Finance and Economics Discussion Series
Divisions of Research & Statistics and Monetary Affairs
Federal Reserve Board, Washington, D.C.

The Differential Impact of Bank Size on Systemic Risk

Amy G. Lorenc and Jeffery Y. Zhang

2018-066

Please cite this paper as:
Lorenc, Amy G., and Jeffery Y. Zhang (2018). "The Differential Impact of Bank Size on Systemic Risk," Finance and Economics Discussion Series 2018-066. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2018.066.

The Differential Impact of Bank Size on Systemic Risk

Amy G. Lorenc and Jeffery Y. Zhang[1]

August 21, 2018

Abstract

We examine whether financial stress at larger banks has a different impact on the real economy than financial stress at smaller banks. Our empirical results show that stress experienced by banks in the top 1 percent of the size distribution leads to a statistically significant and negative impact on the real economy. This impact increases with the size of the bank. The negative impact on quarterly real GDP growth caused by stress at banks in the top 0.15 percent of the size distribution is more than twice as large as the impact caused by stress at banks in the top 0.75 percent, and more than three times as large as the impact caused by stress at banks in the top 1 percent. These results are broadly informative as to how the stringency of regulatory standards should vary with bank size, and support the idea that the largest banks should be subject to the most stringent requirements while smaller banks should be subject to successively less stringent requirements.

Keywords: Bank Size, Bank Failures, Systemic Risk, Financial Regulation, Tailoring

JEL: G21, G28

[1] We thank Brian Chernoff, Michael Gibson, Art Lindo, Elizabeth MacDonald, Dennis Mawhirter, Marco Migueis, Michael Suher, Teng Wang, and other colleagues in the Division of Supervision and Regulation for helpful discussions. We also thank Sean Campbell of the Financial Services Forum for his contributions to this project during his time in the Division of Supervision and Regulation. Please note that the views presented in this article are the authors' alone and do not necessarily represent the views of the Board of Governors of the Federal Reserve System or the views of the United States government.

I. Introduction

As part of an ongoing effort to understand the determinants of systemic risk, we examine the impact of bank stress on the real economy. The experiences of past financial crises (Bernanke 1983, Calomiris and Mason 2003, Kupiec and Ramirez 2013, Reinhart and Rogoff 2009) and of the most recent one (Bernanke 2015, Chodorow-Reich 2014, Geithner 2015, Gorton 2010) have taught us that stress within the aggregate banking sector causes stress in the real economy. This article considers whether stress at larger banks has a different impact on the real economy than stress at smaller banks.

Our analysis primarily builds upon Bernanke's seminal 1983 article, in which he investigates the impact of deposits held at failed banks on economic growth during the Great Depression. Using the deposits of banks that failed or received assistance from the Federal Deposit Insurance Corporation (FDIC) from 1960 through 2017 as a proxy for bank stress, our empirical results show that financial stress at large banks has a statistically significant and negative impact on the real economy.[2] This impact increases with bank size. For instance, scaling our empirical results to the size distribution of banks in the fourth quarter of 2017, we find that the negative impact on real quarterly GDP growth caused by stress at banks with greater than $250 billion in total assets is more than twice as large as the impact caused by stress at banks with greater than $50 billion in total assets, and more than three times as large as the impact caused by stress at banks with greater than $30 billion in total assets. These results are qualitatively similar when analyzing the impact on the unemployment rate.

[2] As shown later, the results are nearly identical when we use the *assets* of banks that have failed as a proxy for financial stress at banks.

The literature on the connection between bank size and systemic risk is sparse. Allen, Bali, and Tang (2012) construct a measure of systemic risk, designated CATFIN, and show that the CATFIN of both large and small banks can forecast macroeconomic declines, though the CATFIN of large banks can successfully forecast lower economic activity sooner than that of small banks. In their article, a bank is small if its stock market capitalization is below the top quintile among firms traded on the NYSE. Relatedly, using quarterly Call Reports data from 1976 to 1993, Kashyap and Stein (2000) show that declines in aggregate loan supply due to monetary policy shocks are driven primarily by smaller banks that are liquidity constrained. In their article, smaller banks are those in the bottom 95 percent of the size distribution, with average assets below $400 million in 1993 dollars.

In addition to contributing to the academic literature, our results broadly inform the policy "threshold" debate that ensues as regulators seek to limit the damage done to the real economy in future financial crises while minimizing the costs of increased regulation (Quarles 2018, U.S. Congress 2018). To the extent smaller banks are unlikely to have a material impact on the economy upon failure, regulators might seek to tailor regulatory burdens accordingly.

Determining where to draw the line between banks that should and should not be subject to enhanced regulation has proven to be a difficult task. For one, size is not the only predictor of the potential impact that a bank under stress would have on the economy. In particular, the complexity of a bank's operations could also play a role (OFR 2017). Unfortunately, reliable indicators of bank complexity are not available over the sample period examined in this paper. We therefore focus on size alone, using total assets as a proxy. Notably, total assets are highly correlated with most measures of bank complexity. Using Call Reports data from the first quarter of 2005 to the first quarter of 2018, we find that the correlation between a bank's total trading assets (proxy of complexity) and its total assets (proxy of size) is over 90 percent. This implies that results similar to those presented in this paper are likely to hold for indicators of bank complexity.

