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

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Abstract

This paper 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 experience a significant increase in unplanned 30-day readmission rates of recently discharged patients, significantly lower attentiveness in providing correct treatment and procedures, and are rated substantially lower in patient satisfaction. Overall, the results indicate that 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, functioning partially as public-sector institutions that provide a public good to their local communities.[1] Beyond this, hospitals are crucial to the economy, with healthcare spending in the United States accounting for nearly 18% of GDP. Furthermore, a key justification for the partial shutdown of the global economy in response to the COVID-19 pandemic was concerns regarding hospital overcapacity. 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, and thus affect real 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 social externality—health consequences—that can arise from credit shocks. Research on this topic may therefore have important social consequences and policy implications.

We attempt to shed some light on the above question by using lending supply shocks to hospitals. Specifically, we utilize the staggered pattern of stress tests 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. In other words, 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)).[2,3] We empirically compare outcomes for treated hospitals compared to unaffected hospitals in a staggered difference-in-differences specification.

[1] For example, the Emergency Medical Treatment & Labor Act of 1986 states that hospital emergency departments must provide medical examinations to anyone upon request for a medical condition, regardless of their ability to pay. Specifically, the law applies to any hospital that accepts Medicare payments, which in the U.S. is nearly all hospitals.

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

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

This allows us to 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 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 successful stress test.

We first establish that bank stress tests constitute a negative credit shock to connected hospitals. 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. 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 outcomes change as a result. We find that, in response to the credit shock, affected hospitals experience an increase in revenue and profitability. This increase appears to be driven by changes in hospitals' operations. In particular, in response to tighter credit conditions, we find evidence that hospitals make heavier use of their existing resources by increasing their bed utilization and physician billing, while decreasing their use of less-profitable services such as ICU beds. These 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, we find that affected hospitals experience a significant *decline* in quality of care and health outcomes. We use three distinct measures for quality of care and health outcomes. First, we examine patient health following treatment using 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 initial treatment. 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 item relevant to the treatment and hospital stay.

Across all three measures, the results show that hospital performance declines following credit supply shocks. We find that patients are significantly more likely to be readmitted within 30 days of discharge for affected hospitals. Similarly, these hospitals are more likely to be penalized by the federal government for higher than average readmission rates following a shock to credit supply. Additionally, we find that affected hospitals exhibit increased delay in providing treatment and a lower propensity in performing requisite medical procedures for the specific medical conditions. Lastly, patient evaluations regarding efficacy of treatment and attentiveness of the medical staff are consistently lower for affected hospitals. Collectively, these results suggest that patient health outcomes and quality of care are adversely affected for hospitals which experience a shock to credit access.

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 admittances. 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 readmittances 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.[4].

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 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. Likewise, hospitals which are more reliant on bank loan financing are naturally more affected by stress tests on their lenders. Finally, hospitals for which the majority

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

of their existing lenders are stress-tested have fewer options for alternative financing from establishing 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 patient health outcomes, quality of care, attentiveness, and patient satisfaction. These results are in line with a credit supply channel driving our effects.

Our 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 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 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 may indirectly affect health outcomes.

Finally, our analysis is also related to the literature at the intersection of healthcare and finance. Adelino et al. (2015) use nonprofit 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. Gao et al. (2020) examines the effect of the Affordable Care Act on hospital municipal bond spreads. Our paper contributes

to this literature by documenting a link between hospitals and credit markets, and showing how credit markets may indirectly affect healthcare. To the best of our knowledge, this 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.

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 detail our empirical strategy and data. Section 4 provides the main results, while Section 5 includes 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 (hereafter 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 three scenarios (baseline, adverse, and extremely adverse). 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 bank holding companies with assets of at least $50 billion, and had to be completed by September 30, 2012. However, the Final Rule to the DFA required stress tests by 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 DFA stress tests are designed to guage 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. (2020) document strong evidence that credit supply was negatively impacted among stress-tested banks. In particular, stress-tested banks significantly increased loan spreads and reduced loan supply for risky borrowers, and managed higher capital ratios in response to the stress tests.

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 one-time Supervisory Capital Assessment Program (SCAP) in February 2009. The SCAP amounted to 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 large 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 DFA differs from both the SCAP and CCAR.

In light of the SCAP and CCAR, we use the implementation of DFAST as our primary empirical setting. As noted above, the SCAP was implemented during an emergency period to prevent collapse of the financial system.[5] 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 aim of the 2011 CCAR was to provide additional oversight regarding capital distributions to shareholders of the largest banks. In contrast to these two prior programs, the DFA was passed by the U.S. Congress and signed into law, and served as the country's central legislation regarding stress tests. Moreover, the aim of DFAST is to ensure financial health of individual banks and the banking system. Accordingly, DFAST applies to a wider set of banks and carried a stricter examination than the 2011 CCAR through its "severely adverse scenario" tests. While DFAST appears to be the most suitable stress test program for our setting, it is possible that the other programs may generate similar effects under the same channel (discussed below). In Section 5.1, we evaluate this possibility in detail.

Hospital borrowing

Hospitals, both for-profit and non-profit, rely partially on debt to finance their operations. Consistent with this, a large number of hospitals were borrowing from stress-tested banks (see Table 1). Of the 18 banks stress-tested in 2012, 15 had loans to 416 hospital borrowers.

[5]Moreover, the lack of market response to the disclosure of SCAP results suggests that the program did not bring significant new information to the market.

Moreover, hospitals are particularly risky borrowers. Indeed, healthcare municipal bonds tend to have significantly higher yields and riskiness ratings than non-healthcare bonds, and accounted for 20% of all municipal bond defaults from 1999 to 2010 (Gao et al. (2019)).[6] (Non-profit hospitals may borrow through municipal bonds, however this option is not available for for-profit hospitals.) Therefore, stress-tested banks may be inclined to reduce granting credit to risky hospital borrowers or to raise interest rates in order to compensate for this risk following heightened risk-management incentives induced by the stress tests.

Hospitals may react to this credit shock by seeking credit from alternative lenders. However, as has been well-established in the finance literature, long-term lending relationships help to lower information asymmetry between borrowers and lenders and allow for lower interest rates.[7] New lenders without an established relationship would thus require higher interest rates or provide less capital as a result of greater information asymmetry. Indeed, as shown in Table 2, hospitals that borrowed from a stress-tested bank experienced an economically substantial and significant increase in the spread and fee, decrease in loan amount, and lower maturity. Additionally, the propensity to borrow from a new lender increased for affected hospitals. These results reinforce the findings of Acharya et al. (2018) and Cortés et al. (2020) and are consistent with the argument that hospital borrowers experienced a shock to credit supply following 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 may 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 per-patient revenue through greater testing or increased admittances and overnight stays. 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. On the other hand, if (perhaps erroneous) testing or admittances 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.

[6] As noted by Gao et al. (2020), healthcare municipal bonds have an average yield of 3.22%, while te average for non-healthcare municipal bonds is 2.39%.

[7] 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.

3 Research Design

3.1 Data and Summary Statistics

Medicare-certified hospitals (providers), which includes 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 Centers for Medicare & Medicaid Services (CMS) maintains the cost report data in the Healthcare Provider Cost Reporting Information System (HCRIS). We download all of the available reported information from CMS's website. For each provider, this covers common items in a financial statement such as total assets (TA), income ($Income$), total liabilities ($Debt$), revenues,[8] cash holdings ($Cash$) and operational costs ($Cost$). In addition, it covers hospital utilization information, from which we extract total inpatient discharges, total occupied bed days, total available bed days ($BedDay$),[9] total number of employed physicians, interns, and residents,[10] as well as the total salary expenditure for them. 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.

