Merchants of death: The effect of credit supply shocks on hospital outcomes*

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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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JEL classification: G21, G31, G32, I11, I15

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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). As we elaborate later, the increases in debt servicing costs are economically significant for hospitals in our sample, due to low profit margins within the hospital industry.

We then explore how hospital financial and operating outcomes change as a result. We find that, in response to the credit shock, affected hospitals experience an *increase* in revenue and profitability. For example, affected hospitals exhibit a 5.7% increase in total patient revenues. This increase appears to be driven by changes in hospitals' operations to increase patient volume. 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,

[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.

on average, relative to an unaffected hospital. Moreover, affected hospitals accommodate 2.35 more patients per bed each year, which amounts to 367 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 and 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 1,495 patients readmitted per year in aggregate across affected hospitals. Similarly, with respect to patient mortality from pneumonia—a common hospital-acquired condition (Rothberg et al. (2014))—the results show an increase of 859 patient deaths a year across affected hospitals.

To provide additional context to these results, we consider readmissions in terms of relative performance. The U.S. Centers for Medicare & Medicaid Services (CMS) assesses excess

[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.

hospital 30-day readmissions relative to the national average. CMS levies sizable, escalating penalties, in the form of Medicare payment reductions, against hospitals which perform worse than the national average with respect to risk-adjusted 30-day readmissions. We find that an affected hospital is 4.6% more likely to be in the worst-performing group for general readmissions, based on CMS criteria, thereby triggering the heaviest payment penalty. These findings are also similar for 30-day readmissions among the individual diagnostic conditions we consider.

With respect to patient experiences, we find that 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 revenues and profit margins through increased resource utilization and cost efficiency. Specifically, affected hospitals increase admissions per diagnosis-related group (DRG) by 4.9%, 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, we find that 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, we find that 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 revenues 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 patient revenues, 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. 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, dropping outcome-related control variables, controlling for time-varying geographical differences, and conditioning on hospitals that belong to a hospital system. 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.

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

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. 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 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. Section 6 examines heterogeneity tests, including differential responses due to hospital characteristics as well as heterogeneous exposure to the treatment. Section 7 provides various robustness tests. The final section concludes.

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).[6]

[6]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 commercial real estate and corporate debt markets" (Board Gov. Fed. Reserve Syst. (2020)). For more details,

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.[7] 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

see https://www.federalreserve.gov/publications/june-2020-supervisory-scenarios.htm.

[7] 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 Section 7.4.

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. As we discuss in more detail in Section 3.1, almost all of the hospitals in our sample (93%) have debt financing. The size of bank loans that hospitals utilize is substantial, comprising 33.7% of total hospital assets and 60% of total liabilities for the average hospital utilizing such loans in our sample. Servicing this debt is also costly for hospitals, amounting to an average of $7.0 million in interest expenses per year for a given hospital in our sample that utilizes bank lending.[8] 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)).[9] 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.[10] 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

[8] Hospitals in our sample that utilize bank loans have an average of $144.3 million in total borrowing across bank loans, while the average interest rate for bank loans to hospital borrowers in our sample is roughly 4.88%, based on the combined spread and fees on loans and the prevailing (LIBOR) interest rate over our sample.

[9] 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)).

[10] In our sample, 79% of the treated hospitals take out new loans following their exposure to the stress tests.

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, 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

[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.

[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. Beyond this, a sizable literature has shown that even temporary financing shocks can have long-term negative economic effects on firms due to financing frictions combined with weak balance sheets (e.g., Bernanke and Gertler (1989), Kiyotaki and Moore (1997), Bernanke et al. (1999)). Such forces are likely present among hospital borrowers, given their thin profit margins and high leverage relative to assets. An increase in financing costs thus further erodes hospital financial conditions, causing affected hospitals to be in a relatively worse position in the next year financially that is not easily recovered.

[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.

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 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

[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 resolution 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)).

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 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 items in a financial statement such as total assets (TA), income ($Income$),[19] total liabilities ($Liab$), revenues, which includes inpatient ($InPatRev$), outpatient ($OutPatRev$), and total patient revenues ($PatRev$), cash holdings ($Cash$), and operational costs ($Cost$). In addition, the data include hospital utilization information, including total inpatient discharges, total occupied bed days, and total

[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.

[19] $Income$ is defined as net patient revenues (Worksheet G-3, line 3) plus total other income (line 25).

available bed days ($BedDay$).[20]

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.[21] 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 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 (HF), and pneumonia (PN). We additionally collect risk-standardized 30-day mortality data for patients treated for these conditions, also provided by CMS.

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

[20] 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).

[21] 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.

patients' hospital experiences, such as the overall rating of the hospital (*Overall*), efficacy of pain control (*PainCtrl*), whether they would recommend the hospital (*Recommend*), communication with nurses (*NurseCom*) and doctors (*DocCom*), the cleanliness (*Clean*) and quietness (*Quiet*) of the hospital environment, and discharge information (*Info*). 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 before 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.,

[22]For example, the survey question for the variable *Info* 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* 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.

[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."

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 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. Typical hospital borrowing is $78.4 million from an individual lending agreement and $144.3 million across lending agreements. The average ratio between the loan size and the borrower's total assets is 33.7%. 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 Table 2. We include a host of control variables in our specifications to account for differences in observable characteristics, as we describe in more detail in the next section, and further establish that there are parallel trends between the treatment and control groups. We also 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 3.[27]

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

[27]Specifically, we construct our treatment and control groups by matching based on the year 2011 values of $Cash/TA$, $LogBedDay$, $PatRev/TA$, 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

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:

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

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, 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 revenues, and thus not controlling for size may induce omitted variable bias when examining responses to the credit supply shock. Similarly, a hospital may experience an idiosyncratic change in its revenues that can spur changes in its operations, which can muddy the interpretation of operational decisions unless controlled for. We therefore include the following controls. $LogIncome_{i,t-1}$ is the lagged logarithm of one plus total hospital income, as a control for size based on income (following Adelino et al. (2019)).[28] $LogBedDay_{i,t-1}$ is the logarithm of one plus available bed days,[29] to control for size based on physical hospital capacity. Liabilities scaled by total assets ($Liab/TA$) is included as a control for a hospital's leverage (i.e., capital structure) to account for a hospital's reliance on debt and its influence on firm financing and operating decisions (see, e.g., Myers and Majluf (1984), Leary and Roberts (2005)). Cash holdings scaled by total assets ($Cash/TA_{i,t-1}$) controls for the ability of a hospital to

in Table 3, 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).

[28] As noted previously, *Income* is calculated as net patient revenue plus total other income. An alternative control for hospital size would be to include the lagged logarithm of total assets. Our results are robust to doing so.

[29] 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.

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)). Finally, we include total patient revenue scaled by total assets ($PatRev/TA_{i,t-1}$) to control for the revenues that come from patient services as a proportion of the hospital's total operational asset base.[30] 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. A potential concern with the inclusion of these lagged control variables is that they are likely to be affected by the shock in the post-period, which has the potential to bias our inferences. To alleviate these concerns, we show that our main results hold when we drop all lagged controls of outcome variables.[31]

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.[32]

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

[30] This is along the lines of Adelino et al. (2019) and is included to account for changes in a hospital's investment opportunity set, i.e., the hospitals ability to obtain cash flows from patient services compared to other revenue sources, including financial investments.

[31] We also present parallel trend graphs without controls in Appendix Figure B.1 and show in Table B.1 that we obtain qualitatively similar results when dropping all controls.

[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 sub-sample 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.19).

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)).[33] 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.

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 sub-sample. Finally, we include a host of robustness checks related to controlling for potential differences between hospitals as well as other sample composition effects.

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,

[33] We note that affected hospitals do not concentrate in certain areas, as shown by Figure 5.

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 4 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 63–75 bps, an increase of about 16–19% of the sample average of 3.88% (Table 1). In columns (3) and (4), we find that loan size decreases by 36% and loan maturity decreases by 8.4% 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 $NewLender_{k,i,j,t}$, 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 $NewLender_{k,i,j,t}$ is positive and significant, which implies that hospitals are 13.2% 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.2, we add deals by public *non-hospital* borrowers to the initial sample in Table 4.[34] 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.2, 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 A.3.[35]) Collectively, these results validate the use of the 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

[34] 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.

[35] Appendix Table A.3 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.

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 5. We first consider the effect of the credit shock on the overall profit margin of the hospital.[36] In column (1) of Table 5, Panel A, we find that affected borrowers saw a significant increase of 1.2 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 4 indicating lower amounts for new loans.[37] Finally, we consider revenues generated from patients in columns (3) through (5). The results are strikingly consistent with a shift in utilization—affected hospitals generate significantly higher patient revenues, including from both inpatient and outpatient services, following the tightened credit constraints.

For additional interpretation of these estimates, a back of the envelope calculation using column (1) of Table 4 indicates an increase of \$1.08 million in interest payments for the average affected hospital (a sizable increase of 19% relative to the sample mean).[38] 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 reduces average profit by 13.5%. In comparison, the average affected hospital increases its profit by between \$1.084 to \$1.416 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 5. Second, a hospital that expects to have less-favorable debt financing terms in future periods can improve revenues in the *current* period to build sufficient internal reserves for the future.

[36] Profit margin is defined as profit (i.e., net income) divided by *Income* (i.e., gross income). Hospital profit is taken from line 29 of HCRIS Worksheet G-3 and is defined as *Income* minus operating expenses (line 4) and other expenses (line 28).

[37] In untabulated results, we confirm that the results are robust to using the logarithm of liabilities, which indicates that our results are not driven by possible changes in the denominator (total assets).

[38] 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 $\times$ 75 bps = \$1.08 million.

[39] We calculate this range in the change in profits by running our main specification using raw profit as the dependent variable; we consider both total profit (line 29 of Worksheet G-3), which corresponds to an increase of \$1.084 million, and profit from patient services (line 5), corresponding to an increase of \$1.416 million. 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)).

To further examine the potential sources of these increased patient revenues, we consider bed utilization and discharge rates in columns (6) and (7) of Table 5. *BedUtil* in column (6) 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 (7) 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 2.35 more patients per bed, equivalent to 367 more patients per hospital per year.[40]

For robustness, Panel B of Table 5 provides the estimates using a propensity score-matched sample, while Panel C drops all lagged control variables that are related to the outcome variables we examine. We see that the results are very similar in these analyses. This suggests that potential differences between the control and treatment groups or the presence of lagged outcome variables as controls are not materially affecting the inferences of our analysis.

We explore additional operating and investing decisions in Appendix Table A.4. 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.[41] 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. Finally, hospitals can increase revenues 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.[42]

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

[40] This is calculated by multiplying 2.35 with the average number of hospital beds in our sample (156.28).

[41] 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)).

[42] 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.

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 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 Table 6; we include results for the main sample in Panel A and results for the propensity score-matched sample and dropped lagged outcome controls specification in Panels B and C, respectively (we also include parallel trend figures, discussed in Section 4.4). 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 10.1% increase in unplanned pneumonia readmissions relative to unaffected hospitals, a 2.7% increase in heart failure readmissions, and a 2.6% increase in AMI readmissions. This translates to an additional 1,495 patients readmitted per year indirectly due to the negative credit shock in aggregate across affected hospitals.[43]

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.[44] 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.[45] As noted previously, CMS levies penalties, in the form of reductions in Medicare payments, for high unplanned readmissions relative to the national average.[46] 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 6 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

[43]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 6. At the individual hospital level, we observe 2.96 more readmissions per affected hospital per year.

[44]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.

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

[46]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).

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 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)).[47]

Table 7 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 9.6% increase in mortality for affected hospitals; this amounts to an additional 859 pneumonia deaths per year indirectly due to the shock to credit access across affected hospitals (or 1.7 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.

