addition, the vast majority of hospital-bank lending relationships in our sample were established prior to DFAST.[32]

We further validate our inferences related to these arguments in a number of ways. First, we show that the parallel trends assumption holds in our setting. Second, as mentioned previously, for all of our main tests, we demonstrate that our main results hold when restricted to a sample of hospitals tightly matched in terms of observables. We also show that the parallel trends assumption holds for this matched subsample. Finally, we include a host of robustness checks related to controlling for potential differences between hospitals as well as other sample composition effects.

[31] We note that affected hospitals do not concentrate in certain areas, as shown by Figure 3.

[32] We exploit heterogeneity in bank loan financing reliance in further tests. Moreover, in untabulated tests, we confirm that the parallel trends assumption holds for the subsample of hospitals that rely more on bank financing. This reinforces the notion that it is specifically variation related to *bank* loans and shocks to specific lenders that are affecting treated hospitals. We also show that the effects hold when restricting our sample to only hospitals that received commercial loans during the sample period (Appendix Table A.22).

4 Results

4.1 Stress Tests and Credit Supply

We begin our analysis by examining the effect of stress tests on hospital loans. While Acharya et al. (2018) and Cortés et al. (2020) have previously shown that stress tests negatively impact credit supply, we investigate whether these effects are present for our sample of hospital borrowers as well. To do so, we estimate equation (2) at the *loan facility* level:

$$\begin{aligned} Y_{k,i,j,t} &= \alpha + \beta STExposed_{i,t-1} + \gamma' Controls_{i,t-1} \\ &\quad + \mu_j + \eta_t + \mathit{TypeFE} + \mathit{PurposeFE} + \varepsilon_{k,i,j,t}. \end{aligned} \tag{2}$$

The variable $Y_{k,i,j,t}$ represents the characteristics of loan k between hospital i and bank j which was originated in year t. These characteristics include the loan spread and fee, amount, and maturity. $STExposed_{i,t-1}$ is equal to one if hospital i borrowed from a bank that was stress-tested in year $t-1$ or earlier, and thus has been indirectly exposed to the stress tests. We note that outcome Y is measured for each loan k between hospital i and bank j, but the value of $STExposed_{i,t}$ is determined by hospital i's exposure and is independent of the particular lender j in this loan. For example, consider a hospital i that has a lending relationship with a stress-tested bank j' in year $t-1$. If hospital i switches to a *new* lender j (potentially untested) in year t, then $STExposed_{i,t} = 1$ for this deal between i and j. This specification therefore allows us to capture the possibility that the hospital switches to a new bank with potentially different loan characteristics (e.g., higher spread). As noted in Section 2, starting a relationship with a new lender generally entails a higher cost of debt to compensate for the greater degree of asymmetric information. We include control variables for the hospital's logarithm of total assets, patient revenues over total assets, leverage (total liabilities over total assets), and tangibility (total fixed assets over total assets). We also include bank (μ_j), year (η_t), loan type (*TypeFE*), and loan purpose (*PurposeFE*) fixed effects. Following Drucker and Puri (2009), loan types include *Revolvers* and *Term Loans*. Loan purposes include *Acquisition*, *General*, *LBO*, *Recapitalization*, *Miscellaneous*, and *Other*.

Table 3 provides the results. In columns (1) and (2), we examine loan interest rates, defined as the spread (in basis points, bps) over LIBOR plus one-time fees on the drawn portion of the loan. We see that borrowing costs (i.e., interest rates on the loans) for affected hospitals increase significantly by 68–74 bps, an increase of about 17.5–19% of the sample average of 3.88% (Table 1). In columns (3) and (4), we find that loan size decreases by 36.5%

and loan maturity decreases by 8.5% for affected hospitals. These results are consistent with Acharya et al. (2018) and Cortés et al. (2020) and suggest that hospital credit access was negatively impacted by stress testing, as exemplified through a higher cost of debt and lower loan amounts and maturities for affected hospitals. Moreover, the large impact of the credit shock on loan interest rates and amounts underscores the riskiness of hospital borrowers (as noted previously, hospitals exhibit higher default rates compared to other industries).

In column (5), we consider the possibility that hospitals may switch lenders following a stress test, as switching to a new lender with which the borrower has no relationship entails a higher cost of credit (e.g., Ostromogolsky (2016)). To explore this, we define the variable $New\,Lender_{k,i,j,t}$, which is an indicator variable equal to one if hospital i had no previous lending relationship with bank j prior to year t. The coefficient on $New\,Lender_{k,i,j,t}$ is positive and significant, which implies that hospitals are 12.6% more likely to switch to new lenders when their current lender is subject to a stress test.

The above results evaluate the impact of stress tests in a sample of hospital loans. A related question is how stress-tested banks change their lending terms to hospitals relative to other firms. In Appendix Table A.3, we add deals by public *non-hospital* borrowers to the initial sample in Table 3.[33] We find that, while stress-tested banks increase the spread for all firms by 14 basis points, the spread increases by an additional 35 basis points for hospital borrowers. Moreover, we find a significant decrease in the loan amount only for hospital deals. The more severe response to credit supply for hospital borrowers is consistent with prior evidence that hospitals are particularly risky borrowers. The heightened risk management incentives from banks following the stress tests therefore results in banks imposing a greater cost of debt on hospitals relative to other, less risky borrowers. For robustness, in columns (3) and (4) of Table A.3, we restrict the deals to banks that have previously provided loans to hospitals in our sample. The sample size drops by around only 10%, which helps to alleviate the possible selection concern that only a small group of banks specialize in hospital loans.

Finally, we do not find any changes in the healthcare municipal bond market occurring at the time of the stress tests at the county level for affected hospitals. Specifically, we find that the rates of return—and thus the cost of borrowing—related to healthcare municipal bonds in a county with affected hospitals do not change, which suggests that the shock to credit access is specifically related to *bank* borrowing and is not part of a broader shock to hospital borrowing in other debt channels. (We provide these results in Appendix Table

[33]We focus on public firms for comparison in order to include financial and other firm characteristics from the Compustat database as control variables, although we obtain similar conclusions when we include all other firms with loans and exclude firm characteristics as controls.

A.4.[34]) Collectively, these results validate the use of DFAST as a negative shock to hospital credit access.

Overall, these results are consistent with the notion that stress testing negatively impacts credit supply for hospitals. As discussed in Section 2, banks subject to stress tests are more inclined to improve their capital adequacy ratios by raising interest rates or lowering loan amounts. Moreover, hospitals may turn to new lenders to make up the loss in credit access, but, due to higher information asymmetries, face higher interest rates in these loans from new lenders.

4.2 Hospital Financing and Operating Decisions

We now examine the direct impact that the negative credit supply shock had on hospital financing and operating decisions for affected borrowers. We then investigate the indirect impact these decisions had on quality of care and patient health outcomes in the following section.

As discussed in Section 3.1, we consider key financial statement information provided through the HCRIS database. The results, which employ specification (1), are presented in Table 4. We first consider the effect of the credit shock on the overall profit margin of the hospital.[35] In column (1) of Table 4, Panel A, we find that affected borrowers saw a significant increase of 1.1 percentage points in their profit margins. We next examine leverage and other liabilities in column (2). We see a significant reduction in liabilities for affected hospitals. This suggests that affected hospitals utilize debt less following the credit shock, consistent with our previous results in Table 3 indicating lower amounts for new loans. Finally, we consider the level of net income (i.e., profit) scaled by total assets in column (3). The results are consistent with a shift in financing sources—affected hospitals become both more efficient and generate significantly higher internally generated funds following the tightened credit constraints, bolstering internal financing with a lower reliance on debt financing.[36]

[34]Appendix Table A.4 explores bond yields, which represents the average rate of return that an investor can expect from purchasing the bond, as well as spreads, which represents the difference between the average bond rates of return and low-risk benchmark investments (U.S. Treasury bonds and highly-rated corporate bonds). All of the coefficient estimates are insignificant and small in magnitude; for example, a county with an exposed hospital experiences an insignificant 0.023 percentage point change in healthcare municipal bond yields.

[35]Profit margin is defined as profit (i.e., net income) divided by *Income*, which is defined as net patient revenues (Worksheet G-3, line 3) plus total other income (line 25). Hospital profit is taken from line 29 of HCRIS Worksheet G-3 and is defined as *Income* minus *Cost*, where *Cost* is defined as operating expenses (line 4) and other expenses (line 28). Profit margin is winsorized at the 1% level.

[36]We scale net income by total assets to account for size; we cannot take the log of this variable due to the presence of negative values. We additionally show in Table A.5 that the increase in net income is driven

To provide additional texture to these results, a back of the envelope calculation using column (1) of Table 3 indicates an increase of \$1.07 million in interest payments for the average affected hospital (a sizable increase of 19% relative to the sample mean).[37] This increase is also economically meaningful for affected hospitals—for example, average hospital profit in our sample is \$8.01 million per year, and thus the increase in interest expense constitutes 13.4% of net income (17.4% for the median hospital), representing a sizable drop in profits.[38] To provide a comparison with this estimate, we consider the raw change in net income and find that the average affected hospital increases its net income by about \$1.12 million following the credit shock.[39] There are a few potential explanations for why hospitals may boost internally generated funds by more than the higher cost of debt. First, the hospital may recognize the need to rely less on debt in future periods, as shown in column (2) of Table 4. Second, a hospital that expects to have less favorable debt financing terms in future periods can improve income in the *current* period to build sufficient internal reserves for the future.

To further examine the potential sources of the increase in profitability, we consider bed utilization and discharge rates in columns (4) and (5) of Table 4. *Bed Utilization* in column (4) represents the utilized hospital bed days over all available bed days. In other words, it is the fraction of time that a hospital bed is used in a given year. *Discharge Rate* in column (5) is the number of total inpatient discharges in a year over total available beds. Hence, this measure represents the number of patients using each hospital bed in a year. We see that both bed utilization and discharge rates significantly increase for affected hospitals, with these hospitals accommodating 2.4 more patients per bed, equivalent to 375 more patients per hospital per year.[40] Likewise, each hospital bed is occupied 8.4 more days per year, which amounts to 668 more occupied bed days a year per affected hospital.[41]

by an increase in income generated from patients.

[37]The average loan amount per hospital across lending agreements in a given year is \$144.30 million. The increase in interest expense is therefore calculated as \$144.30 million $\times$ 74 bps = \$1.07 million.

[38]Net income for the median hospital is \$2.12 million. The median loan amount per hospital across lending agreements in a given year is \$50 million, which implies an interest expense increase of \$0.37 million for the median hospital. As a fraction of median net income, this increase is 17.4%.

[39]For the purpose of magnitude comparison, we calculate this change in net income by running our main specification using raw net income as the dependent variable; we consider both total net income (line 29 of Worksheet G-3), which corresponds to an increase of \$1.12 million, and net income from patient services (line 5), corresponding to an increase of \$1.48 million. These estimates are included in Appendix Table A.5. We use levels as we cannot take the log of the profit variable due to the presence of negative values, which is not a concern for our other variables. Instead, to reduce the influence of outliers, for our magnitude discussions related to profit we winsorize profit at the 5% level (e.g., Dranove et al. (2017)).

[40]This is calculated by multiplying 2.4 with the average number of hospital beds in our sample (156.28).

[41]The coefficient from column (4) indicates an increase in bed utilization of 2.3%, which translates to $0.23 \times 365 = 8.4$ additional days of bed occupancy in a year. Hospitals in our sample have an average of

For robustness, Panel B of Table 4 provides the estimates using a propensity score-matched sample. We see that the results are very similar in this analysis. This suggests that potential differences between the control and treatment groups are not materially affecting the inferences of our analysis. Relatedly, our results are similar in a subsample restricted to only for-profit hospitals (Table 12), providing further evidence that the results are not being driven by differences in ownership type.

We explore additional operating and investing decisions in Appendix Table A.5. As discussed previously, impediments to credit access can constrain expenditures for capital investment. In line with this notion, we find that the book value for buildings significantly decreases for affected hospitals.[42] Furthermore, the negative credit supply shock may constrain hospitals from investing in new equipment. We find that hospital tangible assets (total fixed assets over total assets) insignificantly decreases after exposure to a stress-tested lender. Relatedly, hospitals can accommodate more patients by increasing capacity; however we do not see a significant increase in the total number of beds within affected hospitals, which suggests that hospitals cannot easily increase bed capacity. Hospitals can also increase profitability by more aggressively pursuing unpaid patient invoices. We find a significant decrease in bad debt expense for affected hospitals, which is consistent with fewer write-offs of expected patient collections.[43] Finally, we examine the disparate sources of revenues and find an increase in both inpatient and outpatient revenues, with the former exhibiting a larger magnitude, in line with our earlier results of increases in bed utilization and discharge rates.

Put together, these results suggest that hospitals which experience a negative credit supply shock—and thus reduced financial slack—respond by changing their operations. By accommodating more patients, as evidenced by increased bed utilization and discharges, hospitals are able to increase their revenues generated by patients and profitability on the margin. This is consistent with other papers that have shown an increase in financial efficiency for borrowers following tightened financial constraints (e.g., Hovakimian (2011)). In Section 5, we utilize additional data to provide further evidence on the underlying mechanisms for the observed increase in profitability and bed utilization. While the operational

79.5 beds, leading to an increase across beds of 668 days.

[42] These effects are consistent with previous studies showing a reduction in investment following a negative credit shock (e.g., Campello et al. (2010), Duchin et al. (2010), Gropp et al. (2019), Dwenger et al. (2020)).

[43] We use bad debt expense and not uncompensated care because CMS modified the cost report instructions in 2017, which changed how hospitals calculate their uncompensated care costs. Hospitals were allowed to retroactively adjust their uncompensated care costs for 2015 and 2016, although not all hospitals did. This change in measurement makes the uncompensated care variable unsuitable for time-series analysis. See Medicaid and CHIP Payment and Access Commission (2021) for details.

changes employed by affected hospitals can improve profit margins, these changes may not improve patient care. We explore this question in the next section.

4.3 Patient Health Outcomes and Quality of Care

We now investigate whether the shock to credit supply indirectly affected patient health outcomes and quality of care. As noted in Section 2, increased inpatient admissions and outpatient services and tests may improve quality of care if this implies greater attentiveness. Conversely, the increase in admissions and procedures may be clinically unnecessary and thus may not affect, or could worsen, patient outcomes. For example, a greater volume of patients more severely strains staff and physician time, which can lead to less attention and a lower quality of care.

We consider several measures of health outcomes and care quality to explore our central research question. We first examine the impact on hospital performance using readmission rates. We then investigate whether changes in performance adversely affect patient mortality outcomes. Finally, we consider the potential effect on patient experiences through the patient satisfaction surveys.

Readmission and mortality

Our primary measures of health outcomes are unplanned, risk-standardized readmission rates, which track unplanned inpatient readmissions to a hospital within 30 days from discharge from a previous hospital stay. As noted in prior studies, these measures reflect adequacy of care; a patient that was treated properly in the original admission is less likely to be unexpectedly in need of care shortly following discharge. The results are presented in Panel A of Table 5 (we also include parallel trend figures, discussed in the following section). Columns (1)–(3) present the logarithm of the number of patients readmitted within 30 days who were diagnosed with pneumonia, heart failure, or AMI, respectively. We see significant increases across all three measures. The effects are also economically large—using the point estimates from Panel A, affected hospitals have a 10.2% increase in unplanned pneumonia readmissions relative to unaffected hospitals and a 3.0% increase in both heart failure and AMI readmissions. This translates to an additional 1,570 patients readmitted per year indirectly due to the negative credit shock in aggregate across affected hospitals.[44]

[44]We calculate this number based on the unconditional means for readmissions of each diagnostic group (reported in Table A.1) and their estimated percentage increases among affected hospitals from Table 5. At the individual hospital level, we observe 3.11 more readmissions per affected hospital per year.

Columns (4)–(6) consider the rates of unplanned readmissions, which captures the per-patient likelihood of being readmitted for each medical condition, and shows a similar effect: across all three diagnostic groups, we see a 0.3% increase in the readmission rate for affected hospitals. Additionally, in column (7), we find that readmission rates increase for a broader set of diagnostic groups and with a similar magnitude, which suggests that the effect is not limited to the three diagnostic groups for which we have detailed data.[45] Moreover, we note that the coefficient estimates belie the magnitude of the effects, as readmission rates are extremely difficult for hospitals to reduce. To put this number in context, the Affordable Care Act, in an attempt to improve healthcare quality, established the Hospital Readmissions Reduction Program (HRRP) in 2010 and reduced the readmission rate for pneumonia by 0.4% after a substantial effort.[46] Furthermore, CMS levies penalties, in the form of reductions in Medicare payments, for high unplanned readmissions relative to the national average.[47] For additional texture on the above effects, we consider the likelihood that a hospital is in the worst-performing group relative to the national rate in terms of readmissions, based on CMS criteria. Column (8) of Table 5 shows that an affected hospital is significantly more likely to be in the bottom-performing group following a credit shock. These outcomes are relevant from the hospital's perspective, as hospitals in this set receive the maximum penalty by the federal government. This finding therefore underscores the magnitude of the increase in readmission rates.

Along similar lines, we consider 30-day mortality rates and levels as a measure of patient health outcomes. A mortality is defined as a patient death within 30 days of discharge from a hospital admission (including admitted patient deaths within the hospital). One limitation of this analysis is that a significant number of observations for heart failure and AMI mortality rates are missing from our dataset, since many hospitals do not report these numbers. Moreover, mortality rates for certain diagnostic groups, such as heart failure, exhibit considerable autocorrelation, as a deterioration in quality of care for these conditions may not readily impact the mortality rate. That is, unlike 30-day readmissions, patient deaths from heart failure may take months or years to transpire and thus may not be captured within our post-period. Therefore, we focus primarily on pneumonia mortality, as we have more data

[45]In addition to the aforementioned three, this measure includes conditions such as chronic obstructive pulmonary disease, coronary artery bypass graft surgery, elective primary total hip arthroplasty and/or total knee arthroplasty, as well as several others.

[46]See "The Hospital Readmissions Reduction Program has succeeded for beneficiaries and the Medicare program" by the Medicare Payment Advisory Commission in 2018.

[47]The benchmark has since been updated through the Cures Act to be one of five peer groups based on the proportion of the hospital's patients that are dually eligible for Medicare and full-benefit Medicaid (effective starting 2019).

for this condition, and pneumonia, unlike heart failure, is a less persistent condition and thus the measure is more likely to reflect changes in healthcare quality. In addition, pneumonia is a common hospital-acquired condition which hospital overcrowding can increase the spread of, and so can be especially indicative of quality of care (see, e.g., Rothberg et al. (2014)).[48]

Table 5, Panel B presents the results of this analysis. Columns (1)–(3) show the coefficient estimates for the change in the logarithm of patient deaths from pneumonia, heart failure, and AMI, respectively. We see a significant increase in pneumonia and AMI deaths for affected hospitals and an insignificant increase for heart failure mortality levels. With respect to pneumonia, the point estimates in Panel A indicate that there is a 9.8% increase in mortality for affected hospitals; this amounts to an additional 718 pneumonia deaths per year indirectly due to the shock to credit access across affected hospitals (or 1.4 additional pneumonia deaths per affected hospital per year). We explore pneumonia mortality further in columns (4)–(6) by considering the per-hospital mortality-level increase, mortality rate, and the likelihood the hospital falls in the worst-performing group of pneumonia deaths relative to their peer group, respectively. We see a significant increase for affected hospitals across all three measures. Results for both readmissions and mortality under the propensity score-matched specification are included in Appendix Table A.6.

Patient satisfaction

Finally, we explore patient satisfaction information from HCAHPS as a subjective measure of care quality. These measures include survey responses from randomly chosen adult patients shortly after discharge. Table 6 shows that, across all question categories, patient satisfaction significantly declines at affected hospitals relative to unaffected hospitals. The magnitudes of reduction are also consistent across all measures. Notably, patient communication with doctors and nurses becomes significantly worse, patients are less satisfied with pain control, and patients are less likely to recommend the hospital. These results are in line with the aforementioned findings of a decrease in care quality and are consistent with the notion that the medical staff is less attentive to patients in affected hospitals.[49]

Put together, the strongly consistent results across our measures (readmission, mortality, and patient satisfaction) indicate a significant decline in the quality of care and patient health outcomes among hospitals that experience a credit supply shock. This suggests that

[48] Rothberg et al. (2014) find that 34% of the pneumonia hospitalizations are due to hospital-acquired pneumonia infections.

[49] Results on patient satisfaction for the propensity score-matched specification are provided in Panel C of Appendix Table A.6.

hospitals are changing their operations to boost internally generated funds at the expense of patient care quality. In Section 5, we examine in more detail the specific mechanisms through which hospitals may be doing so.

4.4 Parallel Trends

The validity of our DID approach rests on the parallel trends assumption, which we now examine. Specifically, we estimate a variant of equation (1) as follows

$$Y_{i,t} \;=\; \alpha + \sum_{s=-3}^{-1} \beta_s Exposed_{i,t}^{s} + \sum_{s=1}^{k} \beta_s Exposed_{i,t}^{s} + \gamma' Controls_{i,t} + \eta_t + \mu_i + \varepsilon_{i,t}. \quad (3)$$

In equation (3), $Exposed_{i,t}^{s}$ equals one if hospital i was exposed to a stress-tested bank for the first time in year $t-s$, and is equal to zero otherwise. For example, $Exposed_{i,t}^{-3}$ equals one for the year t that is three years before when hospital i's lending banks are first stress-tested ("year 0"). When estimating equation (3), we omit $Exposed_{i,t}^{0}$, thus setting year 0 as the reference year. The interpretation of β_s is that it captures the relative difference between the treatment and control groups in each year, relative to the reference year 0. The parameter k denotes the maximum post-treatment year; k equals five for variables that are available in 2017, and is equal to four otherwise.

