Online Appendix for "Merchants of Death: The Effect of Credit Supply Shocks on Hospital Outcomes"

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A Additional Results

A.1 Heterogeneity Tests

In this section, we provide more detail regarding the heterogeneity tests discussed in Section 5, including differential responses due to hospital characteristics, such as market power, cash reserves, or system status, or through heterogeneous exposure to the treatment.

A.1.1 Heterogeneity in Hospital Responses

As mentioned in Section 5, we consider possible heterogeneity in responses based on hospital market power and competition. To measure market power, we first calculate each hospital system's inpatient revenues as a fraction over total inpatient revenues within that hospital's referral region (HRR) prior to the shock. We then interact our main treatment variable with *High Revenue Share*$_i$, which is an indicator variable equal to one if hospital i's system's share of inpatient revenues in its respective HRR is above the sample median, and zero otherwise. In Appendix Table A.13, we see that hospitals that are part of systems which hold a greater

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fraction of their HRR's inpatient revenues prior to the shock generally exhibit a stronger response to the tighter credit constraints. This differential response is possibly due to less competition in these HRRs—hospitals which hold a greater share of revenues may face less competition from other hospitals. As such, these affected hospitals can more easily change their operating decisions with less risk of losing patients to competitor hospitals. Moreover, hospitals with less competition can more easily build stronger ties with physician practices to increase inpatient admissions through physician referrals.

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

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

A.1.2 Treatment Heterogeneity

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

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

from this threshold):

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

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

Table 13 shows that the baseline effects are centered around the hospitals that are exposed to stress tests through banks closer to the threshold. The economic magnitudes in the close-bank subgroup are very similar to the estimates in Sections 3.2 and 3.3. In contrast, the effects for the far-bank subgroup are weaker—the coefficients are either insignificant or of a much smaller magnitude.

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

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

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

A.2 Robustness

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

A.2.1 Controlling for Regional Differences

A potential concern with our results is that they are influenced by the geographical region that a hospital is located in. For example, if hospitals that are borrowing from banks tend to be geographically clustered, and the number of patients in such areas dramatically increased after 2012, then we may obtain similar baseline results unrelated to stress tests and negative credit supply.[2] Alternatively, local economic conditions in an area may affect both bank lending and hospital outcomes, thus potentially confounding the channels that we aim to identify.[3]

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

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

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

for Medicare beneficiaries. The United States is divided into 306 HRRs. The geographical distribution of affected hospitals is provided in Figure 3 of the paper. As the figure shows, we do not find a systematic clustering of hospitals exposed to stress tests, since these hospitals are mostly dispersed across the U.S.[4] 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* × *year* fixed effects in our main specifications. The variation from these regressions therefore comes from differences between treated and control hospitals in a given year *within* the same geographical area. Table A.19 provides the estimation results and confirms that our results are robust to controlling for time-varying geographical conditions.

A.2.2 Sample Composition

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

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

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

Bank loan borrowing. We next examine robustness of the sample composition in terms of the borrowing behavior of hospitals in our sample. One concern is that hospitals exposed to the stress tests through their lenders may not be as affected by the tightened credit constraints if they are able to find alternative sources of funding or can avoid taking bank loans after

[4] 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.

the stress tests. While our results in Table 3 help to mitigate this concern, we provide further robustness by restricting our treatment hospitals to those that took out new loans following exposure to the stress tests in the post-period. As noted in Section 1, 79% of treated hospitals borrowed new loans following exposure. In Appendix Table A.21, we see that the results are similar to that of our main tests.

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

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

A.2.3 Placebo Test – Rival Hospitals

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

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

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

A.2.4 Other Stress Test Robustness

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

The DFAST differs from both the 2009 SCAP and the 2011 CCAR. As noted above, the SCAP was implemented during an emergency period to prevent collapse of the financial system.[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 original aim of the 2011 CCAR was to provide additional oversight regarding capital distributions to shareholders of the largest banks.[6] In contrast to these two prior programs, the DFA was passed by the U.S. Congress and signed into law, and served as the country's central legislation regarding stress tests. Moreover, the aim of the DFAST is to ensure the financial health of individual banks and the banking system. Accordingly, the DFAST applied to a wider set of banks and, with its "severely adverse scenario" tests, carried a stricter examination than the 2011 CCAR. (The CCAR has since evolved to be run jointly with DFAST.)

