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. Using detailed data on hospitals and the banks that they borrow from, 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 enhance their profit margins in response to a negative credit shock, but reduce the quality of their care to patients across a variety of measures. In particular, affected hospitals exhibit significantly lower attentiveness in providing timely and effective treatment and procedures, and are rated substantially lower in patient satisfaction. This decline in care quality is reflected in health outcomes: affected hospitals experience a significant increase in risk-adjusted, unplanned 30-day readmission rates of recently discharged patients and in risk-adjusted 30-day patient mortality rates. Overall, 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.

Keywords: Healthcare finance, hospitals, banks, credit supply, lending, health outcomes, stress test.

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 nearly 18% of GDP, and hospitals 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. This link between credit markets and hospitals raises an important question: Do shocks to credit markets transmit to hospital finances, affect hospital performance in providing medical care, and thus affect health outcomes? Put differently, do we observe indirect, negative effects on actual patient health outcomes following lending supply shocks? 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 question, we utilize the staggered pattern of stress tests—regulatory assessments by the Federal Reserve which are designed to gauge a bank's ability to withstand an impending economic crisis—on U.S. banks implemented by the 2010 Dodd-Frank Act in order to cleanly test the effects of shocks to the supply of credit. We 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, in order 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, we examine the change in performance, as measured in 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

[1]Hospital employment in the U.S. exceeds 5.7 million, and hospitals are among the top employers across U.S. cities (Samuelson (2017)). 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.

[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.

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 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] This is consistent with bank stress tests increasing the cost of credit for an affected bank's hospitals, and reinforces the results of Acharya et al. (2018) and Cortés et al. (2020).

We then explore how hospital financial 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 an 8.6% increase in patient revenues, with the average patient paying $1,701 more for healthcare services. This increase appears to be driven by changes in hospitals' operations. In particular, in response to tighter credit conditions, we find evidence that hospitals rely more on their existing resources by increasing bed utilization and physician working intensities. In a given year, each bed in an affected hospital is occupied by eight more days, on average, relative to an unaffected hospital, which amounts to 367 additional patients accommodated per year. 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 use three distinct measures for quality of care and health outcomes. First, we examine patient health following treatment using risk-adjusted, unplanned 30-day hospital readmission rates for various health conditions; this is a widely used measure by both government agencies and academic researchers for quality of care and assesses the effectiveness of treatment.[4] We

[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.

[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 gather data on 30-day risk-adjusted mortality rates for similar conditions. Second, we use data regarding the 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. 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 three sets of measures, the results show that hospital performance declines following credit supply shocks. We find 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 3.2–6.4%, depending on the treatment or procedure. This decline in the quality of care metrics is reflected in patient health outcomes. The results show that patients discharged from affected hospitals are significantly more likely to be readmitted within 30 days. This result is strikingly consistent across the three diagnostic groups for which we have detailed data (heart failure, acute myocardial infraction, pneumonia), and also holds for a wider set of medical conditions. The magnitude of the effect is sizable; we find that restrictions to the access of credit for hospitals indirectly leads to an *additional* 1,674 patients readmitted per year. Similarly, with respect to patient mortality from pneumonia—a common hospital-acquired condition (Rothberg et al. (2014))—the results show an increase of 915 patient deaths a year.

To provide additional context to these results, we consider readmissions in terms of relative performance. In particular, the U.S. Centers for Medicare & Medicaid Services (CMS; part of the Department of Health and Human Services) assesses excess 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, as determined by CMS, thereby triggering the heaviest payment penalty. This amounts to a 58% increased propensity from the 7.9% unconditional average severe punishment rate.

also https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/AcuteInpatientPPS/Readmissions-Reduction-Program.

These findings are also similar for 30-day readmissions among the individual diagnostic conditions we consider.

Lastly, 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. 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 rule out the alternative explanation that the worsened healthcare performance is because hospitals are accommodating more hard-to-treat new patients. Instead, hospital patient composition becomes less severe, younger, and more likely to be privately insured.

Taken together, our findings imply that affected hospitals adjust for the increased cost of debt or the decline in external financing by increasing revenues from patients. This includes greater inpatient admissions. However, 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.[5]

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 that can run counter to profitability. Consequently, hospitals optimize between profits and health provision (i.e., concerns for patient utility) 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.

In additional analyses, we further explore the channel driving the change in health outcomes at affected hospitals. As discussed above, the primary channel through which hospital performance declines is through frictions in credit access. Accordingly, under the predicted channel, hospital borrowers that are more affected by credit supply shocks should experience a more pronounced effect in outcomes and performance. We test for this heterogeneity in a number of ways. First, banks which pass their stress tests with less distance from the failure threshold have a stronger incentive to manage risk relative to banks which pass their

[5]In line with this, we find that physician compensation increases, which is consistent with physicians being busier with more services.

tests with a greater cushion (Cortés et al. (2020)). This shorter distance from the failure 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). Our second test for heterogeneous effects concerns reliance on debt: hospitals which are more reliant on bank loan financing are naturally more affected by stress tests on their lenders. Finally, we consider the proportion of a hospital's banks that were stress-tested. In particular, hospitals for which the majority of their existing lenders are stress-tested have fewer options for alternative financing from established lending relationships, which implies a stronger negative shock to credit access. Across all of these specifications, our findings indicate that hospitals which are more exposed to a negative credit supply shock from stress tests exhibit stronger declines in quality of care, patient health outcomes, and patient satisfaction. These results are in line with a credit supply channel driving the effects.

Our results survive a variety of robustness tests, including running our results on a propensity-score matched sample, controlling for time-varying geographical differences, and conditioning on hospitals that belong to a hospital system.

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

Our analysis is also related to the literature at the intersection of healthcare and finance. Adelino et al. (2015) use non-profit hospitals to test the investment cash-flow sensitivity of non-profit firms, and find that these hospitals respond to increases in their cash flows (due to financial investments) by increasing their investments, in a similar way to public firms. Adelino et al. (2019) examine the care delivery of hospitals that experienced a drop in their investments due to the 2008 financial crisis, and find no aggregate evidence of shifts in care due to the financial crisis, although they find some evidence of a shift toward more profitable treatments for the most severely affected hospitals.[6] Gupta et al. (2021) examine the effect of private equity investments in the quality of care delivered by nursing homes. Another stream of research investigates the impact of government healthcare reforms, such as the Affordable Care Act (ACA), on equity and debt prices. Koijen et al. (2016) consider medical innovation and R&D, and document a premium in the equity returns of healthcare firms (including drug and biologic companies) due to the risk of government reforms. Gao et al. (2020) 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); 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 from patients. This revenue increase is contemporaneous with increases in treatment, including average length of inpatient stay, hospital bed utilization, and outpatient services. As such, the present study is also related to the stream of literature which examines overuse in medical treatment. Overuse in treatment has been linked to physician pay structures (Clemens and Gottlieb (2014)), defensive medicine (Frakes and Gruber (2019)), and overconfidence in specialized treatment (Chandra and Staiger (2020)). Our findings contribute to this literature by identifying credit market frictions as an important channel that can potentially influence care decisions. Moreover, we show that quality of care and patient health outcomes decline following the observed shift

[6] See also Dranove et al. (2017) for evidence on the effect of the financial crisis on hospitals.

in utilization.