Our sample includes yearly hospital observations from 2010 to 2016. We begin our sample 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 by CMS.[11] The cost report takes time to compile, submit, and be processed by CMS. Presently, financial information is complete for most hospitals up to calendar year 2016. We restrict the sample to include only short-term acute care hospitals, though our result is robust to including other types of providers, and controlling for hospital-type fixed effects. We further exclude hospitals controlled by government authorities, as they primarily rely on municipal bond markets for external financing. Our final sample includes 3,658 hospitals.

To measure hospital quality, we merge the above information with two other datasets from CMS that provide objective measures of quality. The first measure of quality of care includes the rate of unplanned readmission to an acute care hospital in the 30 days after discharge from hospitalization, also provided by the Hospital Compare program. The readmission rates are separately documented for heart attack, heart failure, and pneumonia, and is

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

[9] This includes all types of beds (general and special care). We also extract the number of beds in the ICU units.

[10] This is reported in the unit of full-time equivalents.

[11] In our specification, we use lagged financial variables as controls (see Section 3.2).

available between 2010 and 2017.[12] Readmission rates are informative about the efficacy of the initial treatment upon hospitalization, are often-used measures for quality of care. A high readmission rate, for example, implies that the hospital's initial treatments were often not sufficient for full recovery.

The second dataset is from the CMS Hospital Compare program. In this program, CMS requires hospitals to submit information on timely and effective treatment for certain disease categories. In 2005, the first set of 10 "core" process of care measures were created for acute heart infarction (heart attack or AMI), heart failure (HF), pneumonia (PN), and surgical care. Over the years, the program keeps terminating existing measures and medical conditions and switching to others documented in new research. This creates a challenge for this paper since our specification requires consistent yearly coverage both before and after the DFAST. There are 6 measures that are non-missing for most hospitals from 2010 to 2014. For heart attack, we track the portion of patients that receive aspirin at discharge, percutaneous coronary intervention (PCI) within 90 minutes of arrival, and Statin at discharge.[13] For heart failure, we track the portion of patients that receive left ventricular systolic evaluations (LVS) and ACE inhibitors or angiotensin receptor blockers (ACE/ARB) at discharge.[14] For pneumonia, we track the portion of patients that receive the most appropriate antibiotic.

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. 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 an additional measure of more subjective ratings by

[12]The Hospital Compare program also reports risk-adjusted 30-day mortality rates and inpatient complications. We do not use mortality rates because these rates are highly auto-correlated (see, e.g., CMS Medicare Hospital Quality Chartbook), due to the fact that they are only calculated as three-year rolling averages, therefore providing insufficient time-series variation for our DiD analysis. In addition, the complication data is mostly missing prior to 2013, thus allowing no pre-treatment coverage for this variable.

[13]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).

[14]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.

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 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.

Lastly, we combine our hospital data with Dealscan loan data. We keep all loan facilities which have (*i*) a borrower 3-digit SIC code equal to 806, (*ii*) a facility start date after January 1, 2007, and (*iii*) whose loan types are term loans and revolver. Following Ivashina (2009), we identify and keep the lead bank in a syndicate deal.[15] 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 by name. 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).[16]

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 being exposed to the 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 (57%) banks and 416 (77%) hospitals are exposed to the 2012 DFAST. Banks with total consolidated assets of more than $10 billion but less than $50 billion were

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

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

required to implement stress tests under the DFA by the following year, September 30, 2013.

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:

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

In equation (1), $STExposed_{i,t}$ 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. $Controls_{i,t}$ is a vector of control variables that include the lagged logarithm of one plus total hospital income ($LogIncome_{i,t-1}$), the logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), 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, which we will define in detail in Section 4. The parameters η_t and μ_i denote time and firm fixed effects, respectively.

The coefficient of interest in equation (1) is β, which estimates the relative effect of stress test exposure on that hospital, compared to hospital-year observations for which there is no relationship-bank stress test. 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.

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 DFAST did not select a participating bank based on the fact that it predicted that the bank's borrowing hospitals would underperform in the future. Instead, the selection was based on a total assets threshold for the bank ($10 billion), which is beyond the control of the borrowing hospital. Self-selection by hospitals is also not likely to happen. Though the Dodd-Frank Act was enacted on July 21, 2010, the FDIC issued the notice of proposed rulemaking (NPR) on January 23, 2012. This NPR solicited public comments to finalize the implementation, and the effective date and public disclosure policy of results were changed due to major concerns. In the sample, most of the

borrowing hospitals reached a deal with the tested banks before 2012.[17] The actual timing of DFAST was uncertain and thus exogenous to the loan initiation. Furthermore, a hospital had no incentives 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 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. We estimate equation (2) at the *loan facility* level:[18]

$$Y_{k,i,j,t} \quad = \quad \alpha + \beta STExposed_{i,t} + \gamma' Controls_{i,t} + FEs + \varepsilon_{k,i,j,t}. \tag{2}$$

$Y_{k,i,j,t}$ is a loan k's characteristics which started in year t between bank j and hospital i. Note that the value of $STExposed_{i,t}$ is determined by hospital i's exposure and is independent of the particular lender j in each loan. In order to capture the possibility that the hospital switches to a new bank with potentially quite different loan characteristics (e.g., higher spread), we measure the outcome Y for each loan between hospital i and bank j, and thus for each lending relationship.

Table 2 provides the results. In columns (1) and (2), we examine loan interest rates, defined as the spread (in bps) over LIBOR plus one-time fees on the drawn portion of the loan. We see that borrowing costs increase significantly for affected hospitals. Similarly, in columns (3) and (4), we find that the loan amount (the logarithm of one plus facility amount) as well as loan maturity (the logarithm of one plus facility maturity in months) both decrease for hospitals exposed to a lender's stress test. These results are consistent with Acharya et al. (2018) and Cortés et al. (2020), and suggest that hospital credit access

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

[18] For this specification, 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 year, bank, loan type, and loan purpose fixed effects. Following Drucker and Puri (2009), loan types include *Revolvers* and *Term Loans*. Loan purposes include *Acquisition*, *General*, *LBO*, *Recapitalization*, *Miscellaneous*, and *Other*.

was negatively impacted by stress testing. This is 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. $NewLender_{k,i,j,t}$ is a dummy variable taking a value of 1 if hospital i had no previous lending relationship with bank J previously. We see that the coefficient on $NewLender_{k,i,j,t}$ is positive and significant, which implies that hospitals are more likely to switch to new lenders when their current lender is subject to a stress test. Finally, we examine whether banks subject to the stress tests raise interest rates due to heightened risk management incentives. We replace $STExposed_{i,t}$ with $Tested_{j,t}$, which equals 1 if bank j was stress-tested in year $t-1$ or earlier, and 0 otherwise. The coefficient of $Tested_{j,t}$ estimates whether a tested bank will increase the borrowing costs for all future loans.[19] The results confirm that the spread significantly increases for the subgroup of borrowers who choose to keep their relationship banking.

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 asymmetry, face higher interest rates in these loans from new lenders. These results validate the use of the DFAST as an exogenous shock to hospital credit access.

4.2 Hospital Financials and Occupation

Having established the effect of stress tests on credit supply, we now examine how bank stress tests affect hospital outcomes. The results are in Table 3. Across the various profit and revenue outcomes, including profit margin and patient revenue in different groups, stress tests lead to an *increase* in hospital profitability. The growth in profitability is associated with switching financing decisions. Column (5) shows a significant reduction in the leverage, as hospitals respond by utilizing less external debt giving the higher borrowing cost. Column (6) implies that they instead rely more on internal cash reserves for investment and expenditures.