Figures 1 and 2 provide parallel trends for our main outcomes related to hospital financials, bed utilization, readmission rates, mortality, and patient satisfaction. In Figure 1, we show parallel trends for both our main sample (Panel A) and our propensity score-matched sample (Panel B); we include parallel trends for the other main sample and propensity score-matched sample outcomes in Appendix Figures A.1 and A.2. For all of the variables, there are no significant pre-trends prior to the treatment year. However, after the treatment year, the variables all move immediately in the documented directions. This provides evidence that the parallel trends assumption holds in our setting. We provide additional validation tests of the parallel trends in Appendix B.[50]

A potential concern in examining parallel trends in our setting stems from the fact that

[50] To more formally test the parallel trends assumption, we first perform an F-test for each of our outcome variables, which tests whether the differences between treated and control hospitals significantly vary from each other in the years leading up to DFAST implementation. For the few outcomes where there is a significant difference between the pre-period parallel trend coefficients, we examine the validity of our inferences by following the approach of Rambachan and Roth (2023), which tests the extent to which post-period treatment coefficients deviate from a trend based on the pre-period (i.e., using an expected counterfactual trend in the absence of treatment effects). We show that, even under conservative assumptions, our inferences remain valid for our main outcomes when accounting for potential pre-trends.

we utilize a DID specification with a staggered treatment and two-way fixed effects. A recent econometrics literature (e.g., Callaway and Sant'Anna (2021)) has argued that the coefficients of equation (3) can potentially be hard to interpret due to variation of the control groups over time. Moreover, equation (3) tests the parallel trends assumption after conditioning on observed covariates, which can be possibly affected by the shock as well. As a robustness check, we follow the method developed in Callaway and Sant'Anna (2021) to plot the parallel trends (see Appendix B for details). This method does not condition on observed covariates and also provides treatment effects relative to control hospitals that are either never-treated or not-yet-treated, and thus circumvents issues related to interpreting two-way fixed effects DID regressions in a causal manner. We provide these graphs in Appendix B; the main parallel trend plots are very similar to the previous graphs, regardless of whether we include never-treated or not-yet-treated observations as the control group for earlier events. In addition, in Table B.1 of Appendix B, we provide the corresponding regression coefficient estimates of average treatment effects for the treated (ATTs), with never-treated hospitals as the control group, using the procedure of Callaway and Sant'Anna (2021). We also confirm that our main results are similar when dropping all covariates from the main specification (Panel B of Table B.1).

5 Mechanisms

We now explore the mechanisms underlying the main results presented in Section 4. To this end, we utilize additional sources of data. First, we supplement our main data with detailed microdata from the State Inpatient Databases (SID) from the Healthcare Cost and Utilization Project (HCUP). Since the SID covers the inpatient information from all payers (including private insurers), a single state typically has over 0.5 million yearly observations. To perform the regression analysis, we aggregate the encounter information at the annual hospital-DRG level (e.g., Lynk (1995), Krishnan (2001), Melnick and Keeler (2007)), where the DRG indicates the diagnosis-related group recorded for each inpatient admission, regardless of payer status.[51] This permits us to examine effects for patient sub-groups within

[51] Most acute care hospital inpatient stays are reimbursed prospectively on a per discharge basis based on the patient's DRG (Cooper et al. (2019)). For example, the formula used to calculate payment multiplies an individual hospital's payment rate by the relative weights of the DRG. The base payment rate is adjusted based on a wage index applicable and a cost of living adjustment factor to the area where the hospital is located, which tend to be absorbed by the hospital-DRG fixed effects. Each DRG weight represents the average resources required to care for cases in that particular DRG, relative to the average resources used to treat cases in all DRGs, which will be absorbed by the DRG-year fixed effects.

hospitals over time, and thus track hospital operational decisions (such as admission volume) with regard to specific patient populations. For example, all 2014 encounters of patients coded with the DRG "diabetes with complication or comorbidity" in UPMC Presbyterian Hospital are aggregated into one observation.

More specifically, we estimate the following specification at the hospital-DRG-year level:

$$Y_{i,d,t} = \alpha + \beta STExposed_{i,t-1} + \gamma' X_{i,t-1} + \theta' Z_{i,d,t-1} + \eta_{d,t} + \eta_{i,d} + \varepsilon_{i,d,t}. \tag{4}$$

As in our main specification, the treatment and main explanatory variable is $STExposed_{i,t-1}$, which is equal to one if hospital i's relationship lender experienced a stress test in year $t-1$ or earlier, and zero otherwise. As noted previously, fifteen states in the SID through our access have coverage both prior and subsequent to the stress tests, resulting in 1,448 unique hospitals, which covers roughly 40% of the sample in our main analyses in Section 4. Together, we collect roughly 1.75 million hospital-DRG-year observations, with 214,521 of these observations exposed to the treatment.[52] The vector $X_{i,t-1}$ represents the set of hospital-level control variables included in specification (1), while $Z_{i,d,t-1}$ captures patient characteristics in DRG d at hospital i in a given year, including (lagged) average patient age and percentages of patients under each gender and race category provided by the SID. The parameter $\eta_{d,t}$ represents DRG-year fixed effects, which control for any time-varying shocks that broadly affect particular patient populations across all hospitals. For example, CMS periodically adjusts the service intensity weights across DRGs, which may potentially influence treatment behavior and care in different DRGs. Likewise, $\eta_{i,d}$ represents hospital-DRG fixed effects, which control for persistent characteristics of patients in DRGs for a given hospital. Our specification therefore allows us to examine changes in hospital decisions pertaining to specific patient populations following the credit shock, conditional on fixed characteristics related to the patient population within the hospital and any time-varying changes to the patient population across hospitals.

In addition to the HCUP data, we also utilize hospital-level data for the process of care scores from the CMS Hospital Compare dataset.

[52] Our previous hospital-year level results provided in Section 4 also hold for the subsample of states for which we have HCUP data. These results are available upon request.

5.1 Mechanisms – Financial and operating decisions

To better understand the changes in hospital financial and operating decisions and quality of care presented in Section 4.2, we further investigate revenues and costs using the inpatient database discussed above. We find that hospitals are able to achieve the gains in revenues and profitability by enhancing both resource utilization and cost efficiency. We discuss the results related to each of these separately below.

Resource utilization. As noted in Section 4.2, affected hospitals increase revenues from patients following the credit shock. To examine the potential sources of revenue generation, we consider inpatient admissions in Table 7 based on specification (4) above. Column (1) in Table 7, Panel A indicates that inpatient admissions per DRG increased by 4.6% relative to unaffected hospitals. This finding reinforces our earlier results that hospital bed utilization and discharge rates increase for affected hospitals. Column (2) of Panel A further shows that inpatient admissions arising from a physician order point of origin, which account for 73% of admissions, increases by 6.9% per DRG for affected hospitals. In columns (3) and (4), we see that this increase is driven by increases in admissions from the hospital's emergency department (ED), which account for 50.1% of admissions for the average hospital in our SID sample, and by increases in admissions for scheduled non-emergency (i.e., elective) procedures that require an inpatient stay (such as hip replacements). Moreover, admissions arising from inpatient transfers from clinics (column 5) or from other healthcare facilities (column 6) significantly decline.[53] The decline in transfer admissions may be due to decreased hospital bed availability as affected hospitals operate more towards capacity following the credit supply shock.

To better understand this increase in admissions, we interact our main treatment variable, $STExposed_{i,t-1}$, with a given DRG's relative weight in year t, $Weight_{d,t}$, and consider the change in total admissions and ED admissions in particular. We find that the coefficients on the interaction terms are negative and significant (columns 7 and 8),[54] which indicate that the increase in all admissions and those from the ED are greater for DRGs which correspond to conditions that are less complicated or less severe. This set of results is consistent with

[53]In our sample, admissions from inpatient transfers from clinics account for 9.6% of admissions, while transfers from other healthcare facilities account for 7.8% of admissions. Admissions for scheduled elective procedures account for 13.8% of admissions. Physician-ordered admissions include both elective and ED admissions.

[54]To understand the coefficient magnitudes, consider the diagnosis of diabetes in the 2016 MS-DRG system as an example. DRG 637, diabetes with major complication or comorbidity (MCC), has a relative weight of 1.3823, and DRG 639, diabetes without CC/MCC, has a weight of 0.6007. The coefficient in column (7) implies that admissions coded with DRG 637 increase by 4.9% for the average affected hospital, whereas inpatient admissions coded with DRG 639 increase by 5.5%.

hospitals lowering the standard for admission from the ED and admitting patients with less severe conditions.[55] In Appendix Table A.8, we similarly analyze the Case Mix Index (CMI) using our main specification (1), which is provided by CMS and represents the average severity of patient conditions (who are covered by Medicare) for a given hospital-year. In line with the aforementioned results, an affected hospital's CMI significantly decreases, suggesting a less severe patient pool after the shock (column 1 of Appendix Table A.8). These results also help to mitigate concerns that our documented effects in Section 4.3 are driven by contemporaneous declines in patient conditions.

As a falsification test, we consider heart attack and childbirth admissions, which are less gameable by hospitals and thus should not experience a similar increase in admissions.[56] We find insignificant changes under both of these conditions in Appendix Table A.9.

In terms of admissions by primary payer type, the largest increase is among privately insured patients, followed by Medicare patients and lowest among Medicaid patients, as shown in Panel B of Table 7. We find similar results with the CMS data as well, whereby the fraction of discharges that are Medicare patients is significantly lower for affected hospitals, and that of the Medicaid group also insignificantly drops (columns 2 and 3 of Appendix Table A.8).

Hospitals can also increase revenues through coding inpatients to DRGs with higher reimbursement rates (i.e., "upcoding"). As noted previously, in contrast to upcoding, we find that inpatients are coded more to DRGs with *lower* relative weights (columns 7 and 8 in Table 7, Panel A).[57]

Cost efficiency. Affected hospitals also exhibit a significant increase in their profit margins, as documented in Table 4. As profit (or net income) is determined as revenues minus costs, hospitals can attempt to improve cost efficiency to boost their profitability. Similar to an increase in revenues, cost-saving measures allow the hospital to rely on their internally

[55]Relatedly, in Appendix Table A.10, we find that conditions for which ED admissions comprised a lower share of total inpatient admissions for that condition exhibited a larger increase following the shock, consistent with hospitals increasing admissions for conditions that did not often require inpatient hospitalization following an ED visit.

[56]While we find an insignificant change, we note there is some evidence that childbirth admissions are potentially gameable through increasing referrals of childbirth patients from physician offices and prenatal clinics. As stated in U.S. Department of Justice (2016): "According to the criminal information, as part of the scheme, expectant mothers were in some cases told at the prenatal care clinics that Medicaid would cover the costs associated with their childbirth and the care of their newborn only if they delivered at one of the Tenet hospitals, and in other cases were simply told that they were required to deliver at one of the Tenet hospitals, leaving them with the false belief that they could not select the hospital of their choice."

[57]We also do not observe a significant change in average listed prices (i.e., charges) for privately insured patients among affected hospitals relative to unaffected hospitals, as shown in Appendix Table A.11.

generated funds to finance their future operating activities rather than seeking external financing.

As noted previously, inpatient stay reimbursements are set prospectively for a fixed dollar amount based on the DRG for which the patient is assigned. This system is used for Medicare and Medicaid inpatient services, as well as for privately insured patients whose contracted insurer payment structures are based on Medicare or a fixed/prospective payment scheme. This fixed pricing structure appears to be common in private insurance contracts; Cooper et al. (2019) find that fixed payments for privately insured patients comprise about 77% of inpatient cases in their sample.[58] The DRG-based reimbursement accounts for the hospital resources, including medical procedures and the patient's hospital stay, required to treat the condition under a given DRG. Reducing the number of procedures and length of stay for a given patient can therefore allow the hospital to receive the same payment at a lower cost for a given DRG.[59]

To explore this mechanism, we investigate changes in the average number of procedures for a given DRG and the average length of stay per DRG through specification (4). Column (1) of Table 8, Panel A, shows that the average number of procedures for inpatients per DRG significantly decreases for affected hospitals. Aggregating across DRGs within a hospital, the point estimate in column (1) implies a reduction of 408 procedures provided to admitted patients per year for a given affected hospital in our sample.[60] When partitioning by payer type in columns (2)–(4), we find that the largest decrease in procedures is for Medicare patients. In Panel B of Table 8, we see that average length of stay per DRG insignificantly decreases. While length of stay is insignificant when aggregated across payer types, there is a significant decline in the average length of stay among privately insured, Medicaid, and uninsured patients (the last coefficient is reported in column (3) of Appendix Table A.12). For privately insured patients, column (2) signifies 279 fewer days for privately insured inpatient stays aggregated across DRGs for a given affected hospital per year.[61]

[58]The remaining 23% of cases are estimated to be reimbursed as a share of the hospital's listed price (charge). Of the 77% of inpatient cases that are based on fixed payments, Cooper et al. (2019) estimate that 74% of these are determined as a share of Medicare reimbursement rates.

[59]We note that some hospital procedures during inpatient treatment have separate charges that can be on top of the DRG-based reimbursement. Hence, we might expect that charge per patient should decrease by the reduction in number of procedures. However, the fact that average inpatient charge per DRG is almost constant for affected hospitals (column 2 of Table A.11) implies that the main reduction in procedures are for those covered by the DRG-based payments.

[60]About 32 patients are admitted per DRG for a given hospital in our sample, with each inpatient receiving on average 2 procedures. Each hospital codes about 355 DRGs for inpatient care in our sample. The 1.8% decrease from column (1) therefore translates to an aggregate per-hospital reduction of $64 \times 0.018 \times 355$.

[61]The average number of privately insured patients admitted per DRG is 13.65 in our sample, while the average length of stay for these patients is 4.8 days. The average number of DRGs coded for inpatient care

The insignificant decline in Medicare length of stay may be due institutional features specific to Medicare. For example, Medicare requires a minimum inpatient hospital stay of two consecutive days for the admission to be covered by Medicare. Relatedly, Medicare requires a minimum hospital stay of three consecutive days for a Medicare patient to qualify for coverage of a subsequent Skilled Nursing Facility (SNF) inpatient stay or extended care services. Some nursing homes also require a maximum patient temperature prior to discharge before the patient can return to the nursing home.

By reducing the number of procedures and length of stay for patients, hospitals are able to scale back on costs while receiving similar payments through the DRG-based reimbursement from insurers for inpatient admissions, thereby boosting profitability per patient. Moreover, improved inpatient turnover in the hospital allows for greater admissions and thus increased revenues. Indeed, in our discussions with hospital executives and attending physicians, hospitals pay close attention to patient length of stay and the medical staff are sometimes urged to expeditiously discharge patients. For example, attending physicians reported to us that they receive a page when the hospital is close to capacity to indicate the necessity for available beds and faster patient turnover.

Summary. The results above help to explain how affected hospitals achieve gains in revenues and profitability. The results indicate that hospitals primarily increase revenues by admitting more patients and operating closer to capacity. Hospitals appear to be lowering the standard of admission by admitting patients with less severe conditions. These results are also consistent with anecdotal evidence of hospital executives ramping up admissions to increase revenues (as discussed in Section 2). Moreover, the largest increase in admissions is for patients with private insurers, which typically have the highest reimbursement rates. We additionally do not find evidence of increased prices or upcoding. At the same time, hospitals are able to improve cost efficiency and lower the cost of inpatient admissions by reducing the length of inpatient stays as well as scaling back on the number of procedures performed per DRG.

5.2 Mechanism – Quality of Care

An important question is why average quality of care declines for affected hospitals, despite these hospitals admitting more patients with less severe conditions. To investigate the mech-

by a given hospital in a given year in our sample is 355. Across DRGs, the 1.2% decrease from column (2) translates to an aggregate hospital reduction of $13.65 \times 4.8 \times 0.012 \times 355$. Furthermore, in Section 4.2, we showed that *Bed Utilization* increased by 668 days; this prior estimate is the net effect on total patient bed days from increased inpatient admissions and decreased inpatient length of stay.

anisms underlying this decline in care quality, we examine staffing and additional measures of attentiveness of the medical staff.

Staffing. We examine whether affected hospitals increase members of the medical staff to accommodate the increase in admissions and greater bed utilization. The SID contains data on each inpatient's primary attending physician as well as other physicians who also provided care or treatment to the patient. The results are presented in Table 9. We examine the average number of admitted patients cared for by each physician in a given hospital-DRG-year in column (1). The results indicate that attending physicians cared for significantly more admitted patients on average for a given DRG in affected hospitals. This aligns with our aforementioned results of an increase in inpatient admissions, and suggests that individual physician workloads increase following the shock. Column (2) likewise considers the average number of unique physicians that provided care for an individual inpatient. We see that significantly fewer attending physicians are involved in a given inpatient admission. Finally, we consider the number of unique physicians providing care for inpatients in a given DRG. Column (3) indicates that the number of unique physicians remains the same, which implies that hospitals did not increase either their contracted or directly employed physicians to accommodate the increase in inpatient admissions.

Timely and effective care. To measure attentiveness of the medical staff, we utilize process of care scores at the hospital level from the CMS Hospital Compare dataset. Our measures for timely and effective care include the frequency or speed with which patients receive the appropriate treatment or medical procedures after being admitted or upon discharge for the three conditions tracked closely by CMS (pneumonia, heart failure, and AMI). These measures thus reflect attentiveness of the medical staff in treating patients.

For AMI, we use three measures: (*i*) the portion of patients that receive aspirin at discharge; (*ii*) the portion of patients that receive percutaneous coronary intervention (PCI) within 90 minutes of arrival; and (*iii*) the portion of patients that receive a Statin prescription at discharge.[62] For heart failure, we use the portion of patients that receive left ventricular systolic evaluations (LVS) upon arrival and ACE inhibitors or angiotensin receptor blockers (ACE/ARB) at discharge.[63] For pneumonia, we use the portion of patients that receive the

[62]PCI is a nonsurgical procedure performed to improve blood flow of coronary circulation. Research evidence shows that it is preferable to intravenous thrombolysis for the treatment of AMI (Keeley et al. (2003)). Statins are a class of drugs often prescribed by doctors to help lower cholesterol levels in the blood. Treatment with Statins initiated within three to six months after AMI reduces mortality in patients with elevated cholesterol levels (Group et al. (1994); Sacks et al. (1996)).

[63]Systolic dysfunction—when the left ventricle of the heart fails to contract normally and distribute enough blood into circulation—is a major cause of heart failure. In line with this, when the American College of

most appropriate antibiotic at discharge.

The results are presented in Table 10. Columns (1) to (3) correspond to AMI treatments, columns (4) and (5) to heart failure treatments, and column (6) corresponds to a routine pneumonia treatment. The results show a significant reduction in timely and effective care (with the exception of receiving aspirin at discharge for AMI patients, which is marginally insignificant). As an example, patients are 1.3% less likely to receive a percutaneous coronary intervention (PCI) within the recommended 90 minutes of arrival to an affected hospital after a heart attack (AMI, column 2). PCI treatment within the 90-minute window is critical, as the survival likelihood drops significantly when the time to treatment exceeds 90 minutes. Indeed, every 10-minute treatment delay beyond this window results in an additional 3.3 deaths per 100 patients (Scholz et al. (2018)).

Moreover, across five of the six measures, the likelihood of failing to provide correct or timely treatment increases by 0.5–1.3% for affected hospitals. This represents a 14–20% increase relative to the sample mean of 3.2–6.5%, depending on the treatment or procedure. The results suggest that the medical staff in affected hospitals become significantly less attentive following the credit supply shock.

Summary. The above results help to link the changes in operational efficiency to changes in patient health outcomes and quality of care. Collectively, the results imply that physicians and the medical staff in affected hospitals have greater strains on their time and attention following the shock to credit supply. Hospital bed utilization increases through greater admissions and faster patient turnover. Meanwhile, the number of physicians in these hospitals remains unchanged, resulting in physicians admitting and providing care for more patients. This additional workload appears to negatively affect the quality of care provided for patients: admitted patients receive worse treatment and care, as evidenced by the process of care scores.[64] The decline in quality of care is eventually reflected in patient health outcomes, as readmissions and mortality rates rise for affected hospitals. Hence, the results suggest a channel for how impediments to credit access indirectly translate to a negative impact on patient health outcomes and quality of care.

The results also do not necessarily imply that affected hospitals were operating subopti-

Cardiology and the American Heart Association (ACC/AHA) issued detailed guidelines for the evaluation and management of heart failure in 1995, the primary focus was on systolic dysfunction. ACE inhibitors relax the veins and arteries to lower blood pressure and significantly improve the long-term survival rate after heart failure (Pfeffer et al. (1992)). ARBs are considered a reasonable alternative to ACE inhibitors, particularly in patients with intolerance to ACE inhibitors.

[64]This channel is also consistent with Silver (2021), who finds that quality of care is lower when emergency room doctors work faster due to workplace peer effects.

mally prior to the credit supply shock. While hospitals seek to maximize profitability like other firms, they also have a health provision objective that may run counter to maximizing profitability. As such, hospitals optimize between profits and health provision (i.e., concerns over patient utility) in their objective function. Under tighter financial constraints, revenues collected from patients and profitability become more essential for the hospital. In turn, affected hospitals are forced to re-optimize and shift their decisions more towards revenues and profitability and away from healthcare quality.[65]

6 Heterogeneity and Robustness Tests

We perform a number of additional analyses regarding heterogeneity in responses to further establish the channels behind the results, as well as a variety of robustness tests. In presenting the results of these tests, we focus on a key subset of outcomes from the previous tables to minimize clutter; we note that the results are generally consistent across the other measures.[66] For several of the tests, we provide more details regarding the specifications and additional discussion of the results in Online Appendix A.

6.1 Heterogeneity in Hospital Responses

We first consider heterogeneity in responses based on the hospital's reliance on bank loans. If a hospital is more dependent on bank loan financing, then the negative credit shock induced by stress tests should be more severe. To explore this, we first calculate each hospital's bank loan reliance, which we define to be the hospital's (non-matured) loan amount divided by its total income, both measured in the year prior to the hospital's credit supply shock. We then consider a specification where we interact our main treatment variable, $STExposed_{i,t-1}$, with $HighReliance_i$, which is an indicator that takes the value of one if hospital i's pre-shock loan reliance is above-median, and zero otherwise. The results are provided in Table 11 and show a consistent pattern of stronger effects for the affected hospitals that are more reliant

[65] Previous studies have found that for-profit and non-profit hospitals behave similarly in response to financial incentives and shocks (e.g., Duggan (2000)), and therefore are unlikely to have substantial differences in their objective functions. We note that our results generally hold for both for-profit and non-profit hospitals, as shown in Table 12.