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 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).[7] 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. Consequently, following a stress test, banks are more inclined to improve their capital adequacy ratios and 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.

[7]These scenarios are determined based on current economic conditions. 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, see https://www.federalreserve.gov/publications/june-2020-supervisory-scenarios.htm.

(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 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 5.4.

Hospital borrowing

Hospitals, both for-profit and non-profit, rely partially on debt to finance their operations (Koijen et al. (2016)). As we discuss in more detail in Section 3.1, the vast majority of hospitals in our sample have leverage, and the average hospital holds a substantial amount of debt.[8] Moreover, hospitals are particularly risky borrowers. For example, healthcare municipal bonds have significantly higher yields and lower ratings than non-healthcare bonds (Gao et al. (2020)). Furthermore, healthcare bonds accounted for 20% of all municipal bond defaults from 1999 to 2010 (Gao et al. (2019)).[9] 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) and Cortés et al. (2020)), banks may be inclined to reduce credit to risky hospital borrowers or to raise interest rates following stress tests.

Hospitals may react to this credit shock by seeking credit from alternative lenders. However, as has been well-established in the banking literature, long-term lending relationships help to lower asymmetric information between borrowers and lenders, thus reducing the cost of credit for borrowers.[10] New lenders without an established relationship would thus require higher interest rates or provide less credit as a result of greater asymmetric information. 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 and decrease in loan amounts, and are more likely to borrow from a new lender. These results reinforce the find-

[8]Roughly 93% of the hospital-year observations in our sample have positive leverage, and the mean (median) leverage ratio (Debt/Total Assets) in our sample is 56% (46%).

[9]Non-profit hospitals may borrow through tax-free municipal bonds, 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. (2020)).

[10]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.

ings 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.

Following a shock to credit supply, hospitals may be faced with less external financing or a higher cost of debt. As a result, hospitals can implement cost-saving measures, such as reducing hospital staff (including doctors and nurses), or more aggressively pursuing delinquent patient bills. Additionally, as patients are the primary source of revenue, hospitals may be inclined to increase revenues through higher resource utilization, such as more intensive use of outpatient hospital services, increased inpatient admissions, or longer stays for admitted patients.[11] Such hospital responses do not suggest a clear prediction on actual patient health outcomes. In particular, reduced staff or greater admitted volume may lead to less attention and thus worse quality of care (e.g., Silver (2020)). On the other hand, if testing and procedures, some of which may be unnecessary, or inpatient admissions are increased in order to compensate for the decreased funds, then patient health may be unaffected or even improved if such measures imply greater attention and care (e.g., Clemens and Gottlieb (2014)).

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

[11]Medicare payments to hospitals are based on the inpatient/outpatient prospective payment system. Specifically, inpatient revenues are determined by the diagnostic 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.

such as total assets (TA), income ($Income$), total liabilities ($Debt$), revenues,[12] cash holdings ($Cash$), and operational costs ($Cost$). In addition, the data include hospital utilization information, including total inpatient discharges, total occupied bed days, total available bed days ($BedDay$),[13] and the total number of employed physicians, nurses, interns, and residents,[14] as well as the total salary expenditure for them.

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.[15] 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 hospital), though our results are robust to including other types of providers, and controlling for hospital-type fixed effects. We further exclude government-sponsored hospitals (such as Veterans Affairs hospitals and clinics), as they primarily rely on municipal bond markets for external financing.[16] 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 readmission to an acute care hospital in the 30 days after discharge from hospitalization, obtained from the CMS Hospital Compare program. 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, implies 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 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 30-day mortality numbers and

[12] This includes inpatient ($InPatrev$), outpatient ($OutPatrev$), and total patient revenues ($Patrev$).

[13] 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).

[14] These are reported in the unit of full-time equivalents. We refer to them as medical staff and obtain hospital total salary expenditure from Worksheet S-3, Part II, Line 1 and Column 1. The average hospital salary is calculated by total salary over number of medical staff.

[15] 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.

[16] Other examples of such hospitals include community hospitals specializing in charity care.

risk-standardized mortality rates for patients treated for these conditions, also provided by CMS.

The second dataset is also 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.[17] 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.[18] 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.[19] For pneumonia, we use the portion of patients that receive the most appropriate antibiotic at discharge.

These measures indicate the frequency for which medical staff has taken proper medical procedures when dealing with certain common conditions. As such, these measures capture attentiveness or competency of the medical staff. Furthermore, these measures are indicative of whether there are systems in place for the hospital that ensure compliance with best practices and quality metrics. We note that the selected measures are used widely for quality of care in the extant literature (e.g., Cooper et al. (2019), Beaulieu et al. (2020)).

We supplement these measures with additional measures which provide subjective evaluation by patients. 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

[17]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 10 "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.

[18]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 3 to 6 months after AMI reduces mortality in patients with elevated cholesterol levels (Group et al. (1994); Sacks et al. (1996)).

[19]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.

conditions between 48 hours and six weeks after discharge. The core questions cover the critical aspects of patients' hospital experiences, such as the overall rating of the hospital ($Overall$), 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.[20]

Lastly, we combine our hospital data with Dealscan loan data in order to identify treated and control hospitals. We keep all loan 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*) whose loan types are term loans or revolver. Following Ivashina (2009), we identify and keep the lead bank in a syndicate deal.[21] This generates 2,432 facility-lender combinations. The hospital-related borrowers in Dealscan are either individual providers (e.g., Houston Methodist Hospital) or hospital organizations and systems (e.g., HCA Healthcare). We then manually match borrowers to the HCRIS sample. For each individual hospital, HCRIS reports whether it belongs to a hospital chain and the organization name if it does. When we identify a borrower that is a hospital system, we assign each of the individual hospitals that are part of the system as being exposed to the loan deal. There are 1,447 facility-lender combinations in which we identify that the borrower is a Medicare-certified hospital (or the controlling system of a Medicare-certified hospital).[22]

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 sample hospital when tested for the first time. In total, this leads to 537 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 (77% of the affected hospitals) are exposed to the first DFAST that occurred in 2012. Banks with total consolidated assets of more than

[20]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.

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

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

\$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 important sources of external financing for hospitals. A typical loan deal has a size of \$737.37 million, accounting for around 33.7% of the borrower's total assets. Summary statistics for all of our other variables are provided in Appendix Table A.1.