A hospital may increase its revenues in a number of different ways. It may either charge higher prices for the same services, or increase the total number of services. The former

[19] The value of $Tested_{j,t}$ is determined by bank j's exposure status and is independent of the particular borrower in the deal. This captures the (rare) possibility of banks switching to new hospitals afterward. Our results are identical if we redefine $Tested_{i,j,t}$ to require that the borrower i has a relationship with bank j before t.

is mostly infeasible for Medicare hospitals, as their reimbursement rates are pre-set—CMS uses the inpatient prospective payment system (IPPS) to calculate the base payment rate from each diagnosis-related group's average charges.[20] However, we find strong evidence for the latter channel—that hospitals increase the total number of services—in Table 4. In columns (1) and (2), we document significant increases for two different measures of hospital occupation. *Occupation Rate* in column (1) is the utilized hospital bed days over all available bed days. *Discharge Rate* in column (2) is the total inpatient discharges in a year over total available bed days. To understand the economic magnitude, an available bed in an affected hospital is 2.2% more likely to be utilized every day (column (1)), and it accommodates 2.35 more patients every year (column (2)), relative to an unexposed hospital. Column (3) indicates that not only are more inpatients staying in the hospital, but physicians are also busier with more services. In a typical productivity-based compensation, physicians receive a percentage of their billings or a flat rate based on a specific procedure. An affected hospital's physician receives around $1,750 more in salary each year, in line with the greater number of services provided.[21]

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 Hospital Care Quality

At the same time that affected hospitals face earnings pressures and have to accommodate more patients, the negative credit supply shock also constrains them from investing in new equipment and hiring more physicians.[22] Hospitals must also provide the additional services

[20]Furthermore, in the Online Appendix, we confirm that stress test exposure has insignificant effects on hospital cost-to-charge ratios.

[21]It is also possible that hospitals divest in order to reduce operational costs. For example, we find that the percentage of ICU unit beds out of all beds reduces significantly after a hospital is exposed to the stress tests in column (4).

[22]In the Online Appendix, we confirm that hospital tangibility (total fixed assets over total assets) and the number of employees insignificantly decrease after stress tests. We also find a significant reduction in

given the existing facilities and human resources, which challenges hospital management and care. It is thus important to evaluate whether hospital care quality deteriorates.

To examine this, we first examine measures of hospital care quality related to readmissions. Table 5 examines unplanned 30-day patient readmission rates for three disease groups: heart attack (AMI), heart failure (HF), and pneumonia (PN). Columns (1) to (3) evaluate the raw readmission rates and document that an affected hospital experiences significant 0.3% higher yearly readmission rates across all three diseases. The magnitude is also economically meaningful, as the readmission is typically difficult for hospitals to reduce. For example, after the Affordable Care Act established the Hospital Readmissions Reduction Program (HRRP) in 2010, national readmission rates fell by 0.6% for AMI, 0.5% for HF, and 0.4% for PN every year between 2010 and 2016.[23] HPPP also penalizes Medicare hospitals for "excess" readmissions compared to "expected" levels and, and reports these hospitals as "worse than the national average" in the Hospital Compare data.[24] In columns (4) to (6), we find that affected hospitals are 2.7% more likely to be punished for HF readmission, and 1.6% more likely for PN. Therefore, the treatment group faces higher penalization risk when they are increasing operating revenue.

We next examine timely and effective care measures in Table 6, which tests whether patients received appropriate treatments shortly after arrival and upon discharge. Columns (1) to (3) examine standard treatments for AMI, with columns (4) and (5) HF and column (6) for PN.[25] The overall message is consistent with other quality measures: a hospital being exposed to a bank stress test leads to a significant reduction in providing timely and effective care to patients (except for giving Aspirin to AMI patients at discharge, which is marginally insignificant).

As our final test of hospital care quality, explore patient satisfaction information from HCAHPS as a subjective measure of care quality. Table 7 shows that across all question categories, an affected hospital's patients become significantly less likely to give the highest rating. The magnitudes of reduction are also consistent across all measures. This indicates that patients rate service quality as being systematically worse. These effects are consistent

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

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

[24]Specifically, HPPP adjusts the raw readmission rates with risks and estimates the 95% confidence interval for a baseline rate. A hospital is worse than the national average if its true rate is above the confidence interval's upper bound.

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

with the affected hospitals becoming more crowded and care providers also being busier, as patients become less satisfied with quietness, cleanness, and communications.

The above results suggest that care quality by hospitals is reduced following a stress-test-induced reduction in credit supply. This implies that tighter financial conditions, while leading to higher marginal profitability due to operational changes, results in worse patient outcomes. From a social welfare perspective, hospitals are different from general corporations due to their social responsibility. Therefore, this loss to public healthcare represents a significant negative externality of stress test exposure.

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

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

In equation (3), $Exposed_{i,t}^s$ equals 1 if hospital i was exposed to a stress-tested bank for the first time in $t-s$, and 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 ("year 0"). When estimating equation (3), we drop $Exposed_{i,t}^0$ such that the impact of stress-test exposure in year 0 serves as the reference year. The interpretation of β_s is the relative difference between the treatment and control groups s years after year 0. k is the maximal post-treatment period, which equals 5 for the variables that are available in 2017, and 4 otherwise.[26]

Figures 1 – 3 provide parallel trends for the variables corresponding to Tables 3 – 5. For all of the variables, there is no significant trend before 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.

[26]Since the outcome variables for timely and effective care in Table 6 are only available up to 2014, the post-treatment period is too short to compare trends meaningfully. Therefore, we focus on the variables in Tables 3 – 5.

4.5 Treatment Heterogeneity

To validate the negative credit supply channel, we explore heterogeneity in hospitals' exposure to bank stress tests, documenting that our results are stronger in the treatment subgroup where we expect them to be more affected.

In our first test, we exploit the fact that lenders vary in their stress test performance. For banks that are closer to failing their stress tests (i.e., weaker banks), they tend to reduce their credit supply more dramatically and generate more financial pressure for the borrowing hospitals. 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):

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

The logic behind equation (4) is as follows. DFAST sets a different regulatory threshold for the three stresses capital ratios (6% for the Tier 1 ratio; 8% for the Total risk-based capital ratio; and 4% for the leverage ratio). Using the minimum out of the three distances captures the variation in binding conditions across banks and years.[27] For each treated hospital i, we calculate the average msd for all of its 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 weaker or stronger bank. In particular, $WeakExposed_{i,t}$ takes a value of 1 if hospital i was exposed in year $t-1$ or earlier *and* the average msd of its tested lenders was below median, and 0 otherwise. $StrongExposed_{i,t}$ takes a value of 1 hospital i was exposed in year $t-1$ or earlier and the average msd of its tested lenders was above median, and 0 otherwise.

Table 8 provides the results for a subset of key variables from previous tables: $Margin$ and $PatRev/TA$ for hospital profitability, $Occupation\,Rate$ and $Discharge\,Rate$ for hospital utilization, and $Overall$ and $PainCtrl$ rating for quality. We focus on a subset in order to minimize clutter; however, our results are mostly consistent using other measures. Table 8 shows that the baseline effects are centered around the hospitals that are exposed to stress tests through weaker banks. The economic magnitudes of β in the weak-bank subgroup are very close to the estimates in Section 4.2 and 4.3. On the contrary, the effects for the strong-bank subgroup are weaker—the coefficients are either insignificant or of a much

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

smaller magnitude.