We argue that using DFAST is appropriate for our setting due to the fact that DFAST applied to a wider set of banks and had more formal legal and regulatory ramifications. It

[5]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.

[6]See, e.g., "Revised Temporary Addendum to SR letter 09-4: Dividend Increases and Other Capital Distributions for the 19 Supervisory Capital Assessment Program Bank Holding Companies." November 17, 2010. Available at: http://www.federalreserve.gov/boarddocs/srletters/2009/SR0904_Addendum.pdf.

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

A.3 CMS Risk-Standardization

In this section, we provide details regarding the risk-adjustment calculations made by CMS to the hospital-level quality of care variables, such as readmission and mortality rates, we consider in Section 3. We also discuss this risk adjustment in light of a changing mix of patients. The discussion regarding CMS's empirical model draws from Centers for Medicare & Medicaid Services (2023a,b), which can be found on the CMS website.

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

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

which CMS refers to as the standardized readmission ratio. The term $\hat{p}_{ij}$ is the fitted value for the likelihood of readmission based on the coefficient estimates and the estimated idiosyncratic hospital fixed effect for hospital i from the cross-sectional regression (j indexes

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

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

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

A.4 Appendix Tables and Figures

Table A.1: Variable Definitions and Summary Statistics

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

Variable	Definition	N	Mean	Std	P25	Median	P75
Panel A: Financial Variables from HCRIS							
Profit Margin	Profit margin	36,871	0.032	0.283	−0.009	0.038	0.092
TA	Total assets ($ million)	34,559	208.865	473.230	24.725	75.030	214.807
Income	Sum of net patient revenue and total other income ($ million)	38,584	164.926	224.391	24.961	80.525	210.819
Net Income	Income minus total costs ($ million)	37,342	8.01	15.785	−0.417	2.124	12.129
Liabilities/TA	Total liabilities over total assets	34,526	0.565	0.516	0.248	0.467	0.724
Cash/TA	Cash holdings over total assets	34,042	0.073	0.117	0.002	0.034	0.099
Patient Revenue	Total patient revenue ($ million)	37,342	555.005	901.017	62.933	239.742	693.586
Bed Utilization	Proportion of time a hospital bed is occupied in a year	34,988	0.443	0.231	0.263	0.450	0.614
Discharge Rate	Inpatient discharges over total beds	34,995	41.933	19.545	29.120	43.577	54.601
CMI	Case mix index	22,192	1.508	0.315	1.297	1.488	1.685
Medicare Pct	Percent of Medicare discharge out of all discharges	31,518	0.404	0.153	0.302	0.392	0.491
Medicaid Pct	Percent of Medicaid discharge out of all discharges	30,152	0.120	0.100	0.043	0.091	0.171
Panel B: Readmission and Mortality Measures from Hospital Compare							
Pneumonia Readmissions	Number of pneumonia patients readmitted	24,450	18.953	16.495	6.837	14.156	26.283
Heart Failure Readmissions	Number of heart failure patients readmitted	23,191	26.100	26.645	7.030	17.559	36.018
AMI Readmissions	Number of AMI patients readmitted	15,011	13.062	12.609	4.084	9.099	17.467
Pneumonia Readmission Rate	Rate of PN patients readmitted	24,450	0.173	0.014	0.163	0.172	0.181
Heart Failure Readmission Rate	Rate of HF patients readmitted	23,191	0.225	0.019	0.213	0.223	0.237
AMI Readmission Rate	Rate of AMI patients readmitted	15,011	0.174	0.017	0.163	0.172	0.183
All Readmission Rate	Rate of all major-disease patients readmitted	18,732	0.155	0.009	0.149	0.154	0.160
All Readmissions Worst	Flagged as being in the worst group for readmitting patients	20,583	0.079	0.270	0.000	0.000	0.000
Pneumonia Mortality Num	Pneumonia patient mortality number	24,390	14.512	12.997	5.195	10.391	19.685
Pneumonia Mortality Rate	Pneumonia patient mortality rate	24,390	0.139	0.025	0.120	0.138	0.157
Pneumonia Mortality Worst	Flagged as being in the worst group for pneumonia patient mortality	24,891	0.053	0.224	0.000	0.000	0.000
Heart Failure Mortality Num	Heart failure patient mortality number	22,830	11.226	10.601	3.420	7.935	15.400
AMI Mortality Num	AMI patient mortality number	16,574	9.398	8.244	3.308	7.032	12.733