3.2 Empirical Specification

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

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

In equation (1), $STExposed_{i,t-1}$ is an indicator variable that takes a value of 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 i's relationship bank is defined as a lending bank that has non-matured loans with hospital i in year t. $Controls_{i,t-1}$ is a vector of control variables that include: the lagged logarithm of one plus total hospital income ($LogIncome_{i,t-1}$),[23] the logarithm of one plus available bed days ($LogBedDay_{i,t-1}$),[24] cash holdings scaled by total assets ($Cash/TA_{i,t-1}$), liabilities scaled by total assets ($Debt/TA_{i,t-1}$), and total patient revenue scaled by total assets ($Patrev/TA_{i,t-1}$). $Y_{i,t}$ is the outcome variable, which includes measures of hospital financial and care quality information. The parameters η_t and μ_i denote year and hospital fixed effects, respectively.

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.[25]

[23]This variable controls for size based on total revenue, as in Adelino et al. (2019). An alternative control for hospital size would be to include the lagged logarithm of total assets. Our results are robust to doing so.

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

[25]Our treatment and control hospitals are not statistically different in terms of how much debt financing they use. We exploit heterogeneity in loan financing reliance in further tests.

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. Furthermore, in the sample, most of the borrowing hospitals entered into loans with the stress-tested banks before 2012.[26] Thus, the actual timing of DFAST implementation was uncertain and therefore exogenous to the loan initiation. Furthermore, a hospital had no incentive to borrow from a particular bank based on the fact that this bank would be stress-tested soon. We further validate our argument by showing that the parallel trends assumption holds in our setting.

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:

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

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. $STExposed_{i,t-1}$ is equal to 1 if hospital i borrowed from a bank that was stress-tested in year $t-1$ or earlier, and thus has been indirectly exposed to the stress tests. We note that outcome Y is measured for each loan k between hospital i and bank j, but the value of $STExposed_{i,t}$ is determined by hospital i's exposure and is

[26]For example, there were 39 existing loans affected by the 2012 DFAST; 31 (80% of affected loans) started in 2011 or earlier.

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 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, profitability (income over total assets), leverage (total debt over total assets) and tangibility (total fixed assets over total assets). We also include bank (μ_j), year (η_t), loan type ($Type_l$), and loan purpose ($Purpose_m$) 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 2 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 increase significantly by 63 bps, about 16% of the sample average, for affected hospitals. 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 for affected hospitals.

In column (5), we consider the possibility that hospitals may switch lenders following a stress test. To explore this, we define a variable $NewLender_{k,i,j,t}$, which is an indicator variable equal to 1 if hospital i had no previous lending relationship with bank j. 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.

Overall, these results are consistent with the notion that stress testing negatively impacted 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. 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, which suggests that the shock to credit access is not part of a broader shock to hospital borrowing in other debt channels.[27] Collectively, these results validate the use of the DFAST as a negative shock to hospital credit access.

4.2 Hospital Financing and Operating Decisions

We next examine the direct impact that the negative credit supply shock had on hospital financing and operating decisions, and outcomes for affected borrowers. In the following section, we then investigate the indirect impact these decisions had on patient health outcomes.

The results are presented in Tables 3 and 4. We first consider the effect of the credit shock on the overall profit margin of the hospital. In column (1) of Table 3, we find that affected borrowers saw a significant increase of 1.2% in their profit margin, which is more than one-third of the sample mean of 3.2%. To better understand this result, we examine leverage and cash holdings in columns (2) and (3), respectively. We see a significant reduction in both leverage and cash for affected hospitals. This suggests that affected hospitals utilize debt less following the credit shock, and instead rely more on internal cash reserves to finance operations and investment. We next consider revenues generated from patients in columns (4) through (7). The results are strikingly consistent with a shift in utilization—affected hospitals generate significantly *more* revenue per patient, including from both inpatient and outpatient services, following the shock. Indeed, the average revenue per admitted inpatient increases by about $1,701 for affected hospitals.[28]

With column (1) in Table 2, a back of the envelope estimation of increased interest payments is $1.07 million. The above results imply a $1.39 million increased operational profits for a typical affected hospital.[29] This value is greater than the additional interest costs because affected hospitals may rely more on internal cash flows for investments, as shown in column (3) of Table 3.

As noted earlier (see fn. 11), hospitals can influence revenues generated from patients by, for example, increasing inpatient admissions, providing more tests and procedures for outpatient services, coding inpatients to riskier diagnostic related groups (DRGs), or increasing the length of stay for admitted patients. To further examine the potential sources of these increased patient revenues, we consider occupancy and discharge rates in columns (1) and (2) of Table 4. *Occupancy* in column (1) represents the utilized hospital bed days over all

[27] We provide these results in Appendix Table A.4.

[28] Average payment per inpatient is defined as inpatient revenues divided by total inpatient discharges. This measure is often viewed as a proxy for hospitalization price; see, e.g., Dafny (2005) and Dafny (2009).

[29] The average affected loan amount per hospital is $144.30 million, and $1.07 million = $144.30 million × 74 bps. $1.39 million = $555 million (average patient revenue) × 0.057 (Table 3 column 4) × (0.032 + 0.012). 0.032 is the average profit margin and 0.012 is the treatment effect from Table 3 column (1).

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 (2) is the total inpatient discharges in a year over total available bed days. Hence, this measure represents the number of patients using each hospital bed in a year. We see that both occupancy and discharge rates significantly increase for affected hospitals. Affected hospitals accommodate 2.35 more patients per bed, or equivalently 367 more patients per hospital per year.[30] We examine the change in medical staff compensation in column (3), and find that average compensation significantly increases following the credit shock, consistent with physicians billing more or providing more services. Supporting the latter channel, we document the average annual service hours increase by 22.607 hours.[31]

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 increasing bed utilization and shifting resources away from less-profitable areas such as ICUs, hospitals are able to increase their profitability on the margin. This is consistent with other papers that have shown an increase in financial efficiency for borrowers following tightening financial constraints (e.g., Hovakimian (2011)). However, while these operation changes may improve profit margins, they may not improve patient care—for example, by expanding the tasks for physicians and utilizing the same facilities for more patients, the quality of care may deteriorate. We explore this in the next section.

4.3 Main Results – Patient Health Outcomes and Care Quality

As the central analysis of this study, we 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, a greater volume of patients more severely strains staff and physician time, which may lead to less attention and a lower quality of care.[32]

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

[31] Another possibility for hospitals to increase revenues is to raise charges for tests and procedures. However, pricing and rates for procedures, tests, and services are typically negotiated with insurers in advance with annual contracts. Hospitals are therefore less flexible in raising charges in response to recent shocks to financing. Consistent with this notion, in Online Appendix Table A.2, we show that stress test exposure has an insignificant effect on hospital cost-to-charge ratios.

[32] We note that the negative credit supply shock also constrains hospitals from investing in new equipment and from hiring more physicians and staff. In Online Appendix Table A.2, we show that hospital tangibility (total fixed assets over total assets) and the number of employees insignificantly decrease after exposure to a stress-tested lender. We also find a significant reduction in building construction. These effects are

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 quality of care performance metrics, as discussed in Section 3. We then investigate whether changes in performance adversely affect patient health outcomes. Finally, we consider the potential effect on patient experiences through the patient satisfaction surveys.