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 8 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

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

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.

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 hospitals are changing their operations to boost revenues 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

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

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 5 for variables that are available in 2017, and is equal to 4 otherwise.

Figures 1–4 provide parallel trends for our main outcomes related to hospital financials, bed utilization, readmission rates, mortality, and patient satisfaction. In each figure, we show parallel trends for our main sample in Panel A, and parallel trends for our propensity score-matched sample in Panel B. 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.[48]

[48]The parallel trends assumption also holds within sub-samples. For example, we later show that hospitals with a greater reliance on bank loans respond more to the stress test shock. In untabulated tests, we show that the parallel trends for the sub-group of hospitals that have above-median bank loan reliance look very similar to those of our main sample, indicating that there are no significant pre-trends for this group. These figures are available upon request.

A potential concern in examining parallel trends in our setting stems from the fact that 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 restrict heterogeneity with respect to observed covariates, the period in which units are first treated, or the evolution of treatment effects. We provide these graphs in Appendix B; the main parallel trend plots are very similar to the previous graphs, regardless of whether we include "not-yet-treated" observations as the control group for earlier events. In addition, in Table B.1 of Appendix B, we confirm that our main results are similar when dropping all covariates from the main specification.

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.[49] This permits us to examine effects for patient sub-groups within 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

[49]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.

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. 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.

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 9 based on specification (4) above. Column (1) in Table 9, Panel A indicates that inpatient admissions per DRG increased by 4.9% 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 7.7% 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% 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. 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),[50] 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 hospitals lowering the standard for admission from the ED and admitting patients with less severe conditions. In Appendix Table A.6, 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.6). 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

[50] 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 5.2% for the average affected hospital, whereas inpatient admissions coded with DRG 639 increase by 5.8%.

gameable by hospitals and thus should not experience a similar increase in admissions.[51] We find insignificant changes under both of these conditions in Appendix Table A.7.

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 9. 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.6).

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 9, Panel A).[52]

Cost efficiency. Affected hospitals also exhibit a significant increase in their profit margins, as documented in Table 5. 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 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.[53] The DRG-based reimbursement accounts for the hospital resources, including medical procedures and the patient's hospital stay, required to treat the

[51]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."

[52]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.8.

[53]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.

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.[54]

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 10, 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.[55] 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 10, 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.9). 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.[56]

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,

[54]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.8) implies that the main reduction in procedures are for those covered by the DRG-based payments.

[55]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 $64 \times 0.018 \times 355$.

[56]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 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 $13.65 \times 4.8 \times 0.012 \times 355$.

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 mechanisms 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 11. 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.[57] 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.[58] For pneumonia, we use the portion of patients that receive the most appropriate antibiotic at discharge.

The results are presented in Table 12. 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 1.4% 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.

[57]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)).

[58]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 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.

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 0.5–1.4% for affected hospitals. This represents a 14–22% 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.[59] 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 suboptimally 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.[60]

[59]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.

[60]Previous studies have found that for-profit and not-for-profit hospitals behave similarly in response to financial incentives and shocks (e.g., Duggan (2000), Dranove et al. (2017)), 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 14.

6 Heterogeneity Tests

In this section, we consider a number of heterogeneity tests to further establish the channels behind the results, including differential responses due to hospital characteristics, such as reliance on bank financing, ownership status, market power, cash reserves, or system status, or through heterogeneous exposure to the treatment. 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.

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 13 and show a consistent pattern of stronger effects for the affected hospitals that are more reliant on loan financing. We also note that 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).

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 $Profit_i$, 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 Table 14, 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.

We next consider possible heterogeneity in responses based on hospital market power and competition. To measure market power, we first calculate each hospital'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 $HRevFrac_i$, which is an indicator variable equal to one if hospital i's share of inpatient revenues in its respective HRR is above the sample median, and zero otherwise. In Appendix Table A.10, we see that hospitals 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 $HCash_i$, 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.11, 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 is part of a large (national) or local system. These results are presented in Appendix Tables A.12 and A.13, respectively. 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.

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 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):

$$msd = \min(\textit{Tier 1 capital} - 6\%, \textit{Risk-based capital} - 8\%, \textit{Stressed leverage} - 4\%). \qquad (5)$$

The logic behind equation (5) 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.[61] For each treated hospital i, we calculate the average msd for all of its stress-tested lenders, weighted by loan amount. We then rerun 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 15 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

[61] 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.

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, 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 $HighSTExposed_{i,t-1}$ and $LowSTExposed_{i,t-1}$, 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.14 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.

7 Robustness

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

7.1 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.[62] Alternatively, local economic conditions in an area may affect both bank

[62]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.

lending and hospital outcomes, thus potentially confounding the channels that we aim to identify.[63]

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 5. 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.[64] Furthermore, this figure shows that, within a particular state or 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.15 provides the estimation results and confirms that our results are robust to controlling for time-varying geographical conditions.

7.2 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.

To address this concern, in Appendix Table A.16, we restrict our sample to hospitals belonging to a healthcare system from 2010 to 2016, and we add a *System* fixed effect in

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

[64]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.

our regression to denote the specific system a hospital is a part of.[65] We further cluster the standard errors at the hospital system level. The results in Table A.16 are consistent with the baseline estimation, showing that the effect is not driven by differences between hospital systems and independent hospitals.

We also examine additional 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 Table A.13). 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.17).

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 4 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.18, we see that the results are similar to that of our main tests.

We similarly consider a sub-sample 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.19, 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. Appendix Table A.20 reports the results. The findings are similar to those of our main analysis as well as the heterogeneity test results reported in Table 14.

7.3 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

[65] Note that this fixed effect is not absorbed by the hospital fixed effects because, for a given hospital, its parent organization can change over time due to M&As. We also include hospital-year observations for independent hospitals that later are acquired by a healthcare system. For these cases, the hospital's parent system is coded as "Independent."

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:

$$Y_{i,t} = \alpha + \beta NearExposed_{i,t-1} + \gamma' Controls_{i,t-1} + \eta_t + \mu_i + \varepsilon_{i,t}. \tag{6}$$

$NearExposed_{i,t-1}$ 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 (6) is otherwise the same as our main specification (1). The results are presented in Appendix Table A.21. We find that rival hospitals largely do not exhibit significant responses to their local competitor's credit shock. One exception is that discharge rate significantly decreases for these rival hospitals, which may be due to exposed hospitals taking greater market share of admitted patients by receiving a larger share of physician referrals following the shock (as discussed in Section 2, affected hospitals can increase inpatient admissions by building stronger ties with physician practices and receiving the referrals). However, 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.

7.4 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.[66] 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.[67] In 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.22.

[66] 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.

[67] 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, 2010. Available at: `http://www.federalreserve.gov/boarddocs/srletters/2009/SR0904_Addendum.pdf`.

8 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.

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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). *Amt* is the 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 it at the borrowing time. *LoanRatio* is the loan amount divided by the borrower's total assets. We aggregate total assets across all subsidiary hospitals if the borrower is a hospital chain/system.

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
Amt ($ million)	78.402	312.565	7.955	13.231	25.132
LoanRatio	0.337	0.338	0.087	0.182	0.539

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

This table provides the summary statistics of hospital characteristics in the year of 2011 (the last year before the DFAST announcement) for the entire sample and separately for the treatment and control groups.

Panel A: Full Sample

	Obs.	*Mean*	*Std*	*P25*	*Median*	*P75*
Patient Revenue ($ million)	3,589	533.403	822.180	63.871	236.320	684.212
Log(Income)	3,588	17.960	2.570	17.195	18.284	19.228
Liab/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
LogDischarge	3,572	8.091	1.568	6.989	8.378	9.330
LogBedDay	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
Hos Chain	3,658	0.678	0.467	0.000	1.000	1.000

Panel B: Treatment Group

	Obs.	*Mean*	*Std*	*P25*	*Median*	*P75*
Patient Revenue ($ million)	498	752.811	738.826	222.485	527.120	1047.157
Log(Income)	498	18.580	1.765	18.089	18.779	19.421
Liab/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
LogDischarge	496	8.747	1.192	8.267	8.968	9.543
LogBedDay	497	10.744	0.855	10.343	10.884	11.338
For-profit	504	0.492	0.500	0.000	0.000	1.000
Hos Chain	505	0.988	0.108	1.000	1.000	1.000

Panel C: Control Group

	Obs.	*Mean*	*Std*	*P25*	*Median*	*P75*
Patient Revenue ($ million)	3,091	498.053	829.528	54.577	195.440	611.114
Log(Income)	3,090	17.860	2.664	17.069	18.168	19.173
Liab/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
LogDischarge	3,076	7.985	1.595	6.858	8.204	9.251
LogBedDay	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
Hos Chain	3,153	0.628	0.483	0.000	1.000	1.000

Table 3: Summary Statistics for the Propensity Score Matched Sample

This table provides the summary statistics for the propensity score matched sample in the year of 2011 (the last year before the DFAST announcement). We match based on $PatRev/TA$, $Cash/TA$, $LogBedDay$, and pneumonia mortality rate, and keep the nearest two neighbors for each treatment hospital. We restrict our matched sample to a precision difference cutoff of 0.003.

	Control Obs.	*Treat Obs.*	*Mean of Control*	*Mean of Treat*	*Diff.*	*t-stat*	*p-value*
Patient Revenue ($ million)	659	353	690.812	726.687	−35.875	−0.700	0.485
Total Assets ($ million)	659	353	262.122	211.694	50.427	1.550	0.124
PatRev/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
Liab/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(PNReadm)	609	326	2.752	2.755	−0.004	−0.100	0.937
Log(PNMort)	609	325	2.334	2.330	0.004	0.100	0.930
Overall	637	342	0.671	0.669	0.003	0.500	0.609

Table 4: 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. $STExposed$ take 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. $LogAmt$ is the logarithm of the loan facility amount. $LogMaturity$ is the logarithm of the loan facility maturity (in months). $NewLender$ 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, profitability (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 t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
	Spread&Fee	*Spread&Fee*	*LogAmt*	*LogMaturity*	*NewLender*
$STExposed_{i,t-1}$	74.764***	63.166**	−0.362***	−0.084*	0.132*
	(2.968)	(2.020)	(−2.842)	(−1.718)	(1.834)
Controls	Y	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	305.089	305.089	312.565	16.346	0.494
Adj R^2	0.21	0.39	0.60	0.43	0.34

Table 5: 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. *Margin* is profit margin, defined as $(Income - Cost)/Income$. *LogPatRev* is the logarithm of one plus the total patient revenue. $Liab/TA$ is total liabilities over total assets. *LogInPatRev* and *LogOutPatRev* are the logarithm of one plus total inpatient and outpatient revenues, respectively. *BedUtil* is the average daily fraction of hospital beds that are occupied. *Discharge Rate* is inpatient discharges over total bed days. In Panel A, control variables include the lagged logarithm of one plus total hospital income ($LogIncome_{i,t-1}$), lagged logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), lagged cash holdings over total assets ($Cash/TA_{i,t-1}$), lagged liabilities over total assets ($Liab/TA_{i,t-1}$), and lagged total patient revenue over total assets ($PatRev/TA_{i,t-1}$). Panel B replicates the analysis using a propensity score matched sample. Panel C drops $LogIncome_{i,t-1}$, $Liab/TA_{i,t-1}$, and $PatRev/TA_{i,t-1}$ from the control variables. 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 t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Main Specification