Another source of heterogeneity across hospitals is how reliant a hospital is on bank loans. If a hospital is more dependent on external financing, particularly on loans, then the negative credit shock induced by stress tests should become a more severe shock to its operations. In order to explore this, we calculate each hospital's (unmatured) loan amount divided by its total income and run a similar specification as the previous table, except that we split the treatment variable into $RelExposed_{i,t}$ and $NRelExposed_{i,t}$, which take a value of 1 if hospital i was exposed in year $t-1$ or earlier and its loan reliance over income was above or below median, respectively, and 0 otherwise. The results are provided in Table 9 and show a consistent pattern of stronger effects in the more reliant treated hospitals.

The final heterogeneity relies on the fact that hospitals can have multiple bank relationships. When stress tests jeopardize only a fraction of a hospital's bank relationships, an affected hospital can seek financing from other (unaffected) banks with which the hospital has a relationship. In contrast, when the *majority* of a hospital's bank relationships are affected, then this constitutes a more severe credit shock to the hospital. 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 also increases 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 (unmatured) loan amount, and run a similar specification splitting the treatment variable into $HighExposed_{i,t}$ and $LowExposed_{i,t}$, 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 10 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 various robustness tests.

5.1 Evaluating Other Stress Tests

In this section, we evaluate the possible effects of other stress tests in our analysis. One such introduction is SCAP in 2009. We do not condition on SCAP in 2009 in our DiD specification since most of our outcome variables are only consistently available after 2010,

resulting in a lack of pre-treatment variation. However, it appears 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.

Another stress test program is CCAR, which is part of the Federal Reserve's evaluation of some bank holding companies' proposal to make dividend distributions, and initially the Federal Reserve did not intend to disclose firm-specific results. It is a possibility that CCAR in 2011 could generate similar effects to DFAST since (*i*) the timing was close to the initial implementation of DFAST and (*ii*) firm-specific results were revealed on March 13, 2012, and could generate market pressures on bank holding companies. In the Online Appendix Table xx – xx, we replicate the baseline results while adding the CCAR treatment. This moves the first treatment year for 296 affected hospitals one year ahead. The estimation results are consistent with Tables 3 to 6, but both the economic magnitudes and statistical significance become smaller. For example, the yearly leverage difference between the treatment and control group reduces from the baseline estimation 5.2% to 3.6%, and the revenue difference is insignificant. This indicates that CCAR generates smaller impacts, if any, than DFAST.

5.2 Controlling for Regional Differences

A potential concern with our results is that they are influenced by the geographical region that a hospital is located in. For example, if hospitals that are borrowing from banks tend to be geographically clustered, *and* the number of patients in such areas dramatically increased after 2012, then we may obtain similar baseline results unrelated to stress tests and negative credit supply.

To address this concern, we map each hospital's location to a hospital referral region (HRRs) 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. We first plot the geographical distribution of affected hospitals in Figure 4. We do not find systematic clustering and stress test exposure is mostly evenly distributed across states.[28]

To formally control for geographic effects, we include $HRR \times year$ fixed effects in our main specifications. The variation from these regressions therefore comes from differences between

[28] 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.

treated and control hospitals in a given year *within* the same geographical area. Table 11 provides the estimation results and confirm 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 merger and acquisition (M&A) activities. Hospital mergers generate local market concentration, which tends to reduce healthcare quality while increasing prices.[29] At the same time, hospital systems have more collateral and balance sheet hard information, and are more likely to borrow from large bank corporations. Furthermore, M&As are typically associated with external debt financing. This generates a concern that the baseline effects we find are due to this consolidation process, and we are thus capturing the different operational trends of large healthcare system branches compared to independent hospitals.

To address this concern, in Table 12, we restrict our sample hospitals to ones belonging to a healthcare system from 2010 to 2016, and we add a *System* fixed effect in our regression. 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.[30] We further cluster the standard errors at the hospital system level. The results in Table 12 are consistent with the baseline estimation, showing that the effect is not driven by differences between hospital systems and independent hospitals.

5.4 Alternative Timing

Our baseline result is a staggered DiD specification, utilizing the fact that bank holding corporations gradually participated in DFAST. An alternative specification is a simple DiD framework, where hospitals were exposed to the final announcement of DFAST in 2012, independent of the actual timing when their borrowers are tested.

For example, BBVA Compass first participated in DFAST in 2013, which led to three borrowers being exposed to the stress tests. However, in 2012, BBVA had learned it needed to conduct annual tests and disclose the results to the public afterwards. It is therefore possible that the bank could reduce its risky loans as a precaution ahead of the actual

[29] See Gaynor et al. (2015) for review.

[30] 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."

implementation of the stress tests. In this case, one could argue that the three borrowers had experienced the negative credit supply shock in 2012. Online Appendix Tables xx – xx exhibit the results of this alternative timing and confirm the robustness to it.

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, but deliver lower quality care to patients.

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: Yearly Distribution of New Tested Lenders and Exposed Hospitals

This table summarizes the yearly distribution of first-time stress-tested banks and the exposed hospitals. Column (1) shows the number of new banks that were stress tested *and* lending to the sample hospitals in a given year. Column (2) shows the number of existing loans to the sample hospital by newly stress-tested banks in the year when they were stress tested for the first time. Column (3) shows the number of sample hospitals borrowing from the lenders in Column (1) in that year.

	(1)	(2)	(3)
Year	***Tested Lenders***	***Existing Loans***	***Exposed Hospitals***
2012	15	52	416
2013	4	26	43
2014	3	3	32
2015	1	4	40
2016	3	4	6

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. $Tested$ takes a value of 1 if bank j was stress tested 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)	(2)	(3)	(4)	(5)	(6)	(7)
	Spread&Fee	***Spread&Fee***	***LogAmt***	***LogMaturity***	***NewLender***	***Spread&Fee***	***Spread&Fee***
STExposed	74.764***	63.166**	-0.362***	-0.084*	0.132*		
	(2.968)	(2.020)	(-2.842)	(-1.718)	(1.834)		
Tested						192.790**	185.110*
						(2.144)	(1.994)
LogTA		-2.790	0.093**	0.012	0.014		-5.478
		(-0.552)	(2.197)	(1.307)	(1.455)		(-1.065)
Profitability		3.993	0.146***	0.017*	0.017		2.017
		(0.458)	(3.515)	(1.682)	(1.489)		(0.221)
Leverage		-16.275	-0.402***	-0.008	0.217***		-32.757
		(-0.708)	(-3.400)	(-0.277)	(5.051)		(-1.319)
Tangibility		27.279	0.298	0.275***	-0.172		50.611
		(0.144)	(0.746)	(3.197)	(-1.111)		(0.280)
Year FE	Y	Y	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y	Y	Y
Loan Type FE	N	Y	Y	Y	Y	N	Y
Loan Purpose FE	N	Y	Y	Y	Y	N	Y
N	1,052	717	810	801	810	1,052	717
Adj R^2	0.21	0.39	0.60	0.43	0.34	0.21	0.40