The rest of this article is organized as follows: Section II presents the data and regression specifications used in our empirical analysis. In particular, it carefully describes the proxy we use for bank stress. Section III contains the baseline results for our GDP and unemployment rate regressions. It also presents the baseline results in the form of a hypothetical scenario in which we assume a particular level of bank stress. Section IV describes a series of robustness checks such as using monthly data instead of quarterly data to confirm our contemporaneous modeling assumption, performing a check for reverse causality, and using bank assets instead of deposits to proxy bank stress. Section V concludes with a brief discussion of policy implications and suggestions for future research.

II. Data and Methodology

A. Data

We examine the relationship between stress experienced by banks of different sizes and real economic activity. To do so, we employ proxies for bank size, bank stress, and real economic activity. As is standard practice, we use total assets in the Call Reports as a proxy for bank size.[3]

We define stress experienced by an individual bank as a failure or assistance transaction included in the FDIC's historical statistics on banking.[4] This dataset contains transactions for U.S. commercial banks and savings institutions and data on the total assets and deposits of the insured failed bank, as well as a number of other fields. We create a time series measure of stress in the broader banking sector equal to the total deposits of banks that have failed within a particular quarter and use this as our baseline measure of bank stress.

We perform our analysis over the period from first quarter of 1960 to the third quarter of 2017, which includes the savings and loan crisis of the 1980s and 1990s and the Great Recession. This long sample period is necessary to ensure an appropriate number of observations.

To illustrate our bank stress measure, consider Figures 1 and 2. In Figure 1, we plot deposits at all failed banks over our full sample period of 1960 to 2017. Note that we first inflation adjust the series using the Consumer Price Index (CPI) and then we take the natural logarithm.

---

[3] We also performed the analysis described in this article using bank holding company (BHC) data from the Y-9C. The results show a similar relationship between stress experienced by BHCs and impact on the real economy. The greatest economic impact results from stress at the largest BHCs, and the impact declines as the universe of BHCs included in the analysis encompasses smaller and smaller BHCs.

[4] For simplicity, we refer to both failures and assistance transactions as "failures" in the remainder of this paper. The FDIC historical statistics on banking dataset is available at https://www5.fdic.gov/hsob. Similarly, "failed deposits" in this paper refer to deposits at institutions that failed or received assistance transactions.