[66] In untabulated results, we provide parallel trend plots for the heterogeneity tests and furthermore provide validation of the inferences in the potential presence of pre-trends for these tests using the approach of Rambachan and Roth (2023), described in Online Appendix B. These results are available upon request. We note that the coefficient for profit margin in the for-profit heterogeneity analysis (Panel A of Table 12) does not satisfy the validation approach of Rambachan and Roth (2023). However, the coefficient for this variable from the heterogeneity regression analysis in Table 12 is also insignificant.

on loan financing.[67]

Another important potential source of heterogeneity in responses is through ownership status of the hospital, such as whether the hospital is for-profit or non-profit. To examine this, we consider a similar specification as above except we interact our main treatment variable with $ForProfit_i$, which is an indicator variable equal to one if hospital i is a for-profit hospital, and zero otherwise. The results of this test, which are reported in Panel A of Table 12, show that affected for-profit hospitals generally have a stronger response than affected non-profit hospitals in terms of both operational decisions and declines in quality of care. Interestingly, for-profits exhibit a lower change in their profit margins following the tightened credit constraints. This result is consistent with for-profit hospitals operating more efficiently financially or placing a greater emphasis on profits over health provision prior to the shock, thereby having less room for improvement on that dimension.

In additional analyses, we find that hospitals with greater market power (Table A.13) or lower cash holdings prior to the shock (Table A.14) exhibit a stronger response to the tightened credit constraints. The latter result suggests that greater cash reserves can help to mitigate the impact of the credit supply shock, as hospitals with greater cash balances can rely more on internal reserves, thus incurring a lower cost to the stress tests. As we discuss in the following section, this result has potential policy implications. Finally, we do not find significant differences based on hospital location (rural vs. urban) or whether the hospital belongs to a large system. Additional details regarding these tests are provided in Section A.1 of the Online Appendix.

6.2 Treatment heterogeneity

To further validate that our results are driven by a credit supply channel, we explore heterogeneity in affected hospitals' treatment exposure to bank stress tests. In particular, if the credit supply channel is at play, we would expect our results to be stronger for affected hospitals borrowing from banks that are more affected by stress tests. To examine this, we exploit the fact that lenders vary in their stress test performance. Banks that are closer to the regulatory minimum face greater regulatory pressure and therefore tend to reduce their credit supply more, thus generating greater financial pressure for the hospitals they lend to. We define $CloseExposed_{i,t-1}$ (resp. $FarExposed_{i,t-1}$) to take a value of one if hospital i was exposed to a stress-tested bank in year $t-1$ or earlier *and* the hospital's lenders had a

[67]The parallel trends figures for the above-median bank loan reliance subgroup are very similar to those of our main sample presented in Section 4.4 (available upon request).

below-median (resp. above-median) average distance between stress test outcomes and the regulatory minimum thresholds, and zero otherwise. Table 13 shows that the baseline effects are centered around the hospitals that are exposed to stress tests through banks closer to the threshold. We additionally find that treated hospitals with a greater portion of their total loans from stress-tested banks exhibit stronger responses to the shock (Table A.18); we refer readers to Online Appendix A.1 for details.

6.3 Robustness

In addition to the propensity score-matched analysis discussed in Section 4, we analyze a number of robustness tests. We briefly summarize the results here and provide considerable more detail and discussion in Online Appendix A.2.

To mitigate concerns that our results are driven by sample composition, we restrict the sample in a variety of ways and run the main specifications on the resulting subsamples. Specifically, we separately consider subsamples of only for-profit hospitals (Table 12, Panel B), hospitals that are part of smaller systems with no more than five members (Table A.20), treatment hospitals that took out new loans following exposure to the stress tests (Table A.21), and hospitals that borrowed from commercial banks (Table A.22). Across the various subsample analyses, we find results similar to that of our main analysis. Additional robustness tests include controlling for regional differences by including hospital referral region (HRR) by time fixed effects and a placebo test that considers the responses by untreated hospitals that are within the same city as treated hospitals. Finally, we provide more detail and analysis regarding the timing of the DFAST and other programs implemented by the Federal Reserve.

7 Concluding remarks

This paper explores the effect of credit supply shocks on hospitals. We utilize variation in stress tests conducted on banks and examine outcomes for the hospitals that these tested banks lend to. We find evidence that hospitals experience more expensive credit and reduce the amount of debt they utilize after the banks which they have relationships with undergo stress tests. In response to this negative credit supply shock, affected hospitals engage in revenue-increasing and cost-cutting actions, thereby increasing revenues and profitability. However, we also find that hospitals deliver lower-quality care to patients in response to the tightened credit constraints. In particular, we find that hospitals experience a significant increase in readmission and mortality rates for major conditions and a reduction in patient satisfaction measures. The decrease in quality of care appears to be driven by decreased attentiveness by physicians and the medical staff; doctors care for more patients at affected hospitals and the timeliness of procedures drops.

Overall, our results suggest that hospitals, like other businesses, respond to increased financial pressure through changes in their operations, and in particular are dependent on credit markets. Moreover, our study helps to shed light on the importance of credit access to hospitals, and how impediments to this access can influence real operating decisions and ultimately the quality of care that patients receive. Consequently, an implication of the analysis is that hospital default risk and the corresponding impediments to credit access are important determinants of the quality of care that hospitals provide. Regulatory or public policy intervention may help to limit the impact of hospital default risk on quality of care. One such proposal is for the federal government to provide subsidized loans to hospitals—allowing hospitals another channel to access external financing—so that access to credit (and the uncertainties associated with it) has a less deleterious effect on hospital operating decisions. The federal government currently does this in some form with the banking and housing sectors (with government-backed mortgages). While access to the municipal bond market partially serves this purpose, healthcare bond issuance is generally specific to funding infrastructure construction or other targeted projects and investments.

Another implication of our analysis is that higher levels of capital reserves help to mitigate the effects of the credit supply shock, as shown in our heterogeneity tests. As such, a requirement that hospitals maintain capital buffers can allow hospitals to remain well-capitalized when credit access tightens and could therefore prevent hospitals from altering operating decisions in response. Likewise, as high default risk exacerbates impediments to credit access, another potential policy prescription is to regulate hospital financial leverage, thereby lowering default risk. Our study can thus help to inform potential regulations or policies regarding hospital credit access to ultimately improve the quality of care that patients receive. Furthermore, the implications of our analysis can help to mitigate the deleterious effects of other profit shocks that extend beyond credit access, such as the immediate aftermath of the COVID event, which critically impacted hospital finances.

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Tables and Figures

Table 1: Lender and Exposed Hospital Distributions and Summary Statistics

Panel A summarizes the yearly distribution of first-time stress-tested banks and exposed hospitals. In Panel A, column (1) shows the number of new banks that were stress-tested *and* were lending to hospitals in the sample in a given year. Column (2) shows the number of existing loans to hospitals by these newly-tested lenders in each year. Column (3) shows the affected number of hospitals that borrow from the lenders in column (1) in each year. Panel B provides summary statistics for the main loan variables in our sample. *Spread&Fee* is the interest rate spread over LIBOR plus fees on the drawn portion of the loan (in basis points). *Maturity* is the the loan facility maturity (in months). *Loan Amount* is the individual facility amount for each hospital borrower (in $ millions). If the borrower is a hospital chain/system, we divide the facility amount by the number of subsidiary hospitals in the system at the borrowing time. *Total Yearly Amount* is the total amount of new debt (in $ millions) across individual facilities taken out by a given hospital in a given year.

Panel A: Tested Lenders Distribution

Year	(1) Tested Lenders	(2) Existing Loans	(3) Exposed Hospitals
2012	15	52	400
2013	4	26	41
2014	3	3	27
2015	1	4	33
2016	3	4	4
Total	26	89	505

Panel B: Loan Characteristics

	(1) Mean	(2) Std	(3) P25	(4) Median	(5) p75
Spread&Fee	388.479	305.089	200.000	325.000	475.000
Maturity	57.603	16.346	49.000	60.000	60.000
Loan Amount ($ millions)	78.402	312.565	7.955	13.231	25.132
Total Yearly Amount	144.296	271.408	24.168	50.000	133.333

Table 2: Summary Statistics for Full Sample and by Treatment Status

This table provides the summary statistics of hospital characteristics in 2011 (the last year before the DFAST announcement) for the entire sample and separately for the treatment and control groups. All variables are defined at the hospital-year level. *Net Income* is *Income* minus *Cost*. *Cost* is total costs (operating and other expenses). *Income* consists of net patient revenue and other income. *Liabilities* is total liabilities. *Cash* is cash holdings. *TA* is total assets; all variables scaled by *TA* are winsorized at the 1% level. *Discharges* is the number of inpatient discharges. *Bed Days* is the number of available beds multiplied by 365. *For-profit* is an indicator variable equal to one if the hospital is a for-profit hospital, and zero otherwise. *Hospital System* is an indicator variable equal to one if the hospital is a part of a hospital system, and zero otherwise.

Panel A: Full Sample

	Obs.	*Mean*	*Std Dev*	*P25*	*Median*	*P75*
Net Income/TA	3,511	0.058	0.226	−0.007	0.040	0.101
Log(Income)	3,511	18.237	1.330	17.272	18.317	19.254
Liabilities/TA	3,510	0.584	0.533	0.255	0.483	0.747
Cash/TA	3,461	0.073	0.119	0.002	0.035	0.098
Log(Discharges)	3,572	8.091	1.568	6.989	8.378	9.330
Log(Bed Days)	3,575	10.276	1.068	9.119	10.411	11.123
For-profit	3,633	0.217	0.412	0.000	0.000	0.000
Hospital System	3,658	0.678	0.467	0.000	1.000	1.000

Panel B: Treatment Group

	Obs.	*Mean*	*Std Dev*	*P25*	*Median*	*P75*
Net Income/TA	494	0.104	0.234	−0.005	0.065	0.171
Log(Income)	494	18.694	1.014	18.104	18.789	19.422
Liabilities/TA	496	0.577	0.630	0.117	0.424	0.813
Cash/TA	485	0.034	0.083	0.000	0.001	0.040
Log(Discharge)	496	8.747	1.192	8.267	8.968	9.543
Log(Bed Days)	497	10.744	0.855	10.343	10.884	11.338
For-profit	504	0.492	0.500	0.000	0.000	1.000
Hospital System	505	0.988	0.108	1.000	1.000	1.000

Panel C: Control Group

	Obs.	*Mean*	*Std Dev*	*P25*	*Median*	*P75*
Net Income/TA	3,017	0.051	0.223	−0.007	0.037	0.093
Log(Income)	3,017	18.162	1.361	17.142	18.202	19.186
Liabilities/TA	3,014	0.585	0.515	0.272	0.491	0.742
Cash/TA	2,976	0.079	0.123	0.006	0.042	0.105
Log(Discharge)	3,076	7.985	1.595	6.858	8.204	9.251
Log(Bed Days)	3,078	10.200	1.080	9.119	10.282	11.059
For-profit	3,129	0.172	0.378	0.000	0.000	0.000
Hospital System	3,153	0.628	0.483	0.000	1.000	1.000

Table 3: Hospital Loan Characteristics

This table provides the regression results for equation (2). Each observation represents a loan facility k, borrowed by hospital i from bank j in year t. $STExposed$ takes a value of 1 if at least one of hospital i's relationship banks experienced a stress test in year $t-1$ or earlier, and 0 otherwise. $Spread\&Fee$ is the interest rate (in basis points) spread over LIBOR plus fees on the drawn portion of the loan. $Log(Loan\,Amount)$ is the logarithm of the loan facility amount. $Log(Maturity)$ is the logarithm of the loan facility maturity (in months). $New\,Lender$ takes a value of 1 if hospital i has never borrowed from bank j before year t, and 0 otherwise. Control variables include borrower i's logarithm of total assets, income over total assets, liabilities (total liabilities over total assets), and tangibility (total fixed assets over total assets). Year, bank, loan type, and loan purpose fixed effects, are included as indicated. The mean and standard deviation for each dependent variable (denoted Y) are reported (presented non-logged if the dependent variable is a logarithm). Standard errors are clustered at the lender level and provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) *Spread&Fee*	(2) *Spread&Fee*	(3) *Log(Loan Amount)*	(4) *Log(Maturity)*	(5) *New Lender*
$STExposed_{i,t-1}$	74.023***	68.235**	−0.365***	−0.085*	0.126*
	(25.206)	(29.585)	(0.128)	(0.049)	(0.073)
Controls	N	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y
Loan Type FE	N	Y	Y	Y	Y
Loan Purpose FE	N	Y	Y	Y	Y
N	1,052	717	810	801	810
Y Mean	388.479	388.479	78.402	57.603	0.420
Y Std Dev	305.089	305.089	312.565	16.346	0.494
Adj R^2	0.15	0.31	0.60	0.44	0.34

Table 4: Hospital Financial and Operational Performance

This table provides the regression results for equation (1) for financial and operational outcome variables. *STExposed* takes a value of 1 if at least one of hospital i's relationship banks experienced a stress test in year $t-1$ or earlier, and 0 otherwise. *Profit Margin* is profit margin, defined as $(Income - Cost)/Income$. *Liabilities*$/TA$ is total liabilities over total assets. $Net\,Income/TA$ is hospital net income $(Income - Cost)$ over total assets. *Bed Utilization* is the average daily fraction of hospital beds that are occupied. *Discharge Rate* is inpatient discharges over total bed days. Control variables include the lagged logarithm of one plus available bed days ($Log(Bed\,Days_{i,t-1})$), and lagged cash holdings over total assets ($Cash/TA_{i,t-1}$). Panel B replicates the analysis using a propensity score matched sample. Year and hospital fixed effects are included, as indicated. The mean and standard deviation for each dependent variable (denoted Y) are reported (presented non-logged if the dependent variable is a logarithm). Standard errors are clustered at the hospital level and provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Main Specification

	(1) *Profit Margin*	(2) *Liabilities/TA*	(3) *Net Income/TA*	(4) *Bed Utilization*	(5) *Discharge Rate*
$STExposed_{i,t-1}$	0.011*	−0.082***	0.012*	0.023***	2.398***
	(0.006)	(0.016)	(0.007)	(0.004)	(0.409)
Controls	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y
N	23,804	23,231	23,233	23,269	23,267
Y Mean	0.032	0.565	0.053	0.443	41.933
Y Std Dev	0.283	0.516	0.124	0.231	19.545
Adj R^2	0.21	0.76	0.63	0.94	0.80

Panel B: Propensity Score Matched Sample

	(1) *Profit Margin*	(2) *Liabilities/TA*	(3) *Net Income/TA*	(4) *Bed Utilization*	(5) *Discharge Rate*
$STExposed_{i,t-1}$	0.024***	−0.081***	0.020**	0.022***	2.196***
	(0.007)	(0.021)	(0.009)	(0.005)	(0.566)
Controls	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y
N	6,919	6,775	6,770	6,785	6,785
Adj R^2	0.29	0.78	0.67	0.92	0.77

Table 5: Hospital Care Quality: Readmission and Mortality Rates

This table provides the estimation results for equation (1), focusing on 30-day readmission and mortality. In Panel A, the outcome variables in columns (1)–(3) measure the logarithm of the number of unplanned readmissions for pneumonia (*Log(Pneumonia Readmissions)*, heart failure (*Log(Heart Failure Readmissions)*, and acute myocardial infarction (denoted AMI; *Log(AMI Readmissions)*, respectively. The outcome variables in columns (4)–(6) measure the readmission rates for pneumonia, heart failure, and AMI, respectively. The outcome variable in column (7) is the readmission rate for all diseases (*All Readmission Rate*). The outcome variable in column (8) is a dummy variable that takes a value of 1 if the hospital's CMS-reported readmission rate for all diseases is in the worst-performing group among hospitals nationwide, and 0 otherwise. In Panel B, *Log(Pneumonia Mortality Num)*, *Log(Heart Failure Mortality Num)*, and *Log(AMI Mortality Num)* are the logarithms of the number of pneumonia, heart failure, and AMI deaths, respectively. *Pneumonia Mortality Num* is the number of pneumonia deaths. *Pneumonia Mortality Rate* is the mortality rate for patients treated for pneumonia. *Pneumonia Mortality Worst* is a dummy variable that takes a value of 1 if the hospital is in the worst category in terms of pneumonia deaths relative to the national average, and 0 otherwise. $STExposed$ takes a value of 1 if at least one of hospital i's relationship banks experienced a stress test in year $t-1$ or earlier, and 0 otherwise. Control variables include the lagged logarithm of one plus available bed days ($Log(Bed\,Days_{i,t-1})$) and lagged cash holdings over total assets ($Cash/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. The mean and standard deviation for each dependent variable (denoted Y) are reported (presented non-logged if the dependent variable is a logarithm). Standard errors are clustered at the hospital level and provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Readmission

	(1) *Log(Pneumonia Readmissions)*	(2) *Log(Heart Failure Readmissions)*	(3) *Log(AMI Readmissions)*	(4) *Pneumonia Readmission Rate*	(5) *Heart Failure Readmission Rate*	(6) *AMI Readmission Rate*	(7) *All Readmission Rate*	(8) *All Readmissions Worst*
$STExposed_{i,t-1}$	0.102***	0.030***	0.030**	0.003***	0.003***	0.003***	0.002***	0.047***
	(0.012)	(0.011)	(0.013)	(0.001)	(0.001)	(0.001)	(0.000)	(0.013)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y	Y	Y
N	21,611	20,078	12,674	23,432	22,186	14,349	17,694	19,354
Y Mean	18.953	26.100	13.062	0.173	0.225	0.174	0.155	0.079
Y Std Dev	16.495	26.645	12.609	0.014	0.019	0.017	0.010	0.270
Adj R^2	0.96	0.98	0.96	0.72	0.77	0.82	0.67	0.48

Panel B: Mortality

	(1) *Log(Pneumonia Mortality Num)*	(2) *Log(Heart Failure Mortality Num)*	(3) *Log(AMI Mortality Num)*	(4) *Pneumonia Mortality Num*	(5) *Pneumonia Mortality Rate*	(6) *Pneumonia Mortality Worst*
$STExposed_{i,t-1}$	0.098***	0.003	0.022*	1.737***	0.002***	0.018*
	(0.012)	(0.010)	(0.011)	(0.336)	(0.001)	(0.010)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	21,566	19,850	14,073	21,566	23,396	23,844
Y Mean	14.512	11.226	9.398	15.307	0.139	0.053
Y Std Dev	12.997	10.601	8.244	13.144	0.025	0.224
Adj R^2	0.96	0.98	0.97	0.90	0.84	0.31

Table 6: Hospital Care Quality: Patient's Perspective

This table provides the estimation results for equation (1), focusing on hospital care quality from the patient's perspective. The outcome variables are the shares of patients that give the highest rating to questions on overall care quality (*Overall Rating*), pain control, recommendation of the hospital to similar patients (*Recommend*), cleanliness, doctor communication, nurse communication, recovery information, and quietness, respectively. *STExposed* takes a value of 1 if at least one of hospital i's relationship banks experienced a stress test in year $t-1$ or earlier, and 0 otherwise. Control variables include the lagged logarithm of one plus available bed days ($Log(Bed\,Days_{i,t-1})$) and lagged cash holdings over total assets ($Cash/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. The mean and standard deviation for each dependent variable (denoted Y) are reported (presented non-logged if the dependent variable is a logarithm). Standard errors are clustered at the hospital level and provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) *Overall Rating*	(2) *Pain Control*	(3) *Recommend*	(4) *Cleanliness*	(5) *Doctor Communication*	(6) *Nurse Communication*	(7) *Recovery Information*	(8) *Quietness*
$STExposed_{i,t-1}$	−0.008***	−0.007***	−0.006***	−0.006***	−0.006***	−0.003***	−0.005***	−0.009***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y	Y	Y
N	21,372	21,358	21,370	21,372	21,372	21,372	21,371	21,372
Y Mean	0.702	0.703	0.710	0.726	0.809	0.783	0.853	0.600
Y Std Dev	0.089	0.055	0.097	0.076	0.052	0.056	0.046	0.101
Adj R^2	0.82	0.59	0.85	0.76	0.77	0.78	0.72	0.85

Table 7: Hospital DRG Inpatient Admission Decisions

This table provides the regression results for equation (4) for DRG inpatient admission decisions. *STExposed* takes a value of 1 if at least one of hospital i's relationship banks experienced a stress test in year $t-1$ or earlier, and 0 otherwise. In Panel A, $Weight_{d,t}$ is the MS-DRG relative weight of DRG d in year t. *Admissions* is the number of admissions assigned DRG d to hospital i in year t. *Physician Order Admissions* is the number of admissions via physician orders. *ED Admissions* is the number of admissions via physician orders that originate from emergency departments. *Elective Admissions* is the number of admissions via physician orders that are elective. *Clinic Admissions* is the number of admissions through clinics and physician centers. *Transfer Admissions* is the number of admissions transferred from other healthcare facilities such as (other) hospitals, SNFs, and ICFs. In Panel B, we study admission decisions based on insurance types. Columns (1), (2), and (3) study the admission amount for privately insured, Medicare, and Medicaid patients, respectively. Hospital-level control variables include the lagged logarithm of one plus available bed days ($Log(Bed\,Days_{i,t-1})$) and lagged cash holdings over total assets ($Cash/TA_{i,t-1}$). Hospital-DRG level control variables include the lagged average patient age and percentages of patients being female, white, black, and Hispanic. DRG-Year and Hospital-DRG fixed effects are included, as indicated. The mean and standard deviation for each dependent variable (denoted Y) are reported (presented non-logged if the dependent variable is a logarithm). Standard errors are clustered at the hospital level and provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: General Admission Decisions