Table 3: Hospital Financial Performance

This table provides the regression results for equation (1), focusing on the 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 $(Income - Cost)/Income$. $PatRev/TA$ is the total patient revenue over total assets. $InPatRev/TA$ and $OutPatRev/TA$ are total inpatient and outpatient revenues over total assets, respectively. $Cash/TA$ is cash holdings over total assets. $Debt/TA$ is total debt over total assets. Control variables (all lagged) include the logarithm of one plus total hospital income ($LogIncome_{i,t-1}$), logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), cash holdings over total assets ($Cash/TA_{i,t-1}$), debt over total assets ($Debt/TA_{i,t-1}$), and total patient revenue over total assets ($Patrev/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)
	Margin	***Patrev/TA***	***InPatrev/TA***	***OutPatrev/TA***	***Cash/TA***	***Debt/TA***
$STExposed_{i,t}$	0.012**	0.168*	0.117*	0.100**	-0.006***	-0.052***
	(2.077)	(1.862)	(1.766)	(2.289)	(-2.583)	(-4.275)
$LogIncome_{i,t-1}$	0.041***	0.022	-0.016	0.027	0.001	-0.001
	(2.842)	(0.686)	(-0.797)	(1.175)	(0.640)	(-0.305)
$LogBedDay_{i,t-1}$	0.054	0.166	0.155*	0.052	0.003	0.022
	(1.637)	(1.232)	(1.945)	(0.762)	(0.868)	(1.171)
$Cash/TA_{i,t-1}$	0.027	-1.021**	-0.359	-0.600***	0.469***	-0.149**
	(0.681)	(-2.059)	(-1.266)	(-2.780)	(20.948)	(-2.413)
$Debt/TA_{i,t-1}$	-0.003	-0.305**	-0.119	-0.155**	0.004	0.451***
	(-0.387)	(-2.225)	(-1.352)	(-2.511)	(1.004)	(20.041)
$PatRev/TA_{i,t-1}$	-0.001	0.429***	0.218***	0.206***	-0.001	-0.008***
	(-0.416)	(16.127)	(12.216)	(18.477)	(-1.300)	(-2.844)
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	23,780	23,231	23,231	23,231	23,119	23,223
$Adj\ R^2$	0.22	0.81	0.83	0.81	0.76	0.81

Table 4: Hospital Bed Utilization

This table provides the regression results for equation (1), focusing on hospital bed utilization. *Occupation Rate* is the inpatient bed days utilized over total bed days. *Discharge Rate* is the inpatient discharges over total bed days. *Salary* is the average salary per capita for physicians, interns and residents. *ICU Bed Rate* is the ICU units over available beds. $STExposed$ takes a value of 1 if at least one of hospital i's relationship banks experienced a stress test in year $t-1$ or earlier, and 0 otherwise. Control variables (all lagged) include the logarithm of one plus total hospital income ($LogIncome_{i,t-1}$), logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), cash holdings over total assets ($Cash/TA_{i,t-1}$), debt over total assets ($Debt/TA_{i,t-1}$), and total patient revenue over total assets ($PatRev/TA_{i,t-1}$). Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)
	Occupation Rate	***Discharge Rate***	***Salary***	***ICU Bed Rate***
$STExposed_{i,t}$	0.022***	2.350***	1750.260***	-0.003**
	(5.973)	(5.752)	(5.017)	(-2.399)
$LogIncome_{i,t-1}$	0.014***	1.293***	25.910	0.001
	(3.177)	(2.764)	(0.075)	(1.592)
$LogBedDay_{i,t-1}$	-0.070***	-5.725***	-1592.091**	-0.035***
	(-8.111)	(-6.357)	(-2.276)	(-9.932)
$Cash/TA_{i,t-1}$	0.020*	0.194	-343.252	-0.006
	(1.860)	(0.168)	(-0.244)	(-1.525)
$Debt/TA_{i,t-1}$	-0.007**	-0.901***	-814.115*	0.001
	(-2.571)	(-3.072)	(-1.899)	(0.750)
$PatRev/TA_{i,t-1}$	0.001***	0.140***	167.347**	0.000
	(2.647)	(3.125)	(2.274)	(0.182)
Year FE	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y
N	23,245	23,243	23,148	16,445
$Adj\ R^2$	0.94	0.80	0.93	0.83

Table 5: Hospital Quality: Unplanned 30-day Readmission Rates

This table provides the estimation results for equation (1), focusing on unplanned 30-day readmission rates. The outcome variables in columns (1)–(3) measure the raw readmission rates for acute myocardial infarction, heart failure, and pneumonia patients, respectively. The outcome variables in columns (4)–(6) are dummy variables that indicate whether the hospital's CMS-reported readmission rates for acute myocardial infarction, heart failure, and pneumonia patients are significantly worse than their respective national averages. $STExposed$ 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 (all lagged) include the logarithm of one plus total hospital income ($LogIncome_{i,t-1}$), logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), cash holdings over total assets ($Cash/TA_{i,t-1}$), debt over total assets ($Debt/TA_{i,t-1}$), and 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) ***AMI Rate***	(2) ***HF Rate***	(3) ***PN Rate***	(4) ***AMI Worse***	(5) ***HF Worse***	(6) ***PN Worse***
$STExposed_{i,t}$	0.003***	0.003***	0.003***	0.006	0.027***	0.016*
	(4.280)	(3.911)	(4.613)	(1.171)	(3.355)	(1.891)
$LogIncome_{i,t-1}$	0.000	0.000	0.000	0.002	0.005**	-0.001
	(1.210)	(1.373)	(1.189)	(1.620)	(2.533)	(-0.541)
$LogBedDay_{i,t-1}$	0.001	0.002*	0.002*	0.014	0.030***	0.037***
	(1.041)	(1.655)	(1.760)	(1.211)	(2.695)	(3.635)
$Cash/TA_{i,t-1}$	0.002	0.000	0.001	0.022*	-0.001	-0.001
	(0.897)	(0.229)	(0.725)	(1.680)	(-0.064)	(-0.086)
$Debt/TA_{i,t-1}$	-0.001***	-0.000	-0.000	-0.008	-0.006	-0.000
	(-2.697)	(-0.972)	(-0.405)	(-1.265)	(-1.073)	(-0.104)
$PatRev/TA_{i,t-1}$	0.000***	0.000	0.000	0.001*	0.001	-0.000
	(3.249)	(1.131)	(1.048)	(1.881)	(0.637)	(-0.614)
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	14,738	22,602	23,862	14,738	22,602	23,862
$Adj\ R^2$	0.77	0.71	0.62	0.22	0.36	0.32

Table 6: Hospital Quality: Timely and Effective Care

This table provides estimation results for equation (1), focusing on the base on timely and effective care quality. The outcome variables in columns (1)–(3) measure the shares of acute myocardial infarction 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 (all lagged) include the logarithm of one plus total hospital income ($LogIncome_{i,t-1}$), logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), cash holdings over total assets ($Cash/TA_{i,t-1}$), debt over total assets ($Debt/TA_{i,t-1}$), and 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***
$STExposed_{i,t}$	-0.001	-0.014***	-0.005**	-0.008***	-0.008***	-0.008***
	(-1.155)	(-3.112)	(-2.390)	(-5.712)	(-3.512)	(-3.388)
$LogIncome_{i,t-1}$	0.001	0.000	0.007	0.001	-0.002***	0.001
	(0.843)	(0.102)	(1.039)	(0.822)	(-2.670)	(0.852)
$LogBedDay_{i,t-1}$	0.005	0.015	-0.011	0.008	0.009	0.009
	(0.961)	(0.730)	(-1.353)	(1.412)	(1.620)	(0.803)
$Cash/TA_{i,t-1}$	0.005	0.009	0.010	0.012	-0.032**	-0.002
	(0.560)	(0.301)	(0.863)	(0.846)	(-2.150)	(-0.172)
$Debt/TA_{i,t-1}$	0.002	-0.008	-0.005*	0.004	-0.003	0.006
	(0.543)	(-1.211)	(-1.796)	(1.093)	(-0.827)	(1.128)
$PatRev/TA_{i,t-1}$	-0.000	0.001	-0.001**	-0.001	-0.001	-0.000
	(-0.415)	(1.483)	(-2.509)	(-1.540)	(-1.305)	(-0.455)
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 7: 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 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. Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Overall	***PainCtrl***	***Recommend***	***Clean***	***DocCom***	***NurseCom***	***Info***	***Quiet***
$STExposed_{i,t}$	-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)
$LogIncome_{i,t-1}$	0.002	0.001	0.002**	-0.000	0.001**	0.001**	0.001	-0.001
	(1.439)	(1.013)	(1.988)	(-0.102)	(2.298)	(2.130)	(0.979)	(-1.291)
$LogBedDay_{i,t-1}$	-0.005	-0.000	-0.006*	-0.010***	0.000	-0.004*	-0.002	-0.005
	(-1.464)	(-0.135)	(-1.863)	(-3.431)	(0.218)	(-1.685)	(-1.202)	(-1.241)
$Cash/TA_{i,t-1}$	0.002	0.007	0.004	0.005	0.000	0.008	-0.003	-0.014**
	(0.371)	(1.188)	(0.533)	(0.769)	(0.061)	(1.628)	(-0.862)	(-2.276)
$Debt/TA_{i,t-1}$	0.003*	0.002	0.004**	0.003*	-0.000	0.001	0.001	0.009***
	(1.879)	(1.351)	(1.994)	(1.777)	(-0.346)	(1.091)	(0.790)	(4.457)
$PatRev/TA_{i,t-1}$	-0.000	0.000	-0.000	-0.000	0.000	-0.000	-0.000	-0.001***
	(-0.774)	(0.194)	(-0.903)	(-0.701)	(1.189)	(-0.006)	(-0.025)	(-4.657)
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 8: Heterogeneity Across Stress-tested Banks