Figure 1: Deposits of All Failed Banks, 1960-2017

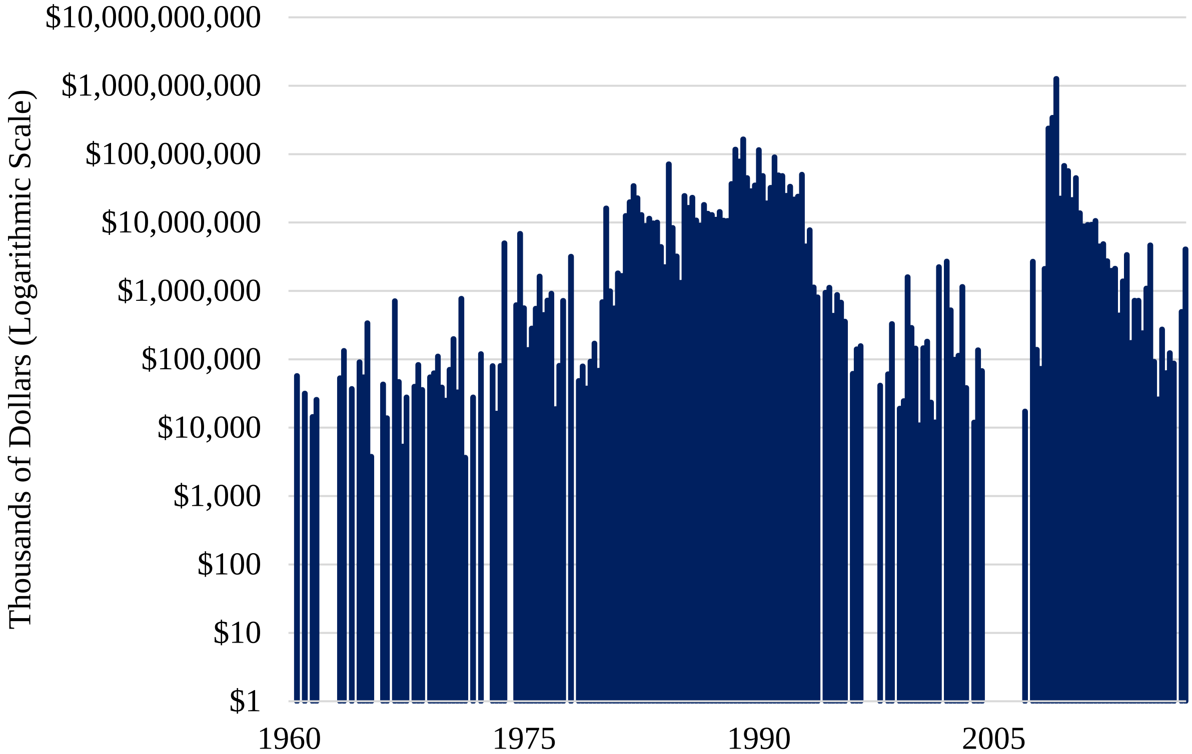
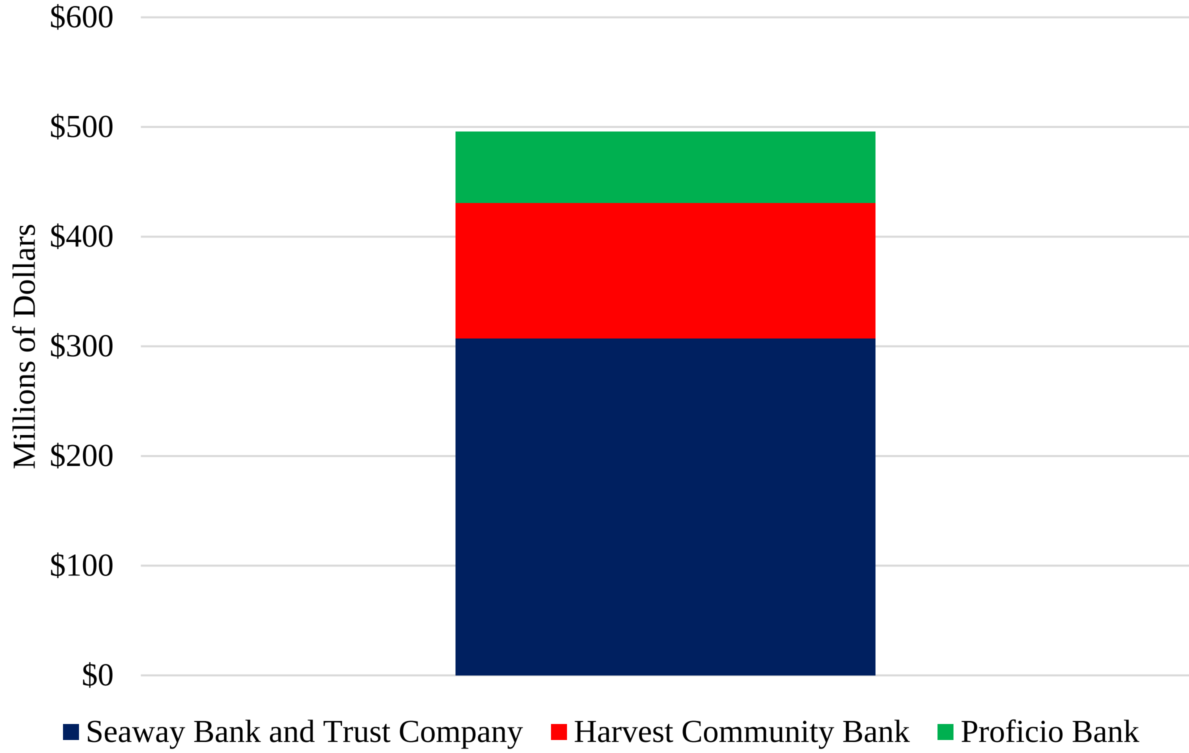