	(1) *Margin*	(2) *Liab/TA*	(3) *LogPatRev*	(4) *LogInPatRev*	(5) *LogOutPatRev*	(6) *BedUtil*	(7) *Discharge Rate*
$STExposed_{i,t-1}$	0.012**	−0.052***	0.057*	0.086***	0.068*	0.022***	2.350***
	(2.077)	(−4.275)	(1.903)	(2.845)	(1.851)	(5.973)	(5.752)
Controls	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y	Y
N	23,780	23,223	23,793	23,793	23,793	23,245	23,243
Y Mean	0.032	0.565	555.005	310.637	244.368	0.443	41.933
Y Std	0.283	0.516	901.017	555.333	379.260	0.231	19.545
Adj R^2	0.22	0.81	0.93	0.95	0.81	0.94	0.8

Panel B: Propensity Score Matched Sample

	(1) *Margin*	(2) *Liab/TA*	(3) *LogPatRev*	(4) *LogInPatRev*	(5) *LogOutPatRev*	(6) *BedUtil*	(7) *Discharge Rate*
$STExposed_{i,t-1}$	0.025***	−0.051***	0.061*	0.079**	0.055	0.021***	2.159***
	(3.475)	(−3.268)	(1.649)	(2.158)	(1.114)	(4.243)	(3.804)
Controls	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y	Y
N	6,917	6,773	6,919	6,919	6,919	6,783	6,783
Adj R^2	0.22	0.81	0.93	0.95	0.81	0.94	0.8

Panel C: Drop Outcome-related Controls

	(1) *Margin*	(2) *Liab/TA*	(3) *LogPatRev*	(4) *LogInPatRev*	(5) *LogOutPatRev*	(6) *BedUtil*	(7) *Discharge Rate*
$STExposed_{i,t-1}$	0.011*	−0.082***	0.061**	0.091***	0.066*	0.023***	2.398***
	(1.751)	(−5.075)	(2.079)	(3.101)	(1.779)	(5.976)	(5.858)
Non-Outcome Controls	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y	Y
N	23,804	23,231	23,817	23,817	23,817	23,269	23,267
Adj R^2	0.21	0.76	0.93	0.95	0.81	0.94	0.80

Table 6: Hospital Care Quality: Readmission Rates

This table provides the estimation results for equation (1), focusing on 30-day readmission rates. The outcome variables in columns (1)–(3) measure the logarithm of the number of unplanned readmissions for Pneumonia ($LogPNReadm$), heart failure ($LogHFReadm$), and acute myocardial infarction ($LogAMIReadm$), respectively. The outcome variables in columns (4)–(6) measure the readmission rates for Pneumonia ($PNReadmRate$), heart failure ($HFReadmRate$), and acute myocardial infarction ($AMIReadmRate$), respectively. The outcome variable in Column (7) is the readmission rate for all diseases ($AllReadmRate$). 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 nation-wide, 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. In Panel A, control variables include the lagged logarithm of one plus total hospital income ($LogIncome_{i,t-1}$), lagged logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), lagged cash holdings over total assets ($Cash/TA_{i,t-1}$), lagged liabilities over total assets ($Liab/TA_{i,t-1}$), and lagged total patient revenue over total assets ($PatRev/TA_{i,t-1}$). Panel B replicates the analysis using a propensity score matched sample. Panel C drops $LogIncome_{i,t-1}$, $Liab/TA_{i,t-1}$, and $PatRev/TA_{i,t-1}$ from the control variables. 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 t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Main Specification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	LogPNReadm	*LogHFReadm*	*LogAMIReadm*	*PNReadmRate*	*HFReadmRate*	*AMIReadmRate*	*AllReadmRate*	*AllReadmWorst*
$STExposed_{i,t-1}$	0.101***	0.027**	0.026**	0.003***	0.003***	0.003***	0.002***	0.046***
	(8.678)	(2.475)	(1.972)	(5.763)	(4.898)	(5.070)	(5.103)	(3.500)
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	21,588	20,062	12,668	23,408	22,165	14,341	17,678	19,336
Y Mean	18.953	26.100	13.062	0.173	0.225	0.174	0.155	0.079
Y Std	16.495	26.645	12.609	0.014	0.019	0.017	0.010	0.270
Adj R^2	0.96	0.98	0.97	0.72	0.77	0.82	0.67	0.48

Panel B: Propensity Score Matched Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	LogPNReadm	*LogHFReadm*	*LogAMIReadm*	*PNReadmRate*	*HFReadmRate*	*AMIReadmRate*	*AllReadmRate*	*AllReadmWorst*
$STExposed_{i,t-1}$	0.063***	0.031**	0.016	0.003***	0.002**	0.002***	0.001***	0.028*
	(4.371)	(2.251)	(0.958)	(3.574)	(2.343)	(3.442)	(3.195)	(1.685)
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	7,255	7,036	5,033	7,604	7,434	5,552	5,509	5,692
Adj R^2	0.96	0.97	0.96	0.71	0.76	0.82	0.67	0.46

Panel C: Drop Outcome-related Controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	LogPNReadm	*LogHFReadm*	*LogAMIReadm*	*PNReadmRate*	*HFReadmRate*	*AMIReadmRate*	*AllReadmRate*	*AllReadmWorst*
$STExposed_{i,t-1}$	0.102***	0.030***	0.030**	0.003***	0.003***	0.003***	0.002***	0.047***
	(8.737)	(2.758)	(2.201)	(5.692)	(4.936)	(5.255)	(4.965)	(3.558)
Non-Outcome 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
Adj R^2	0.96	0.98	0.96	0.72	0.77	0.82	0.67	0.48

Table 7: Hospital Care Quality: Mortality

This table provides estimation results for equation (1), focusing on mortality outcomes. $LogPNMort$, $LogHFMort$, and $LogAMIMort$ are the logarithms of the number of pneumonia, heart failure, and AMI deaths, respectively. $PNMortNum$ is the number of pneumonia deaths. $PNMorRate$ is the mortality rate for patients treated for pneumonia. $PNMortWorst$ 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. In Panel A, control variables include the lagged logarithm of one plus total hospital income ($LogIncome_{i,t-1}$), lagged logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), lagged cash holdings over total assets ($Cash/TA_{i,t-1}$), lagged liabilities over total assets ($Liab/TA_{i,t-1}$), and lagged total patient revenue over total assets ($PatRev/TA_{i,t-1}$). Panel B replicates the analysis using a propensity score matched sample. Panel C drops $LogIncome_{i,t-1}$, $Liab/TA_{i,t-1}$, and $PatRev/TA_{i,t-1}$ from the control variables. 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 t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Main Specification

	(1) *LogPNMort*	(2) *LogHFMort*	(3) *LogAMIMort*	(4) *PNMortNum*	(5) *PNMortRate*	(6) *PNMortWorst*
$STExposed_{i,t-1}$	0.096***	0.001	0.020*	1.704***	0.002***	0.018*
	(8.182)	(0.076)	(1.814)	(5.066)	(2.609)	(1.744)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	21,543	19,834	14,065	21,543	23,372	23,820
Y Mean	14.512	11.226	9.398	15.307	0.139	0.053
Y Std	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

Panel B: Propensity Score Matched Sample

	(1) *LogPNMort*	(2) *LogHFMort*	(3) *LogAMIMort*	(4) *PNMortNum*	(5) *PNMortRate*	(6) *PNMortWorst*
$STExposed_{i,t-1}$	0.067***	0.014	0.019	0.836**	0.002**	0.035***
	(4.551)	(1.176)	(1.356)	(2.014)	(2.412)	(2.780)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	7,247	6,957	5,499	7,247	7,604	7,636
Adj R^2	0.96	0.97	0.96	0.90	0.85	0.35

Panel C: Drop Outcome-related Controls

	(1) *LogPNMort*	(2) *LogHFMort*	(3) *LogAMIMort*	(4) *PNMortNum*	(5) *PNMortRate*	(6) *PNMortWorst*
$STExposed_{i,t-1}$	0.098***	0.003	0.022*	1.737***	0.002***	0.018*
	(8.288)	(0.325)	(1.928)	(5.175)	(2.746)	(1.740)
Non-Outcome 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
Adj R^2	0.96	0.98	0.97	0.90	0.84	0.31

Table 8: 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*), pain control (*PainCtrl*), recommendation of the hospital to similar patients (*Recommend*), cleanliness (*Clean*), doctor communication (*DocCom*), nurse communication (*NurseCom*), recovery information (*Info*), and quietness (*Quiet*), 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. In Panel A, control variables include the lagged logarithm of one plus total hospital income ($LogIncome_{i,t-1}$), lagged logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), lagged cash holdings over total assets ($Cash/TA_{i,t-1}$), lagged liabilities over total assets ($Liab/TA_{i,t-1}$), and lagged total patient revenue over total assets ($PatRev/TA_{i,t-1}$). Panel B replicates the analysis using a propensity score matched sample. Panel C drops $LogIncome_{i,t-1}$, $Liab/TA_{i,t-1}$, and $PatRev/TA_{i,t-1}$ from the control variables. 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 t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Main Specification

	(1) *Overall*	(2) *PainCtrl*	(3) *Recommend*	(4) *Clean*	(5) *DocCom*	(6) *NurseCom*	(7) *Info*	(8) *Quiet*
$STExposed_{i,t-1}$	−0.008***	−0.006***	−0.006***	−0.006***	−0.006***	−0.003***	−0.005***	−0.008***
	(−4.561)	(−4.752)	(−3.430)	(−3.364)	(−6.076)	(−2.951)	(−5.108)	(−4.025)
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	21,349	21,335	21,347	21,349	21,349	21,349	21,348	21,349
Y Mean	0.702	0.703	0.710	0.726	0.809	0.783	0.853	0.600
Y Std	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

Panel B: Propensity Score Matched Sample

	(1) *Overall*	(2) *PainCtrl*	(3) *Recommend*	(4) *Clean*	(5) *DocCom*	(6) *NurseCom*	(7) *Info*	(8) *Quiet*
$STExposed_{i,t-1}$	−0.006**	−0.006***	−0.005**	−0.005**	−0.005***	−0.003*	−0.003**	−0.007***
	(−2.490)	(−3.028)	(−2.248)	(−2.202)	(−4.001)	(−1.830)	(−2.242)	(−2.745)
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	6,694	6,694	6,694	6,694	6,694	6,694	6,694	6,694
Adj R^2	0.80	0.55	0.86	0.69	0.77	0.77	0.75	0.84

Panel C: Drop Outcome-related Controls

	(1) *Overall*	(2) *PainCtrl*	(3) *Recommend*	(4) *Clean*	(5) *DocCom*	(6) *NurseCom*	(7) *Info*	(8) *Quiet*
$STExposed_{i,t-1}$	−0.008***	−0.007***	−0.006***	−0.006***	−0.006***	−0.003***	−0.005***	−0.009***
	(−4.751)	(−4.905)	(−3.651)	(−3.511)	(−6.049)	(−3.060)	(−5.202)	(−4.487)
Non-Outcome 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
Adj R^2	0.82	0.59	0.85	0.76	0.77	0.78	0.72	0.85

Table 9: 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. $Admit$ is the number of admissions assigned DRG d to hospital i in year t. $OrderAdmit$ is the number of admissions via physician orders. $EDAdmit$ is the number of admissions via physician orders that originate from emergency rooms. $EleAdmit$ is the number of admissions via physician orders that are elective. $ClinicAdmit$ is the number of admissions through clinics and physician centers. $TrAdmit$ 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 total hospital income ($LogIncome_{i,t-1}$), lagged logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), lagged cash holdings over total assets ($Cash/TA_{i,t-1}$), lagged liabilities over total assets ($Liab/TA_{i,t-1}$), and lagged total patient revenue over total assets ($PatRev/TA_{i,t-1}$). 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 t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: General Admission Decisions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(Admit)	*Log(OrderAdmit)*	*Log(EDAdmit)*	*Log(EleAdmit)*	*Log(ClinicAdmit)*	*Log(TrAdmit)*	*Log(Admit)*	*Log(EDAdmit)*
$STExposed_{i,t-1}$	0.049***	0.077**	0.119***	0.064***	−0.123***	−0.035**	0.063***	0.138***
	(4.154)	(2.091)	(2.869)	(3.076)	(−3.818)	(−2.324)	(4.303)	(2.911)
$Weight_{d,t}$ $\times STExposed_{i,t-1}$							−0.008***	−0.011**
							(−2.692)	(−2.128)
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
N	1,651,795	1,409,215	1,409,215	1,409,215	1,409,215	1,409,215	1,651,795	1,409,215
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