	(1) *Log(Admissions)*	(2) *Log(Physician Order Admissions)*	(3) *Log(ED Admissions)*	(4) *Log(Elective Admissions)*	(5) *Log(Clinic Admissions)*	(6) *Log(Transfer Admissions)*	(7) *Log(Admissions)*	(8) *Log(ED Admissions)*
$STExposed_{i,t-1}$	0.046***	0.069*	0.112***	0.062***	−0.129***	−0.035**	0.060***	0.132***
	(0.012)	(0.037)	(0.041)	(0.021)	(0.033)	(0.015)	(0.015)	(0.047)
$Weight_{d,t}$							−0.008***	−0.011**
$\times STExposed_{i,t-1}$							(0.003)	(0.005)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
DRG-Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Hospital-DRG FE	Y	Y	Y	Y	Y	Y	Y	Y
Y Mean	31.756	22.811	15.900	4.241	2.704	4.198	31.756	15.900
Y Std Dev	125.327	86.353	55.727	44.758	26.851	65.367	125.327	86.353
N	1,651,990	1,409,410	1,409,410	1,409,410	1,409,410	1,409,410	1,651,990	1,409,410
Adj R^2	0.92	0.85	0.85	0.77	0.71	0.80	0.92	0.85

Panel B: Admission Decisions Based on Insurance Types

Insurance:	(1) *Private* *Log(Admissions)*	(2) *Medicare* *Log(Admissions)*	(3) *Medicaid* *Log(Admissions)*
$STExposed_{i,t-1}$	0.040***	0.031**	0.024**
	(0.014)	(0.012)	(0.012)
Controls	Y	Y	Y
DRG-Year FE	Y	Y	Y
Hospital-DRG FE	Y	Y	Y
N	1,651,990	1,651,990	1,651,990
Y Mean	9.825	12.941	6.606
Y Std Dev	62.097	37.934	49.371
Adj R^2	0.85	0.87	0.83

Table 8: Hospital DRG Inpatient Procedure and Stay Decisions

This table provides the regression results for equation (4) for the number of procedures (Panel A) and the length of stay (Panel B). *STExposed* takes a value of 1 if at least one of hospital i's relationship banks experienced a stress test in year $t-1$ or earlier, and 0 otherwise. *Avg Num Procedures* is the average number of procedures for each case in DRG d at year t. *Avg Length of Stay* is the average length of stay per case in DRG d at year t. In both panels, columns (2), (3), and (4) consider the outcome separately for privately insured patients, Medicare patients, and Medicaid patients, respectively. Hospital-level control variables include the lagged logarithm of one plus available bed days ($Log(Bed\,Days_{i,t-1})$) and lagged cash holdings over total assets ($Cash/TA_{i,t-1}$). Hospital-DRG level control variables include the lagged average patient age and percentages of patients that are female, white, black, and Hispanic. DRG-Year and Hospital-DRG fixed effects are included, as indicated. Standard errors are clustered at the hospital level and provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Number of Procedures

	(1)	(2)	(3)	(4)
Insurance:	*All*	*Private*	*Medicare*	*Medicaid*
	Log(Avg Num Procedures)	*Log(Avg Num Procedures)*	*Log(Avg Num Procedures)*	*Log(Avg Num Procedures)*
$STExposed_{i,t-1}$	−0.018***	−0.011*	−0.017**	−0.014*
	(0.006)	(0.007)	(0.007)	(0.008)
Controls	Y	Y	Y	Y
DRG-Year FE	Y	Y	Y	Y
Hospital-DRG FE	Y	Y	Y	Y
N	1,643,370	1,161,686	1,388,557	859,807
Adj R^2	0.81	0.74	0.77	0.71

Panel B: Length of Stay

	(1)	(2)	(3)	(4)
Insurance:	*All*	*Private*	*Medicare*	*Medicaid*
	Log(Avg Length of Stay)	*Log(Avg Length of Stay)*	*Log(Avg Length of Stay)*	*Log(Avg Length of Stay)*
$STExposed_{i,t-1}$	−0.008	−0.012**	−0.004	−0.011*
	(0.006)	(0.005)	(0.006)	(0.006)
Controls	Y	Y	Y	Y
DRG-Year FE	Y	Y	Y	Y
Hospital-DRG FE	Y	Y	Y	Y
N	1,651,986	1,161,686	1,388,557	859,807
Adj R^2	0.69	0.60	0.62	0.58

Table 9: Hospital DRG Staffing Decisions

This table provides the regression results for equation (4) for hospital staffing decisions. *STExposed* takes a value of 1 if at least one of hospital *i*'s relationship banks experienced a stress test in year $t-1$ or earlier, and 0 otherwise. *Admissions per Physician* is the average number of admissions attended by each physician in hospital *i*'s DRG *d* in year *t*. *Physicians per Patient* is the average number of physicians involved in each admission in hospital *i*'s DRG *d* in year *t*. *Unique Physicians* is the number of unique physicians providing care for patients in hospital *i*'s DRG *d* in year *t*. Hospital-level control variables include the lagged logarithm of one plus available bed days ($Log(BedDays_{i,t-1})$) and lagged cash holdings over total assets ($Cash/TA_{i,t-1}$). Hospital-DRG level control variables include the lagged average patient age and percentages of patients that are female, white, black, and Hispanic. DRG-Year and Hospital-DRG fixed effects are included, as indicated. Standard errors are clustered at the hospital level and provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) *Log(Admissions per Physician)*	(2) *Log(Physicians per Patient)*	(3) *Log(Unique Physicians)*
$STExposed_{i,t-1}$	0.075***	−0.035***	−0.169
	(0.028)	(0.009)	(0.151)
Controls	Y	Y	Y
DRG-Year FE	Y	Y	Y
Hospital-DRG FE	Y	Y	Y
N	1,255,084	1,651,990	1,651,990
Adj R^2	0.84	0.90	0.95

Table 10: Hospital Care Quality: Timely and Effective Care

This table provides estimation results for equation (1), focusing on timely and effective care quality. The outcome variables in columns (1)–(3) measure the shares of acute myocardial infarction (AMI) patients receiving Aspirin at discharge (*Aspirin*), percutaneous coronary intervention within 90 minutes of arrival (*PCI*), and Statin at discharge (*Statin Rx*). The outcome variables in columns (4)–(5) measure the shares of heart failure patients receiving: evaluation of the left ventricular systolic function (*LVS*), and angiotensin converting enzyme (ACE) inhibitors or angiotensin receptor blockers (ARB) at discharge (*ACE/ARB*). Column (6) measures the share of pneumonia patients receiving the most appropriate antibiotic (*Antibiotic*). *STExposed* takes a value of 1 if at least one of hospital i's relationship banks experienced a stress test in year $t-1$ or earlier, and 0 otherwise. Control variables include the lagged logarithm of one plus available bed days ($Log(Bed\,Days_{i,t-1})$) and lagged cash holdings over total assets ($Cash/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) *Aspirin*	(2) *PCI*	(3) *Statin Rx*	(4) *LVS*	(5) *ACE/ARB*	(6) *Antibiotic*
$STExposed_{i,t-1}$	−0.002	−0.013***	−0.005***	−0.009***	−0.008***	−0.008***
	(0.001)	(0.004)	(0.002)	(0.001)	(0.002)	(0.002)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	9,203	6,327	6,937	14,384	11,193	14,657
Adj R^2	0.43	0.51	0.60	0.78	0.49	0.58

Table 11: Heterogeneity Across Bank Loan Reliance

This table provides estimation results when interacting the treatment variable with the hospital's reliance on bank loans. We define *reliance* as a hospital's non-matured loan amount over its total income. $HighReliance_i$ takes a value of 1 if hospital i's *reliance* in the year before the credit supply shock for hospital i is above-median, and 0 otherwise. *Profit Margin* is defined as $(Income - Cost)/Income$. *Bed Utilization* is the average daily fraction of hospital beds that are occupied. *Discharge Rate* is inpatient discharges over total bed days. *All Readmission Rate* is the readmission rate for all diseases. *Antibiotic* measures the share of pneumonia patients receiving the most appropriate antibiotic. *Overall Rating* is the share of patients that give the highest rating to questions on overall care quality. Control variables include the lagged logarithm of one plus available bed days ($Log(Bed\,Days_{i,t-1})$), and lagged cash holdings over total assets ($Cash/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) *Profit Margin*	(2) *Bed Utilization*	(3) *Discharge Rate*	(4) *All Readmission Rate*	(5) *Antibiotic*	(6) *Overall Rating*
$STExposed_{i,t-1}$	0.004	0.011**	0.693	0.001	−0.003	−0.004
	(0.010)	(0.006)	(0.549)	(0.001)	(0.003)	(0.003)
$HighReliance_i \times STExposed_{i,t-1}$	0.010	0.025***	2.665***	0.003***	−0.010**	−0.004
	(0.010)	(0.007)	(0.721)	(0.001)	(0.004)	(0.003)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	23,804	23,269	23,267	17,694	15,126	21,372
Adj R^2	0.21	0.94	0.80	0.67	0.58	0.82

Table 12: Heterogeneity Across For-Profit and Non-Profit Hospitals and For-Profit Restricted Sample

This table provides estimation results when interacting the treatment variable with a hospital's tax status. Panel A estimates the interaction results in the main sample. $ForProfit_i$ takes a value of 1 if hospital i is a for-profit hospital, and 0 otherwise. *Profit Margin* is defined as $(Income - Cost)/Income$. *Bed Utilization* is the average daily fraction of hospital beds that are occupied. *Discharge Rate* is inpatient discharges over total bed days. *All Readmission Rate* is the readmission rate for all diseases. *Antibiotic* measures the share of pneumonia patients receiving the most appropriate antibiotic. *Overall Rating* is the share of patients that give the highest rating to questions on overall care quality. Panel B estimates the main specification when restricting the sample to for-profit hospitals only. Control variables include the lagged logarithm of one plus available bed days ($Log(Bed\,Days_{i,t-1})$), and lagged cash holdings over total assets ($Cash/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

Panel A: Heterogeneity in Main Sample

	(1) *Profit Margin*	(2) *Bed Utilization*	(3) *Discharge Rate*	(4) *All Readmission Rate*	(5) *Antibiotic*	(6) *Overall Rating*
$STExposed_{i,t-1}$	0.016**	0.013**	1.409***	0.001*	−0.004	−0.004*
	(0.007)	(0.005)	(0.527)	(0.000)	(0.003)	(0.002)
$ForProfit_i \times STExposed_{i,t-1}$	−0.011	0.019***	1.970***	0.002***	−0.006	−0.008**
	(0.010)	(0.007)	(0.741)	(0.001)	(0.004)	(0.003)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	23,765	23,244	23,239	17,694	15,126	21,372
Adj R^2	0.21	0.94	0.80	0.67	0.58	0.82

Panel B: For-Profit Sample

	(1) *Profit Margin*	(2) *Bed Utilization*	(3) *Discharge Rate*	(4) *All Readmission Rate*	(5) *Antibiotic*	(6) *Overall Rating*
$STExposed_{i,t-1}$	−0.003	0.036***	3.901***	0.003***	−0.003	−0.007**
	(0.019)	(0.006)	(0.844)	(0.001)	(0.004)	(0.003)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	5,002	4,898	4,898	3,620	2,904	4,619
Adj R^2	0.21	0.91	0.58	0.68	0.60	0.85

Table 13: Heterogeneity Across Stress-tested Banks

This table provides estimation results when splitting the treatment group by the lending bank's stress test performance. Following Cortés et al. (2020), we define the minimum stress-test distance (*msd*) for banks as

$$msd = \min(\textit{Tier 1 capital} - 6\%, \textit{Risk-based capital} - 8\%, \textit{Stressed leverage} - 4\%).$$

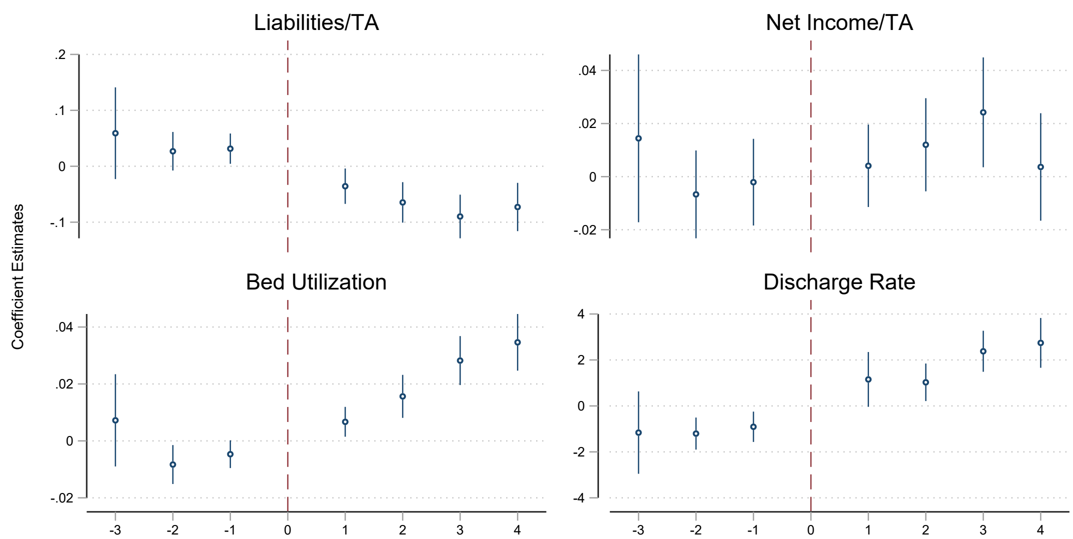
For each treated hospital i, we calculate the average *msd* for all of its tested lenders, weighted by the loan amount. $CloseExposed_{i,t-1}$ ($FarExposed_{i,t-1}$) takes a value of 1 if hospital i was exposed in year $t-1$ or earlier *and* the average *msd* of its tested lenders is below (above) median, and 0 otherwise. *Profit Margin* is defined as $(Income - Cost)/Income$. *Bed Utilization* is the average daily fraction of hospital beds that are occupied. *Discharge Rate* is inpatient discharges over total bed days. *All Readmission Rate* is the readmission rate for all diseases. *Antibiotic* measures the share of pneumonia patients receiving the most appropriate antibiotic. *Overall Rating* is the share of patients that give the highest rating to questions on overall care quality. Control variables include the lagged logarithm of one plus available bed days ($Log(Bed\,Days_{i,t-1})$) and lagged cash holdings over total assets ($Cash/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) *Profit Margin*	(2) *Bed Utilization*	(3) *Discharge Rate*	(4) *All Readmission Rate*	(5) *Antibiotic*	(6) *Overall Rating*
$CloseExposed_{i,t-1}$	0.011*	0.024***	2.100***	0.001***	−0.009***	−0.009***
	(0.006)	(0.004)	(0.440)	(0.000)	(0.003)	(0.002)
$FarExposed_{i,t-1}$	−0.002	0.013***	0.772	0.002***	−0.003	0.001
	(0.008)	(0.005)	(0.480)	(0.000)	(0.004)	(0.002)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	23,780	23,245	23,243	17,678	15,113	21,349
Adj R^2	0.22	0.94	0.80	0.67	0.58	0.82

Figure 1: Parallel Trends: Hospital Financial and Bed Utilization Performance

This figure provides parallel trends for the financial and bed utilization outcome variables by graphing estimation results for equation (3). Each coefficient represents the relative difference between the treatment and control group s years after the first exposure year ("year 0"). All coefficient estimates are relative to year 0. 95% confidence intervals are indicated by the solid lines. We plot the parallel trends in the full sample in Panel A and in the propensity score matched sample in Panel B.

Panel A: Main Specification



Panel B: Propensity Score Matched Sample

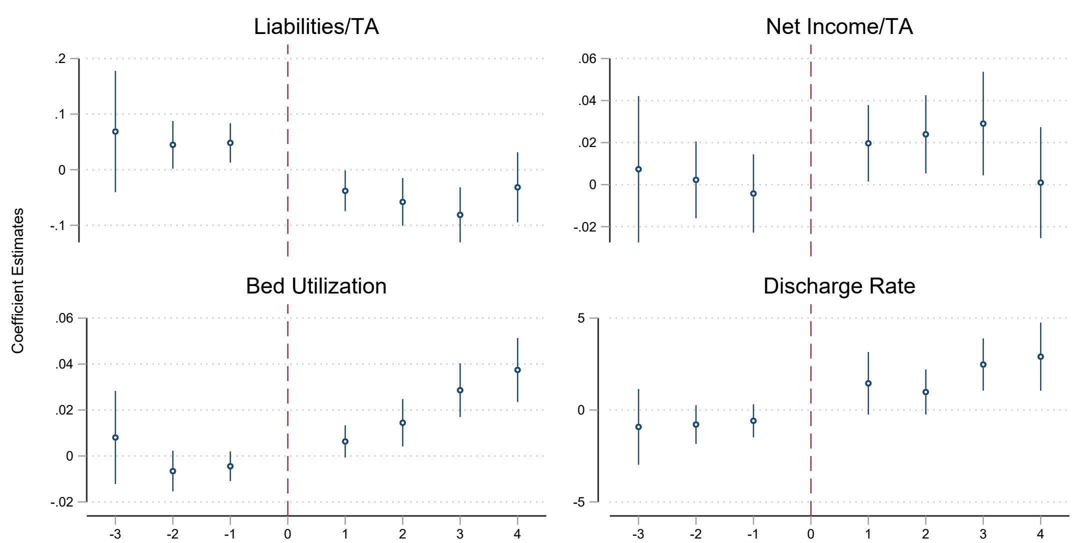
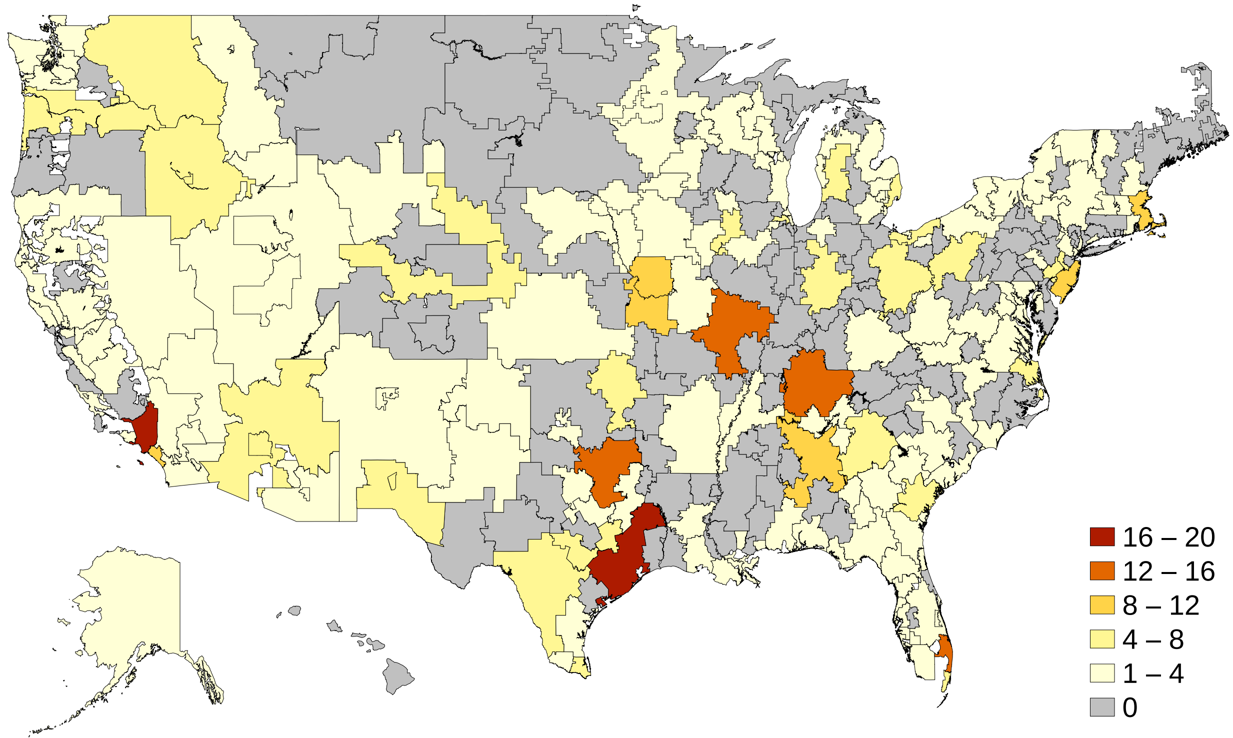


Figure 2: Parallel Trends: Healthcare Quality

This figure provides parallel trends for the readmission, mortality, and survey outcome variables by graphing estimation results for equation (3). Each coefficient represents the relative difference between the treatment and control group s years after the first exposure year ("year 0"). PN is pneumonia, HF is heart failure, and AMI is acute myocardial infarction. All coefficient estimates are relative to year 0. 95% confidence intervals are indicated by the solid lines.

Figure 3: Geographical Distribution of Hospitals Exposed to the Stress Tests

This figure shows the number of hospitals exposed to bank stress tests in different hospital referral regions (HRRs). Grey areas represent the control group.



Online Appendix
(For Online Publication)

A Additional Results

A.1 Heterogeneity Tests

In this section, we provide more detail regarding the heterogeneity tests discussed in Section 6, including differential responses due to hospital characteristics, such as market power, cash reserves, or system status, or through heterogeneous exposure to the treatment.

A.1.1 Heterogeneity in Hospital Responses

As mentioned in Section 6, we consider possible heterogeneity in responses based on hospital market power and competition. To measure market power, we first calculate each hospital system's inpatient revenues as a fraction over total inpatient revenues within that hospital's referral region (HRR) prior to the shock. We then interact our main treatment variable with $\textit{High Revenue Share}_i$, which is an indicator variable equal to one if hospital i's system's share of inpatient revenues in its respective HRR is above the sample median, and zero otherwise. In Appendix Table A.13, we see that hospitals that are part of systems which hold a greater fraction of their HRR's inpatient revenues prior to the shock generally exhibit a stronger response to the tighter credit constraints. This differential response is possibly due to less competition in these HRRs—hospitals which hold a greater share of revenues may face less competition from other hospitals. As such, these affected hospitals can more easily change their operating decisions with less risk of losing patients to competitor hospitals. Moreover, hospitals with less competition can more easily build stronger ties with physician practices to increase inpatient admissions through physician referrals.