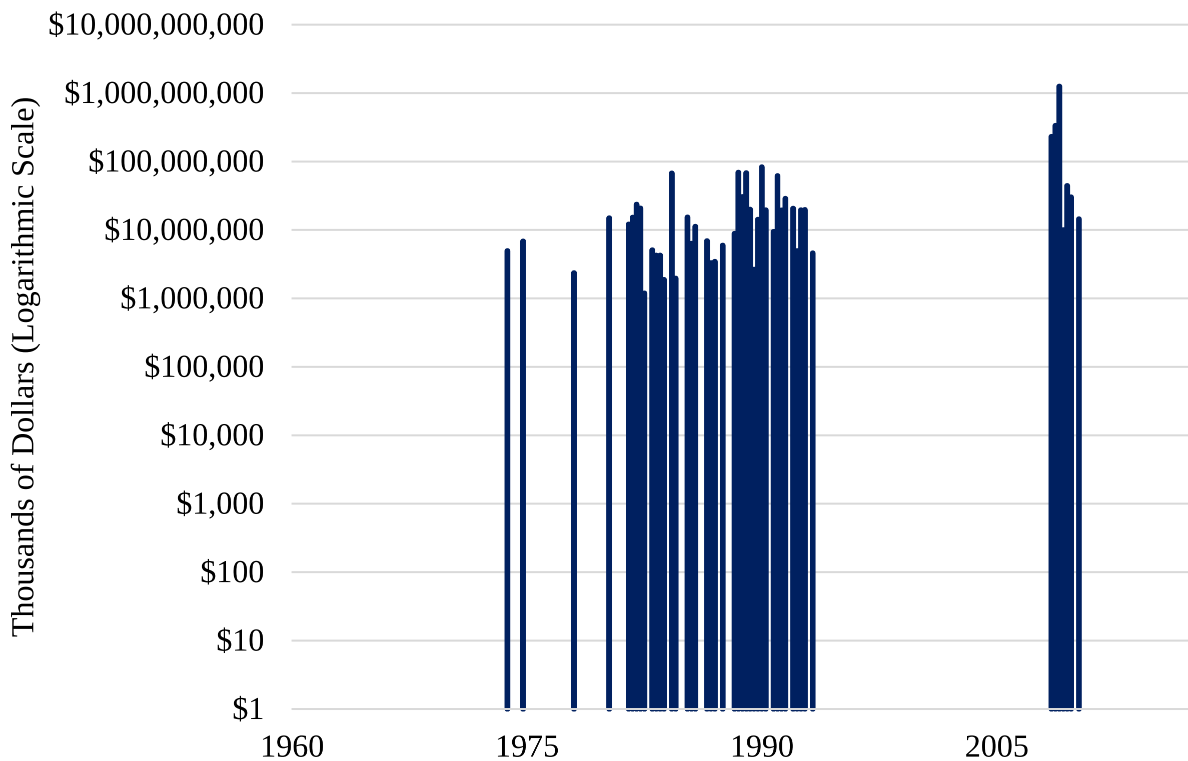
Figure 2 provides more detail on the calculation of the series in the first quarter of 2017. As shown in Figure 2, the series took a value of nearly $500 million in that quarter. This value was caused by the failure of three banks, each with a different amount of deposits. Therefore, at any point in time, the value of the series depends on the number of banks that have failed and the amount of deposits at those banks.

Figure 2: Deposits of All Failed Banks, First Quarter of 2017



Since we are interested in examining the impact of financial stress at banks of varying size on economic performance, we construct measures of large bank stress by including only deposits from failed banks with total assets *above* a percentile of the bank size distribution. To illustrate, Figure 3 depicts the large bank stress measure using the 98th percentile of the bank size distribution as the cutoff. That is, this stress measure includes the deposits of failed banks only when the bank that failed was one of the largest 2 percent of banks in that quarter. For example, during the financial crisis—in the third quarter of 2008—the cutoff for the 98th percentile of the bank size distribution was $4.7 billion in total assets. Of the nine bank failures that occurred in that quarter, two were above the 98th percentile threshold: Washington Mutual Bank and IndyMac Bank F.S.B. The deposits of these banks are included in Figure 3. The deposits of the seven other, smaller failed banks are included in the aggregate measure of bank stress shown in Figure 1 but not in the measure of large bank stress shown in Figure 3.[5]

Figure 3: Deposits of Failed Banks above the 98th Percentile Size Threshold, 1960-2017



We use two quarterly variables to proxy economic performance in our baseline model—real GDP growth and the change in the civilian unemployment rate. The GDP series is already at a quarterly frequency. We convert the monthly unemployment rate series to a quarterly frequency by taking the unemployment rate observed in the last month of a particular quarter. Figures 4 and 5 show the series from 1960 onward.

[5] Because we use Call Reports data for our analysis, the size percentiles described in this article correspond to the distribution of *insured depository institutions* (banks). If we want to map the results to the distribution of bank holding companies (BHCs), we must "scale-up" the bank size numbers. To derive the scale-up factors, we analyzed data from the largest BHCs in the first quarter of 2018, specifically the ratio of their insured depository institutions to their total consolidated assets. These ratios range from 0.27 to 0.40. Therefore, the 98th percentile corresponds to a range of $31 billion to $45 billion in BHC size.