	(1)	(2)	(3)
Insurance	*Private*	*Medicare*	*Medicaid*
	Log(Admit)	*Log(Admit)*	*Log(Admit)*
$STExposed_{i,t-1}$	0.042***	0.033***	0.028**
	(3.044)	(2.770)	(2.459)
Controls	Y	Y	Y
DRG-Year FE	Y	Y	Y
Hospital-DRG FE	Y	Y	Y
N	1,651,795	1,651,795	1,651,795
Adj R^2	0.85	0.87	0.83

Table 10: 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. $AvgNpr$ is the average number of procedures for each case in DRG d at year t. $AvgLOS$ 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 total hospital income ($LogIncome_{i,t-1}$), lagged logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), lagged cash holdings over total assets ($Cash/TA_{i,t-1}$), lagged liabilities over total assets ($Liab/TA_{i,t-1}$), and lagged total patient revenue over total assets ($PatRev/TA_{i,t-1}$). 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 t-statistics are 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(AvgNPr)	*Log(AvgNPr)*	*Log(AvgNPr)*	*Log(AvgNPr)*
$STExposed_{i,t-1}$	−0.018***	−0.011*	−0.017***	−0.014*
	(−2.959)	(−1.755)	(−2.594)	(−1.829)
Controls	Y	Y	Y	Y
DRG-Year FE	Y	Y	Y	Y
Hospital-DRG FE	Y	Y	Y	Y
N	1,643,175	1,161,584	1,388,404	859,729
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(AvgLOS)	*Log(AvgLOS)*	*Log(AvgLOS)*	*Log(AvgLOS)*
$STExposed_{i,t-1}$	−0.008	−0.012**	−0.004	−0.011*
	(−1.382)	(−2.302)	(−0.636)	(−1.671)
Controls	Y	Y	Y	Y
DRG-Year FE	Y	Y	Y	Y
Hospital-DRG FE	Y	Y	Y	Y
N	1,651,791	1,161,584	1,388,404	859,729
Adj R^2	0.69	0.60	0.62	0.58

Table 11: 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. $AdmPerPhy_{i,d,t}$ is the average number of admissions attended by each physician in hospital i's DRG d in year t. $PhyPerPat_{i,d,t}$ is the average number of physicians involved in each admission in hospital i's DRG d in year t. $UniquePhy_{i,d,t}$ 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 total hospital income ($LogIncome_{i,t-1}$), lagged logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), lagged cash holdings over total assets ($Cash/TA_{i,t-1}$), lagged liabilities over total assets ($Liab/TA_{i,t-1}$), and lagged total patient revenue over total assets ($PatRev/TA_{i,t-1}$). 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 t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) *Log(AdmPerPhy)*	(2) *Log(PhyPerPat)*	(3) *Log(UniquePhy)*
$STExposed_{i,t-1}$	0.021***	−0.015***	0.009
	(5.011)	(−3.009)	(0.004)
Controls	Y	Y	Y
DRG-Year FE	Y	Y	Y
Hospital-DRG FE	Y	Y	Y
N	1,254,889	1,651,795	1,651,795
Adj R^2	0.87	0.95	0.94

Table 12: 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 total hospital income ($LogIncome_{i,t-1}$), lagged logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), lagged cash holdings over total assets ($Cash/TA_{i,t-1}$), lagged liabilities over total assets ($Liab/TA_{i,t-1}$), and lagged total patient revenue over total assets ($PatRev/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and t-statistics are 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*
$STExposed_{i,t-1}$	−0.001	−0.014***	−0.005**	−0.008***	−0.008***	−0.008***
	(−1.155)	(−3.112)	(−2.390)	(−5.712)	(−3.512)	(−3.388)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	9,199	6,325	6,933	14,372	11,189	14,644
Adj R^2	0.43	0.51	0.60	0.78	0.49	0.58

Table 13: 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. $Margin$ is profit margin, defined as $(Income - Cost)/Income$. *BedUtil* is the average daily fraction of hospital beds that are occupied. *Discharge Rate* is inpatient discharges over total bed days. *AllReadmRate* 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. Control variables include the lagged logarithm of one plus total hospital income ($LogIncome_{i,t-1}$), lagged logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), lagged cash holdings over total assets ($Cash/TA_{i,t-1}$), lagged liabilities over total assets ($Liab/TA_{i,t-1}$), and lagged total patient revenue over total assets ($PatRev/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) *Margin*	(2) *BedUtil*	(3) *Discharge Rate*	(4) *AllReadmRate*	(5) *Antibiotic*	(6) *Overall*
$STExposed_{i,t-1}$	0.005	0.012**	0.771	0.001	−0.002	−0.004
	(0.565)	(2.155)	(1.421)	(1.191)	(−0.722)	(−1.501)
$HighReliance_i \times STExposed_{i,t-1}$	0.012	0.023***	2.426***	0.003***	−0.010**	−0.004
	(1.141)	(3.053)	(3.390)	(3.616)	(−2.264)	(−1.244)
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

Table 14: Heterogeneity Across For-Profit and Non-Profit Hospitals

This table provides estimation results when interacting the treatment variable with a hospital's tax status. $Profit_i$ takes a value of 1 if hospital i is a for-profit hospital, and 0 otherwise. $Margin$ is profit margin, defined as $(Income - Cost)/Income$. *BedUtil* is the average daily fraction of hospital beds that are occupied. *Discharge Rate* is inpatient discharges over total bed days. *AllReadmRate* 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. Control variables include the lagged logarithm of one plus total hospital income ($LogIncome_{i,t-1}$), lagged logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), lagged cash holdings over total assets ($Cash/TA_{i,t-1}$), lagged liabilities over total assets ($Debt/TA_{i,t-1}$), and lagged total patient revenue over total assets ($PatRev/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1) *Margin*	(2) *BedUtil*	(3) *Discharge Rate*	(4) *AllReadmRate*	(5) *Antibiotic*	(6) *Overall*
$STExposed_{i,t-1}$	0.016**	0.013**	1.378***	0.001*	−0.004	−0.004
	(2.456)	(2.432)	(2.618)	(1.907)	(−1.350)	(−1.560)
$Profit_i \times STExposed_{i,t-1}$	−0.009	0.019***	1.941***	0.002***	−0.006	−0.008**
	(−0.900)	(2.736)	(2.648)	(2.905)	(−1.617)	(−2.551)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	23,741	23,220	23,215	17,678	15,113	21,349
Adj R^2	0.21	0.94	0.80	0.67	0.58	0.82

Table 15: 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

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

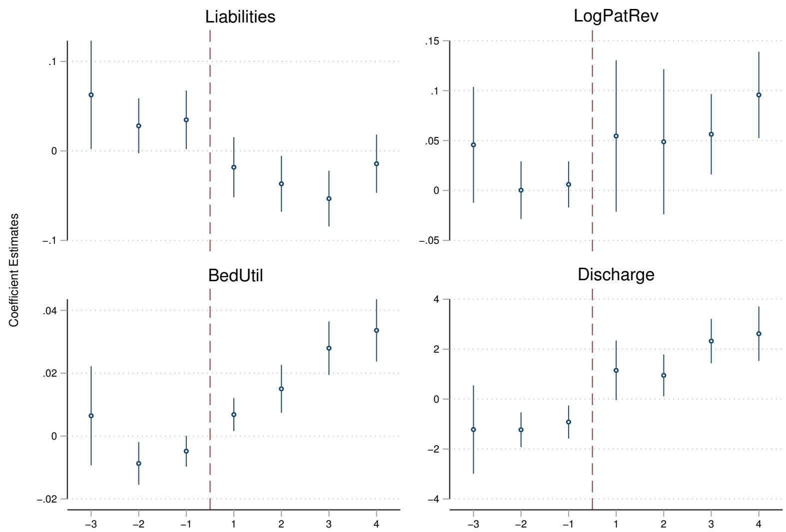
For each treated hospital i, we calculate the average *msd* for all of its tested lenders, weighted by the loan amount. $CloseExposed_{i,t-1}$ ($FarExposed_{i,t-1}$) takes a value of 1 if hospital i was exposed in year $t-1$ or earlier *and* the average *msd* of its tested lenders is below (above) median, and 0 otherwise. $Margin$ 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. *AllReadmRate* 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. Control variables include the lagged logarithm of one plus total hospital income ($LogIncome_{i,t-1}$), lagged logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), lagged cash holdings over total assets ($Cash/TA_{i,t-1}$), lagged liabilities over total assets ($Liab/TA_{i,t-1}$), and lagged total patient revenue over total assets ($PatRev/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) *Margin*	(2) *BedUtil*	(3) *Discharge Rate*	(4) *AllReadmRate*	(5) *Antibiotic*	(6) *Overall*
$CloseExposed_{i,t-1}$	0.013**	0.024***	2.028***	0.001***	−0.009***	−0.008***
	(2.285)	(5.526)	(4.619)	(3.548)	(−3.200)	(−4.452)
$FarExposed_{i,t-1}$	−0.004	0.013***	0.793*	0.002***	−0.003	0.001
	(−0.607)	(2.910)	(1.665)	(4.925)	(−0.674)	(0.388)
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

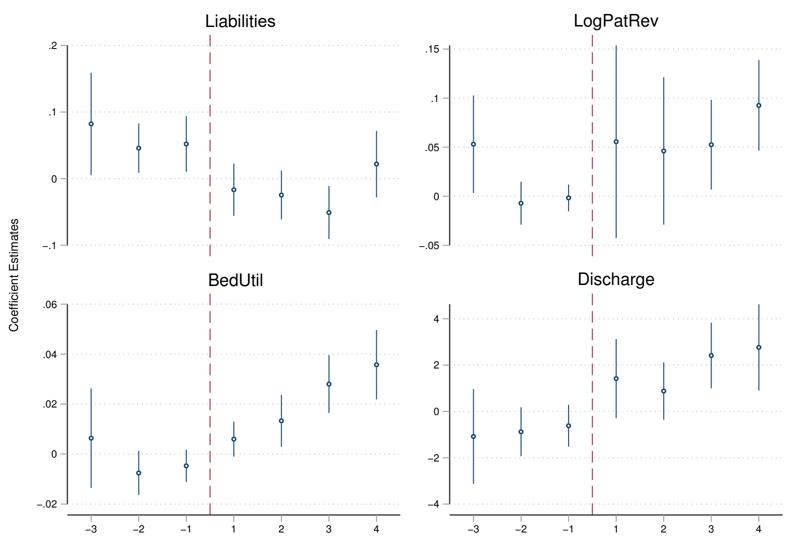
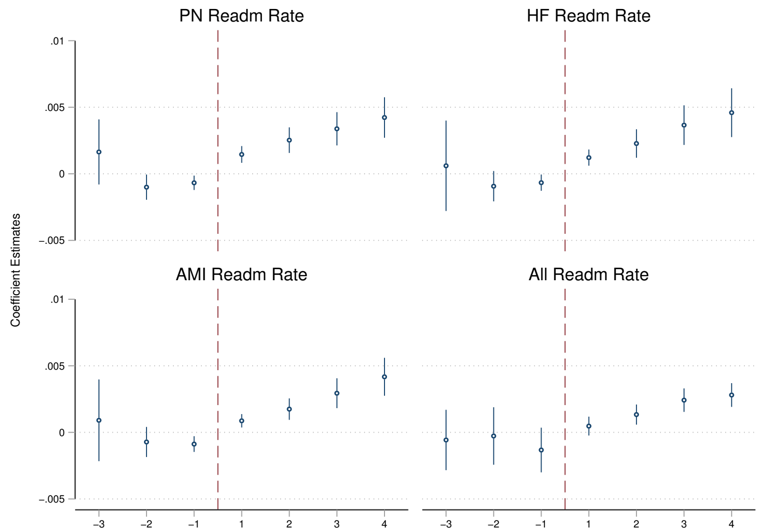