Furthermore, we explore heterogeneity in responses based on hospital cash holdings prior to the stress tests; hospitals which have greater cash balances prior to the tighter credit constraints can rely more on internal reserves, allowing for an alternative to debt financing and thus incurring a lower cost to the stress tests. We interact our main treatment variable with $\textit{High Cash}_i$, which is an indicator variable equal to one if hospital i's pre-shock cash balance (scaled by total assets) is above-median, and zero otherwise. The results, reported in Appendix Table A.14, indicate that affected hospitals with above-median cash holdings prior to the shock are better able to weather the rate increase and alter operating decisions less (thus mitigating deleterious effects on performance and health outcomes). Specifically, hospitals with more cash increase bed utilization and admissions to a lesser degree and have less severe (although still negative) effects on their quality of care.

Finally, we explore heterogeneity in hospital responses based on location (rural vs. urban) and whether the hospital belongs to a large system. These results are presented in Appendix Tables A.15–A.17. We find slightly weaker operating responses by hospitals in more rural areas and no distinguishable difference in responses from hospitals in large relative to small systems.

A.1.2 Treatment Heterogeneity

To further validate that our results are driven by a credit supply channel, we explore heterogeneity in affected hospitals' treatment exposure to bank stress tests. In particular, if the credit supply channel is at play, we would expect our results to be stronger for affected hospitals borrowing from banks that are more affected by stress tests.

To examine this, we first exploit the fact that lenders vary in their stress test performance. Banks that are closer to the regulatory minimum tend to reduce their credit supply more, thus generating greater financial pressure for the hospitals they lend to. Following Cortés et al. (2020), we calculate the minimum stress-test distance (msd), which measures how far a tested bank is from the regulatory minimum (with a higher msd indicating that it is farther from this threshold):

$$msd = \min(\textit{Tier 1 capital} - 6\%, \textit{Risk-based capital} - 8\%, \textit{Stressed leverage} - 4\%). \quad \text{(A.1)}$$

The logic behind equation (A.1) is as follows. The Dodd-Frank Act sets a different regulatory threshold for three capital ratios (6% for the tier 1 ratio; 8% for the total risk-based capital ratio; and 4% for the leverage ratio). We calculate the distance that each stress-tested bank is from these regulatory minimum thresholds, and then use minimum distance out of these three measures. This captures how binding the stress test is for each affected bank across the different regulatory measures.[68] For each treated hospital i, we calculate the average msd for all of its stress-tested lenders, weighted by loan amount. We then re-run equation (1), but split our treatment variable into two separate variables which indicate whether a hospital was exposed to a stress test through a bank that was close to the threshold or far from the threshold. To examine heterogeneity in terms of exposure to the treatment specifically, in the following specifications we split the treatment into two groups to separately compare the response of each group relative to the control group (rather than with an interaction as in the previous analyses). More specifically, we define $CloseExposed_{i,t-1}$ to take a value of one if hospital i was exposed to a stress-tested bank in year $t-1$ or earlier *and* the average msd of its stress-tested lenders was below-median, and zero otherwise. Similarly, $FarExposed_{i,t-1}$ takes a value of one if hospital i was exposed to a stress-tested bank in year $t-1$ or earlier and the average msd of its tested lenders was above-median, and zero otherwise.

Table 13 shows that the baseline effects are centered around the hospitals that are exposed to stress tests through banks closer to the threshold. The economic magnitudes in the close-bank subgroup are very similar to the estimates in Sections 4.2 and 4.3. In contrast, the effects for the far-bank subgroup are weaker—the coefficients are either insignificant or of a much smaller magnitude.

A final source of treatment heterogeneity that we explore is related to the fact that hospitals can have lending relationships with more than one bank. In particular, if a hospital is borrowing from multiple banks, then it will be more affected when stress tests affect a greater fraction of the hospital's bank relationships. Furthermore, if a hospital is left with,

[68] Cortés et al. (2020) note that in 42% of tests, the Tier 1 ratio is closest to the minimum; 26% of the time, the total risk-based capital is closest to binding; and, 64% of the time, the leverage ratio is most likely to bind.

say, only one unaffected relationship lender, it allows that lender to exploit its superior information and extract monopoly rents through future loans. This hold-up problem would increase borrowing costs for the hospital (Sharpe (1990), Rajan (1992)). Following this logic, we divide each treated hospital's loan amount from stress-tested lenders by its total (non-matured) loan amount, and run a similar specification splitting the treatment variable into $\textit{High Amount Exposed}_{i,t-1}$ and $\textit{Low Amount Exposed}_{i,t-1}$, which take a value of one if hospital i was exposed in year $t-1$ or earlier and its stress-tested loan fraction is above or below 50%, respectively, and zero otherwise. Table A.18 provides the results, which confirm that hospitals with a greater portion of their total loans from stress-tested banks exhibit more pronounced responses to the tightened credit constraints.

A.2 Robustness

In this section, we provide and discuss various robustness tests.

A.2.1 Controlling for Regional Differences

A potential concern with our results is that they are influenced by the geographical region that a hospital is located in. For example, if hospitals that are borrowing from banks tend to be geographically clustered, and the number of patients in such areas dramatically increased after 2012, then we may obtain similar baseline results unrelated to stress tests and negative credit supply.[69] Alternatively, local economic conditions in an area may affect both bank lending and hospital outcomes, thus potentially confounding the channels that we aim to identify.[70]

To address these concerns, we examine whether our main results are likely to be driven by geographical clustering. More specifically, we map each hospital's location to a hospital referral region (HRR), which we obtain from the Dartmouth Atlas database. These regions are composed of zip codes grouped together based on the referral patterns for tertiary care for Medicare beneficiaries. The United States is divided into 306 HRRs. The geographical distribution of affected hospitals is provided in Figure 3. As the figure shows, we do not find a systematic clustering of hospitals exposed to stress tests, since these hospitals are mostly dispersed across the U.S.[71] Furthermore, this figure shows that, within a particular state or

[69]The literature has shown that geographical variation can matter in terms of explaining differences in healthcare market outcomes (Chandra and Staiger (2007), Gottlieb et al. (2010), Finkelstein et al. (2016)). Furthermore, our sample period includes the enactment of the Patient Protection and Affordable Care Act (ACA), which provides low-income residents with expanded access to health insurance. After a U.S. Supreme Court ruling in June 2012, states gradually expanded their Medicaid programs over time, which studies have shown increased hospital revenues and decreased the probability of hospital closures, e.g., Duggan et al. (2019) and Lindrooth et al. (2018). Thus, if stress test-exposed hospitals are geographically clustered within areas that experienced Medicaid expansion, this has the potential to explain some of our results. However, we note that Borgschulte and Vogler (2020) find evidence of improved healthcare quality due to the ACA, which is inconsistent with this channel driving our results.

[70]We note that this latter channel is unlikely to explain our results, since the affected banks in our sample are large national banks.

[71]Although the Houston and Los Angeles areas have the largest number of affected hospitals, their closest neighbor regions all tend to have low exposure and thus can serve as suitable local control groups.

even within an HRR, there is variation in terms of our treatment, suggesting that our effects cannot be fully explained by changes occurring at different geographical levels.

However, to formally control for time-varying geographic effects, we also include *HRR* $\times$ *year* fixed effects in our main specifications. The variation from these regressions therefore comes from differences between treated and control hospitals in a given year *within* the same geographical area. Table A.19 provides the estimation results and confirms that our results are robust to controlling for time-varying geographical conditions.

A.2.2 Sample Composition

We now consider a number of robustness checks related to the composition of our sample.

Hospital systems. A concurrent trend after 2010 in healthcare markets is that healthcare systems and organizations engaged in more mergers and acquisitions (M&A). Hospital mergers generate local market concentration, which tends to reduce healthcare quality while increasing prices (see Gaynor et al. (2015) for review). Furthermore, M&A transactions can be funded with external debt financing, which generates a concern that the baseline effects we find are due to this consolidation process; in other words, we are potentially capturing differential operating trends between large healthcare system branches and independent hospitals.

We examine a number of robustness checks to establish that our results are not driven by effects related to hospital systems. First, we find no significantly different response between hospitals that are part of a large hospital system compared to a smaller one (Appendix Tables A.16 and A.17). Second, our results are robust to dropping hospitals that are part of systems with more than five members, indicating that our results are not concentrated among hospitals within large systems (Appendix Table A.20).

Bank loan borrowing. We next examine robustness of the sample composition in terms of the borrowing behavior of hospitals in our sample. One concern is that hospitals exposed to the stress tests through their lenders may not be as affected by the tightened credit constraints if they are able to find alternative sources of funding or can avoid taking bank loans after the stress tests. While our results in Table 3 help to mitigate this concern, we provide further robustness by restricting our treatment hospitals to those that took out new loans following exposure to the stress tests in the post-period. As noted in Section 2, 79% of treated hospitals borrowed new loans following exposure. In Appendix Table A.21, we see that the results are similar to that of our main tests.

We similarly consider a subsample of hospitals (both treatment and control) restricted to those that borrowed from commercial banks. The results of this analysis are presented in Appendix Table A.22, indicating similar results as in our main analysis.

Hospital ownership. Finally, we restrict our sample to only for-profit hospitals to examine the differential responses by our treated for-profit hospitals relative to other hospitals with for-profit status. Panel B of Appendix Table 12 reports the results. The findings are similar to those of our main analysis as well as the heterogeneity test results reported in Panel A of Table 12.

A.2.3 Placebo Test – Rival Hospitals

As a placebo test, we consider the responses by hospitals that are within the same city as hospitals exposed to the stress tests, but who are themselves *not affected* by the shock. In other words, we consider the effect on local non-exposed hospitals from a rival's tightened credit constraints as a placebo test. We examine this test with the following specification:

$$Y_{i,t} = \alpha + \beta NearExposed_{i,t-1} + \gamma' Controls_{i,t-1} + \eta_t + \mu_i + \varepsilon_{i,t}. \tag{A.2}$$

$NearExposed_{i,t-1}$ is equal to one if hospital i is in the same city as a hospital exposed to the stress tests by year $t-1$, and hospital i itself is not affected. We additionally drop all hospital-year observations of hospitals exposed to the stress tests. Specification (A.2) is otherwise the same as our main specification (1). The results are presented in Appendix Table A.23. We find that rival hospitals largely do not exhibit significant responses to their local competitor's credit shock. Overall, the results from this falsification test imply that only affected hospitals respond to the credit supply shock. Moreover, an additional implication of this analysis is that it finds evidence against a broader negative shift in health outcomes among hospitals within the same city as affected hospitals.

A.2.4 Other Stress Test Robustness

We next discuss additional robustness related to the implementation of stress tests. In addition to the Dodd-Frank Act stress tests (DFAST) there were also other stress test programs implemented in the years prior. While the DFA implemented stress test requirements for large banks as a matter of law, the Federal Reserve began to more closely monitor the capital adequacy of the largest banks during the 2008–2009 financial crisis. In particular, the Federal Reserve initiated the Supervisory Capital Assessment Program (SCAP) in February 2009, which implemented one-time preliminary stress tests on the nineteen U.S. banks with assets of at least $100 billion in order to ensure solvency of the banking sector following the collapse of Lehman Brothers. Ten of the banks were required to raise additional capital, either privately or through the U.S. Treasury's Capital Assistance Program (only one bank used the latter). Subsequently, the Federal Reserve initiated the Comprehensive Capital Analysis and Review (CCAR) program in 2011 to ensure that the nineteen largest banks had enough capital to resume capital distributions to investors through dividend payments and share repurchases (Board Gov. Fed. Reserve Syst. (2011), Hirtle (2014), Hirtle and Lehnert (2015)).

The DFAST differs from both the 2009 SCAP and the 2011 CCAR. As noted above, the SCAP was implemented during an emergency period to prevent collapse of the financial system.[72] The CCAR is intended for stronger governance and supervision of bank capital planning, as banks must develop formal guidelines for capital distribution, and the Federal Reserve can object to such plans. As such, the original aim of the 2011 CCAR was to provide additional oversight regarding capital distributions to shareholders of the largest banks.[73] In

[72]Moreover, Morgan et al. (2014) find no significant stock market responses to the disclosure of SCAP results, which suggests that the program did not bring significant new information to the market.

[73]See, e.g., "Revised Temporary Addendum to SR letter 09-4: Dividend Increases and Other Capital Distributions for the 19 Supervisory Capital Assessment Program Bank Holding Companies." November 17,

contrast to these two prior programs, the DFA was passed by the U.S. Congress and signed into law, and served as the country's central legislation regarding stress tests. Moreover, the aim of the DFAST is to ensure the financial health of individual banks and the banking system. Accordingly, the DFAST applied to a wider set of banks and, with its "severely adverse scenario" tests, carried a stricter examination than the 2011 CCAR. (The CCAR has since evolved to be run jointly with DFAST.)

We argue that using DFAST is appropriate for our setting due to the fact that DFAST applied to a wider set of banks and had more formal legal and regulatory ramifications. It is possible, however, that the SCAP and CCAR tests also elicited similar responses. We examine the effects of these tests further and our results suggest that this is not the case. In terms of SCAP, while we cannot formally test its effects due to our data only being consistently available after 2010, it is unlikely that SCAP drives our main results. In our sample, one third of the affected hospitals had non-matured loans with SCAP participants in 2009. Furthermore, we see no indication of an effect in our pre-treatment period from the parallel trend graphs, suggesting that SCAP did not generate any significant effect on our outcome variables. In terms of CCAR, it is plausible that some of our effects are driven by these stress tests given that they occur so close to DFAST. As a robustness test, we also include CCAR stress tests when defining our treatment. We find similar results, but with lower economic magnitudes and significance, suggesting that CCAR generates a smaller effect than the DFAST stress tests. The results are provided in Appendix Table A.24.

A.3 CMS Risk-Standardization

In this section, we provide details regarding the risk-adjustment calculations made by CMS to the hospital-level quality of care variables, such as readmission and mortality rates, we consider in Section 4. We also discuss this risk adjustment in light of a changing mix of patients. The discussion regarding CMS's empirical model draws from Centers for Medicare & Medicaid Services (2023a,b), which can be found on the CMS website.

When determining its measures, CMS adjusts for patient age, comorbid diseases, and indicators of patient frailty (and, for some measures, gender and race). CMS adjusts for these factors as follows. Consider readmission rates. CMS first regresses the patient characteristics mentioned above on the (log) probability of readmission for a given patient with these characteristics in a given year, and determines a hospital-specific effect (i.e., estimates a hospital fixed effect). CMS then uses the estimated values to make comparisons relative to an estimated counterfactual based on how the average hospital would perform with these same patient characteristics. For example, for readmissions, following the first stage regression analysis, CMS calculates the ratio

$$\hat{s}_i = \frac{\sum_{j=1}^{n_i} \hat{p}_{ij}}{\sum_{j=1}^{n_i} \hat{e}_{ij}}, \tag{A.3}$$

which CMS refers to as the standardized readmission ratio. The term $\hat{p}_{ij}$ is the fitted value for the likelihood of readmission based on the coefficient estimates and the estimated id-

2010. Available at: http://www.federalreserve.gov/boarddocs/srletters/2009/SR0904_Addendum.pdf.

iosyncratic hospital fixed effect for hospital i from the cross-sectional regression (j indexes patients). The term $\hat{e}_{ij}$ uses the same coefficient estimates from the regression, but instead uses the *population* mean fixed effect, determined from the entire sample of hospitals. As such, the standardized readmission ratio measures the divergence for hospital i's log likelihood of readmission relative to an estimated counterfactual readmission likelihood for the average hospital with this same set of patient characteristics. Hospitals with a systematic effect greater than the national rate will have a ratio above one, while those with a lower estimated systematic effect will have a ratio below one. CMS then multiples this ratio with the observed sample readmission rate to get the risk-standardized readmission rate for hospital i. (For more detail on the empirical specification used by CMS, see Centers for Medicare & Medicaid Services (2023a,b).)

With this analysis, CMS is essentially controlling for patient-specific risk factors that contribute to the likelihood of readmission, and then comparing the hospital-specific effect to the mean systematic effect for all hospitals within the sample. A changing mix of patients, such as a larger fraction of patients that have no comorbidities, therefore should not affect the systematic hospital factor, conditional on the quality of the services the hospitals provide staying the same. Moreover, a larger share of healthier (i.e., less risky) patients should imply a lower readmission rate under this calculation, given that less-risky patients have an ex ante lower likelihood of readmission.

Thus, with the same log-likelihood of readmission conditional on patient characteristics, a greater admitted volume of patients by itself should not have any effect on the hospital-specific factor for readmission, conditional on the quality of hospital services remaining constant. As such, a higher readmission rate, as calculated by CMS, implies that hospital service quality is changing. Moreover, admitting patients who have an ex ante lower likelihood of readmission—who previously would not have met the standard for hospitalization due to, for example, a milder condition within the same DRG—but have a similar risk profile to other patients within the DRG, should, all else being equal, result in a *lower* readmission rate (due to a lower percentage of patients eventually requiring readmission). Improving the composition of patients could therefore have a positive impact on improving the calculated readmission rates.

A.4 Appendix Tables and Figures

Table A.1: Variable Definitions and Summary Statistics

This table presents summary statistics for the variables used in this study. Panels A, B, C, and E are at the hospital-year level. Panel D is at the hospital-DRG-year level. Variables in Panels B through E are from 2010 to 2016; statistics for the financial variables in Panel A are from 2007 to 2016, as a number of these variables are used as control variables in estimating specification (2).

Variable	Definition	N	Mean	Std	P25	Median	P75
Panel A: Financial Variables from HCRIS							
Profit Margin	Profit margin	36,871	0.032	0.283	−0.009	0.038	0.092
TA	Total assets ($ million)	38,584	208.865	473.230	24.725	75.030	214.807
Income	Sum of net patient revenue and total other income ($ million)	34,559	164.926	224.391	24.961	80.525	210.819
Net Income	Income minus total costs ($ million)	37,342	8.01	15.785	−0.417	2.124	12.129
Liabilities/TA	Total liabilities over total assets	34,526	0.565	0.516	0.248	0.467	0.724
Cash/TA	Cash holdings over total assets	34,042	0.073	0.117	0.002	0.034	0.099
Patient Revenue	Total patient revenue ($ million)	37,342	555.005	901.017	62.933	239.742	693.586
Bed Utilization	Proportion of time a hospital bed is occupied in a year	34,988	0.443	0.231	0.263	0.450	0.614
Discharge Rate	Inpatient discharges over total beds	34,995	41.933	19.545	29.120	43.577	54.601
CMI	Case mix index	22,192	1.508	0.315	1.297	1.488	1.685
Medicare Pct	Percent of Medicare discharge out of all discharges	31,518	0.404	0.100	0.302	0.392	0.491
Medicaid Pct	Percent of Medicaid discharge out of all discharges	30,152	0.120	0.0100	0.043	0.091	0.171
Panel B: Readmission and Mortality Measures from Hospital Compare							
Pneumonia Readmissions	Number of pneumonia patients readmitted	24,450	18.953	16.495	6.837	14.156	26.283
Heart Failure Readmissions	Number of heart failure patients readmitted	23,191	26.100	26.645	7.030	17.559	36.018
AMI Readmissions	Number of AMI patients readmitted	15,011	13.062	12.609	4.084	9.099	17.467
Pneumonia Readmission Rate	Rate of PN patients readmitted	24,450	0.173	0.014	0.163	0.172	0.181
Heart Failure Readmission Rate	Rate of HF patients readmitted	23,191	0.225	0.019	0.213	0.223	0.237
AMI Readmission Rate	Rate of AMI patients readmitted	15,011	0.174	0.017	0.163	0.172	0.183
All Readmission Rate	Rate of all major-disease patients readmitted	18,732	0.155	0.009	0.149	0.154	0.160
All Readmissions Worst	Flagged as being in the worst group for readmitting patients	20,583	0.079	0.270	0.000	0.000	0.000
Pneumonia Mortality Num	Pneumonia patient mortality number	24,390	14.512	12.997	5.195	10.391	19.685
Pneumonia Mortality Rate	Pneumonia patient mortality rate	24,390	0.139	0.025	0.120	0.138	0.157
Pneumonia Mortality Worst	Flagged as being in the worst group for pneumonia patient mortality	24,891	0.053	0.224	0.000	0.000	0.000
Heart Failure Mortality Num	Heart failure patient mortality number	22,830	11.226	10.601	3.420	7.935	15.400
AMI Mortality Num	AMI patient mortality number	16,574	9.398	8.244	3.308	7.032	12.733

(continued)

Panel C: Patient Satisfaction Measures from HCAHPS							
Overall Rating	Percentage of patients giving the highest rating for overall care quality	22,128	0.702	0.089	0.650	0.700	0.760
Pain Control	Percentage of patients giving the highest rating for pain control	22,118	0.703	0.055	0.670	0.700	0.730
Recommend	Percentage of patients giving the highest rating for recommendation to others	22,127	0.710	0.097	0.650	0.710	0.780
Cleanliness	Percentage of patients giving the highest rating for cleanliness	22,129	0.726	0.076	0.680	0.720	0.770
Doctor Communication	Percentage of patients giving the highest rating for doctor communication	22,129	0.809	0.052	0.780	0.810	0.840
Nurse Communication	Percentage of patients giving the highest rating for nurse communication	22,129	0.783	0.056	0.750	0.780	0.820
Recovery Information	Percentage of patients giving the highest rating for recovery information	22,126	0.853	0.046	0.830	0.860	0.880
Quietness	Percentage of patients giving the highest rating for quietness	22,129	0.600	0.101	0.530	0.590	0.660
Panel D: Hospital DRG Variables from HCUP							
Admissions	Number of admissions assigned to a given DRG in a hospital	1,706,357	31.756	125.327	3.000	7.000	22.000
Physician Order Admissions	Number of admissions via physician orders	1,456,702	22.811	86.353	2.000	5.000	17.000
ER Order Admissions	Number of admissions via physician orders that come from emergency rooms	1,456,702	15.900	55.727	1.000	3.000	11.000
Elective Admissions	Number of admissions via physician orders that are elective	1,456,702	4.241	44.758	0.000	0.000	1.000
Clinic Admissions	Number of admissions through clinics and physician centers	1,456,702	2.704	26.851	0.000	0.000	1.000
Transfer Admissions	Number of admissions transferred from other healthcare facilities	1,456,702	4.198	65.367	0.000	0.000	1.000
Private Admissions	Admission amount for privately insured patients	1,706,357	9.825	62.097	0.000	2.000	5.000
Medicare Admissions	Admission amount for Medicare patients	1,706,357	12.941	37.934	1.000	3.000	10.000
Medicaid Admissions	Admission amount for Medicaid patients	1,706,357	6.606	49.371	0.000	1.000	3.000

(continued)

Avg Num Procedures	Average number of procedures for each case in a DRG	1,697,998	2.021	2.130	0.500	1.455	2.855
Private Avg Num Procedures	Average number of procedures for privately insured patients	1,228,183	1.973	2.242	0.400	1.308	2.833
Medicare Avg Num Procedures	Average number of procedures for Medicare patients	1,449,327	1.974	2.183	0.417	1.333	2.833
Medicaid Avg Num Procedures	Average number of procedures for Medicaid patients	931,681	1.889	2.326	0.250	1.000	2.600
Avg Length of Stay	Average length of stay per case in a DRG	1,706,353	5.357	4.971	2.667	4.000	6.400
Private Avg Length of Stay	Average length of stay for privately insured patients	1,228,183	4.800	5.220	2.000	3.333	5.571
Medicare Avg Length of Stay	Average length of stay for Medicare patients	1,449,327	5.576	4.897	3.000	4.273	6.778
Medicaid Avg Length of Stay	Average length of stay for Medicaid patients	931,681	5.748	7.765	2.167	3.667	6.333
Admissions per Physician	Average number of admissions attended by each physician	1,285,642	2.301	6.193	1.000	1.273	1.973
Physicians per Patient	Average number of physicians involved in each admission	1,706,357	1.093	0.732	1.000	1.150	1.583
Unique Physicians	Number of unique physicians serving patients in a DRG	1,706,357	7.923	14.090	1.000	3.000	9.000
Panel E: Timely and Effective Care Measures from Hospital Compare							
Aspirin	Percentage of AMI Patients receiving Aspirin at Discharge	10,282	0.979	0.069	0.990	1.000	1.000
PCI	Percentage of AMI Patients receiving PCI within 90 mins of Arrival	6,603	0.935	0.097	0.920	0.960	1.000
Statin Rx	Percentage of AMI Patients receiving Statin Rx at Discharge	7,374	0.968	0.068	0.970	0.990	1.000
LVS	Percentage of HF Patients receiving LVS	15,028	0.965	0.111	0.980	1.000	1.000
ACE/ARB	Percentage of HF Patients receiving ACE/ARB at Discharge	12,146	0.952	0.092	0.940	0.980	1.000
Antibiotic	Percentage of PN Patients receiving appropriate antibiotic at Discharge	15,286	0.941	0.082	0.930	0.960	0.990

Table A.2: Summary Statistics for the Propensity Score Matched Sample

This table provides the summary statistics for the propensity score matched sample in 2011 (the last year before the DFAST announcement).