Figure 4: Quarterly Real Gross Domestic Product Growth

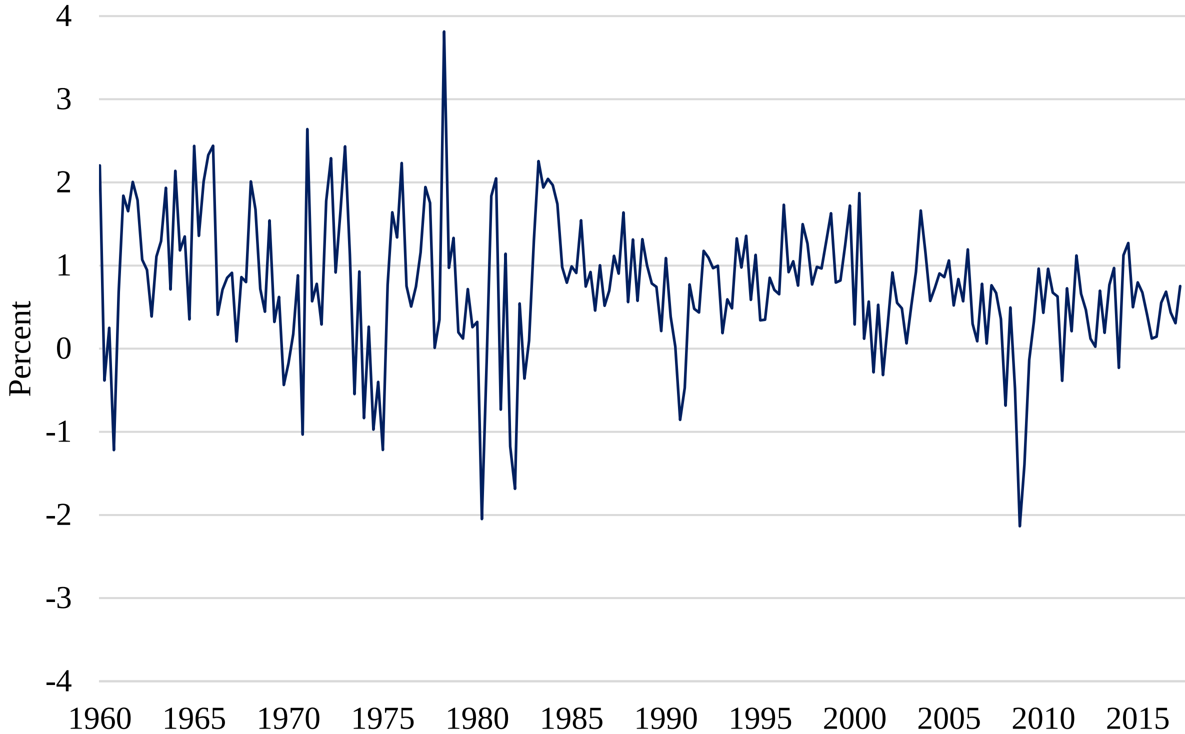
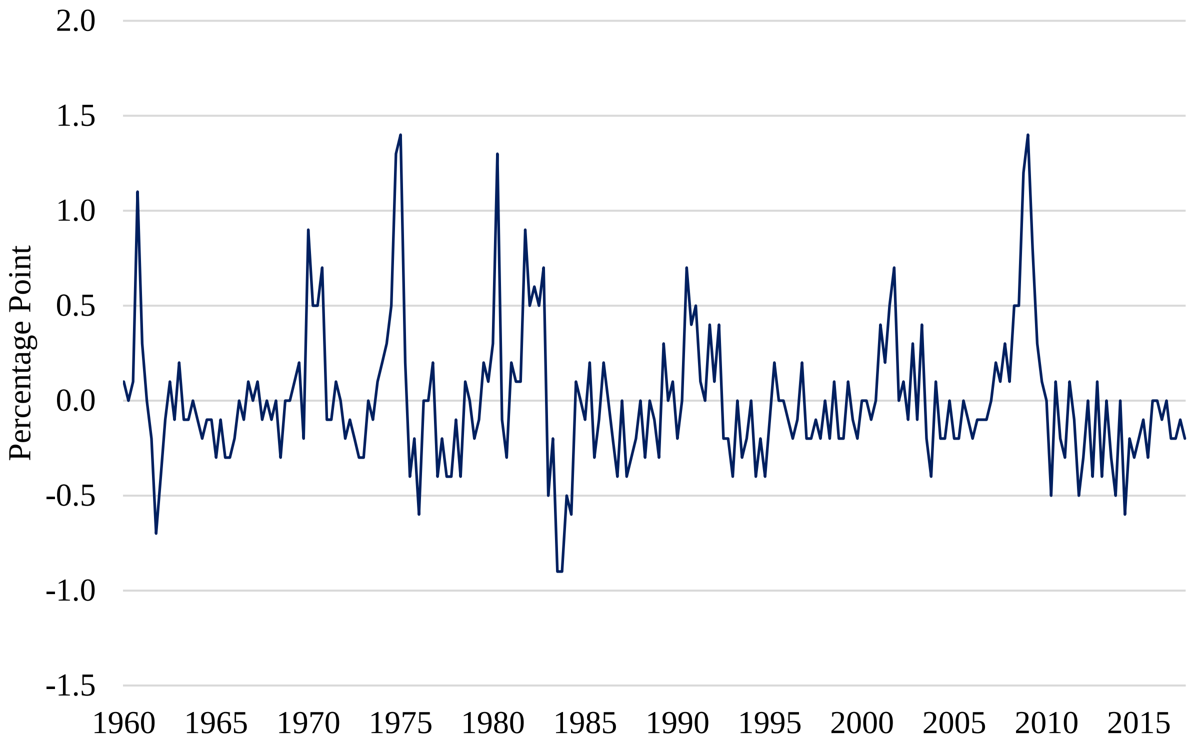