(continued)

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

(continued)

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Panel A: Readmission

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

Panel B: Mortality

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

Panel C: Patient's Perspective

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

Table A.7: Coefficient Estimates for Control Variables

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

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

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

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

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

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

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

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

Table A.10: Hospital ED Inpatient Admission Heterogeneity

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

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

Table A.11: Hospital DRG Inpatient Charges

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

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

Table A.12: Hospital DRG Outcomes for Uninsured Patients

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

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

Table A.13: Heterogeneity Across Hospital Local Market Power

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

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

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

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

	(1)	(2)	(3)	(4)	(5)	(6)
	Profit Margin	*Bed Utilization*	*Discharge Rate*	*All Readmission Rate*	*Antibiotic*	*Overall Rating*
$STExposed_{i,t-1}$	0.007	0.032***	3.347***	0.003***	−0.011***	−0.008***
	(0.008)	(0.005)	(0.517)	(0.000)	(0.002)	(0.002)
$High\,Cash_i$	0.008	−0.020***	−1.974***	−0.002***	0.008*	−0.001
$\times STExposed_{i,t-1}$	(0.009)	(0.007)	(0.743)	(0.001)	(0.004)	(0.003)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	23,804	23,269	23,267	17,694	15,126	21,372
Adj R^2	0.21	0.94	0.80	0.67	0.58	0.82

Table A.15: Heterogeneity Across Hospital Location Rurality

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

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

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

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

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

Table A.17: Heterogeneity Across Hospital System Size

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

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

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

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

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

Table A.19: Robustness: Controlling for Regional Differences

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

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

Table A.20: Robustness: Drop Large Hospital Systems

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

	(1)	(2)	(3)	(4)	(5)	(6)
	Profit Margin	*Bed Utilization*	*Discharge Rate*	*All Readmission Rate*	*Antibiotic*	*Overall Rating*
$STExposed_{i,t-1}$	0.017*	0.021	3.606**	0.002**	−0.023*	−0.012**
	(0.010)	(0.014)	(1.727)	(0.001)	(0.014)	(0.005)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	20,929	20,432	20,430	15,275	13,322	18,601
Adj R^2	0.19	0.94	0.80	0.67	0.57	0.82

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

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

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

Table A.22: Restricting to Commercial Loan Borrowers

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

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

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

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

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

Table A.24: Effect of Stress Tests including CCAR

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

	(1)	(2)	(3)	(4)	(5)	(6)
	Profit Margin	*Bed Utilization*	*Discharge Rate*	*All Readmission Rate*	*Antibiotic*	*Overall Rating*
$STExposed^{CCAR}_{i,t-1}$	0.014***	0.016***	1.869***	0.002***	−0.005***	−0.007***
	(0.005)	(0.003)	(0.362)	(0.000)	(0.002)	(0.002)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	23,804	23,269	23,267	17,694	15,126	21,372
Adj R^2	0.21	0.94	0.80	0.67	0.58	0.82