Timely and effective care

Our measures for timely and effective care include the frequency or speed with which patients receive the appropriate treatment 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. The results are presented in Table 5. Columns (1) to (3) examine standard treatments for AMI, columns (4) and (5) correspond to heart failure treatments, and column (6) corresponds to a routine pneumonia treatment.[33]

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. Indeed, every 10-minute treatment delay beyond this window results in an additional 3.3 deaths per 100 patients (Scholz et al. (2018)).

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 3.2–6.4%, depending on the treatment or procedure. We note that this comparison understates the magnitude of the increase, as the sample mean includes the post-treatment rates. These results are particularly striking given that the procedures and treatments captured by the measures are standard (indeed, necessary) practice.

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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)).

[33] The meaning and relevance of these measures are discussed in Section 3.1.

Readmission and mortality

Our primary measures of health outcomes are unplanned risk-standardized readmission rates, which tracks unplanned inpatient readmissions within 30 days from discharge. As noted in prior studies, this measure reflects 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 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—affected hospitals have a 10.1% increase in unplanned pneumonia readmissions relative to unaffected hospitals, a 2.5% increase in heart failure readmissions, and a 2.6% increase in AMI readmissions. This translates to an additional 1,674 patients readmitted per year indirectly due to the negative credit shock.[34]

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.[35] 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, which reduced the readmission rate for pneumonia by only 0.4% after a substantial effort.[36] As noted previously, CMS levies penalties, in the form of reductions in Medicare payments, for high unplanned readmissions relative to the hospital's peer group. For additional texture on the above effects, we consider the likelihood that a hospital is in the worst-performing group relative to its peers in terms of readmissions, as determined by CMS. Column (8) of Table 6 shows that an affected hospital is significantly

[34]We calculate this number based on the unconditional means for readmissions of each diagnostic group and their estimated percentage increases among affected hospitals from Table 6. At the individual hospital level, we observe 3.12 more readmissions per affected hospital per year.

[35]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.

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

more likely to be in the bottom-performing group following a credit shock. This effect is also large—affected hospitals are 58% likely to be in the worst-performing group relative to the sample mean. These outcomes are also 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 unplanned readmission rates.

Along similar lines, we consider mortality rates and levels as a measure of patient health outcomes. One limitation of this analysis is that a significant number of observations for heart failure and AMI mortality rates are missing from our dataset, since many hospitals do not report these numbers. Moreover, mortality rates for certain diagnostic groups, such as heart failure, exhibit considerable autocorrelation as a deterioration in quality of care for these conditions may not readily impact the mortality rate. That is, unlike unplanned readmissions within 30 days, 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)).[37]

Table 7 presents the results of this analysis. Columns (1)–(3) show the coefficient estimates for the change in the logarithm of mortality 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, this is a 9.6% increase in mortality for affected hospitals; this amounts to an additional 915 pneumonia deaths per year indirectly due to the shock to credit access (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.

Collectively, the above results indicate a significant deterioration in patient health outcomes indirectly caused by the negative credit supply shock. The decline in health outcomes aligns with the heightened failure rates in providing effective and timely treatment observed earlier. These findings are also consistent with our results in Section 4.2 that point to in-

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

creased inpatient admissions, which may lead to less attentiveness in care among hospital physicians and staff.

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 are less likely to recommend the hospital. These results are in line with the aforementioned findings on timely and effective care, as the medical staff is less attentive to patients in affected hospitals.

Patient Composition

A concern for the previous results is that when affected hospitals are admitting more patients, they have to include those with more severe conditions. These patients are less likely to recover, more likely to be readmitted, and less likely to be satisfied. To alleviate this concern, we download the Case Mix Index (CMI) from the CMS Impact files. A hospital's CMI represents the average DRG relative weight for that hospital, by summing the DRG weights for all Medicare discharges and dividing by the number of discharges. Column (1) Table 9 shows that an affected hospital's CMI significantly reduces, suggesting a less severe patient pool after the shock. We also investigate the insurance types of patients since the literature (e.g. Ferro et al. (2019)) have shown that Medicaid and Medicare patients tend to have a higher chance of readmission compared to privately-insured patients. We find that the percentage of Medicare users significantly reduce after the shock (column 2), and that of the Medicaid group also insignificantly drops (column 3). These results also indicate that affected hospitals are accommodating less severe, younger, and privately-insured patients, which can cause potential overtreatment.

Summary

Put together, the strongly consistent results across our three disparate measures (readmission and mortality, effective care, and patient satisfaction) indicate a decline in the quality of care and patient health outcomes among hospitals that experience a credit supply shock. The results also suggest a clear channel for how impediments to credit access indirectly translate to a negative impact on patient health. In order to compensate for the increased cost of debt or liquidity shortfall, hospitals turn to their own internally generated revenues and cash reserves. To bolster revenues, hospitals admit more patients and provide more tests for outpatient services (Section 4.2). This increase in hospital occupancy places a greater strain on medical staff time and attention. As a result, patients receive less attention and treatment quality deteriorates, as evidenced by the reduction in timely and effective care and higher levels of patient dissatisfaction. In turn, patient health in affected hospitals suffers as conditions are not treated properly.[38] Consequently, both readmission and mortality rates increase. Overall, the results indicate that frictions to credit markets can have negative social externalities that relate to public health.

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 (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.[39]

4.4 Parallel Trends

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

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

In equation (3), $Exposed_{i,t}^{s}$ equals 1 if hospital i was exposed to a stress-tested bank for the first time in year $t-s$, and is equal to 0 otherwise. For example, $Exposed_{i,t}^{-3}$ equals 1 for the year t that is three years before when hospital i's lending banks are first stress-tested

[38] This channel is also consistent with Silver (2020), who finds that quality of care is lower when emergency room doctors work faster due to workplace peer effects.

[39] 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 hold for both for-profit and not-for-profit hospitals.

("year 0"). When estimating equation (3), we omit $Exposed^0_{i,t}$, 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.[40]

Figures 1–4 provide parallel trends for our main outcomes related to hospital financials, bed utilization, readmission rates, mortality, and patient satisfaction. 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.

4.5 Treatment Heterogeneity

To further validate that our results are driven by a credit supply channel, we explore heterogeneity in hospitals' exposure to bank stress tests. In particular, if the credit supply channel is at play, we would expect our results to be stronger for 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 failing their stress tests 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 stress test failure threshold (with a higher msd indicating that it is safer):

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

The logic behind equation (4) 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 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.[41] For each treated hospital i, we calculate the average msd for all of its

[40]Since the outcome variables for timely and effective care in Table 5 are only available up to 2014, the post-treatment period is too short to compare trends meaningfully.