Figure 5: Change in Quarterly Unemployment Rate



B. Methodology

Our baseline methodology assumes that bank stress affects economic performance within the same quarter (i.e., contemporaneously). The baseline regression specifications for GDP and the unemployment rate are, respectively:

$$\log\left(\frac{GDP_t}{GDP_{t-1}}\right) = \alpha_g + \beta_g \log\left(Stress_{t,p}\right) + \phi_g \log\left(Stress_{t,1-p}\right) + \gamma_g \log\left(\frac{GDP_{t-1}}{GDP_{t-2}}\right) + \varepsilon_{t,g}$$

$$(UR_t - UR_{t-1}) = \alpha_u + \beta_u \log\left(Stress_{t,p}\right) + \phi_u \log\left(Stress_{t,1-p}\right) + \gamma_u (UR_{t-1} - UR_{t-2}) + \varepsilon_{t,u}$$

The quarter in which the contemporaneous effect takes place is denoted by subscript *t* and the specific percentile of the bank size distribution used to calculate the stress measure is denoted by subscript *p*. Note that the complement to the set of banks above percentile *p* is denoted by *1-p*. We update the relevant total asset distribution and percentiles for a given value of *p* each quarter. The subscripts g and u correspond to regressions using GDP and the unemployment rate, respectively. We include an AR(1) persistence term γ in each regression to account for well-documented persistence in real economic activity.

$Stress_{t,p}$ captures the total deposits of failed banks *above* a certain percentile *p* of the size distribution during quarter *t*. Similarly, $Stress_{t,1-p}$ corresponds to the total deposits of failed banks *below* a certain percentile *p* of the size distribution during quarter *t*. We include the stress measure for the *1-p* set of banks in order to control for the impact of stress at smaller banks.

The first regression we run is at the 99.9th percentile, and we continue running the regressions in intervals of 0.05 for the top 2 percent of the distribution, i.e., 99.85th percentile, 99.80th percentile, 99.75th percentile, and so on. After each regression, we record the estimated values of α, β, ϕ, and γ. The parameter of interest is β, which captures the impact of stress at banks above size percentile p (large banks) on real GDP growth or the change in the unemployment rate. The parameter ϕ, on the other hand, captures the impact of stress at banks below size percentile p (small banks). We therefore allow the impact of financial stress to differ across large and small banks.

III. Baseline Results

Table 1 presents the estimated parameters of interest at select percentiles in the top 2 percent of the bank size distribution for our baseline GDP regression. Each estimated β_g coefficient represents the contemporaneous change in quarterly real GDP growth associated with a 1 percent increase in deposits among failed banks *above* a particular percentile. Each estimated ϕ_g coefficient represents the contemporaneous change in quarterly real GDP growth associated with a 1 percent increase in deposits among failed banks *below* a particular percentile. Therefore, β_g and ϕ_g represent the impact on GDP of stress at large and small banks, respectively.

For example, the estimated β_g at the 99.8th percentile is -0.063, which means that a 1 percent increase in deposits among failed banks above the 99.8th percentile is associated with a contemporaneous 0.063 percentage point drop in quarterly real GDP growth. This result is significant at the 1 percent level. The estimated ϕ_g at the 99.8th percentile is -0.008, which means that a 1 percent increase in deposits among failed banks below that percentile is associated with a contemporaneous 0.008 percentage point decline in quarterly real GDP growth. This result, however, is not statistically significant.

These empirical results show that financial stress at banks in the top 1 percent of the bank size distribution yields a statistically significant and negative impact on the real economy. The estimated β_g coefficients are highly significant through the 99.3rd percentile and then lose significance past the 99th percentile. Notably, none of the estimated ϕ_g coefficients are statistically significant, which implies that it is indeed stress at the large banks affecting the real economy.