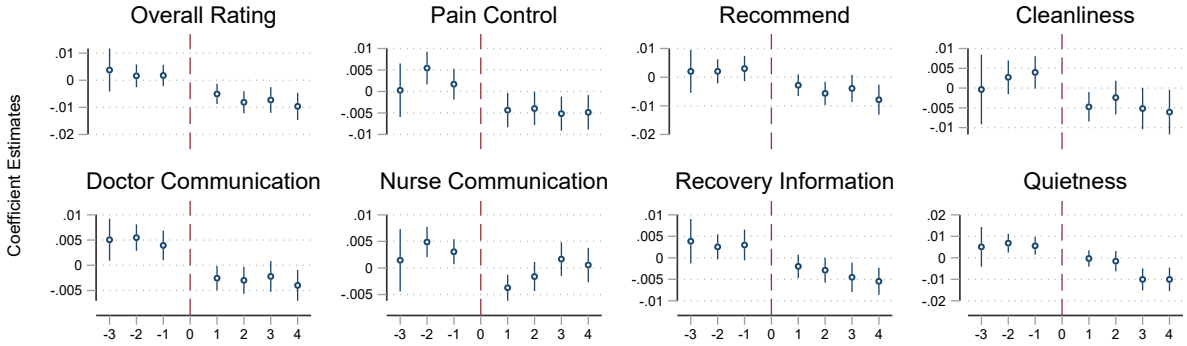
Figure A.1: Parallel Trends: Healthcare Quality, Propensity Score-matched Sample

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

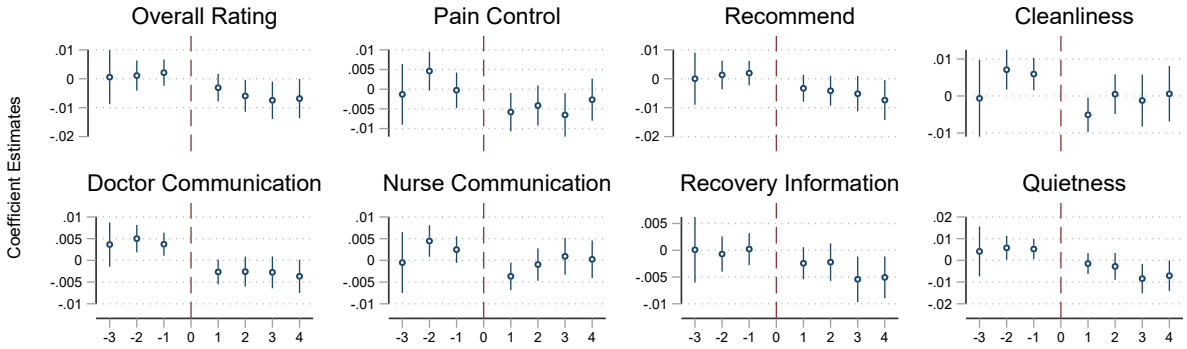
Figure A.2: Parallel Trends: All Survey Results

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

Panel A: Main Specification



Panel B: Propensity Score Matched Sample



B Validation of Parallel Trends

Alternative Construction of Parallel Trends

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

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

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

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

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

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

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

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

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

and

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

These ATTs are then aggregated via:

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

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

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

Validation of Treatment Effects

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

For the few outcome variables mentioned above that "fail" this test—where there is a significant difference between the pre-period parallel trend coefficients—we examine the validity of our inferences more closely following Rambachan and Roth (2023). The logic behind

this approach is to statistically assess the extent to which the post-period DID coefficients deviate from a linear trend based on the pre-period (i.e., using an expected counterfactual trend in the absence of treatment effects). A significant deviation thus indicates that the treatment effect is likely to hold and inferences are therefore likely to be valid, despite the parallel trends assumption being violated. To provide more detail, the second differences (SD) approach of Rambachan and Roth (2023) requires specifying an exogenous threshold parameter M which bounds the extent to which the parallel trends slope can change between consecutive periods post-treatment, and assesses the significance of treatment effects relative to these bounds.[7]