[41]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

stress-tested lenders, weighted by loan amount. We then re-run equation (1), but split our treatment variable into two separate variables which indicate whether a hospital was exposed to a stress test through a bank that was close to the threshold or far from the threshold. More specifically, we define $CloseExposed_{i,t-1}$ to take a value of 1 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 0 otherwise. Similarly, $FarExposed_{i,t-1}$ takes a value of 1 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 0 otherwise.

Table 10 provides the results for key outcomes from the previous tables.[42] Table 10 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 Section 4.2 and 4.3. In contrast, the effects for the far-bank subgroup are weaker—the coefficients are either insignificant or of a much smaller magnitude.

Another source of heterogeneity across hospitals is how reliant a hospital is on bank loans. If a hospital is more dependent on loan financing, then the negative credit shock induced by stress tests should be more severe. In order to explore this, we first calculate each hospital's loan reliance, which we define to be the hospital's (non-matured) loan amount divided by its total income. We then run a similar specification as in the previous table, except that we split the treatment variable into $HighLevExposed_{i,t-1}$ and $LowLevExposed_{i,t-1}$, which take a value of 1 if hospital i was exposed to a stress-tested bank in year $t-1$ or earlier and its loan reliance was above- or below-median, respectively, and 0 otherwise. The results are provided in Table 11 and show a consistent pattern of stronger effects for the affected hospitals that were more reliant on loan financing.

A final source of 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,

to bind.

[42] We focus on a key subset of our outcomes in order to provide minimize clutter; we note that our results are generally consistent across our other measures.

and run a similar specification splitting the treatment variable into $HighSTExposed_{i,t-1}$ and $LowSTExposed_{i,t-1}$, which take a value of 1 if hospital i was exposed in year $t-1$ or earlier and its stress-tested loan fraction is above or below 50%, respectively, and 0 otherwise. Table 12 provides the results, which confirm that hospitals with a greater portion of their total loans from stress-tested banks are driving the baseline effects.

5 Robustness

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

5.1 Propensity Score Matching

A potential concern is that our treated and control hospitals have different characteristics, which would affect the interpretation of our results. In order to address this concern, we re-run our main specifications using propensity score matching to construct our treatment and control groups.[43] Summary statistics for the differences between the treatment and control samples are provided in Appendix Table A.5, and show no statistically significant difference between the treated and control hospitals. The results are provided in Table 13. As the table shows, our main effects are robust to matching based on observable characteristics, providing evidence that our results are not driven by differences between treated and control hospitals.

5.2 Controlling for Regional Differences

Another 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.[44] Alternatively, local economic conditions in an area may affect

[43] We match based on Rev/TA, $log(Discharge)$, $Cash/TA$, and for-profit status. We match based on the nearest two neighbors for each treatment hospital. We restrict our matched sample to a precision difference cutoff of 0.0025.

[44] The literature has shown that geographical variation can matter in terms of explaining differences in healthcare markets 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.,

both bank lending and hospital outcomes, thus potentially confounding the channels that we aim to identify.[45]

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 picture shows, we do not find a systematic clustering of hospitals exposed to stress tests, as these hospitals are mostly dispersed across the U.S.[46] 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 14 provides the estimation results, and confirms that our results are robust to controlling for time-varying geographical conditions.

5.3 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 Table 15, we restrict our sample to hospitals belonging to a healthcare system from 2010 to 2016, and we add a *System* fixed effect in our regression

2019; 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.

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

[46] 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.

to denote the specific system a hospital is a part of.[47] We further cluster the standard errors at the hospital system level. The results in Table 15 are consistent with the baseline estimation, showing that the effect is not driven by differences between hospital systems and independent hospitals.

5.4 Other Stress Test Robustness

In this section, we discuss additional robustness tests related to the implementation of stress tests. We provide the results in the Online Appendix.

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 19 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 19 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.[48] 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.[49] In

[47] 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."

[48] 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.

[49] 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." November17, 2010. Available at: http://www.federalreserve.gov/boarddocs/srletters/2009/SR0904_Addendum.

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 (188 out of 537) 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 Table A.3 of the Online Appendix.

6 Conclusion

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 these hospitals tighten their operations in response to a negative credit shock—they show increases in profits and revenues. However, we also find that hospitals deliver lower quality care to patients in response to negative credit shocks across a host of objective and subjective measures. In particular, we find that hospitals experience a significant reduction in timely and effective care, an increase in readmission and mortality rates for major conditions, and a reduction in patient satisfaction measures. Our results are stronger for hospitals that are more affected by the stress-test-induced negative

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credit shocks.

Our results suggest that hospitals, like other for-profit businesses, respond to increased financial pressure through changes in their operations, and in particular are dependent on credit markets. However, hospitals also provide a unique societal role in terms of enhancing or maintaining public health. Our results therefore provide evidence of an important connection between credit markets and public health.

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Tables

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 (in million). *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	416
2013	4	26	43
2014	3	3	32
2015	1	4	40
2016	3	4	6

Panel B: Loan Characteristics

	(1) N	(2) Mean	(3) Std	(4) P25	(5) Median	(6) p75
Spread&Fee	1,061	388.09	303.67	200.00	325.00	475.00
Maturity	1,061	58.75	14.58	56.00	60.00	60.00
Amt ($ million)	1,061	737.37	898.91	200.00	450.00	900.00
LoanRatio	825	0.337	0.338	0.087	0.182	0.539

Table 2: 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), leverage (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. 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.

	(1) *Spread&Fee*	(2) *Spread&Fee*	(3) *LogAmt*	(4) *LogMaturity*	(5) *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
Adj R^2	0.21	0.39	0.60	0.43	0.34

Table 3: Hospital Financial Performance

This table provides the regression results for equation (1) for financial 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. $LogInPatRev$ and $LogOutPatRev$ are the logarithm of one plus total inpatient and outpatient revenues, respectively. $AvgPay$ is total inpatient revenue divided by total inpatient discharges. $Cash/TA$ is cash holdings over total assets. $Debt/TA$ is total debt over total assets. 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 debt 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) *Debt/TA*	(3) *Cash/TA*	(4) *LogPatRev*	(5) *LogInPatRev*	(6) *LogOutPatRev*	(7) *AvgPay*
$STExposed_{i,t-1}$	0.012**	−0.052***	−0.006***	0.057*	0.086***	0.068*	1701.316***
	(2.077)	(−4.275)	(−2.583)	(1.903)	(2.845)	(1.851)	(3.172)
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	23,119	23,793	23,793	23,793	23,248
Adj R^2	0.22	0.81	0.76	0.93	0.95	0.81	0.87

Table 4: Hospital Bed Utilization

This table provides the regression results for equation (1), focusing on hospital bed utilization. *Occupancy* is inpatient bed days utilized over total bed days. *Discharge Rate* is inpatient discharges over total bed days. *Salary* is the average per capita salary for physicians, interns and residents. *AvgHour* is the average per capita service hours reported by these employees. $STExposed$ 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 debt 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) *Occupancy*	(2) *Discharge Rate*	(3) *Salary*	(4) *AvgHour*
$STExposed_{i,t-1}$	0.022***	2.350***	1750.260***	22.607**
	(5.973)	(5.752)	(5.017)	(2.222)
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y
N	23,245	23,243	23,148	18,350
Adj R^2	0.94	0.80	0.93	0.65

Table 5: 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 debt 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) *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 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 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. 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 debt 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) *LogPNReadm*	(2) *LogHFReadm*	(3) *LogAMIReadm*	(4) *PNReadmRate*	(5) *HFReadmRate*	(6) *AMIReadmRate*	(7) *AllReadmRate*	(8) *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
Adj R^2	0.96	0.98	0.97	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. 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 debt 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) *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
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. 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 debt 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) *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
Adj R^2	0.82	0.59	0.85	0.76	0.77	0.78	0.72	0.85

Table 9: 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 debt 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) *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 10: 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 $(Income - Cost)/Income$. $Occupancy$ 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 debt 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, respectively.