Figure 2: Parallel Trends: 30-day Readmission Rates

This figure provides parallel trends for the readmission rate 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

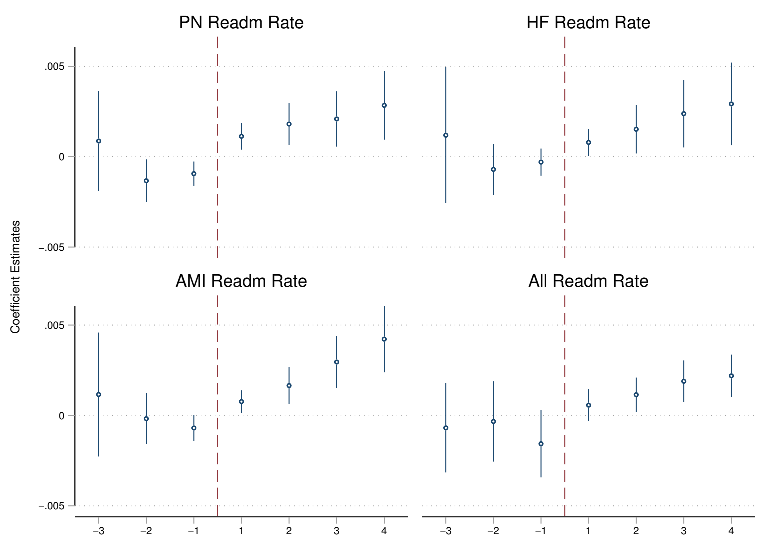
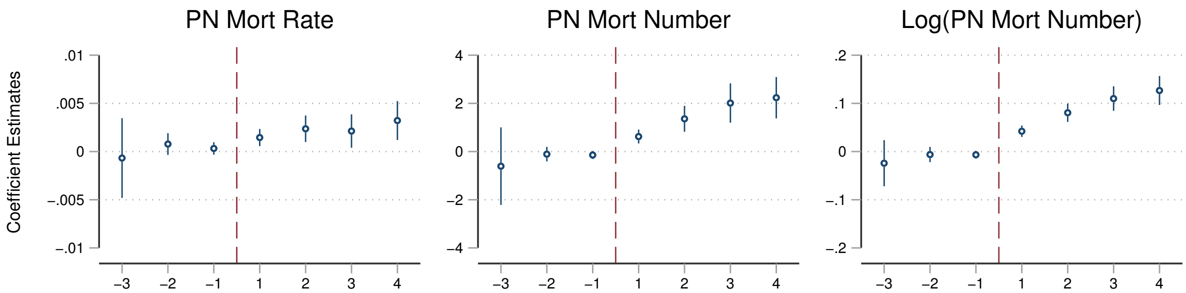


Figure 3: Parallel Trends: Mortality

This figure provides parallel trends for the mortality 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

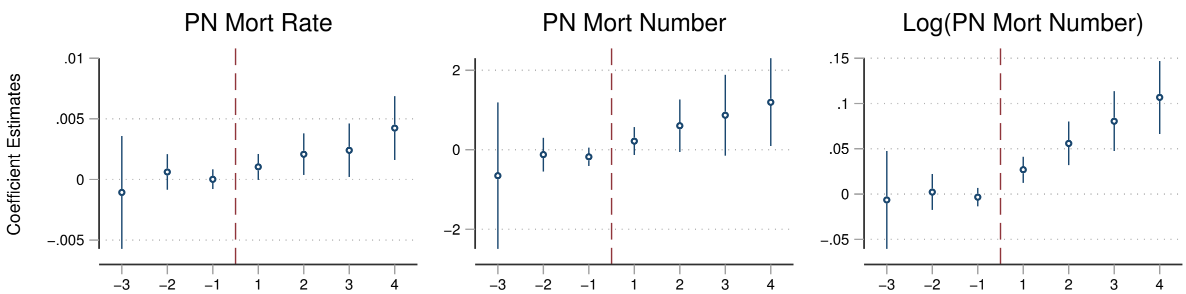
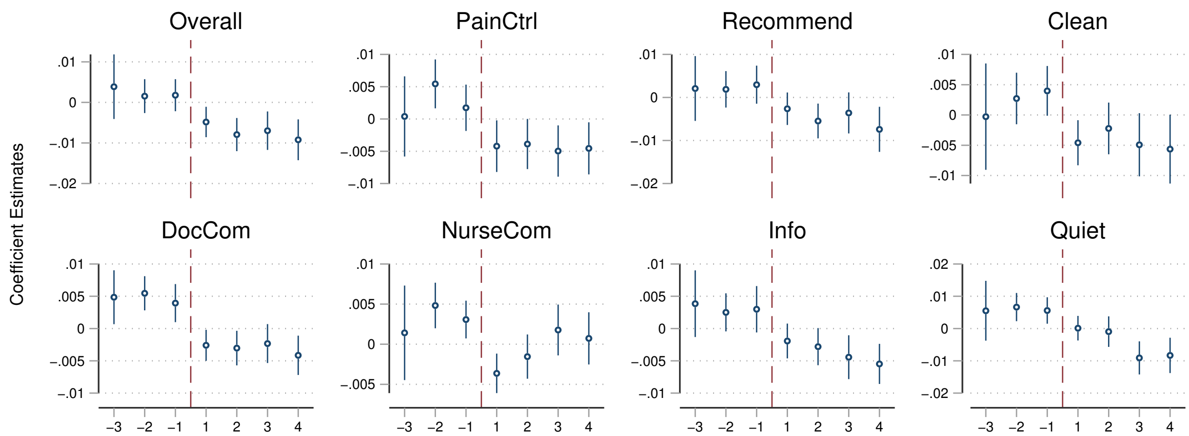


Figure 4: Parallel Trends: Hospital Care Quality from the Patient's Perspective

This figure provides parallel trends for the patient rating of care quality 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

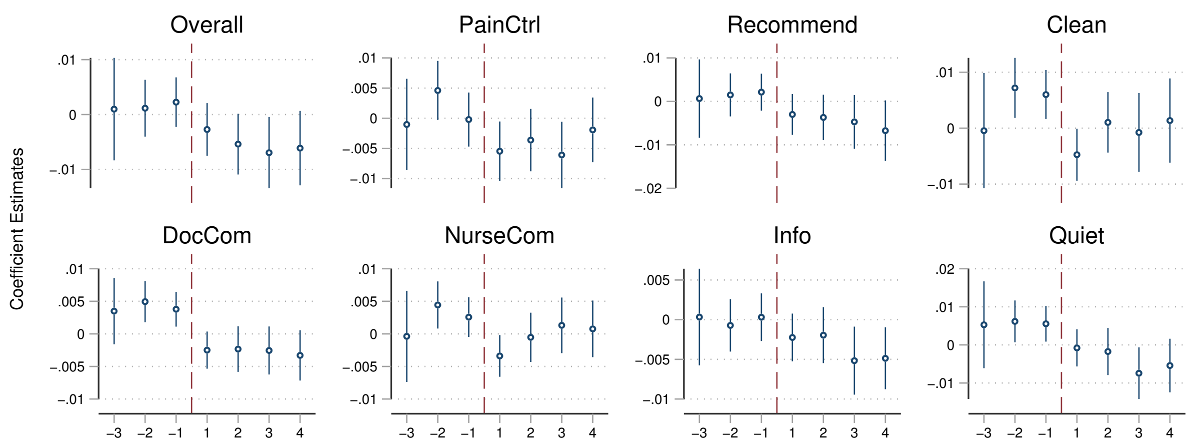
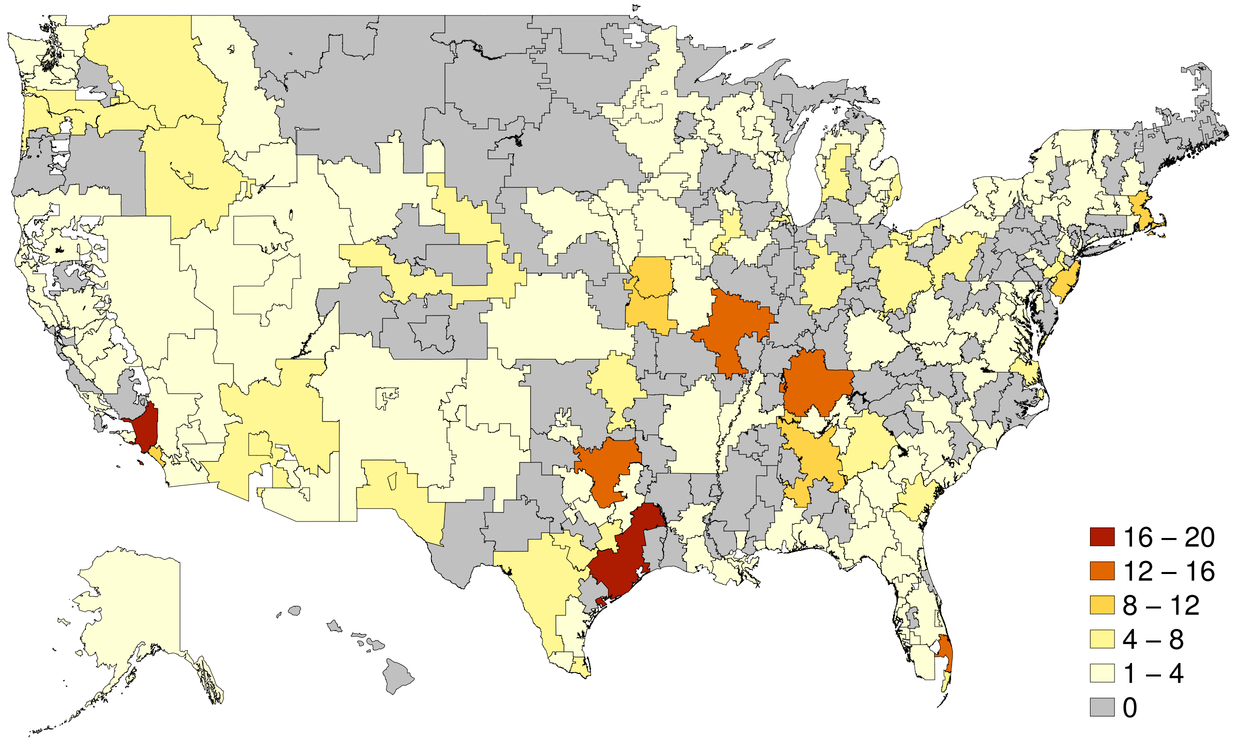


Figure 5: Geographical Distribution of Hospitals Exposed to the Stress Tests

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

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.