This table splits 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 loan amount. $WeakExposed_{i,t}$ ($StrongExposed_{i,t}$) 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. The outcome variables are defined in the same way as Tables 3, 4 and 7. Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)
	Margin	***Patrev/TA***	***Occupation Rate***	***Discharge Rate***	***Overall***	***PainCtrl***
$WeakExposed_{i,t}$	0.013**	0.313***	0.024***	2.028***	-0.008***	-0.006***
	(2.285)	(3.156)	(5.526)	(4.619)	(-4.452)	(-3.868)
$StrongExposed_{i,t}$	-0.004	-0.072	0.013***	0.793*	0.001	0.001
	(-0.607)	(-0.819)	(2.910)	(1.665)	(0.388)	(0.239)
$LogIncome_{i,t-1}$	0.041***	0.023	0.014***	1.288***	0.002	0.001
	(2.839)	(0.703)	(3.176)	(2.758)	(1.453)	(1.039)
$LogBedDay_{i,t-1}$	0.055	0.163	-0.071***	-5.734***	-0.005	-0.000
	(1.638)	(1.209)	(-8.127)	(-6.359)	(-1.469)	(-0.150)
$Cash/TA_{i,t-1}$	0.027	-1.013**	0.020*	0.187	0.003	0.007
	(0.676)	(-2.041)	(1.906)	(0.162)	(0.384)	(1.209)
$Debt/TA_{i,t-1}$	-0.003	-0.301**	-0.007**	-0.912***	0.003*	0.003
	(-0.403)	(-2.197)	(-2.493)	(-3.107)	(1.907)	(1.391)
$PatRev/TA_{i,t-1}$	-0.001	0.428***	0.001***	0.143***	-0.000	0.000
	(-0.409)	(16.080)	(2.625)	(3.181)	(-0.799)	(0.146)
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	23,780	23,231	23,245	23,243	21,349	21,335
$Adj\ R^2$	0.22	0.78	0.94	0.80	0.82	0.59

Table 9: Heterogeneity Across Bank Loan Reliance

This table splits the treatment group by the treated hospital's reliance on bank loans. We define *reliance* as a hospital's unmatured loan amount over its total income. $RelExposed_{i,t}$ ($NRelExposed_{i,t}$) takes a value of 1 if hospital i was exposed in year $t-1$ or earlier *and* its *reliance* is above (below) median, and 0 otherwise. The outcome variables are defined in the same way as Tables 3, 4 and 7. Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)
	Margin	***Patrev/TA***	***Occupation Rate***	***Discharge Rate***	***Overall***	***PainCtrl***
$RelExposed_{i,t}$	0.018**	0.950***	0.033***	2.950***	-0.008***	-0.007***
	(2.490)	(6.492)	(6.423)	(6.388)	(-3.893)	(-4.304)
$NRelExposed_{i,t}$	0.003	-0.304***	0.012**	0.684	-0.005*	-0.004**
	(0.397)	(-3.091)	(2.366)	(1.231)	(-1.873)	(-2.032)
$LogIncome_{i,t-1}$	0.041***	0.024	0.014***	1.287***	0.002	0.001
	(2.841)	(0.712)	(3.170)	(2.749)	(1.444)	(1.010)
$LogBedDay_{i,t-1}$	0.054	0.152	-0.071***	-5.739***	-0.005	-0.000
	(1.633)	(1.119)	(-8.125)	(-6.361)	(-1.450)	(-0.115)
$Cash/TA_{i,t-1}$	0.027	-1.043**	0.019*	0.081	0.003	0.007
	(0.664)	(-2.105)	(1.796)	(0.070)	(0.408)	(1.219)
$Debt/TA_{i,t-1}$	-0.003	-0.288**	-0.007**	-0.904***	0.003*	0.002
	(-0.377)	(-2.108)	(-2.478)	(-3.076)	(1.871)	(1.328)
$PatRev/TA_{i,t-1}$	-0.001	0.421***	0.001**	0.132***	-0.000	0.000
	(-0.440)	(15.730)	(2.400)	(2.924)	(-0.727)	(0.253)
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	23,780	23,231	23,245	23,243	21,349	21,335
Adj R^2	0.22	0.78	0.94	0.80	0.82	0.59

Table 10: Heterogeneity Across Hospital Exposure to Bank Stress Tests

This table splits 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 it total un-matured loan amount. $HighExposed_{i,t}$ ($LowExposed_{i,t}$) 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. The outcome variables are defined in the same way as Tables 3, 4 and 7. Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)
	Margin	***Patrev/TA***	***Occupation Rate***	***Discharge Rate***	***Overall***	***PainCtrl***
$HighExposed_{i,t}$	0.019***	0.188**	0.022***	2.519***	-0.008***	−0.007***
	(3.032)	(1.966)	(5.331)	(5.781)	(-4.545)	(-4.860)
$LowExposed_{i,t}$	-0.025**	-0.108	0.017**	1.132	0.002	-0.003
	(-2.164)	(-0.438)	(2.193)	(1.256)	(0.374)	(-0.757)
$LogIncome_{i,t-1}$	0.041***	0.022	0.014***	1.294***	0.002	0.001
	(2.847)	(0.688)	(3.176)	(2.763)	(1.438)	(1.012)
$LogBedDay_{i,t-1}$	0.055*	0.172	-0.070***	-5.704***	-0.005	-0.000
	(1.657)	(1.271)	(-8.103)	(-6.336)	(-1.523)	(-0.158)
$Cash/TA_{i,t-1}$	0.027	-1.027**	0.019*	0.179	0.003	0.007
	(0.667)	(-2.070)	(1.851)	(0.155)	(0.413)	(1.204)
$Debt/TA_{i,t-1}$	-0.003	-0.304**	-0.007***	-0.897***	0.003*	0.002
	(-0.356)	(-2.222)	(-2.584)	(-3.055)	(1.878)	(1.351)
$PatRev/TA_{i,t-1}$	-0.001	0.428***	0.001***	0.138***	-0.000	0.000
	(-0.473)	(15.982)	(2.680)	(3.083)	(-0.682)	(0.214)
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	23,780	23,231	23,245	23,243	21,349	21,335
$Adj\ R^2$	0.22	0.78	0.94	0.80	0.82	0.59

Table 11: Robustness: Controlling for Regional Differences

This table provides the estimation results for equation (1), controlling for regional differences in each year. For each hospital, we retrieve its hospital referral region (HRR) from the Dartmouth Atlas database. We replicate the estimations in Tables 3, 4 and 7, except that we include HRR-by-year and hospital fixed effects. Control variables (all lagged) include the logarithm of one plus total hospital income ($LogIncome_{i,t-1}$), logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), cash holdings over total assets ($Cash/TA_{i,t-1}$), debt over total assets ($Debt/TA_{i,t-1}$), and total patient revenue over total assets ($PatRev/TA_{i,t-1}$). 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.