	(1) *Margin*	(2) *Occupancy*	(3) *Discharge Rate*	(4) *AllReadmRate*	(5) *Antibiotic*	(6) *Overall*
$CloseExposed_{i,t-1}$	0.012**	0.024***	2.013***	0.001***	−0.009***	−0.008***
	(2.058)	(5.483)	(4.591)	(3.548)	(−3.200)	(−4.027)
$FarExposed_{i,t-1}$	−0.007	0.013***	0.783*	0.002***	−0.003***	−0.000
	(−1.044)	(2.797)	(1.656)	(4.925)	(−0.674)	(−0.164)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	25,397	23,715	23,713	17,678	15,113	23,950
Adj R^2	0.22	0.94	0.80	0.67	0.58	0.81

Table 11: Heterogeneity Across Bank Loan Reliance

This table provides estimation results when splitting the treatment group by the treated hospital's reliance on bank loans. We define *reliance* as a hospital's non-matured loan amount over its total income. $HighLevExposed_{i,t-1}$ ($LowLevExposed_{i,t-1}$) takes a value of 1 if hospital i was exposed to a stress test in year $t-1$ or earlier *and* its *reliance* is above (below) median, and 0 otherwise. $Margin$ is profit margin, defined as $(Income - Cost)/Income$. *Occupancy* 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 debt 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) *Occupancy*	(3) *Discharge Rate*	(4) *AllReadmRate*	(5) *Antibiotic*	(6) *Overall*
$HighLevExposed_{i,t-1}$	0.018**	0.033***	3.008***	0.003***	−0.013***	−0.009***
	(2.474)	(6.451)	(6.530)	(6.465)	(−3.815)	(−3.931)
$LowLevExposed_{i,t-1}$	0.001	0.012**	0.656	0.001	−0.002	−0.004
	(0.065)	(2.342)	(1.187)	(1.464)	(−0.633)	(−1.629)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	25,397	23,715	23,713	17,678	15,113	23,950
Adj R^2	0.22	0.94	0.80	0.67	0.58	0.81

Table 12: 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 $(Income - Cost)/Income$. *Occupancy* 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 debt 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) *Occupancy*	(3) *Discharge Rate*	(4) *AllReadmRate*	(5) *Antibiotic*	(6) *Overall*
$HighSTExposed_{i,t-1}$	0.014**	0.022***	2.373***	0.002***	−0.008***	−0.008***
	(2.235)	(5.520)	(5.661)	(5.067)	(−3.216)	(−4.691)
$LowSTExposed_{i,t-1}$	−0.031**	0.014*	0.557	0.001	−0.001	0.002
	(−2.432)	(1.673)	(0.524)	(1.056)	(−0.195)	(0.488)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	25,397	23,715	23,713	17,678	15,113	23,950
Adj R^2	0.22	0.94	0.80	0.67	0.58	0.81

Table 13: Robustness: Propensity Score Matching

This table provides estimation results for equation (1), using a propensity score matched sample. We match on Rev/TA, $log(Discharge)$, $Cash/TA$, and for-profit status based on the nearest two neighbors for each treatment hospital. We restrict our matched sample to a precision difference cutoff of 0.0025. $Margin$ is profit margin, defined as $(Income - Cost)/Income$. *Occupancy* 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 debt over total assets ($Debt/TA_{i,t-1}$), and lagged total patient revenue over total assets ($PatRev/TA_{i,t-1}$). 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.

	(1) *Margin*	(2) *Occupancy*	(3) *Discharge Rate*	(4) *AllReadmRate*	(5) *Antibiotic*	(6) *Overall*
$STExposed_{i,t-1}$	0.015***	0.017***	1.847***	0.002***	−0.008***	−0.006***
	(2.711)	(3.589)	(3.289)	(3.504)	(−2.990)	(−2.373)
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	7,760	7,216	7,216	5,689	4,901	7,796
Adj R^2	0.51	0.93	0.76	0.68	0.55	0.81

Table 14: 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 $(Income - Cost)/Income$. *Occupancy* 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 debt over total assets ($Debt/TA_{i,t-1}$), 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.

	(1) *Margin*	(2) *Occupancy*	(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 15: 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 $(Income - Cost)/Income$. *Occupancy* 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 debt over total assets ($Debt/TA_{i,t-1}$), 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.

	(1) *Margin*	(2) *Occupancy*	(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

Figures

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.

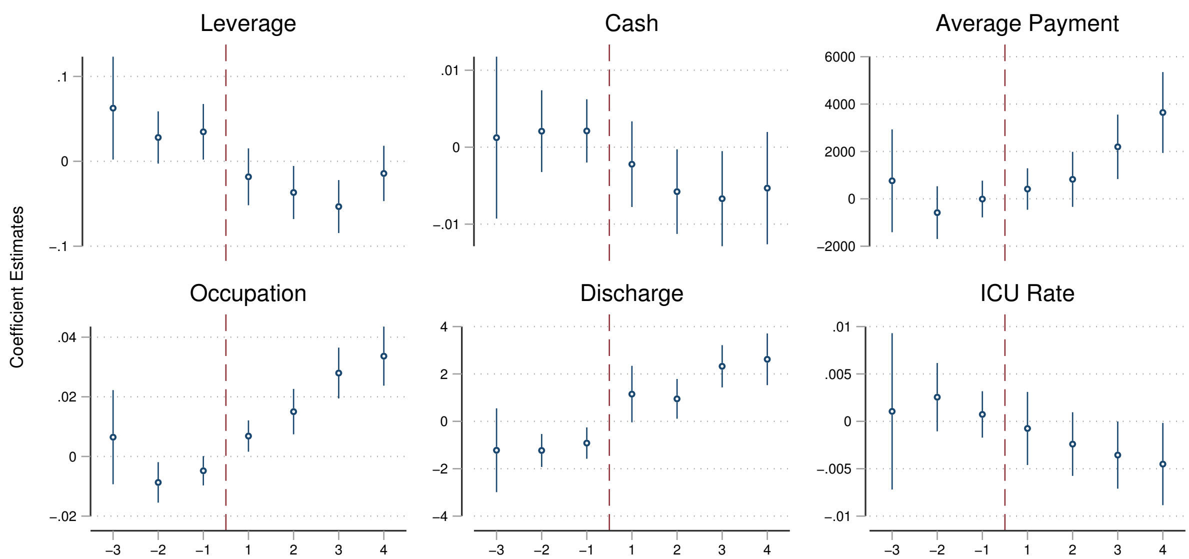


Figure 2: Parallel Trends: 30-day Readmission Rates

This figure provides parallel trends for 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.