Variable	Definition	N	Mean	Std	P25	Median	P75
Panel A: Financial Variables from HCRIS							
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
Liab/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
PatRev	Total patient revenue ($ million)	37,342	555.005	901.017	62.933	239.742	693.586
InPatRev	Total inpatient revenues ($ million)	37,342	310.637	555.333	18.041	102.666	376.104
OutPatRev	Total outpatient revenue ($ million)	37,342	244.368	379.260	40.705	127.908	306.900
BedUtil	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
MedicarePct	Percent of Medicare discharge out of all discharges	31,518	0.404	0.100	0.302	0.392	0.491
MedicaidPct	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							
PNReadmNum	Number of PN patients readmitted	24,450	18.953	16.495	6.837	14.156	26.283
HFReadmNum	Number of HF patients readmitted	23,191	26.100	26.645	7.030	17.559	36.018
AMIReadmNum	Number of AMI patients readmitted	15,011	13.062	12.609	4.084	9.099	17.467
PNReadmRate	Rate of PN patients readmitted	24,450	0.173	0.014	0.163	0.172	0.181
HFReadmRate	Rate of HF patients readmitted	23,191	0.225	0.019	0.213	0.223	0.237
AMIReadmRate	Rate of AMI patients readmitted	15,011	0.174	0.017	0.163	0.172	0.183
AllReadmRate	Rate of all major-disease patients readmitted	18,732	0.155	0.009	0.149	0.154	0.160
AllReadmWorst	Flagged as being in the worst group for readmitting patients	20,583	0.079	0.270	0.000	0.000	0.000
PNMortNum	PN patient mortality number	24,390	14.512	12.997	5.195	10.391	19.685
PNMortRate	PN patient mortality rate	24,390	0.139	0.025	0.120	0.138	0.157
PNMortWorst	Flagged as being in the worst group for PN patient mortality	24,891	0.053	0.224	0.000	0.000	0.000
HFMortNum	HF patient mortality number	22,830	11.226	10.601	3.420	7.935	15.400
AMIMortNum	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	Percentage of patients giving the highest rating for overall care quality	22,128	0.702	0.089	0.650	0.700	0.760
PainCtrl	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
Clean	Percentage of patients giving the highest rating for cleanliness	22,129	0.726	0.076	0.680	0.720	0.770
DocCom	Percentage of patients giving the highest rating for doctor communication	22,129	0.809	0.052	0.780	0.810	0.840
NurseCom	Percentage of patients giving the highest rating for nurse communication	22,129	0.783	0.056	0.750	0.780	0.820
Info	Percentage of patients giving the highest rating for recovery information	22,126	0.853	0.046	0.830	0.860	0.880
Quiet	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							
Admit	Number of admissions assigned to a given DRG in a hospital	1,706,357	31.756	125.327	3.000	7.000	22.000
OrderAdmit	Number of admissions via physician orders	1,456,702	22.811	86.353	2.000	5.000	17.000
EDAdmit	Number of admissions via physician orders that come from emergency rooms	1,456,702	15.900	55.727	1.000	3.000	11.000
EleAdmit	Number of admissions via physician orders that are elective	1,456,702	4.241	44.758	0.000	0.000	1.000
ClinicAdmit	Number of admissions through clinics and physician centers	1,456,702	2.704	26.851	0.000	0.000	1.000
TrAdmit	Number of admissions transferred from other healthcare facilities	1,456,702	4.198	65.367	0.000	0.000	1.000
PrivateAdmit	Admission amount for privately insured patients	1,706,357	9.825	62.097	0.000	2.000	5.000
MedicareAdmit	Admission amount for Medicare patients	1,706,357	12.941	37.934	1.000	3.000	10.000
MedicaidAdmit	Admission amount for Medicaid patients	1,706,357	6.606	49.371	0.000	1.000	3.000

(continued)

AvgNPr	Average number of procedures for each case in a DRG	1,697,998	2.021	2.130	0.500	1.455	2.855
PrivateNPr	Average number of procedures for privately insured patients	1,228,183	1.973	2.242	0.400	1.308	2.833
MedicareNPr	Average number of procedures for Medicare patients	1,449,327	1.974	2.183	0.417	1.333	2.833
MedicaidNPr	Average number of procedures for Medicaid patients	931,681	1.889	2.326	0.250	1.000	2.600
AvgLOS	Average length of stay per case in a DRG	1,706,353	5.357	4.971	2.667	4.000	6.400
PrivateLOS	Average length of stay for privately insured patients	1,228,183	4.800	5.220	2.000	3.333	5.571
MedicareLOS	Average length of stay for Medicare patients	1,449,327	5.576	4.897	3.000	4.273	6.778
MedicaidLOS	Average length of stay for Medicaid patients	931,681	5.748	7.765	2.167	3.667	6.333
AdmPerPhy	Average number of admissions attended by each physician	1,285,642	2.301	6.193	1.000	1.273	1.973
PhyPerPat	Average number of physicians involved in each admission	1,706,357	1.093	0.732	1.000	1.150	1.583
UniquePhy	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: 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 t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	All Lenders		Hospital Lenders	
	(1)	(2)	(3)	(4)
	Spread&Fee	*LogAmt*	*Spread&Fee*	*LogAmt*
$Tested_{j,t-1}$	13.882**	−0.008	12.132*	−0.001
	(2.119)	(−0.483)	(1.805)	(−0.041)
$Tested_{j,t-1} \times Hospital_i$	34.891*	−0.100*	35.598*	−0.098*
	(1.811)	(−1.786)	(1.850)	(−1.751)
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.3: 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 t-statistics are reported 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
	(−0.040)	(0.149)	(0.053)	(0.116)	(0.365)	(0.445)
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.4: Hospital Capital Expenditures, Total Beds, and Bad Debts

This table provides regression results for equation (1), focusing on hospital charges, investments, and bad debt expenses. *Cost-Charge* is the cost-to-charge ratio of hospital services. $Fixed/TA$ is fixed assets over total assets. $Building/TA$ is the book value of building construction over total assets. *BadDebt/TA* is the total amount of hospital bad debt over total assets. *Log(BadDebt)* is the logged (one plus) bad debts. $TotalBed$ is the total number of hospital beds. $STExposed$ 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 total hospital income ($LogIncome_{i,t-1}$), lagged logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), lagged cash holdings over total assets ($Cash/TA_{i,t-1}$), lagged liabilities over total assets ($Liab/TA_{i,t-1}$), and lagged total patient revenue over total assets ($PatRev/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) *Cost-Charge*	(2) *Fixed/TA*	(3) *Building/TA*	(4) *TotalBed*	(5) *BadDebt/TA*	(6) *Log(BadDebt)*
$STExposed_{i,t-1}$	−0.066	−0.007	−0.028***	1.515	−0.004**	−0.084***
	(−0.963)	(−1.108)	(−2.829)	(1.000)	(−2.555)	(−3.040)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	22,721	23,036	21,357	24,149	19,419	19,678
Adj R^2	0.22	0.73	0.73	0.98	0.70	0.85

Table A.5: Complete List of Control Variables

This table provides estimation results for equation (1), listing the coefficients of all control variables. *Margin* is profit margin, defined as $(Income - Cost)/Income$. *BedUtil* is the average daily fraction of hospital beds that are occupied. *Discharge Rate* is inpatient discharges over total bed days. *AllReadmRate* 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. Control variables include the lagged logarithm of one plus total hospital income ($LogIncome_{i,t-1}$), lagged logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), lagged cash holdings over total assets ($Cash/TA_{i,t-1}$), lagged liabilities over total assets ($Liab/TA_{i,t-1}$), and lagged total patient revenue over total assets ($PatRev/TA_{i,t-1}$). Standard errors are clustered at the hospital system level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Margin	*BedUtil*	*Discharge Rate*	*AllReadmRate*	*Antibiotic*	*Overall*
$STExposed_{i,t-1}$	0.012**	0.022***	2.350***	0.002***	−0.007***	−0.008***
	(2.077)	(5.973)	(5.752)	(5.150)	(−3.228)	(−4.561)
$LogIncome_{i,t-1}$	0.041***	0.014***	1.293***	0.002***	0.001	0.002
	(2.842)	(3.177)	(2.764)	(4.638)	(0.723)	(1.439)
$LogBedDay_{i,t-1}$	0.054	−0.070***	−5.725***	−0.000	0.007	−0.005
	(1.637)	(−8.111)	(−6.357)	(−0.980)	(0.648)	(−1.464)
$Cash/TA_{i,t-1}$	0.027	0.020*	0.194	0.000	−0.004	0.002
	(0.681)	(1.860)	(0.168)	(0.283)	(−0.341)	(0.371)
$Liab/TA_{i,t-1}$	−0.003	−0.007**	−0.901***	0.000	0.006	0.003*
	(−0.387)	(−2.571)	(−3.072)	(0.336)	(1.139)	(1.879)
$PatRev/TA_{i,t-1}$	−0.001	0.001***	0.140***	0.000*	−0.000	−0.000
	(−0.416)	(2.647)	(3.125)	(1.817)	(−0.673)	(−0.774)
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	18,756	15,113	21,349
Adj R^2	0.22	0.94	0.80	0.67	0.58	0.82

Table A.6: 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. *MedicarePct* is the percent of Medicare discharge out of all discharges. *MedicaidPct* 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 total hospital income ($LogIncome_{i,t-1}$), lagged logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), lagged cash holdings over total assets ($Cash/TA_{i,t-1}$), lagged liabilities over total assets ($Liab/TA_{i,t-1}$), and lagged total patient revenue over total assets ($PatRev/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) *CMI*	(2) *MedicarePct*	(3) *MedicaidPct*
$STExposed_{i,t-1}$	−0.012**	−0.007***	−0.004
	(−2.300)	(−3.477)	(−1.622)
Controls	Y	Y	Y
Year FE	Y	Y	Y
Hospital FE	Y	Y	Y
N	18,619	23,209	22,085
Adj R^2	0.93	0.92	0.78

Table A.7: 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 total hospital income ($LogIncome_{i,t-1}$), lagged logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), lagged cash holdings over total assets ($Cash/TA_{i,t-1}$), lagged liabilities over total assets ($Liab/TA_{i,t-1}$), and lagged total patient revenue over total assets ($PatRev/TA_{i,t-1}$). 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 t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
DRGs	*Heart Attack*		*Childbirth*	
	Log(Admit)	*Log(AvgChg)*	*Log(Admit)*	*Log(AvgChg)*
$STExposed_{i,t-1}$	0.030	0.059	0.044	−0.001
	(1.064)	(1.609)	(1.470)	(−0.032)
Controls	Y	Y	Y	Y
DRG-Year FE	Y	Y	Y	Y
Hospital-DRG FE	Y	Y	Y	Y
N	12,104	12,104	10,098	10,098
Adj R^2	0.89	0.92	0.96	0.95

Table A.8: 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. $TotalChg$ is the total amount of charges across all admissions in DRG d at year t. $AvgChg$ 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 total hospital income ($LogIncome_{i,t-1}$), lagged logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), lagged cash holdings over total assets ($Cash/TA_{i,t-1}$), lagged liabilities over total assets ($Liab/TA_{i,t-1}$), and lagged total patient revenue over total assets ($PatRev/TA_{i,t-1}$). 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 t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Insurance	(1) *All* *Log(TotalChg)*	(2) *All* *Log(AvgChg)*	(3) *Private* *Log(AvgChg)*	(4) *Medicare* *Log(AvgChg)*	(5) *Medicaid* *Log(AvgChg)*
$STExposed_{i,t-1}$	0.059***	0.001	−0.000	0.005	−0.009
	(2.833)	(0.050)	(−0.033)	(0.403)	(−0.788)
Controls	Y	Y	Y	Y	Y
DRG-Year FE	Y	Y	Y	Y	Y
Hospital-DRG FE	Y	Y	Y	Y	Y
N	1,651,795	1,651,760	1,161,584	1,388,404	859,729
Adj R^2	0.88	0.88	0.83	0.85	0.81