	Control Obs.	*Treat Obs.*	*Mean of Control*	*Mean of Treat*	*Diff.*	*t-stat*	*p-value*
Net Income/TA	659	351	0.067	0.076	−0.009	−0.650	0.509
Total Assets ($ millions)	659	353	195.427	186.633	8.794	0.600	0.535
Patient Revenue/TA	659	353	4.790	4.893	−0.103	−0.500	0.634
Log(Income)	659	353	18.653	18.710	−0.058	−0.700	0.479
Liabilities/TA	659	353	0.590	0.580	0.010	0.250	0.808
Cash/TA	659	353	0.042	0.043	−0.001	−0.150	0.886
Discharges	659	353	9991.740	10130.112	−138.372	−0.200	0.829
Number of Beds	659	353	199.937	204.432	−4.496	−0.400	0.678
For-profit (Dummy)	659	353	0.328	0.366	−0.038	−1.200	0.229
System Affiliated (Dummy)	659	353	0.987	0.986	0.001	0.050	0.948
Log(Pnuemonia Readmissions)	609	326	2.752	2.755	−0.004	−0.100	0.937
Log(Pnuemonia Mortality Num)	609	325	2.334	2.330	0.004	0.100	0.930
Overall Rating	637	342	0.671	0.669	0.003	0.500	0.609

Table A.3: Effects of Stress Tests on Hospital and Non-Hospital Loans

This table provides the regression results for comparing the effects of stress tests on hospital and non-hospital loans. Each observation represents a loan facility k, borrowed by borrower i from bank j in year t. $Tested_{j,t-1}$ takes a value of 1 if bank j is tested in year $t-1$ or earlier, and 0 otherwise. A hospital lender is a bank that has ever provided a loan to a hospital during our sample period. $Hospital_i$ is 1 if the borrower i is a hospital, and 0 otherwise. $Spread\&Fee$ is the interest rate (in basis points) spread over LIBOR plus fees on the drawn portion of the loan. $LogAmt$ is the logarithm of the loan facility amount. Control variables include borrower i's logarithm of total assets, profitability (income over total assets), liabilities (total liabilities over total assets), and tangibility (total fixed assets over total assets). Year, bank, and borrower fixed effects are included. Heteroskedasticity-robust standard errors are provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	All Lenders		Hospital Lenders	
	(1)	(2)	(3)	(4)
	Spread&Fee	*Log(Loan Amount)*	*Spread&Fee*	*Log(Loan Amount)*
$Tested_{j,t-1}$	13.882**	−0.008	12.132*	−0.001
	(6.550)	(0.017)	(6.720)	(0.018)
$Tested_{j,t-1} \times Hospital_i$	34.891*	−0.100*	35.598*	−0.098*
	(19.269)	(0.056)	(19.241)	(0.056)
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y
Borrower FE	Y	Y	Y	Y
N	44,311	47,830	40,102	43,276
Adj R^2	0.51	0.69	0.51	0.69

Table A.4: Hospital Municipal Bonds Issuance Costs in the Counties with Stress Tests Exposure

This table shows that bond issuance costs in the counties with hospitals exposed to stress-tested banks are not affected during the sample period (2010–2016). The unit of observation is a bond upon issuance. $Yield_{k,t}$ is the size-weighted transaction yield at the bond-month level. $Spread_{k,t}$ is the spread to maturity-matched after-tax Treasury rates, and $SpreadMMA_{k,t}$ is the spread to maturity-matched yields from the Municipal Market Advisors AAA-rated curve. All outcome variables are in basis points (bps). $ExposedCounty_{k,l,t}$ takes a value of one if bond k is issued in a county l such that at least one hospital in this county was exposed to a stress test by year t, and 0 otherwise. *Controls* include bond characteristics and county fundamentals. Bond characteristics include: coupon rate, maturity, and the inverse of maturity, log issue size, corresponding Treasury yield, credit rating at the time of issuance, a dummy variable denoting whether it is a GO bond, and indicator variables for each of whether the bond is callable, insured, reoffered, or negotiated. County fundamentals include population level, per capita income, population growth, employment growth, and labor participation. *State-Month FE* are state by year-month fixed effects. *HRR-Month FE* are the hospital referral region by year-month fixed effects. Standard errors are clustered by state year-month, and provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) *Yield*	(2) *Yield*	(3) *Spread*	(4) *Spread*	(5) *SpreadMMA*	(6) *SpreadMMA*
$ExposedCounty_{k,l,t}$	−0.296	2.374	−0.396	1.886	2.671	9.308
	(7.400)	(15.933)	(7.472)	(16.259)	(7.318)	(20.917)
Controls	Y	Y	Y	Y	Y	Y
State-Month FE	Y	Y	Y	Y	Y	Y
HRR-Month FE	N	Y	N	Y	N	Y
N	17,802	17,792	17,802	17,792	17,802	17,792
Adj. R^2	0.95	0.96	0.88	0.89	0.85	0.87

Table A.5: Hospital Capital Expenditures, Total Beds, Bad Debts, and Additional Financial and Operating variables

This table provides regression results for equation (1), focusing on hospital capital expenditures, investments, bad debt expenses, and additional financial and operational variables. $Net\,Income$ is hospital net income (in \$ millions). *Net Patient Income* is the net income from patient services, defined net patient revenue minus operating expenses. *Net Patient Income*/TA is net patient income over total assets. $Fixed\,Assets/TA$ is fixed assets over total assets. $Buildings/TA$ is the book value of building construction over total assets. $Total\,Beds$ is the total number of hospital beds. *BadDebt/TA* is the total amount of hospital bad debt over total assets. *Log(Bad Debt)* is logged (one plus) bad debts. *Log(Inpatient Revenue)* and *Log(Outpatient Revenue)* are the logarithm of total revenues from inpatient and outpatient services, respectively. $STExposed$ takes a value of 1 if at least one of hospital i's relationship banks experienced a stress test in year $t-1$ or earlier, and 0 otherwise. Control variables include the lagged logarithm of one plus available bed days ($LogBedDay_{i,t-1}$) and lagged cash holdings over total assets ($Cash/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) *Net Income*	(2) *Net Patient Income/TA*	(3) *Net Patient Income*	(4) *Fixed Assets/TA*	(5) *Buildings/TA*	(6) *Total Beds*	(7) *Bad Debt/TA*	(8) *Log(Bad Debt)*	(9) *Log(Inpatient Revenue)*	(10) *Log(Outpatient Revenue)*
$STExposed_{i,t-1}$	1.121**	0.021**	1.484***	−0.007	−0.024**	0.985	−0.003**	−0.084***	0.091***	0.066*
	(0.519)	(0.008)	(0.516)	(0.006)	(0.010)	(1.393)	(0.001)	(0.027)	(0.029)	(0.037)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	23,818	23,230	23,818	23,043	21,365	23,296	19,433	19,697	23,817	23,817
Adj R^2	0.76	0.58	0.75	0.73	0.73	0.98	0.70	0.85	0.95	0.81

Table A.6: Additional Results for the Propensity Score Matched Sample

This table replicates the results of Tables 5 (Panels A and B) and 6 (Panel C) on the propensity score matched sample. Control variables include the lagged logarithm of one plus available bed days ($Log(Bed\,Days_{i,t-1})$) and lagged cash holdings over total assets ($Cash/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Readmission

	(1) *Log(Pneumonia Readmissions)*	(2) *Log(Heart Failure Readmissions)*	(3) *Log(AMI Readmissions)*	(4) *Pneumonia Readmission Rate*	(5) *Heart Failure Readmission Rate*	(6) *AMI Readmission Rate*	(7) *All Readmission Rate*	(8) *All Readmissions Worst*
$STExposed_{i,t-1}$	0.064***	0.032**	0.013	0.002***	0.002**	0.002***	0.001***	0.030*
	(0.015)	(0.014)	(0.017)	(0.001)	(0.001)	(0.001)	(0.000)	(0.017)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y	Y	Y
N	7,258	7,039	5,034	7,607	7,437	5,553	5,511	5,694
Adj R^2	0.96	0.97	0.96	0.71	0.76	0.82	0.67	0.45

Panel B: Mortality

	(1) *Log(Pneumonia Mortality Num)*	(2) *Log(Heart Failure Mortality Num)*	(3) *Log(AMI Mortality Num)*	(4) *Pneumonia Mortality Num*	(5) *Pneumonia Mortality Rate*	(6) *Pneumonia Mortality Worst*
$STExposed_{i,t-1}$	0.068***	0.016	0.018	0.824**	0.002**	0.033***
	(0.015)	(0.012)	(0.015)	(0.415)	(0.001)	(0.012)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	7,250	6,960	5,500	7,250	7,607	7,639
Adj R^2	0.96	0.97	0.96	0.90	0.85	0.35

Panel C: Patient's Perspective

	(1) *Overall Rating*	(2) *Pain Control*	(3) *Recommend*	(4) *Cleanliness*	(5) *Doctor Communication*	(6) *Nurse Communication*	(7) *Recovery Information*	(8) *Quietness*
$STExposed_{i,t-1}$	−0.006***	−0.006***	−0.006**	−0.006**	−0.006***	−0.003**	−0.003**	−0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.003)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y	Y	Y
N	6,696	6,696	6,696	6,696	6,696	6,696	6,696	6.696
Adj R^2	0.80	0.55	0.86	0.69	0.77	0.77	0.75	0.84

Table A.7: Coefficient Estimates for Control Variables

This table provides estimation results for equation (1), listing the coefficients of the control variables. *Profit Margin* is profit margin, defined as $(Income - Cost)/Income$. *Bed Utilization* is the average daily fraction of hospital beds that are occupied. *Discharge Rate* is inpatient discharges over total bed days. *All Readmission Rate* is the readmission rate for all diseases. *Antibiotic* measures the share of pneumonia patients receiving the most appropriate antibiotic. *Overall Rating* is the share of patients that give the highest rating to questions on overall care quality. $STExposed$ takes a value of 1 if at least one of hospital i's relationship banks experienced a stress test in year $t-1$ or earlier, and 0 otherwise. Control variables include the lagged logarithm of one plus available bed days ($Log(Bed\,Days_{i,t-1})$) and lagged cash holdings over total assets ($Cash/TA_{i,t-1}$). Standard errors are clustered at the hospital system level and provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) *Profit Margin*	(2) *Bed Utilization*	(3) *Discharge Rate*	(4) *All Readmission Rate*	(5) *Antibiotic*	(6) *Overall Rating*
$STExposed_{i,t-1}$	0.011*	0.023***	2.398***	0.002***	−0.008***	−0.008***
	(0.006)	(0.004)	(0.409)	(0.000)	(0.002)	(0.002)
$Log(Bed\,Days_{i,t-1})$	0.081***	−0.060***	−4.711***	0.000	0.008	-0.004
	(0.030)	(0.009)	(0.901)	(0.000)	(0.012)	(0.003)
$Cash/TA_{i,t-1}$	0.034	0.023**	0.540	0.000	−0.008	0.001
	(0.036)	(0.011)	(1.173)	(0.001)	(0.013)	(0.007)
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	23,804	23,269	23,267	18,773	15,126	21,372
Adj R^2	0.21	0.94	0.80	0.67	0.58	0.82

Table A.8: Hospital Care Quality: Patient Severity and Composition

This table provides the estimation results for equation (1), focusing on hospital patient severity and composition. *CMI* is the hospital's Case Mix Index. *Medicare Pct* is the percent of Medicare discharge out of all discharges. *Medicaid Pct* is the percent of Medicaid discharge out of all discharges. *STExposed* takes a value of 1 if at least one of hospital i's relationship banks experienced a stress test in year $t-1$ or earlier, and 0 otherwise. Control variables include the lagged logarithm of one plus available bed days ($Log(Bed\,Days_{i,t-1})$) and lagged cash holdings over total assets ($Cash/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) *CMI*	(2) *Medicare Pct*	(3) *Medicaid Pct*
$STExposed_{i,t-1}$	−0.011**	−0.008***	−0.005*
	(0.005)	(0.002)	(0.003)
Controls	Y	Y	Y
Year FE	Y	Y	Y
Hospital FE	Y	Y	Y
N	18,638	23,233	22,108
Adj R^2	0.93	0.92	0.78

Table A.9: Hospital DRG Admission Decisions based on Selected DRGs

This table provides the regression results for equation (4) for DRG admission decisions based on two DRGs. $STExposed$ takes a value of 1 if at least one of hospital i's relationship banks experienced a stress test in year $t-1$ or earlier, and 0 otherwise. Columns (1) and (2) study the admission and the average amount of charges per case for heart attack claims (DRGs 280, 281, and 282). Columns (3) and (4) study the admission and the average amount of charges per case for childbirth claims (DRGs 765, 766, 767, and 768). Hospital-level control variables include the lagged logarithm of one plus available bed days ($Log(Bed\,Days_{i,t-1})$) and lagged cash holdings over total assets ($Cash/TA_{i,t-1}$). Hospital-DRG level control variables include the lagged average patient age and percentages of patients that are female, white, black, and Hispanic. DRG-Year and Hospital-DRG fixed effects are included, as indicated. Standard errors are clustered at the hospital level and provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
DRGs	*Heart Attack*		*Childbirth*	
	Log(Admissions)	*Log(Avg Charges)*	*Log(Admissions)*	*Log(Avg Charges)*
$STExposed_{i,t-1}$	0.030	0.065*	0.040	−0.003
	(0.029)	(0.037)	(0.030)	(0.034)
Controls	Y	Y	Y	Y
DRG-Year FE	Y	Y	Y	Y
Hospital-DRG FE	Y	Y	Y	Y
N	12,107	12,107	10,101	10,101
Adj R^2	0.89	0.92	0.96	0.95

Table A.10: Hospital ED Inpatient Admission Heterogeneity

This table provides regression results for for DRG inpatient admission decisions that originated from the emergency department (ED). *STExposed* takes a value of 1 if at least one of hospital i's relationship banks experienced a stress test in year $t-1$ or earlier, and 0 otherwise. *Physician Order Admissions* is the number of admissions via physician orders. *ED Admissions* is the number of admissions via physician orders that originate from emergency rooms. *Pre ED Pct* is the average percentage of inpatient admissions coming from emergency rooms assigned DRG d to a treated hospital i across the years before the shock. Hospital-level control variables include the lagged logarithm of one plus available bed days ($Log(Bed\,Days_{i,t-1})$), and lagged cash holdings over total assets ($Cash/TA_{i,t-1}$). Hospital-DRG level control variables include the lagged average patient age and percentages of patients being female, white, black, and Hispanic. DRG-Year and Hospital-DRG fixed effects are included, as indicated. Standard errors are clustered at the hospital level and provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) *Log(Physician Order Admissions)*	(2) *Log(ED Admissions)*
$STExposed_{i,t-1}$	0.065*	0.108***
	(0.033)	(0.038)
$STExposed_{i,t-1} \times Pre\ ED\ Pct_{i,d}$	−0.033***	−0.028**
	(0.013)	(0.014)
Controls	Y	Y
DRG-Year FE	Y	Y
Hospital-DRG FE	Y	Y
N	1,401,182	1,401,182
Adj R^2	0.85	0.85

Table A.11: Hospital DRG Inpatient Charges

This table provides the regression results for equation (4) for DRG inpatient charges. $STExposed$ takes a value of 1 if at least one of hospital i's relationship banks experienced a stress test in year $t-1$ or earlier, and 0 otherwise. $Total\,Charges$ is the total amount of charges across all admissions in DRG d at year t. $Avg\,Charges$ is the average amount of charges per case in DRG d at year t. Columns (3), (4), and (5) study the average amount of charges per case for privately insured, Medicare and Medicaid patients, respectively. Hospital-level control variables include the lagged logarithm of one plus available bed days ($Log(Bed\,Days_{i,t-1})$) and lagged cash holdings over total assets ($Cash/TA_{i,t-1}$). Hospital-DRG level control variables include the lagged average patient age and percentages of patients that are female, white, black, and Hispanic. DRG-Year and Hospital-DRG fixed effects are included, as indicated. Standard errors are clustered at the hospital level and provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
Insurance:	*All*	*All*	*Private*	*Medicare*	*Medicaid*
	Log(Total Charges)	*Log(Avg Charges)*	*Log(Avg Charges)*	*Log(Avg Charges)*	*Log(Avg Charges)*
$STExposed_{i,t-1}$	0.063***	0.007	0.006	0.012	−0.003
	(0.023)	(0.013)	(0.013)	(0.013)	(0.012)
Controls	Y	Y	Y	Y	Y
DRG-Year FE	Y	Y	Y	Y	Y
Hospital-DRG FE	Y	Y	Y	Y	Y
N	1,651,990	1,651,955	1,161,686	1,388,557	859,807
Adj R^2	0.88	0.88	0.83	0.85	0.81

Table A.12: Hospital DRG Outcomes for Uninsured Patients

This table provides the regression results for equation (4) for inpatient charges, number of procedures, and length of stay for uninsured patients. *STExposed* takes a value of 1 if at least one of hospital i's relationship banks experienced a stress test in year $t-1$ or earlier, and 0 otherwise. *Avg Charges* is the average amount of charges per case in DRG d at year t. *Avg Num Procedures* is the average number of procedures for each case in DRG d at year t. *Avg Length of Stay* is the average length of stay per case in DRG d at year t. Hospital-level control variables include the lagged logarithm of one plus available bed days ($LogBedDay_{i,t-1}$) and lagged cash holdings over total assets ($Cash/TA_{i,t-1}$). Hospital-DRG level control variables include the lagged average patient age and percentages of patients that are female, white, black, and Hispanic. DRG-Year and Hospital-DRG fixed effects are included, as indicated. Standard errors are clustered at the hospital level and provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
Insurance:	*Uninsured*	*Uninsured*	*Uninsured*
	Log(Avg Charges)	*Log(Avg Num Procedures)*	*Log(Avg Length of Stay)*
$STExposed_{i,t-1}$	0.024	−0.014	−0.016**
	(0.015)	(0.009)	(0.007)
Controls	Y	Y	Y
DRG-Year FE	Y	Y	Y
Hospital-DRG FE	Y	Y	Y
N	443,269	443,269	443,269
Adj R^2	0.80	0.68	0.51