As Rambachan and Roth (2023) note, the appropriate value of M varies on a case-by-case basis, and there is not a single recommended value that applies to all situations. For example, testing for a deviation from a strictly linear violation of parallel trends would imply $M = 0$, while higher values of M test for larger deviations from linearity. We follow the recommendation of Rambachan and Roth (2023) and perform a sensitivity check for post-treatment confidence intervals period-by-period, showing how inferences are potentially changed as the value of M is gradually increased. Specifically, we consider values of M ranging from a baseline of $M = 0$ (i.e., a deviation from a linear trend) to a value equal to the standard error of the estimated coefficients. For each value of M, we provide the new confidence interval for each post-treatment coefficient adjusted for the potential trend. A confidence interval that does not contain zero indicates that the post-treatment deviation is significantly large enough to reject the null hypothesis that the effects we observe are simply a continuation of the pre-treatment trends. We note that our selected upper bound value is conservative as it allows the differential trends to change by up to the coefficient's standard error, and assesses the significance of the point estimate relative to that trend.

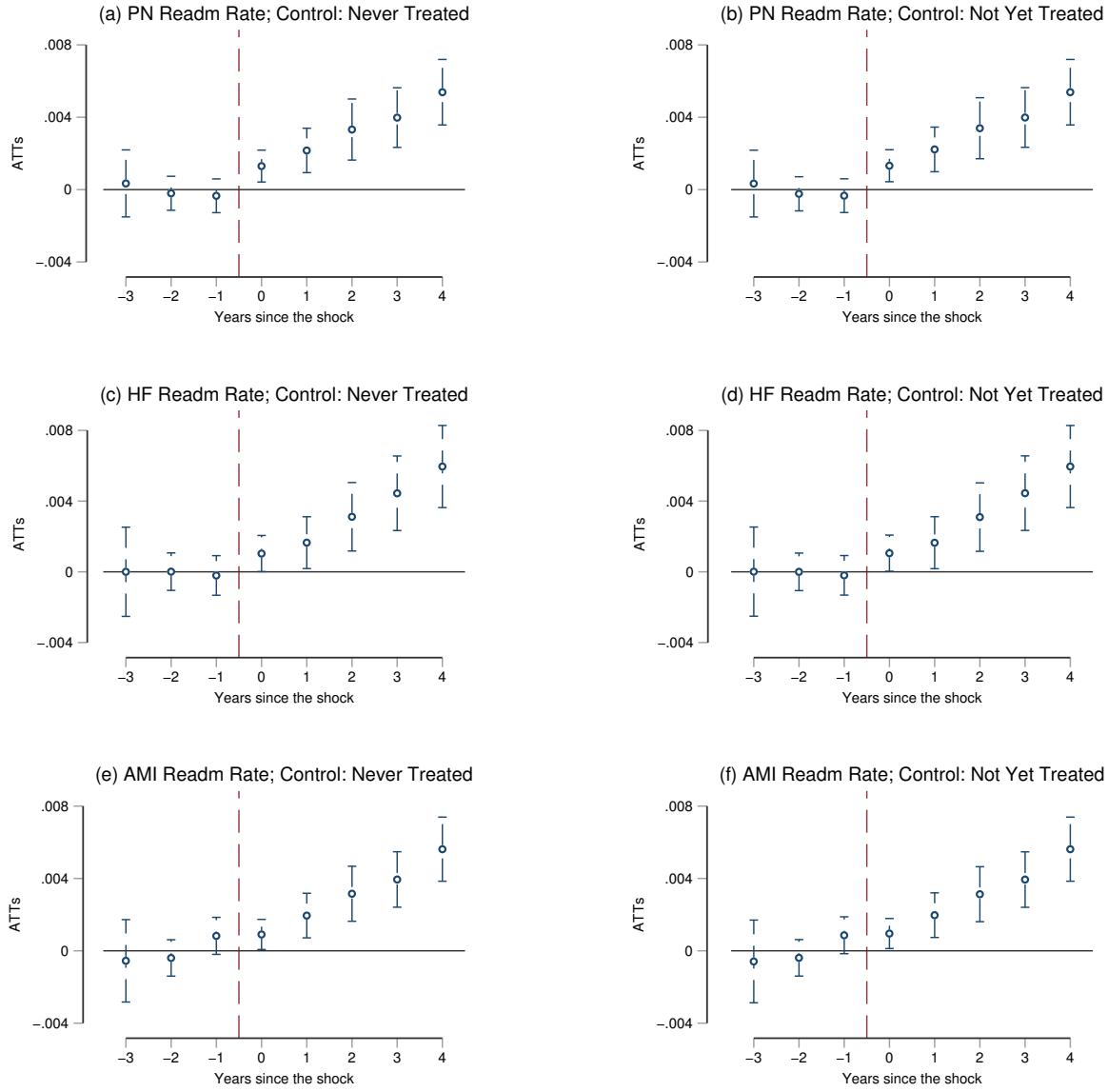
We provide the robust inference results in Table B.3. For reference, we first provide the 95% confidence intervals for the dynamic post-treatment coefficients under our original estimation. In line with our regression results, the treatment effects are all significant (i.e., confidence bounds that do not contain zero). We next provide results for $M = 0$, which tests if the coefficients deviate from a linear trend. We find significant treatment effects for