Table A.9: 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. $AvgChg$ is the average amount of charges per case in DRG d at year t. $AvgNpr$ is the average number of procedures for each case in DRG d at year t. $AvgLOS$ 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 total hospital income ($LogIncome_{i,t-1}$), lagged logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), lagged cash holdings over total assets ($Cash/TA_{i,t-1}$), lagged liabilities over total assets ($Liab/TA_{i,t-1}$), and lagged total patient revenue over total assets ($Patrev/TA_{i,t-1}$). 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 t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Insurance	(1) *Uninsured* *Log(AvgChg)*	(2) *Uninsured* *Log(AvgNPr)*	(3) *Uninsured* *Log(AvgLOS)*
$STExposed_{i,t-1}$	0.011	−0.015*	−0.018**
	(0.780)	(−1.703)	(−2.316)
Controls	Y	Y	Y
DRG-Year FE	Y	Y	Y
Hospital-DRG FE	Y	Y	Y
N	443,228	443,228	443,228
Adj R^2	0.80	0.68	0.51

Table A.10: 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's inpatient revenues as a fraction over its HRR's total inpatient revenues. $HRevFrac_i$ is 1 if a treated hospital's revenue fraction before the shock is above the sample median, and 0 otherwise. $Margin$ is profit margin, defined as $(Income - Cost)/Income$. *BedUtil* is the average daily fraction of hospital beds that are occupied. *Discharge Rate* is inpatient discharges over total bed days. *AllReadmRate* 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. Control variables include the lagged logarithm of one plus total hospital income ($LogIncome_{i,t-1}$), lagged logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), lagged cash holdings over total assets ($Cash/TA_{i,t-1}$), lagged liabilities over total assets ($Liab/TA_{i,t-1}$), and lagged total patient revenue over total assets ($PatRev/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1) *Margin*	(2) *BedUtil*	(3) *Discharge Rate*	(4) *AllReadmRate*	(5) *Antibiotic*	(6) *Overall*
$STExposed_{i,t-1}$	0.005	0.011**	1.653***	0.001**	−0.006	−0.009***
	(0.561)	(2.072)	(3.210)	(2.387)	(−1.580)	(−3.371)
$HRevFrac_i$ $\times STExposed_{i,t-1}$	0.014	0.022***	1.361*	0.001**	−0.002	0.002
	(1.552)	(3.198)	(1.853)	(1.979)	(−0.524)	(0.621)
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

Table A.11: Heterogeneity Across Hospital Pre-shock Cash Balance

This table provides estimation results when interacting the treatment variable with a measure of hospital cash balance. $HCash_i$ is 1 if a treated hospital's $Cash/TA_{i,t}$ before the shock is above the sample median, and 0 otherwise. $Margin$ is profit margin, defined as $(Income - Cost)/Income$. *BedUtil* is the average daily fraction of hospital beds that are occupied. *Discharge Rate* is inpatient discharges over total bed days. *AllReadmRate* 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. Control variables include the lagged logarithm of one plus total hospital income ($LogIncome_{i,t-1}$), lagged logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), lagged cash holdings over total assets ($Cash/TA_{i,t-1}$), lagged liabilities over total assets ($Liab/TA_{i,t-1}$), and lagged total patient revenue over total assets ($PatRev/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)
	Margin	*BedUtil*	*Discharge Rate*	*AllReadmRate*	*Antibiotic*	*Overall*
$STExposed_{i,t-1}$	0.010	0.031***	3.204***	0.003***	−0.010***	−0.007***
	(1.218)	(6.438)	(6.126)	(6.125)	(−4.441)	(−3.586)
$HCash_i$	0.004	−0.019***	−1.766**	−0.002***	0.007*	−0.001
$\times STExposed_{i,t-1}$	(0.383)	(−2.635)	(−2.379)	(−2.988)	(1.702)	(−0.413)
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	0.81	0.67	0.58	0.81

Table A.12: 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). $Margin$ is profit margin, defined as $(Income - Cost)\,/Income$. *BedUtil* is the average daily fraction of hospital beds that are occupied. *Discharge Rate* is inpatient discharges over total bed days. *AllReadmRate* 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. Control variables include the lagged logarithm of one plus total hospital income ($LogIncome_{i,t-1}$), lagged logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), lagged cash holdings over total assets ($Cash/TA_{i,t-1}$), lagged liabilities over total assets ($Liab/TA_{i,t-1}$), and lagged total patient revenue over total assets ($PatRev/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1) *Margin*	(2) *BedUtil*	(3) *Discharge Rate*	(4) *AllReadmRate*	(5) *Antibiotic*	(6) *Overall*
$STExposed_{i,t-1}$	0.021***	0.032***	3.179***	0.002***	−0.009***	−0.009***
	(3.581)	(6.645)	(6.152)	(4.153)	(−2.656)	(−3.425)
$RUCA_i$	−0.005*	−0.005***	−0.458***	−0.000	0.001	0.001
$\times STExposed_{i,t-1}$	(−1.868)	(−3.967)	(−3.091)	(−0.387)	(0.418)	(0.544)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	23,582	23,054	23,052	17,531	14,970	21,159
Adj R^2	0.22	0.94	0.80	0.67	0.58	0.82

Table A.13: 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 ($LargeSys_i$). $Margin$ is profit margin, defined as $(Income - Cost)/Income$. $BedUtil$ is the average daily fraction of hospital beds that are occupied. *Discharge Rate* is inpatient discharges over total bed days. $AllReadmRate$ 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. Control variables include the lagged logarithm of one plus total hospital income ($LogIncome_{i,t-1}$), lagged logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), lagged cash holdings over total assets ($Cash/TA_{i,t-1}$), lagged liabilities over total assets ($Liab/TA_{i,t-1}$), and lagged total patient revenue over total assets ($PatRev/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1) *Margin*	(2) *BedUtil*	(3) *Discharge Rate*	(4) *AllReadmRate*	(5) *Antibiotic*	(6) *Overall*
$STExposed_{i,t-1}$	0.015*	0.021	3.270**	0.002***	−0.026*	−0.012**
	(1.748)	(1.566)	(2.069)	(2.630)	(−1.960)	(−2.432)
$LargeSys_i$	−0.003	0.002	−0.991	−0.000	0.020	0.005
$\times STExposed_{i,t-1}$	(−0.346)	(0.131)	(−0.620)	(−0.445)	(1.518)	(0.919)
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

Table A.14: 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. $HighSTExposed_{i,t-1}$ ($LowSTExposed_{i,t-1}$) 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. $Margin$ 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. *AllReadmRate* 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. Control variables include the lagged logarithm of one plus total hospital income ($LogIncome_{i,t-1}$), lagged logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), lagged cash holdings over total assets ($Cash/TA_{i,t-1}$), lagged liabilities over total assets ($Liab/TA_{i,t-1}$), and lagged total patient revenue over total assets ($PatRev/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) *Margin*	(2) *BedUtil*	(3) *Discharge Rate*	(4) *AllReadmRate*	(5) *Antibiotic*	(6) *Overall*
$HighSTExposed_{i,t-1}$	0.016***	0.022***	2.394***	0.002***	−0.008***	−0.008***
	(2.615)	(5.518)	(5.678)	(5.067)	(−3.216)	(−4.390)
$LowSTExposed_{i,t-1}$	−0.030**	0.014	0.558	0.001	−0.001	0.002
	(−2.330)	(1.630)	(0.517)	(1.056)	(−0.195)	(0.304)
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

Table A.15: Robustness: Controlling for Regional Differences

This table provides estimation results for equation (1), controlling for regional differences in each year. $Margin$ 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. *AllReadmRate* 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. Control variables include the lagged logarithm of one plus total hospital income ($LogIncome_{i,t-1}$), lagged logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), lagged cash holdings over total assets ($Cash/TA_{i,t-1}$), lagged liabilities over total assets ($Liab/TA_{i,t-1}$), and lagged total patient revenue over total assets ($PatRev/TA_{i,t-1}$). Hospital referral region (HRR)-by-year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) *Margin*	(2) *BedUtil*	(3) *Discharge Rate*	(4) *AllReadmRate*	(5) *Antibiotic*	(6) *Overall*
$STExposed_{i,t-1}$	0.009	0.014***	1.886***	0.002***	−0.007**	−0.007***
	(0.784)	(3.288)	(4.197)	(3.932)	(−2.304)	(−3.125)
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	23,611	23,087	23,082	17,565	14,947	21,231
Adj R^2	0.17	0.95	0.81	0.68	0.57	0.82

Table A.16: Robustness: Subsidiaries of Hospital Systems

This table provides estimation results for equation (1), only including hospitals that are subsidiaries of hospital systems. $Margin$ 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. *AllReadmRate* 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. Control variables include the lagged logarithm of one plus total hospital income ($LogIncome_{i,t-1}$), lagged logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), lagged cash holdings over total assets ($Cash/TA_{i,t-1}$), lagged liabilities over total assets ($Liab/TA_{i,t-1}$), and lagged total patient revenue over total assets ($PatRev/TA_{i,t-1}$). Year, hospital, and system fixed effects are included, as indicated. Standard errors are clustered at the hospital system level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) *Margin*	(2) *BedUtil*	(3) *Discharge Rate*	(4) *AllReadmRate*	(5) *Antibiotic*	(6) *Overall*
$STExposed_{i,t-1}$	0.013*	0.023***	2.520***	0.002***	−0.008***	−0.009***
	(1.924)	(3.217)	(3.582)	(3.321)	(−2.729)	(−3.048)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
System FE	Y	Y	Y	Y	Y	Y
N	15,886	15,560	15,562	12,176	10,344	14,675
Adj R^2	0.36	0.94	0.81	0.65	0.50	0.82

Table A.17: 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. *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. *AllReadmRate* 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. Control variables include the lagged logarithm of one plus total hospital income ($LogIncome_{i,t-1}$), lagged logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), lagged cash holdings over total assets ($Cash/TA_{i,t-1}$), lagged liabilities over total assets ($Liab/TA_{i,t-1}$), and lagged total patient revenue over total assets ($PatRev/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1) *Margin*	(2) *BedUtil*	(3) *Discharge Rate*	(4) *AllReadmRate*	(5) *Antibiotic*	(6) *Overall*
$STExposed_{i,t-1}$	0.017*	0.021	3.590**	0.002**	−0.023*	−0.011**
	(1.801)	(1.463)	(2.091)	(2.211)	(−1.652)	(−2.008)
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.18: 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. $Margin$ 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. *AllReadmRate* 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. Control variables include the lagged logarithm of one plus total hospital income ($LogIncome_{i,t-1}$), lagged logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), lagged cash holdings over total assets ($Cash/TA_{i,t-1}$), lagged liabilities over total assets ($Liab/TA_{i,t-1}$), and lagged total patient revenue over total assets ($PatRev/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1) *Margin*	(2) *BedUtil*	(3) *Discharge Rate*	(4) *AllReadmRate*	(5) *Antibiotic*	(6) *Overall*
$STExposed_{i,t-1}$	0.023***	0.034***	2.892***	0.002***	−0.009**	−0.008***
	(3.552)	(6.496)	(5.532)	(4.168)	(−2.392)	(−2.780)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	22,903	22,380	22,378	17,001	14,500	20,506
Adj R^2	0.21	0.94	0.81	0.67	0.58	0.82

Table A.19: 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. *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. *AllReadmRate* 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. Control variables include the lagged logarithm of one plus total hospital income ($LogIncome_{i,t-1}$), lagged logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), lagged cash holdings over total assets ($Cash/TA_{i,t-1}$), lagged liabilities over total assets ($Liab/TA_{i,t-1}$), and lagged total patient revenue over total assets ($PatRev/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1) *Margin*	(2) *BedUtil*	(3) *Discharge Rate*	(4) *AllReadmRate*	(5) *Antibiotic*	(6) *Overall*
$STExposed_{i,t-1}$	0.014*	0.015***	2.113***	0.001***	−0.009***	−0.005**
	(1.651)	(3.130)	(4.259)	(3.441)	(−3.371)	(−2.434)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	6,374	6,283	6,283	5,046	4,248	6,140
Adj R^2	0.49	0.92	0.83	0.67	0.42	0.84