Panel A: Financial

	(1)	(2)	(3)	(4)	(5)
	Margin	***Patrev/TA***	***Debt/TA***	***Occupation Rate***	***Discharge Rate***
$STExposed_{i,t}$	0.011	0.196*	-0.058***	0.015***	1.969***
	(0.931)	(1.888)	(-3.814)	(3.456)	(4.341)
Controls	Y	Y	Y	Y	Y
HRR × Year FE	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y
N	23714	23156	23148	23185	23180
Adj R^2	0.17	0.79	0.81	0.94	0.80

Panel B: Quality

	(1)	(2)	(3)	(4)	(5)
	Overall	***PainCtrl***	***AMI Rate***	***HF Rate***	***PN Rate***
$STExposed_{i,t}$	-0.006***	-0.005***	0.002***	0.003***	0.003***
	(-3.039)	(-2.991)	(3.049)	(3.549)	(3.709)
Controls	Y	Y	Y	Y	Y
HRR × Year FE	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y
N	21310	21296	14501	22538	23809
Adj R^2	0.82	0.58	0.78	0.72	0.62

Table 12: Robustness: Subsidiaries of Hospital Systems

This table provides estimation results for equation (1), only including hospitals that are subsidiaries of hospital systems. We replicate the estimations in Tables 3, 4 and 7, except that we also include hospital system fixed effects. Control variables (all lagged) include the logarithm of one plus total hospital income ($LogIncome_{i,t-1}$), logarithm of one plus available bed days ($LogBedDay_{i,t-1}$), cash holdings over total assets ($Cash/TA_{i,t-1}$), debt over total assets ($Debt/TA_{i,t-1}$), and 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.

Panel A: Financial

	(1)	(2)	(3)	(4)	(5)
	Margin	***Patrev/TA***	***Debt/TA***	***Occupation Rate***	***Discharge Rate***
$STExposed_{i,t}$	0.014*	0.274	-0.023*	0.024***	2.638***
	(1.915)	(0.948)	(-1.826)	(3.004)	(3.597)
Controls	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y
System FE	Y	Y	Y	Y	Y
N	15,967	15,621	15,617	15,640	15,642
$Adj\ R^2$	0.38	0.80	0.81	0.94	0.81

Panel B: Quality

	(1)	(2)	(3)	(4)	(5)
	Overall	***PainCtrl***	***AMI Rate***	***HF Rate***	***PN Rate***
$STExposed_{i,t}$	-0.008***	-0.006***	0.004***	0.004***	0.004***
	(-2.753)	(-2.906)	(6.472)	(3.727)	(7.284)
Controls	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y
System FE	Y	Y	Y	Y	Y
N	14,738	14,736	10,963	15,869	16,516
$Adj\ R^2$	0.82	0.58	0.78	0.71	0.61

Figures

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

This figure graphs estimation results for equation (3), focusing on the financial and bed utilization variables. 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 the difference in year 0. 95% confidence intervals are indicated by the solid lines.

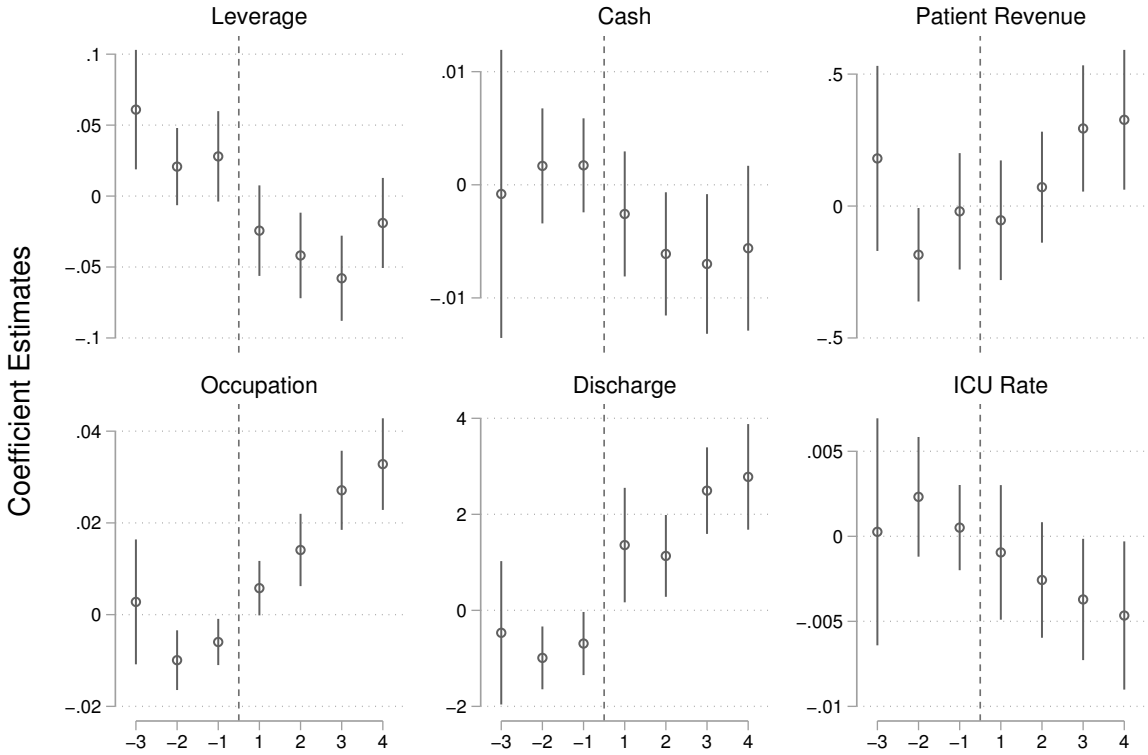


Figure 2: Parallel Trends: Hospital Care Quality from the Patient's Perspective

This figure graphs estimation results for equation (3), focusing on care quality information from the patient's perspective. 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 the difference in year 0. 95% confidence intervals are indicated by the solid lines.