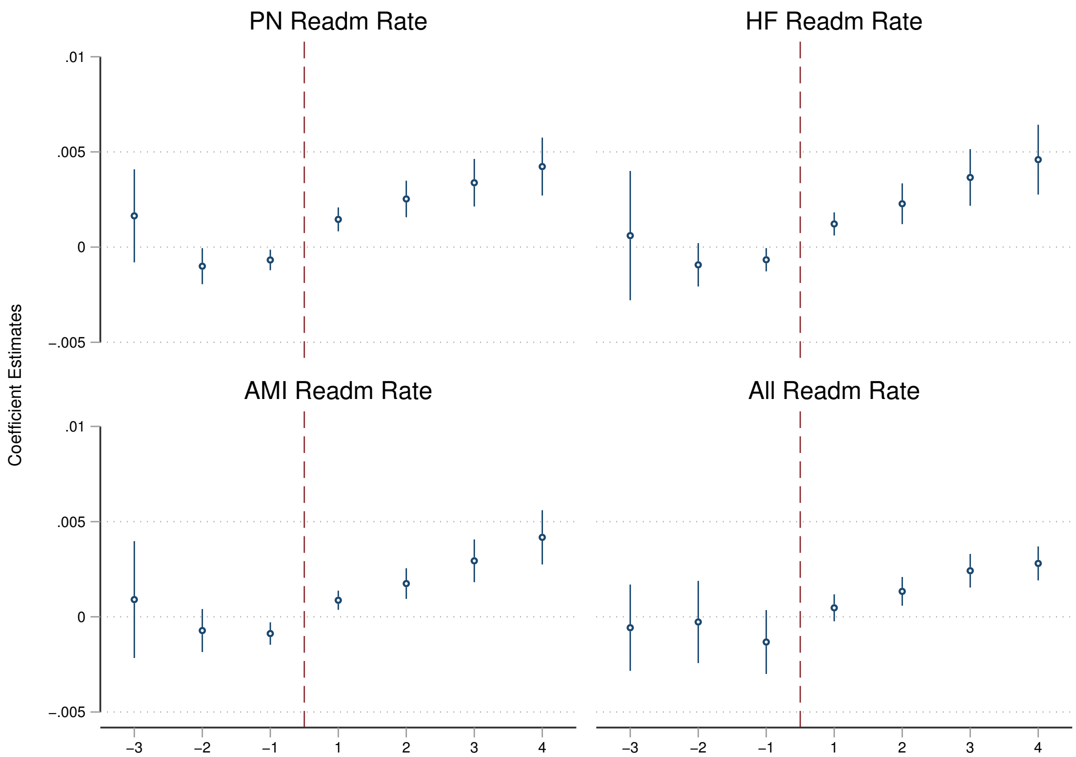


Figure 3: Parallel Trends: Mortality

This figure provides parallel trends for 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.

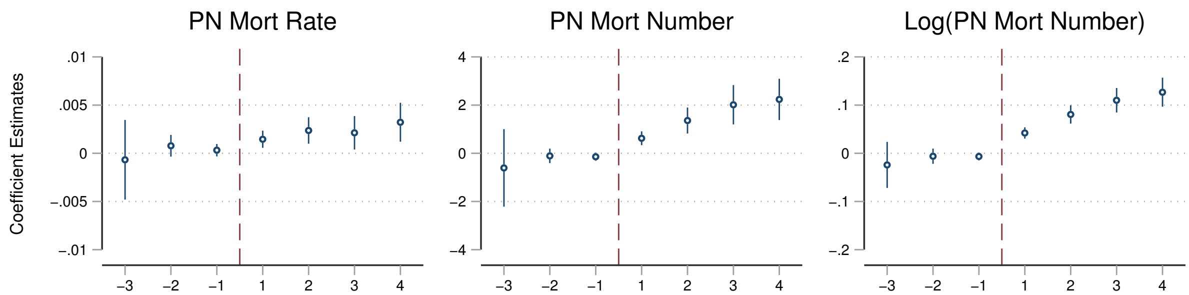


Figure 4: Parallel Trends: Hospital Care Quality from the Patient's Perspective

This figure provides parallel trends for 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.