Table A.20: For-profit Hospitals Only

This table provides estimation results for equation (1), only including for-profit hospitals. *Margin* is profit margin, defined as $(Income - Cost)/Income$. *BedUtil* is the average daily fraction of hospital beds that are occupied. *Discharge Rate* is inpatient discharges over total bed days. *AllReadmRate* 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. Control variables include the lagged logarithm of one plus total hospital income ($LogIncome_{i,t-1}$), lagged logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), lagged cash holdings over total assets ($Cash/TA_{i,t-1}$), lagged liabilities over total assets ($Liab/TA_{i,t-1}$), and lagged total patient revenue over total assets ($PatRev/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital system level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) *Margin*	(2) *BedUtil*	(3) *Discharge Rate*	(4) *AllReadmRate*	(5) *Antibiotic*	(6) *Overall*
$STExposed_{i,t-1}$	0.003	0.037***	3.994***	0.003***	−0.003	−0.007**
	(0.173)	(6.131)	(4.828)	(5.851)	(−0.578)	(−2.468)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	4,998	4,894	4,894	3,618	2,902	4,615
Adj R^2	0.21	0.92	0.58	0.68	0.61	0.86

Table A.21: 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. $Margin$ is profit margin, defined as $(Income - Cost)/Income$. *BedUtil* is the average daily fraction of hospital beds that are occupied. *Discharge Rate* is inpatient discharges over total bed days. *AllReadmRate* 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. Control variables include the lagged logarithm of one plus total hospital income ($LogIncome_{i,t-1}$), lagged logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), lagged cash holdings over total assets ($Cash/TA_{i,t-1}$), lagged liabilities over total assets ($Liab/TA_{i,t-1}$), and lagged total patient revenue over total assets ($PatRev/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1) *Margin*	(2) *BedUtil*	(3) *Discharge Rate*	(4) *AllReadmRate*	(5) *Antibiotic*	(6) *Overall*
$NearExposed_{i,t-1}$	−0.018	−0.002	−1.062***	0.000	−0.004	−0.002
	(1.282)	(−0.479)	(−2.729)	(0.028)	(−1.377)	(−1.108)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	20,432	19,931	19,929	15,028	12,896	18,128
Adj R^2	0.20	0.95	0.80	0.67	0.58	0.81

Table A.22: 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. $Margin$ is profit margin, defined as $(Income - Cost)/Income$. *BedUtil* is the average daily fraction of hospital beds that are occupied. *Discharge Rate* is inpatient discharges over total bed days. *AllReadmRate* 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. Control variables include the lagged logarithm of one plus total hospital income ($LogIncome_{i,t-1}$), lagged logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), lagged cash holdings over total assets ($Cash/TA_{i,t-1}$), lagged liabilities over total assets ($Liab/TA_{i,t-1}$), and lagged total patient revenue over total assets ($PatRev/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) *Margin*	(2) *BedUtil*	(3) *Discharge Rate*	(4) *AllReadmRate*	(5) *Antibiotic*	(6) *Overall*
$STExposed_{i,t-1}^{CCAR}$	0.015**	0.016***	1.825***	0.002***	−0.005**	−0.007***
	(2.509)	(3.524)	(3.583)	(2.759)	(−2.272)	(−3.120)
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

B Alternative Construction of Parallel Trends

In this section, we provide a description and the results for an alternative methodology for examining parallel trends, following Callaway and Sant'Anna (2021). We first estimate the average treatment effects for the treated (ATT) for each year following the stress test shock.

More specifically, 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 (ATT) 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

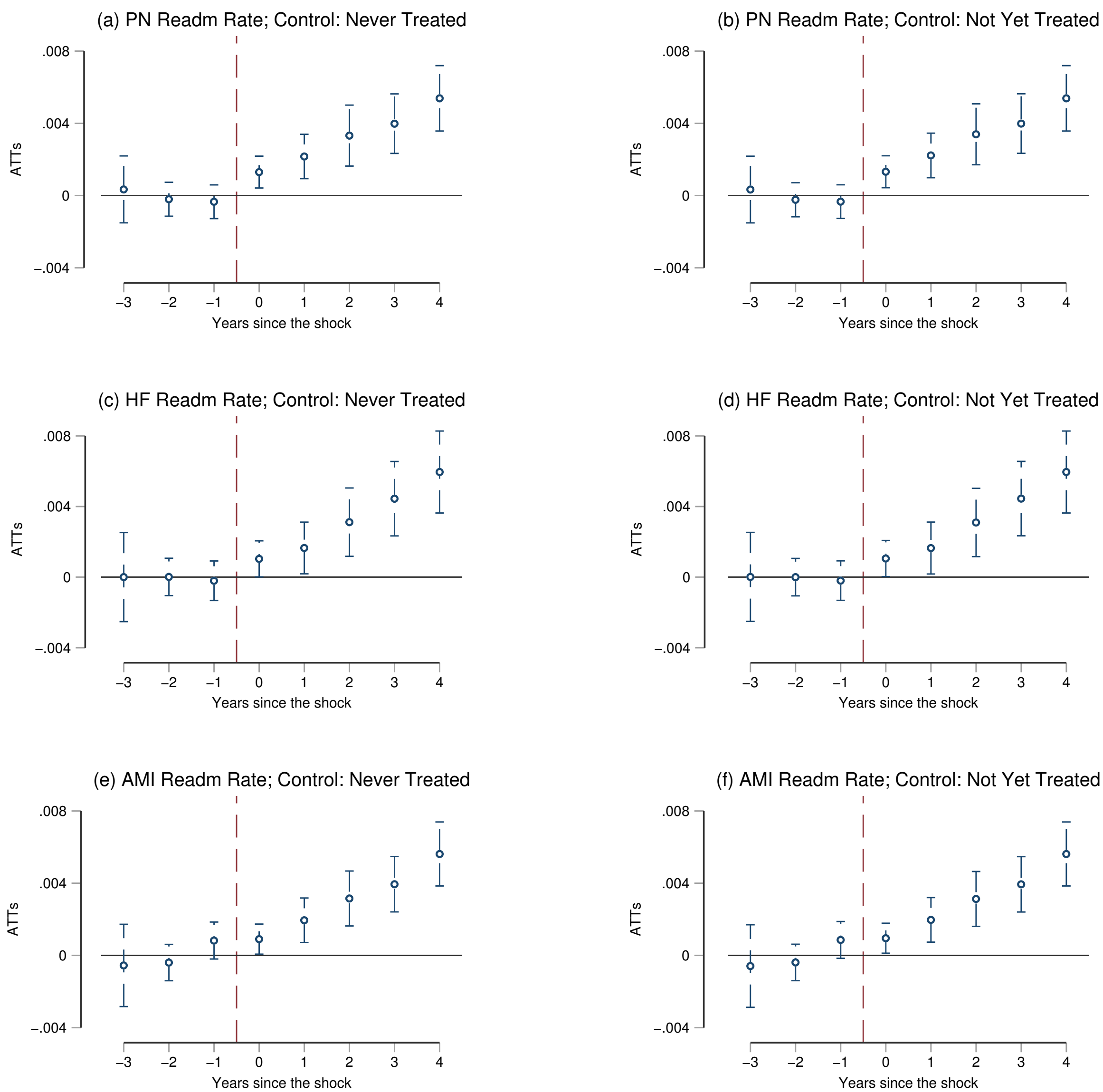
$$ATT^{ny}(g, g + e) = \mathbb{E}[Y_{g+e} - Y_{g+e-1}|G_g = 1] - \mathbb{E}[Y_{g+e} - Y_{g+e-1}|D_t = 0, G_g = 0].$$

These ATTs are then aggregated via:

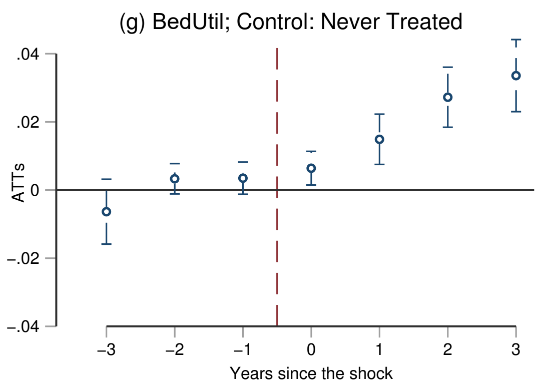
$$\theta(e) = \Sigma_g 1\{g + e \geq \mathbf{t}\}P(G = g|G + e \geq \mathbf{t})ATT(g, g + e).$$

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 the figures below, 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 the last table, we show that our main results are robust to dropping all covariates as control variables.

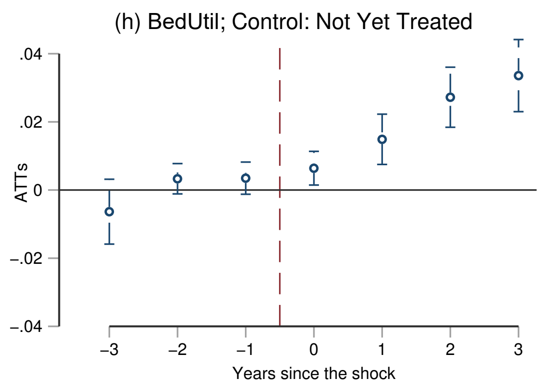
Figure B.1: Parallel Trends: Average Treatment Effects for the Treated



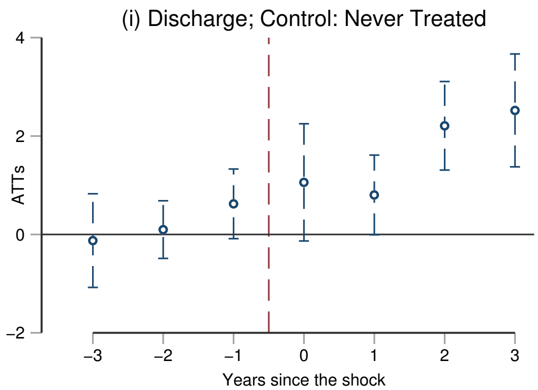
(continued)



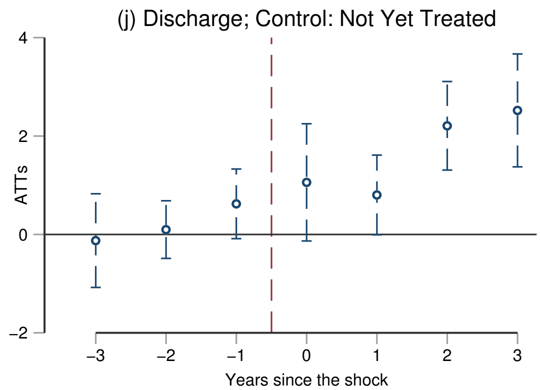
(g) BedUtil; Control: Never Treated
.04
.02
0
−.02
−.04
ATTs
−3
−2
−1
0
1
2
3
Years since the shock



(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: Dropping All Control Variables

This table provides estimation results for equation (1) after dropping all control variables. *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. *AllReadmRate* 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. Hospital and year fixed effects are included, as indicated. Standard errors are clustered at the hospital level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) *Margin*	(2) *BedUtil*	(3) *Discharge Rate*	(4) *AllReadmRate*	(5) *Antibiotic*	(6) *Overall*
$STExposed_{i,t-1}$	0.005	0.021***	2.012***	0.002***	−0.007***	−0.009***
	(0.712)	(5.417)	(4.785)	(4.839)	(−3.416)	(−5.116)
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