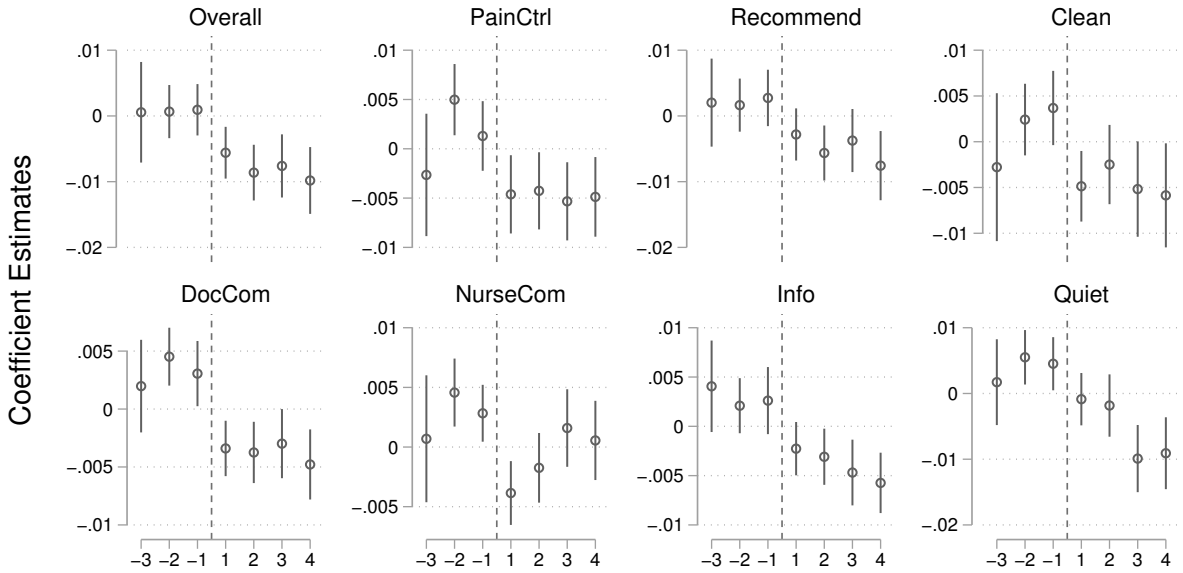


Figure 3: Parallel Trends: Unplanned 30-day Readmission Rates

This figure graphs estimation results for equation (3), focusing on unplanned 30-day readmission rates. 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 the difference in year 0. 95% confidence intervals are indicated by the solid lines.

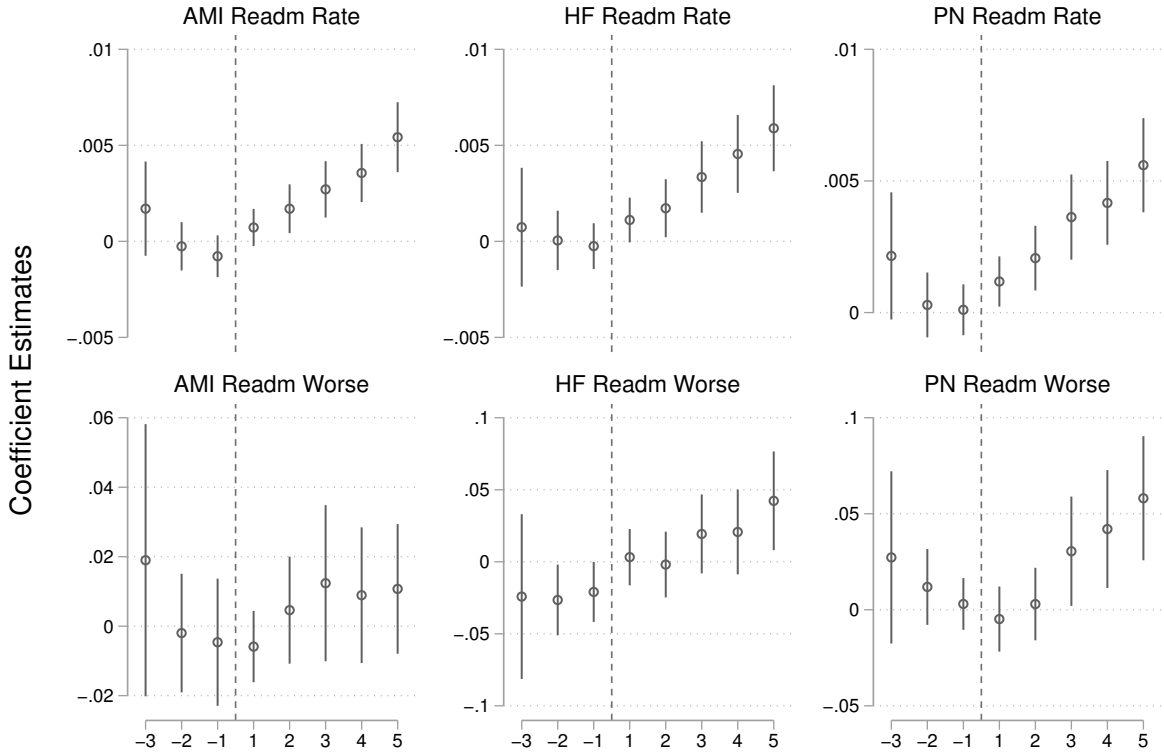
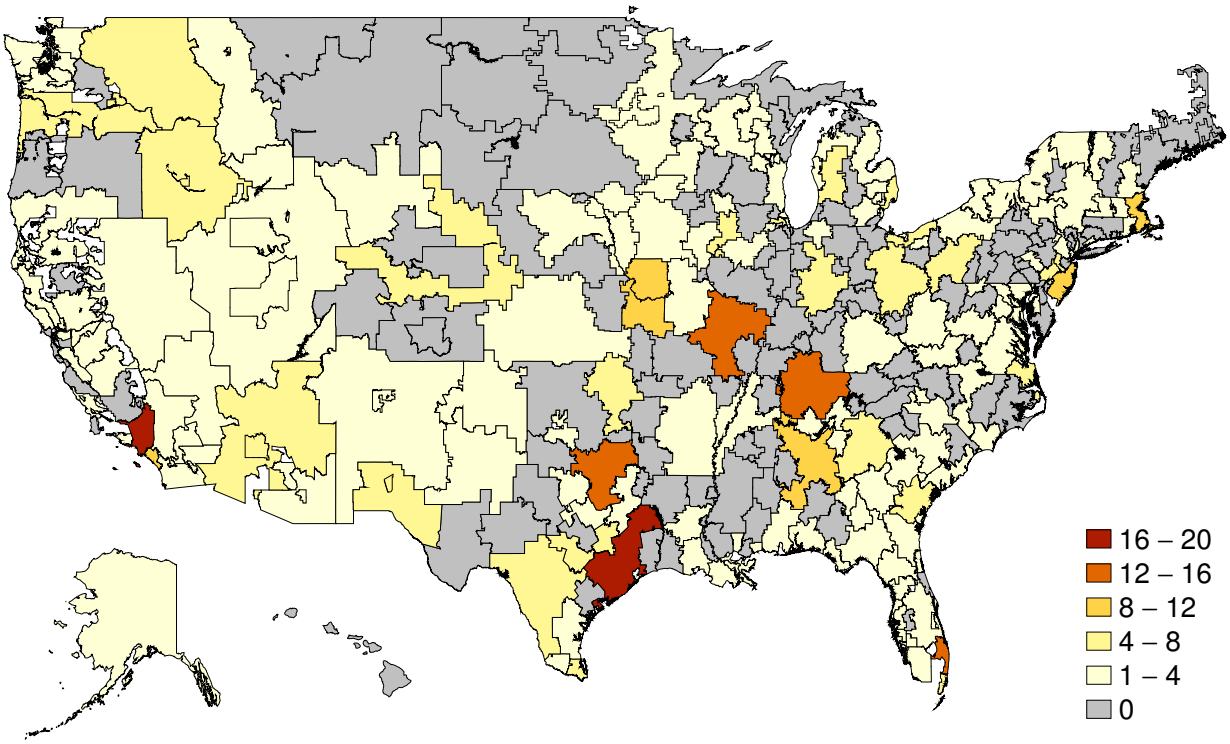


Figure 4: Geographical Distribution of Hospitals Exposed to the Stress Tests

This figure graphs the number of hospital exposed to the stress tests in different regions. Each region represents a unique HRR. Grey areas represent the control group.



Online Appendix