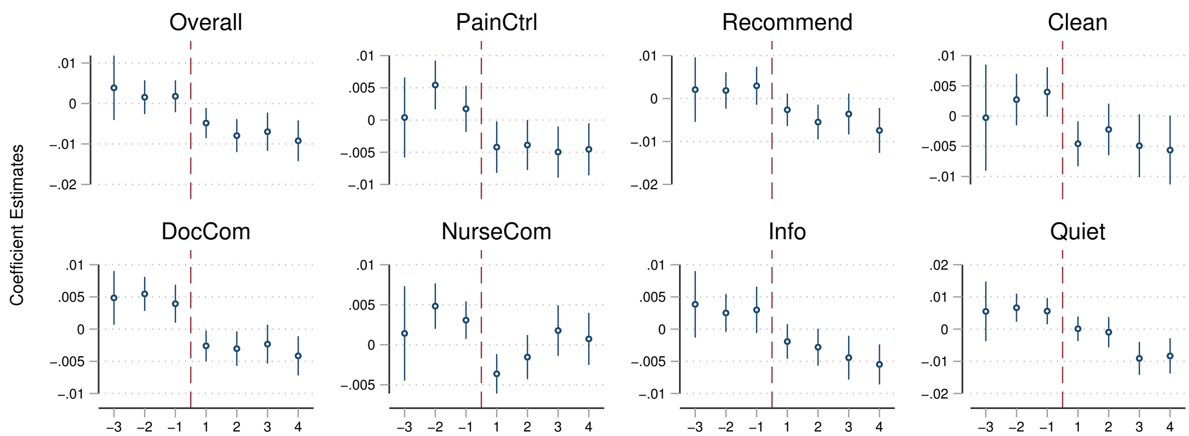
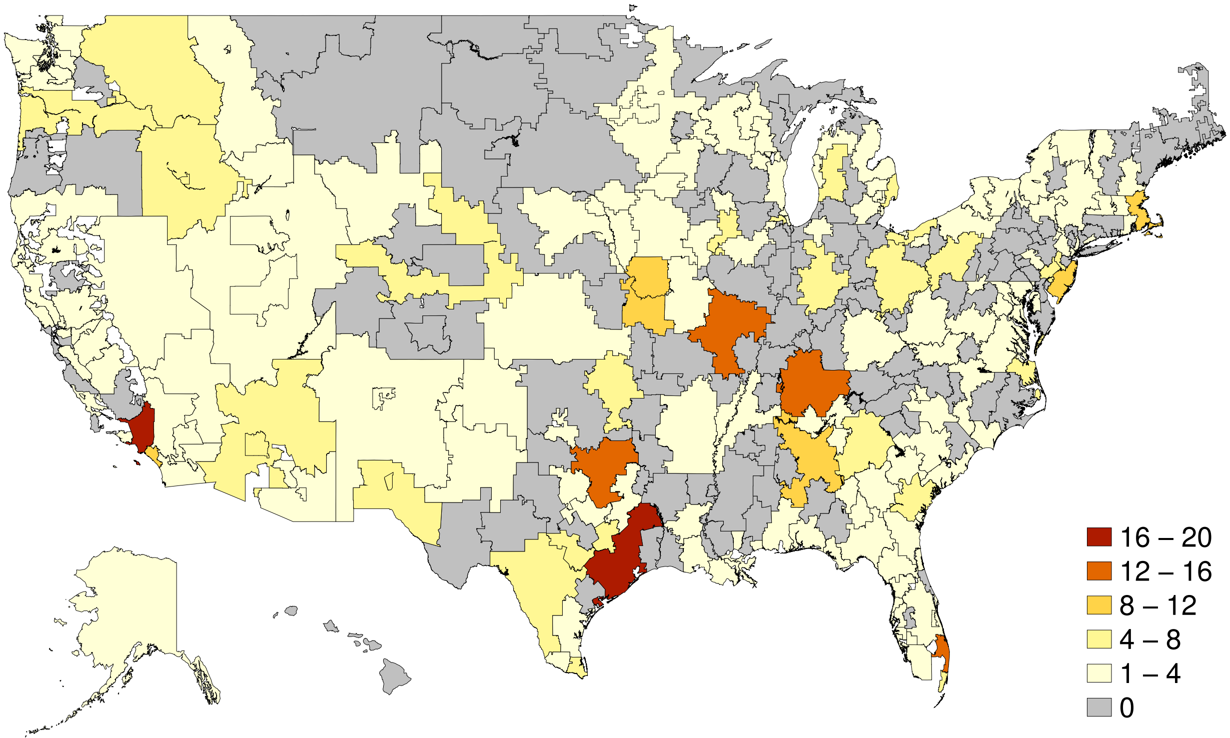


Figure 5: Geographical Distribution of Hospitals Exposed to the Stress Tests

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

Table A.1: Variable Definitions and Summary Statistics

Variable	Definition	N	Mean	Std	P25	Median	P75
Panel A: Financial Variables							
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	Total Income ($ million)	34,559	164.926	224.391	24.961	80.525	210.819
Debt/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
AvgPay	Total inpatient revenue over inpatient discharges (dollars)	35,000	33,707	29,256	16,925	26,496	41,466
Occupancy	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
AvgHour	Average number of working hours by employees in treatment units	24,759	2,230.912	496.717	2,080.000	2,312.230	2,264.480
Salary	Average salary of employees in treatment units	34,877	51,215	29,946	45,026	57,671	67,633
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: Timely and Effective Care							
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	6,726	0.936	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	15,435	0.963	0.113	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	15,749	0.941	0.084	0.930	0.960	0.990

(continued)

Panel C: Readmission and Mortality							
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	19,929	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
Panel D: Patient Satisfaction Measures							
Overall	Percentage of patients giving the highest rating for overall care quality	25,291	0.705	0.089	0.650	0.710	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	25,290	0.711	0.097	0.650	0.720	0.780
Clean	Percentage of patients giving the highest rating for cleanliness	25,292	0.728	0.076	0.680	0.720	0.780
DocCom	Percentage of patients giving the highest rating for doctor communication	25,292	0.809	0.052	0.780	0.810	0.840
NurseCom	Percentage of patients giving the highest rating for nurse communication	25,292	0.785	0.056	0.750	0.790	0.820
Info	Percentage of patients giving the highest rating for recovery information	25,289	0.856	0.046	0.830	0.860	0.890
Quiet	Percentage of patients giving the highest rating for quietness	25,292	0.600	0.100	0.530	0.590	0.660

Table A.2: Hospital Charges and Investments

This table provides regression results for equation (1), focusing on hospital charges and investments. *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. *LogEmployees* is the logarithm of one plus total employed physicians, including residents and interns. $STExposed$ 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 debt 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) *Cost-Charge*	(2) *Fixed/TA*	(3) *Building/TA*	(4) *LogEmployees*
$STExposed_{i,t-1}$	−0.066	−0.007	−0.028***	−0.007
	(−0.963)	(−1.108)	(−2.829)	(−0.911)
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y
N	22,721	23,036	21,357	23,148
Adj R^2	0.22	0.73	0.73	0.99

Table A.3: Stress Tests including CCAR: Financial and Bed Utilization Variables

This table provides the regression results for our main tests, including exposure to CCAR stress tests in our treatment. The outcome variables are defined in the same way as before. $STExposed^{CCAR}$ 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. 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 debt 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) *Occupancy*	(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

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

This table shows that bond issuance costs in the counties with hospitals exposed to stress-tested banks stay constant during the sample period (2009–2019). The unit of observation is a bond upon issuance. $Yield_{k,t}$ is the size-weighted transaction yield at 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 1 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. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1) *Yield*	(2) *Yield*	(3) *Spread*	(4) *Spread*	(5) *SpreadMMA*	(6) *SpreadMMA*
$ExposedCounty_{k,t}$	1.768	7.253	2.003	6.827	1.866	9.306
	(0.385)	(0.717)	(0.425)	(0.655)	(0.401)	(0.728)
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	22485	22466	22324	22305	22485	22466
Adj. R^2	0.95	0.95	0.85	0.87	0.85	0.88

Table A.5: Differences between Treatment and Control Groups after Propensity Score Matching

This table provides statistics for the differences between treatment and control hospitals after propensity score matching. All variables are as previous defined. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Control Obs.	Treat Obs.	Mean of Control	Mean of Treat	Diff.	Std Err	t-stat	p-value
Patient Revenue (mil)	705	373	671.031	671.3435	−.312	51.379	0	.995
Rev/TA	705	373	4.9905	4.9715	.019	.2315	.1	.934
Log(Income)	705	373	18.602	18.5845	.0175	.081	.2	.8275
Debt/TA	704	373	.601	.6035	−.0025	.039	−.05	.9495
Cash/TA	705	373	.049	.0435	.006	.007	.85	.4
Log(Discharge)	705	373	8.58	8.637	−.057	.0785	−.7	.4695
Log(BedDays)	705	373	10.589	10.65	−.061	.058	−1.05	.29
For-profit	705	373	.329	.362	−.033	.0305	−1.1	.2795