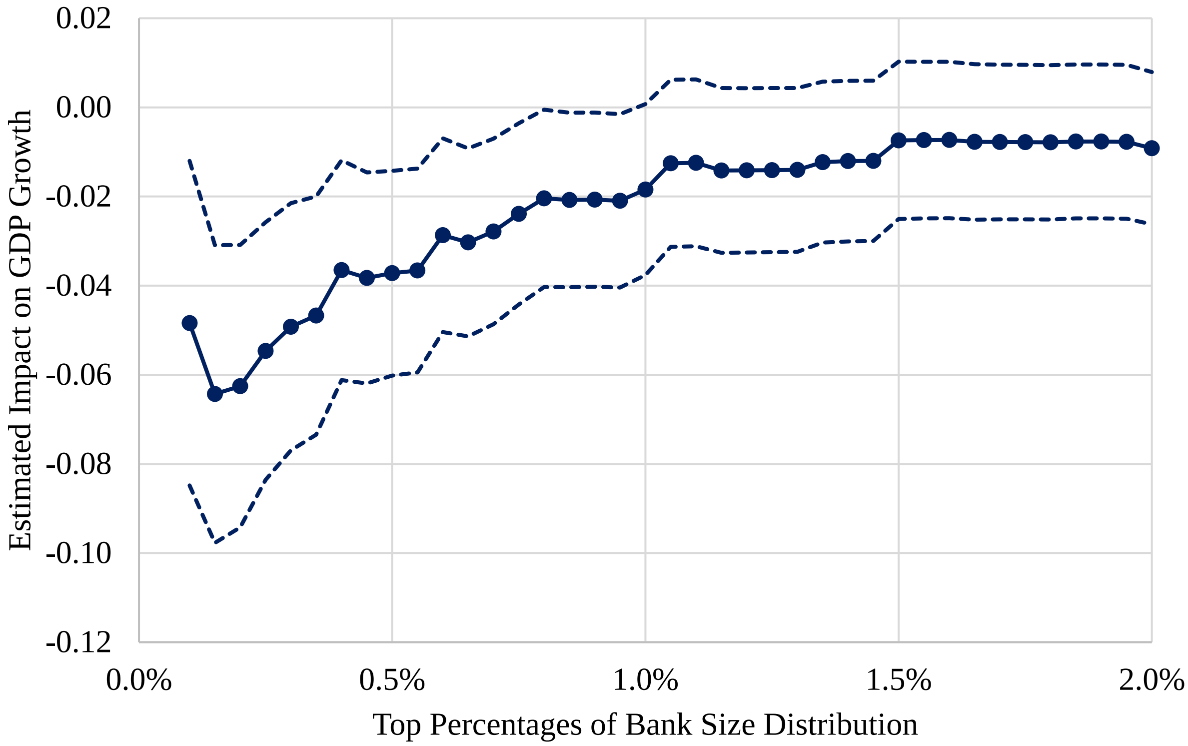
Table 1: GDP Results

Percentile	Estimated β_g	Estimated ϕ_g	R_g^2
99.9	-0.048*** (0.019)	-0.010 (0.009)	0.147
99.8	-0.063*** (0.016)	-0.008 (0.009)	0.175
99.7	-0.049*** (0.014)	-0.006 (0.009)	0.164
99.6	-0.037*** (0.013)	-0.006 (0.009)	0.151
99.5	-0.037*** (0.012)	-0.004 (0.009)	0.156
99.4	-0.029*** (0.011)	-0.005 (0.009)	0.144
99.3	-0.028*** (0.011)	-0.005 (0.009)	0.145
99.2	-0.020** (0.010)	-0.006 (0.009)	0.134
99.1	-0.021** (0.010)	-0.005 (0.009)	0.135
99.0	-0.018* (0.010)	-0.005 (0.009)	0.132
98.5	-0.007 (0.009)	-0.008 (0.010)	0.122
98.0	-0.009 (0.009)	-0.007 (0.010)	0.123

Notes: The asterisks placed next to each point estimate represent the corresponding level of statistical significance. In particular, * corresponds to significance at the 10 percent level, ** corresponds to significance at the 5 percent level, and *** corresponds to significance at the 1 percent level.

Figure 6 plots the estimated β_g coefficients and corresponding confidence intervals for the top 2 percent of the bank size distribution. As shown in the chart, the estimated impact on GDP falls as the threshold defining large banks declines, though the point estimate remains negative at all thresholds. At the point where the confidence interval first includes zero and the estimate is no longer statistically significant, the point estimate is -0.018. Although these point estimates are small, keep in mind that the increase in failed deposits during a financial crisis is substantially higher than one percent.

Figure 6: Impact of Failed Deposits on Quarterly GDP



Notes: This figure shows the estimated β_g coefficients in the top 2 percent of the bank size distribution. The estimated β_g coefficients are depicted by the solid line, and the dashed lines represent the 95th percent confidence interval around the point estimates. Each point on the solid line represents an estimated β_g coefficient.

The results are similar for the change in the unemployment rate. In this case, *positive* values of β_u represent a negative impact on the real economy. Table 2 presents the estimated parameters of interest at select percentiles in the top 2 percent of the bank size distribution for our baseline unemployment regression. Similar to the above discussion, each estimated β_u coefficient represents the contemporaneous change in the unemployment rate associated with a 1 percent increase in deposits among failed banks *above* a particular percentile. Each estimated ϕ_u

coefficient represents the contemporaneous change in the unemployment rate associated with a 1 percent increase in deposits among failed banks *below* a particular percentile. Therefore, β_u and ϕ_u represent the impact on the unemployment rate of stress at large and small banks, respectively.

The estimated β_u at the 99.8th percentile is 0.033. This means that a 1 percent increase in deposits among failed banks above the 99.8th percentile is associated with a contemporaneous 0.033 percentage point increase in the unemployment rate. This result is significant at the 1 percent level. The estimated ϕ_u at the 99.8th percentile is -0.001, which is essentially zero and not statistically significant. In fact, none of the estimated ϕ_u parameters are statistically significant.