Table A.13: Heterogeneity Across Hospital Local Market Power

This table provides estimation results when interacting the treatment variable with a measure of hospital local market power measured by inpatient revenues. We first calculate each hospital system's inpatient revenues as a fraction over its HRR's total inpatient revenues. $High\,Revenue\,Share_i$ is 1 if a treated hospital's system has an above-median share of inpatient revenues of the HRR before the shock, and 0 otherwise. *Profit Margin* is profit margin, defined as $(Income - Cost)/Income$. *Bed Utilization* is the average daily fraction of hospital beds that are occupied. *Discharge Rate* is inpatient discharges over total bed days. *All Readmission Rate* is the readmission rate for all diseases. *Antibiotic* measures the share of pneumonia patients receiving the most appropriate antibiotic. *Overall Rating* is the share of patients that give the highest rating to questions on overall care quality. Control variables include the lagged logarithm of one plus available bed days ($Log(Bed\,Days_{i,t-1})$) and lagged cash holdings over total assets ($Cash/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1) *Profit Margin*	(2) *Bed Utilization*	(3) *Discharge Rate*	(4) *All Readmission Rate*	(5) *Antibiotic*	(6) *Overall Rating*
$STExposed_{i,t-1}$	−0.001	0.011*	1.643***	0.001**	−0.007*	−0.009***
	(0.009)	(0.006)	(0.569)	(0.001)	(0.004)	(0.003)
$High\,Revenue\,Share_i$	0.023**	0.023***	1.480**	0.002**	−0.001	0.002
$\times STExposed_{i,t-1}$	(0.009)	(0.007)	(0.743)	(0.001)	(0.004)	(0.003)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	23,804	23,269	23,267	17,694	15,126	21,372
Adj R^2	0.21	0.94	0.80	0.67	0.58	0.82

Table A.14: Heterogeneity Across Hospital Pre-shock Cash Balance

This table provides estimation results when interacting the treatment variable with a measure of hospital cash balance. $High\,Cash_i$ is 1 if a treated hospital's $Cash/TA_{i,t}$ before the shock is above the sample median, and 0 otherwise. *Profit Margin* is profit margin, defined as $(Income - Cost)/Income$. *Bed Utilization* is the average daily fraction of hospital beds that are occupied. *Discharge Rate* is inpatient discharges over total bed days. *All Readmission Rate* is the readmission rate for all diseases. *Antibiotic* measures the share of pneumonia patients receiving the most appropriate antibiotic. *Overall Rating* is the share of patients that give the highest rating to questions on overall care quality. Control variables include the lagged logarithm of one plus available bed days ($Log(Bed\,Days_{i,t-1})$) and lagged cash holdings over total assets ($Cash/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1) *Profit Margin*	(2) *Bed Utilization*	(3) *Discharge Rate*	(4) *All Readmission Rate*	(5) *Antibiotic*	(6) *Overall Rating*
$STExposed_{i,t-1}$	0.007	0.032***	3.347***	0.003***	−0.011***	−0.008***
	(0.006)	(0.004)	(0.447)	(0.000)	(0.002)	(0.002)
$High\,Cash_i$	0.008	−0.020***	−1.974***	−0.002***	0.008*	−0.001
$\times STExposed_{i,t-1}$	(0.009)	(0.006)	(0.682)	(0.001)	(0.004)	(0.003)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	23,804	23,269	23,267	17,694	15,126	21,372
Adj R^2	0.21	0.94	0.80	0.67	0.58	0.82

Table A.15: Heterogeneity Across Hospital Location Rurality

This table provides estimation results when interacting the treatment variable with a measure of hospital location rurality. $RUCA_i$ is the rural-urban commuting area (RUCA) code of hospital i's location. The U.S. Department of Agriculture assigns 10 primary RUCA codes to urban and rural counties, ranging from 1 (Metropolitan area core) to 10 (Rural areas). *Profit Margin* is profit margin, defined as $(Income - Cost)/Income$. *Bed Utilization* is the average daily fraction of hospital beds that are occupied. *Discharge Rate* is inpatient discharges over total bed days. *All Readmission Rate* is the readmission rate for all diseases. *Antibiotic* measures the share of pneumonia patients receiving the most appropriate antibiotic. *Overall Rating* is the share of patients that give the highest rating to questions on overall care quality. Control variables include the lagged logarithm of one plus available bed days ($Log(Bed\,Days_{i,t-1})$) and lagged cash holdings over total assets ($Cash/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)
	Profit Margin	*Bed Utilization*	*Discharge Rate*	*All Readmission Rate*	*Antibiotic*	*Overall Rating*
$STExposed_{i,t-1}$	0.019***	0.032***	3.258***	0.002***	−0.009***	−0.009***
	(0.006)	(0.005)	(0.518)	(0.000)	(0.003)	(0.003)
$RUCA_i$	−0.005*	−0.005***	−0.475***	−0.000	0.001	0.001
$\times STExposed_{i,t-1}$	(0.003)	(0.001)	(0.149)	(0.000)	(0.002)	(0.001)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	23,606	23,078	23,076	17,547	14,983	21,182
Adj R^2	0.21	0.94	0.80	0.67	0.58	0.82

Table A.16: Robustness: Interaction Effects of Large Hospital Systems

This table shows the robustness of our main results by interacting the treatment variable with an indicator of hospital i affiliated with systems that have more than five branches ($Large\,System_i$). *Profit Margin* is profit margin, defined as $(Income - Cost)\,/Income$. *Bed Utilization* is the average daily fraction of hospital beds that are occupied. *Discharge Rate* is inpatient discharges over total bed days. *All Readmission Rate* is the readmission rate for all diseases. *Antibiotic* measures the share of pneumonia patients receiving the most appropriate antibiotic. *Overall Rating* is the share of patients that give the highest rating to questions on overall care quality. Control variables include the lagged logarithm of one plus available bed days ($Log(Bed\,Days_{i,t-1})$) and lagged cash holdings over total assets ($Cash/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1) *Profit Margin*	(2) *Bed Utilization*	(3) *Discharge Rate*	(4) *All Readmission Rate*	(5) *Antibiotic*	(6) *Overall Rating*
$STExposed_{i,t-1}$	0.014	0.021	3.281**	0.002**	−0.026**	−0.013**
	(0.009)	(0.013)	(1.591)	(0.001)	(0.013)	(0.005)
$Large\,System_i$	−0.004	0.002	−0.952	−0.000	0.020	0.005
$\times STExposed_{i,t-1}$	(0.009)	(0.014)	(1.608)	(0.001)	(0.013)	(0.005)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	23,804	23,269	23,267	17,694	15,126	21,372
Adj R^2	0.21	0.94	0.80	0.67	0.58	0.82

Table A.17: Heterogeneity Across Hospital System Size

This table provides estimation results when interacting the treatment variable with the number of hospital branches. $Branch_i$ is the number of branches in the hospital system for which hospital i belongs, measured in 2012. *Profit Margin* is profit margin, defined as $(Income - Cost)/Income$. *Bed Utilization* is the average daily fraction of hospital beds that are occupied. *Discharge Rate* is inpatient discharges over total bed days. *All Readmission Rate* is the readmission rate for all diseases. *Antibiotic* measures the share of pneumonia patients receiving the most appropriate antibiotic. *Overall Rating* is the share of patients that give the highest rating to questions on overall care quality. Control variables include the lagged logarithm of one plus available bed days ($Log(Bed\,Days_{i,t-1})$), and lagged cash holdings over total assets ($Cash/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1) *Profit Margin*	(2) *Bed Utilization*	(3) *Discharge Rate*	(4) *All Readmission Rate*	(5) *Antibiotic*	(6) *Overall Rating*
$STExposed_{i,t-1}$	0.014**	0.025***	2.503***	0.002***	−0.008***	−0.008***
	(0.006)	(0.004)	(0.431)	(0.000)	(0.002)	(0.002)
$Branch_i$	−0.006***	−0.003	−0.156	−0.000	0.000	−0.001
$\times STExposed_{i,t-1}$	(0.001)	(0.002)	(0.146)	(0.000)	(0.001)	(0.001)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	23,804	23,269	23,267	17,694	15,126	21,372
Adj R^2	0.21	0.94	0.80	0.67	0.58	0.82

Table A.18: Heterogeneity Across Hospital Exposure to Bank Stress Tests

This table provides estimation results when splitting the treatment group by the treated hospital's exposure to bank lender stress tests. We define *exposure* as a treated hospital's loan amount from stress-tested lenders scaled by its total non-matured loan amount. $High\,Amount\,Exposed_{i,t-1}$ ($Low\,Amount\,Exposed_{i,t-1}$) takes a value of 1 if hospital i was exposed in year $t-1$ or earlier *and* its *exposure* is above (below) 0.5, and 0 otherwise. *Profit Margin* is profit margin, defined as $(Income - Cost)\,/Income$. *Bed Utilization* is inpatient bed days utilized over total bed days. *Discharge Rate* is inpatient discharges over total bed days. *All Readmission Rate* is the readmission rate for all diseases. *Antibiotic* measures the share of pneumonia patients receiving the most appropriate antibiotic. *Overall Rating* is the share of patients that give the highest rating to questions on overall care quality. Control variables include the lagged logarithm of one plus available bed days ($Log(Bed\,Days_{i,t-1})$) and lagged cash holdings over total assets ($Cash/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) *Profit Margin*	(2) *Bed Utilization*	(3) *Discharge Rate*	(4) *All Readmission Rate*	(5) *Antibiotic*	(6) *Overall Rating*
$High\,Amount\,Exposed_{i,t-1}$	0.014**	0.022***	2.460***	0.002***	−0.008***	−0.008***
	(0.006)	(0.004)	(0.421)	(0.000)	(0.002)	(0.002)
$Low\,Amount\,Exposed_{i,t-1}$	−0.029**	0.012	0.410	0.001	−0.000	0.002
	(0.013)	(0.009)	(1.099)	(0.001)	(0.006)	(0.005)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	23,804	23,269	23,267	17,694	15,126	21,372
Adj R^2	0.21	0.94	0.80	0.67	0.58	0.82

Table A.19: Robustness: Controlling for Regional Differences

This table provides estimation results for equation (1), controlling for regional differences in each year. *Profit Margin* is profit margin, defined as $(Income - Cost)/Income$. *Bed Utilization* is inpatient bed days utilized over total bed days. *Discharge Rate* is inpatient discharges over total bed days. *All Readmission Rate* is the readmission rate for all diseases. *Antibiotic* measures the share of pneumonia patients receiving the most appropriate antibiotic. *Overall Rating* is the share of patients that give the highest rating to questions on overall care quality. $STExposed$ takes a value of 1 if at least one of hospital i's relationship banks experienced a stress test in year $t-1$ or earlier, and 0 otherwise. Control variables include the lagged logarithm of one plus available bed days ($Log(Bed\,Days_{i,t-1})$) and lagged cash holdings over total assets ($Cash/TA_{i,t-1}$). Hospital referral region (HRR)-by-year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Profit Margin	*Bed Utilization*	*Discharge Rate*	*All Readmission Rate*	*Antibiotic*	*Overall Rating*
$STExposed_{i,t-1}$	0.009	0.015***	2.036***	0.002***	−0.007**	−0.007***
	(0.012)	(0.004)	(0.455)	(0.000)	(0.003)	(0.002)
Controls	Y	Y	Y	Y	Y	Y
HRR × Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	23,738	23,209	23,204	17,642	15,024	21,333
Adj R^2	0.17	0.94	0.80	0.68	0.57	0.82

Table A.20: Robustness: Drop Large Hospital Systems

This table shows the robustness of our main results by dropping the hospital-year observations of hospitals affiliated with systems that have more than five branches. *Profit Margin* is profit margin, defined as $(Income - Cost)/Income$. *Bed Utilization* is inpatient bed days utilized over total bed days. *Discharge Rate* is inpatient discharges over total bed days. *All Readmission Rate* is the readmission rate for all diseases. *Antibiotic* measures the share of pneumonia patients receiving the most appropriate antibiotic. *Overall Rating* is the share of patients that give the highest rating to questions on overall care quality. $STExposed$ takes a value of 1 if at least one of hospital i's relationship banks experienced a stress test in year $t-1$ or earlier, and 0 otherwise. Control variables include the lagged logarithm of one plus available bed days ($Log(BedDays_{i,t-1})$) and lagged cash holdings over total assets ($Cash/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1) *Profit Margin*	(2) *Bed Utilization*	(3) *Discharge Rate*	(4) *All Readmission Rate*	(5) *Antibiotic*	(6) *Overall Rating*
$STExposed_{i,t-1}$	0.017*	0.021	3.606**	0.002**	−0.023*	−0.012**
	(0.010)	(0.014)	(1.727)	(0.001)	(0.014)	(0.005)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	20,906	20,409	20,407	16,249	13,309	18,579
Adj R^2	0.19	0.95	0.80	0.67	0.57	0.82

Table A.21: Restricting treatment sample to hospitals with new loans

We consider our main results with a treatment sample restricted to the 401 treated hospitals that took new bank loans after exposure to the stress tests. All hospital-year observations of affected hospitals that did not take new bank loan financing following stress test exposure are dropped. *Profit Margin* is profit margin, defined as $(Income - Cost)/Income$. *Bed Utilization* is inpatient bed days utilized over total bed days. *Discharge Rate* is inpatient discharges over total bed days. *All Readmission Rate* is the readmission rate for all diseases. *Antibiotic* measures the share of pneumonia patients receiving the most appropriate antibiotic. *Overall Rating* is the share of patients that give the highest rating to questions on overall care quality. *STExposed* takes a value of 1 if at least one of hospital i's relationship banks experienced a stress test in year $t-1$ or earlier, and 0 otherwise. Control variables include the lagged logarithm of one plus available bed days ($Log(Bed\,Days_{i,t-1})$) and lagged cash holdings over total assets ($Cash/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1) *Profit Margin*	(2) *Bed Utilization*	(3) *Discharge Rate*	(4) *All Readmission Rate*	(5) *Antibiotic*	(6) *Overall Rating*
$STExposed_{i,t-1}$	0.010	0.023***	2.086***	0.002***	−0.008***	−0.008***
	(0.007)	(0.004)	(0.415)	(0.000)	(0.003)	(0.002)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	23,125	22,595	22,593	17,164	14,656	20,719
Adj R^2	0.21	0.94	0.81	0.67	0.58	0.82

Table A.22: Restricting to Commercial Loan Borrowers

This table shows the robustness of our main results by focusing on the sample hospitals that borrowed loans from commercial banks. *Profit Margin* is profit margin, defined as $(Income - Cost)/Income$. *Bed Utilization* is inpatient bed days utilized over total bed days. *Discharge Rate* is inpatient discharges over total bed days. *All Readmission Rate* is the readmission rate for all diseases. *Antibiotic* measures the share of pneumonia patients receiving the most appropriate antibiotic. *Overall Rating* is the share of patients that give the highest rating to questions on overall care quality. *STExposed* takes a value of 1 if at least one of hospital i's relationship banks experienced a stress test in year $t-1$ or earlier, and 0 otherwise. Control variables include the lagged logarithm of one plus available bed days ($Log(Bed\,Days_{i,t-1})$) and lagged cash holdings over total assets ($Cash/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1) *Profit Margin*	(2) *Bed Utilization*	(3) *Discharge Rate*	(4) *All Readmission Rate*	(5) *Antibiotic*	(6) *Overall Rating*
$STExposed_{i,t-1}$	0.013	0.014***	2.090***	0.001***	−0.009***	−0.005**
	(0.008)	(0.005)	(0.497)	(0.000)	(0.003)	(0.002)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	6,391	6,300	6,300	5,059	4,257	6,157
Adj R^2	0.47	0.92	0.82	0.67	0.42	0.84

Table A.23: Robustness: Effects on Local Non-Exposed Hospitals

This table shows the robustness of our main results by studying the non-exposed hospitals that are neighbor hospitals of the affected ones. In this regression, we drop all the hospital-year observations of hospitals exposed to stress tests. $NearExposed_{i,t-1}$ is 1 if there is at least one hospital exposed to the stress tests by year $t-1$ in hospital i's local city *and* hospital i itself is not affected, and 0 otherwise. *Profit Margin* is profit margin, defined as $(Income - Cost)/Income$. *Bed Utilization* is inpatient bed days utilized over total bed days. *Discharge Rate* is inpatient discharges over total bed days. *All Readmission Rate* is the readmission rate for all diseases. *Antibiotic* measures the share of pneumonia patients receiving the most appropriate antibiotic. *Overall Rating* is the share of patients that give the highest rating to questions on overall care quality. Control variables include the lagged logarithm of one plus available bed days ($Log(Bed\,Days_{i,t-1})$) and lagged cash holdings over total assets ($Cash/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1) *Profit Margin*	(2) *Bed Utilization*	(3) *Discharge Rate*	(4) *All Readmission Rate*	(5) *Antibiotic*	(6) *Overall Rating*
$NearExposed_{i,t-1}$	−0.019	−0.002	−1.137***	0.000	−0.004	−0.002
	(0.014)	(0.003)	(0.394)	(0.000)	(0.003)	(0.002)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	20,454	19,953	19,951	15,042	12,908	18,149
Adj R^2	0.19	0.94	0.80	0.67	0.58	0.81

Table A.24: Effect of Stress Tests including CCAR

This table provides the regression results for our main tests, including exposure to CCAR stress tests in our treatment. $STExposed^{CCAR}$ takes a value of 1 if at least one of hospital i's relationship banks experienced either a CCAR or Dodd-Frank Act stress test in year $t-1$ or earlier, and 0 otherwise. *Profit Margin* is profit margin, defined as $(Income - Cost)/Income$. *Bed Utilization* is inpatient bed days utilized over total bed days. *Discharge Rate* is inpatient discharges over total bed days. *All Readmission Rate* is the readmission rate for all diseases. *Antibiotic* measures the share of pneumonia patients receiving the most appropriate antibiotic. *Overall Rating* is the share of patients that give the highest rating to questions on overall care quality. Control variables include the lagged logarithm of one plus available bed days ($Log(Bed\,Days_{i,t-1})$) and lagged cash holdings over total assets ($Cash/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) *Profit Margin*	(2) *Bed Utilization*	(3) *Discharge Rate*	(4) *All Readmission Rate*	(5) *Antibiotic*	(6) *Overall Rating*
$STExposed^{CCAR}_{i,t-1}$	0.014***	0.016***	1.869***	0.002***	−0.005**	−0.007***
	(0.006)	(0.005)	(0.538)	(0.001)	(0.002)	(0.002)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	23,780	23,245	23,243	17,678	15,113	21,349
Adj R^2	0.22	0.94	0.80	0.67	0.58	0.82

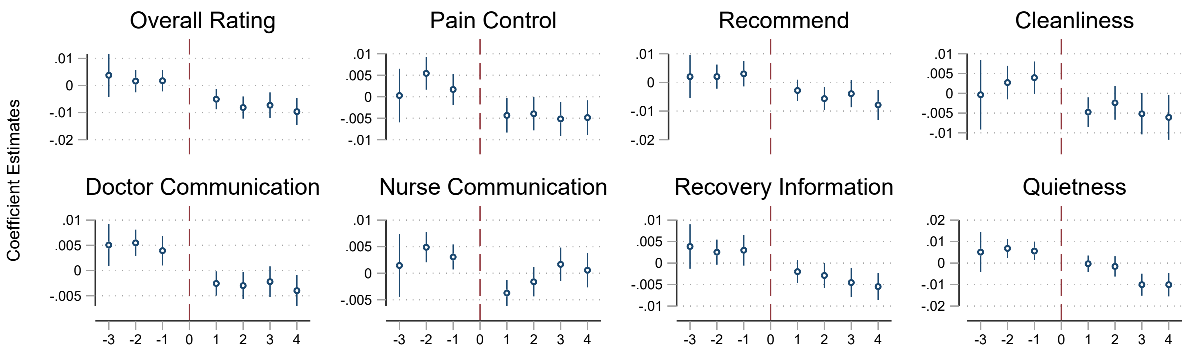
Figure A.1: Parallel Trends: Healthcare Quality, Propensity Score-matched Sample

This figure provides parallel trends for the readmission, mortality, and survey outcome variables by graphing estimation results for equation (3), using the propensity score-matched sample. Each coefficient represents the relative difference between the treatment and control group s years after the first exposure year ("year 0"). PN is pneumonia, HF is heart failure, and AMI is acute myocardial infarction. All coefficient estimates are relative to year 0. 95% confidence intervals are indicated by the solid lines.

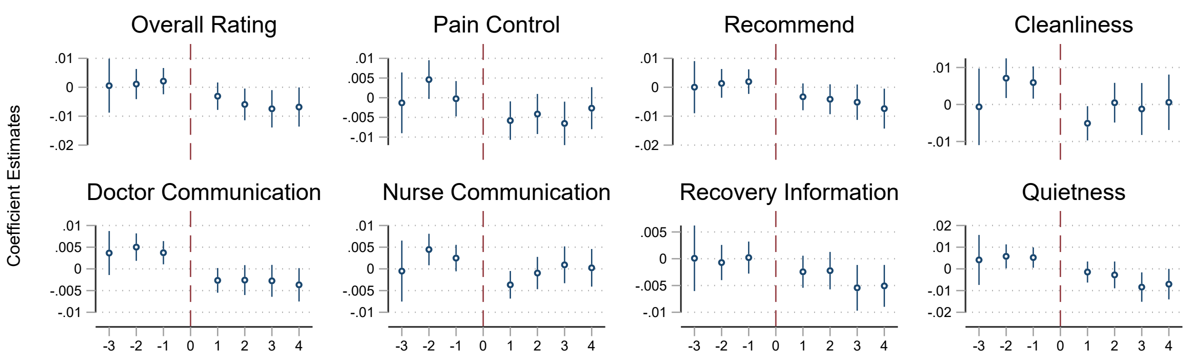
Figure A.2: Parallel Trends: All Survey Results

This figure provides parallel trends for all survey outcome variables by graphing estimation results for equation (3). Each coefficient represents the relative difference between the treatment and control group s years after the first exposure year ("year 0"). All coefficient estimates are relative to year 0. 95% confidence intervals are indicated by the solid lines. We plot the parallel trends in the full sample in Panel A and in the propensity score matched sample in Panel B.

Panel A: Main Specification



Panel B: Propensity Score Matched Sample



B Validation of Parallel Trends

Alternative Construction of Parallel Trends

In this section, we provide a description and the results for an alternative methodology for examining parallel trends, by estimating average treatment effects for the treated and dynamic parallel trend plots following Callaway and Sant'Anna (2021). As noted by Callaway and Sant'Anna (2021), this methodology circumvents the issues raised in the literature relating to interpreting two-way fixed effects DID regressions in a causal manner.