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

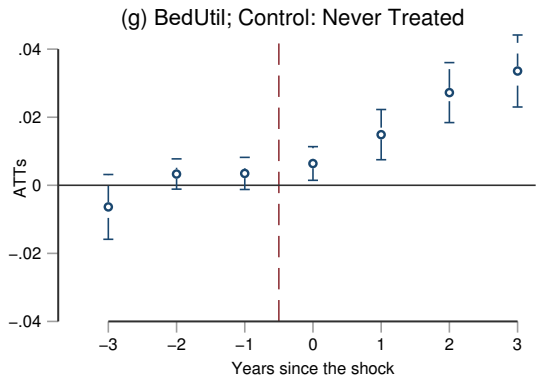
all of the outcome variables from $t = 2$ through $t = 4$—the confidence bounds represent estimates relative to the (linear) counterfactual trend, and thus confidence bounds that do not contain zero implies that we can reject the hypothesis that the treatment effects are a continuation of this trend.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

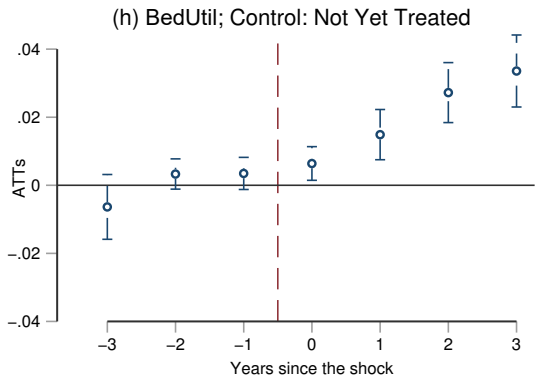
Figure B.1: Parallel Trends: Average Treatment Effects for the Treated

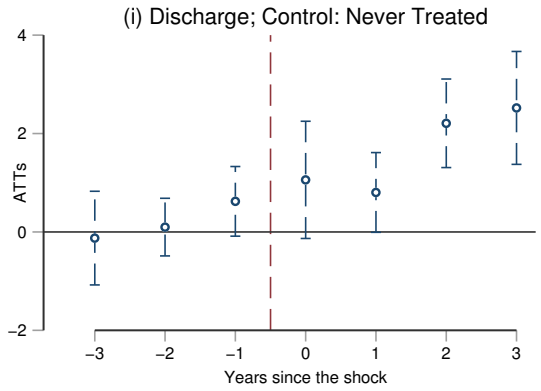
This figure provides average treatment effects for the treated (ATT) for each year following the stress test shock using the methodology of Callaway and Sant'Anna (2021). ATTs relative to the never-treated (left figures) and not-yet-treated (right figures) control hospitals are provided. Each circle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



(continued)


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


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


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


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

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

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

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

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

Panel B: OLS Specification

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

Table B.2: Pre-trend Tests

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

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

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

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

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

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

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

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

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

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

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