Specifically, we estimate the average treatment effects for the treated (ATT) for each year following the stress test shock as follows. Let $D_{i,t}$ denote whether hospital i is treated in year t, $G_{i,g} = 1$ if hospital i is first treated in year g and 0 otherwise, $C = 1$ for the "never-treated" control group, Y_t the outcome variable of interest, $\mathbf{t}$ the first observation period, and $\mathbf{T}$ the final observation period. Lastly, let e denote the number of years since the shock. The average treatment effect on the treated for treatment group g, relative to the never-treated group, in year t is calculated as:

$$ATT^{nev}(g,t) = \mathbb{E}[Y_t - Y_{g-1}|G_g = 1] - \mathbb{E}[Y_t - Y_{g-1}|C = 1].$$

The ATT for the treatment group relative to the not-yet-treated group is:

$$ATT^{ny}(g,t) = \mathbb{E}[Y_t - Y_{g-1}|G_g = 1] - \mathbb{E}[Y_t - Y_{g-1}|D_t = 0, G_g = 0].$$

When $e \geq 0$, these ATTs are aggregated as follows:

$$\theta(e) = \Sigma_g 1\{g + e \leq \mathbf{T}\} P(G = g|G + e \leq \mathbf{T}) ATT(g, g + e),$$

where $P(G = g|G + e \leq \mathbf{T})$ is the unconditional weight of treatment group g among all treatment groups with non-missing observations in the e years since the shock in the sample. When $e < 0$, $\theta(e)$ is calculated similarly, except that $ATT(g, g + e)$ is defined as

$$ATT^{nev}(g, g + e) = \mathbb{E}[Y_{g+e} - Y_{g+e-1}|G_g = 1] - \mathbb{E}[Y_{g+e} - Y_{g+e-1}|C = 1],$$

and

$$ATT^{ny}(g, g + e) = \mathbb{E}[Y_{g+e} - Y_{g+e-1}|G_g = 1] - \mathbb{E}[Y_{g+e} - Y_{g+e-1}|D_t = 0, G_g = 0].$$

These ATTs are then aggregated via:

$$\theta(e) = \Sigma_g 1\{g + e \geq \mathbf{t}\} P(G = g|G + e \geq \mathbf{t}) ATT(g, g + e).$$

Our goal is to validate the unconditional parallel trends assumption for both the never-treated and not-yet-treated groups such that no covariates are included. In Figure B.1, we plot both the ATTs relative to the never-treated (column 1) and not-yet-treated (column 2) groups. Each circle represents the estimated $\theta(e)$, and bootstrapped 95% confidence intervals are included. To conserve space, we plot the key measures for quality of care (readmission rates) and key channel variables (bed utilization rates and discharge rates).

In Panel A of Table B.1, we provide the corresponding regression results for our main outcome variables for the average treatment effects for the treated (ATTs) with never-treated hospitals as the control group. In Panel B of Table B.1, we show that our main regression results (estimated via our primary specification) are similar to dropping all covariates as control variables.

Validation of Treatment Effects

In this section, we provide a more rigorous validation of our parallel trends and evidence that our inferences remain valid even in the presence of potential pre-trends. First, to more carefully examine the various parallel trends that we have and to identify outcomes that are potentially more problematic, we run an F-test for each of our outcome variables that tests the hypothesis that the pre-shock parallel trend coefficients are jointly equal to each other. This test therefore examines whether the differences between the treated and control hospitals vary significantly from each other in the years leading up to DFAST implementation. We perform this test for our main specification outcome variables and also for our propensity score-matched (PSM) sample specification. These results are provided in Table B.2. As the table shows, the F-statistic is insignificant for the almost all outcome variables, which reinforces our previous analysis that the parallel trends assumption is likely to hold in these cases. However, for bed utilization in the main specification and pneumonia readmission rate for the main and PSM specifications, the F-statistic is significant, indicating that the parallel trends assumption warrants further examination for these variables.

For the few outcome variables mentioned above that "fail" this test—where there is a significant difference between the pre-period parallel trend coefficients—we examine the validity of our inferences more closely following Rambachan and Roth (2023). The logic behind this approach is to statistically assess the extent to which the post-period DID coefficients deviate from a linear trend based on the pre-period (i.e., using an expected counterfactual trend in the absence of treatment effects). A significant deviation thus indicates that the treatment effect is likely to hold and inferences are therefore likely to be valid, despite the parallel trends assumption being violated. To provide more detail, the second differences (SD) approach of Rambachan and Roth (2023) requires specifying an exogenous threshold parameter M which bounds the extent to which the parallel trends slope can change between consecutive periods post-treatment, and assesses the significance of treatment effects relative to these bounds.[74]

As Rambachan and Roth (2023) note, the appropriate value of M varies on a case-by-case basis, and there is not a single recommended value that applies to all situations. For example, testing for a deviation from a strictly linear violation of parallel trends would imply $M = 0$, while higher values of M test for larger deviations from linearity. We follow

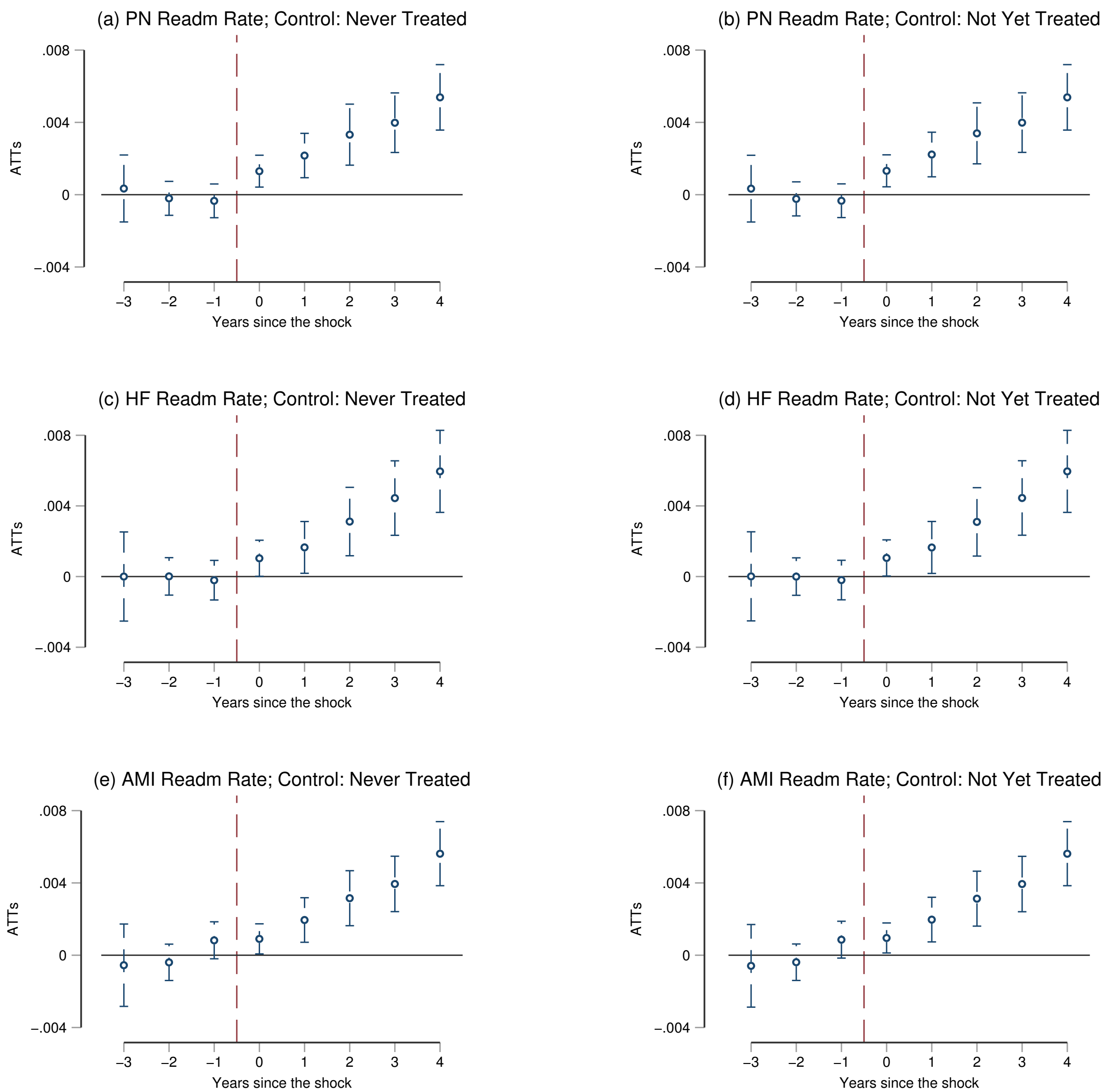
[74]Specifically, define δ_t as the difference in trends for outcomes between period 0 and period t, where $t > 0$ indicates the post-treatment period. For example, if the difference in trends is linear, then $\delta_t = \gamma \cdot t$, where $\gamma \in \mathbb{R}$. The SD approach also allows for inference based on nonlinear trends such that for any period t, the change in the differential trends over time being lower than a threshold parameter M, where $|\,(\delta_{t+1} - \delta_t) - (\delta_t - \delta_{t-1})\,| \leq M$, would imply that the inferred effects are a continuation of a nonlinear pre-trend. For example, in the three periods $(t = -1, 0, 1)$, the SD approach assumes that $\delta_1 = \delta_{-1} \pm M$ are the bounds by which δ_1 must exceed to infer that the effects are not a continuation of the pre-trends.

the recommendation of Rambachan and Roth (2023) and perform a sensitivity check for post-treatment confidence intervals period-by-period, showing how inferences are potentially changed as the value of M is gradually increased. Specifically, we consider values of M ranging from a baseline of $M = 0$ (i.e., a deviation from a linear trend) to a value equal to the standard error of the estimated coefficients. For each value of M, we provide the new confidence interval for each post-treatment coefficient adjusted for the potential trend. A confidence interval that does not contain zero indicates that the post-treatment deviation is significantly large enough to reject the null hypothesis that the effects we observe are simply a continuation of the pre-treatment trends. We note that our selected upper bound value is conservative as it allows the differential trends to change by up to the coefficient's standard error, and assesses the significance of the point estimate relative to that trend.

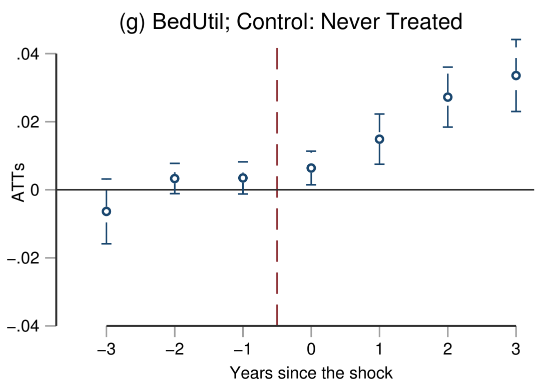
We provide the robust inference results in Table B.3. For reference, we first provide the 95% confidence intervals for the dynamic post-treatment coefficients under our original estimation. In line with our regression results, the treatment effects are all significant (i.e., confidence bounds that do not contain zero). We next provide results for $M = 0$, which tests if the coefficients deviate from a linear trend. We find significant treatment effects for all of the outcome variables from $t = 2$ through $t = 4$—the confidence bounds represent estimates relative to the (linear) counterfactual trend, and thus confidence bounds that do not contain zero implies that we can reject the hypothesis that the treatment effects are a continuation of this trend. These results provide evidence that our inferences are likely valid, even for the variables mentioned above where the parallel trends assumption is more tenuous, as the treatment effects diverge in a statistically significant manner from a counterfactual linear post-trend. To be conservative and provide evidence of the sensitivity of our effect to potential nonlinearities in trends, we also provide results for greater values of M ranging from 25% to 100% of the standard error of the estimated coefficients. For each of the specifications, we obtain significant treatment effects for many of our point estimates even for relatively higher values of M. For instance, for bed utilization in Panel A of Table B.3, the effects for $t = 2$ are significantly different from zero with $M = 0$ through $M = s.e.$, and become stronger for $t = 3$ and $t = 4$. Out of these outcomes, our weakest result is for pneumonia readmission rate in the propensity score-matched sample, where the coefficients become insignificant for values of M from 75% of the standard error; however, we note that this still permits us to assert significance if we assume linear trends, as noted earlier, and even if we allow a substantial degree of nonlinearity in trends.

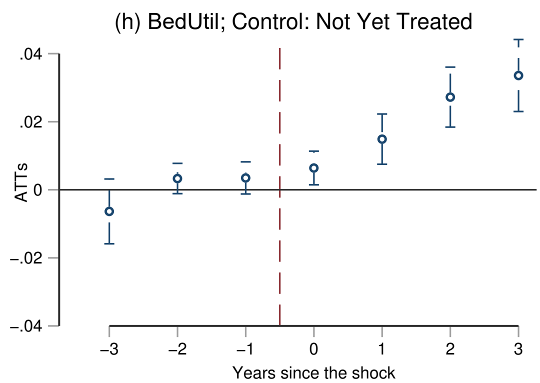
Figure B.1: Parallel Trends: Average Treatment Effects for the Treated

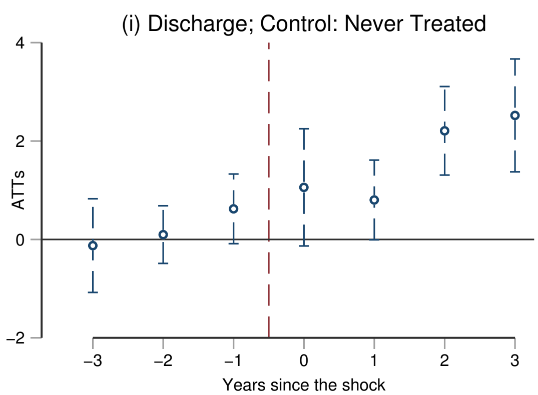
This figure provides average treatment effects for the treated (ATT) for each year following the stress test shock using the methodology of Callaway and Sant'Anna (2021). ATTs relative to the never-treated (left figures) and not-yet-treated (right figures) control hospitals are provided. Each circle represents the estimated ATT, and bootstrapped 95% confidence intervals are included. No control variables are included.



(continued)


(g) BedUtil; Control: Never Treated
.04
.02
0
−.02
−.04
ATTs
−3
−2
−1
0
1
2
3
Years since the shock


(h) BedUtil; Control: Not Yet Treated
.04
.02
0
−.02
−.04
ATTs
−3
−2
−1
0
1
2
3
Years since the shock


(i) Discharge; Control: Never Treated
4
2
0
−2
ATTs
−3
−2
−1
0
1
2
3
Years since the shock

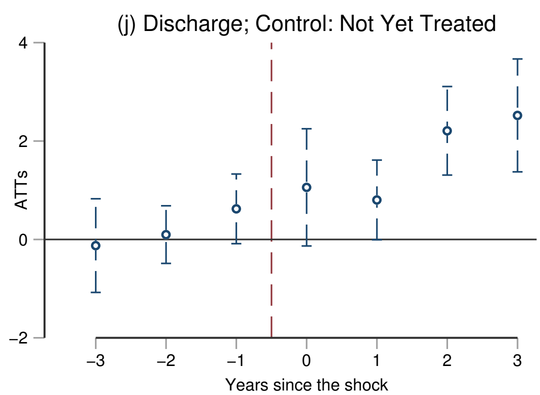

(j) Discharge; Control: Not Yet Treated
4
2
0
−2
ATTs
−3
−2
−1
0
1
2
3
Years since the shock

Table B.1: Robustness: Callaway and Sant'Anna (2021) Estimation and Dropping All Control Variables

This table provides estimation results for equation (1) using the estimation method in Callaway and Sant'Anna (2021) (Panel A) and after dropping all control variables (Panel B). $Margin$ is profit margin, defined as $(Income - Cost)/Income$. *BedUtil* is inpatient bed days utilized over total bed days. *Discharge Rate* is inpatient discharges over total bed days. *All Readmission Rate* is the readmission rate for all diseases. *Antibiotic* measures the share of pneumonia patients receiving the most appropriate antibiotic. *Overall* is the share of patients that give the highest rating to questions on overall care quality. $STExposed$ takes a value of 1 if at least one of hospital i's relationship banks experienced a stress test in year $t-1$ or earlier, and 0 otherwise. In Panel A, we estimate the ATTs following Callaway and Sant'Anna (2021) using the never treated group as the control group. In both panels, no control variables are included. Hospital and year fixed effects are included, as indicated. Standard errors are clustered at the hospital level and provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: ATTs via Callaway and Sant'Anna (2021)

	(1)	(2)	(3)	(4)	(5)	(6)
	Profit Margin	*Bed Utilization*	*Discharge Rate*	*All Readmission Rate*	*Antibiotic*	*Overall Rating*
$STExposed_{i,t-1}$	0.007	0.019***	1.573***	0.002***	−0.004*	−0.008***
	(0.005)	(0.003)	(0.387)	(0.000)	(0.002)	(0.002)
Controls	N	N	N	N	N	N
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	24,394	24,106	24,108	19,845	15,493	22,015

Panel B: OLS Specification

	(1)	(2)	(3)	(4)	(5)	(6)
	Profit Margin	*Bed Utilization*	*Discharge Rate*	*All Readmission Rate*	*Antibiotic*	*Overall Rating*
$STExposed_{i,t-1}$	0.005	0.021***	2.012***	0.002***	−0.007***	−0.009***
	(0.006)	(0.004)	(0.421)	(0.000)	(0.002)	(0.002)
Controls	N	N	N	N	N	N
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	24,409	24,115	24,119	19,860	15,618	22,050
Adj R^2	0.22	0.94	0.79	0.66	0.58	0.82

Table B.2: Pre-trend Tests

This table provides F-statistics and p-values for the pretend tests of the main specification, equation (1), in columns (1) and (2) and for the propensity score-matched sample in columns (3) and (4). The F-test is based on the following joint hypothesis: $\beta_{-3} = \beta_{-2} = \beta_{-1}$, i.e., that all pre-shock coefficients are identical.

	Main Specification		PSM	
	(1)	(2)	(3)	(4)
Outcome Variable	*F-statistic*	*p-value*	*F-statistic*	*p-value*
Liabilities	0.56	0.57	0.23	0.79
Net Income/TA	1.25	0.29	0.26	0.77
Bed Utilization	3.07	0.05	1.54	0.21
Discharge Rate	0.49	0.61	0.20	0.81
Pneumonia Readmission Rate	3.69	0.03	2.68	0.07
Heart Failure Readmission Rate	0.89	0.41	1.45	0.24
AMI Readmission Rate	0.75	0.47	0.96	0.38
All Readmission Rate	0.61	0.54	0.82	0.44
Pneumonia Mortality Rate	1.38	0.25	1.88	0.15
Pneumonia Mortality Num	0.80	0.45	1.53	0.22
Log(Pneumonia Mortality Num)	0.35	0.71	1.03	0.36
Overall Rating	0.15	0.93	0.11	0.96

Table B.3: Robust Inference using Rambachan and Roth (2023)

This table provides robust inference confidence intervals for the post-period treatment coefficients for outcomes that are significant in the pre-trend tests in Table B.2 (i.e., where $p < 0.10$). We follow the "second differences" methodology of Rambachan and Roth (2023), which assumes that the slope of the pre-trend can change by no more than M across consecutive periods. Imposing that $M = 0$ (in bold) implies that the counterfactual difference in trends is linear, whereas larger values of M allow for nonlinearity. t indicates the post-treatment period. For each t, we provide estimates for M from 0 to 100% of the coefficient's standard error. In each row, we list the original 95% confidence interval, and the robust confidence intervals relative to the counterfactual trend based under different assumptions of M.

Panel A: Outcome Variable: Bed Utilization, Specification: Main

M	**t=1**	**t=2**	**t=3**	**t=4**
Original	(0.001, 0.012)	(0.008, 0.023)	(0.02, 0.037)	(0.025, 0.045)
0	**(-0.002, 0.01)**	**(0.004, 0.021)**	**(0.015, 0.034)**	**(0.02, 0.042)**
25%×s.e.	(-0.003, 0.01)	(0.003, 0.021)	(0.014, 0.034)	(0.019, 0.042)
50%×s.e.	(-0.004, 0.01)	(0.001, 0.021)	(0.013, 0.034)	(0.018, 0.042)
75%×s.e.	(-0.006, 0.01)	(0, 0.022)	(0.012, 0.035)	(0.017, 0.043)
100%×s.e.	(-0.007, 0.011)	(0, 0.022)	(0.011, 0.036)	(0.015, 0.044)

Panel B: Outcome Variable: Pneumonia Readmission Rate, Specification: Main

M	**t=1**	**t=2**	**t=3**	**t=4**
Original	(0.001, 0.002)	(0.001, 0.003)	(0.002, 0.005)	(0.002, 0.005)
0	**(0, 0.001)**	**(0.001, 0.003)**	**(0.001, 0.004)**	**(0.002, 0.005)**
25%×s.e.	(0, 0.001)	(0.001, 0.003)	(0.001, 0.004)	(0.002, 0.005)
50%×s.e.	(0, 0.002)	(0.001, 0.003)	(0.001, 0.004)	(0.001, 0.005)
75%×s.e.	(0, 0.002)	(0.001, 0.003)	(0.001, 0.004)	(0.001, 0.005)
100%×s.e.	(0, 0.002)	(0, 0.003)	(0.001, 0.005)	(0.001, 0.005)

Panel C: Outcome Variable: Pneumonia Readmission Rate, Specification: PSM

M	**t=1**	**t=2**	**t=3**	**t=4**
Original	(0, 0.002)	(0.001, 0.003)	(0.001, 0.004)	(0.001, 0.005)
0	**(-0.001, 0.001)**	**(0, 0.002)**	**(0, 0.003)**	**(0, 0.004)**
25%×s.e.	(-0.001, 0.001)	(0, 0.002)	(-0.001, 0.003)	(0, 0.004)
50%×s.e.	(-0.001, 0.001)	(0, 0.002)	(-0.001, 0.003)	(0, 0.004)
75%×s.e.	(-0.001, 0.001)	(-0.001, 0.002)	(-0.001, 0.003)	(-0.001, 0.004)
100%×s.e.	(-0.001, 0.001)	(-0.001, 0.002)	(-0.001, 0.003)	(-0.001, 0.004)