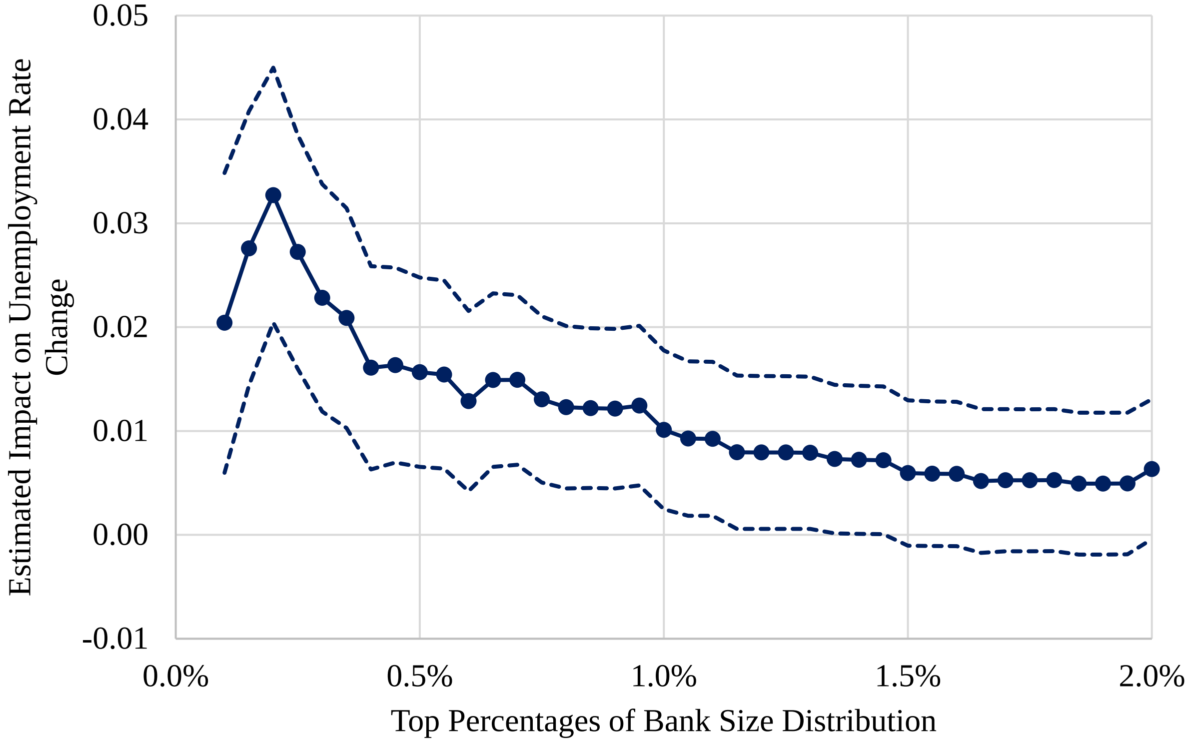
The estimated β_u coefficients are highly significant through the 99th percentile and remain significant through the 98th percentile. This estimated impact is the most severe for stress at the largest banks. Indeed, the estimated impact of stress at banks in the top 0.2 percent of the size distribution is more than three times as large as the estimated impact of stress at banks in the top 1 percent. Figure 7 plots the estimated β_u coefficients and corresponding confidence intervals for the top 2 percent of the bank size distribution.

Table 2: Unemployment Rate Results

Percentile	Estimated β_u	Estimated ϕ_u	R_u^2
99.9	0.020*** (0.007)	0.001 (0.003)	0.289
99.8	0.033*** (0.006)	-0.001 (0.003)	0.343
99.7	0.023*** (0.006)	-0.001 (0.003)	0.314
99.6	0.016*** (0.005)	-0.001 (0.003)	0.296
99.5	0.016*** (0.005)	-0.002 (0.004)	0.298
99.4	0.013*** (0.004)	-0.002 (0.004)	0.290
99.3	0.015*** (0.004)	-0.003 (0.004)	0.303
99.2	0.012*** (0.004)	-0.003 (0.004)	0.293
99.1	0.012*** (0.004)	-0.003 (0.004)	0.293
99.0	0.010*** (0.004)	-0.002 (0.004)	0.284
98.5	0.006* (0.004)	-0.002 (0.004)	0.272
98.0	0.006* (0.003)	-0.002 (0.004)	0.274

Notes: The asterisks placed next to each point estimate represent the corresponding level of statistical significance. In particular, * corresponds to significance at the 10 percent level, ** corresponds to significance at the 5 percent level, and *** corresponds to significance at the 1 percent level.

Figure 7: Impact on Quarterly Unemployment Rate



Notes: This figure shows the estimated β_u coefficients in the top 2 percent of the bank size distribution. The estimated β_u coefficients are depicted by the solid line, and the dashed lines represent the 95th percent confidence interval around the point estimates. Each point on the solid line represents an estimated β_u coefficient.

Last, but not least, we present our baseline results in terms of a hypothetical deviation from trend growth. Performing this exercise requires us to calculate the predicted change in real GDP growth that results from an *assumed* level of bank stress, then comparing the predicted change in GDP with trend GDP. Showing the results in this way allows us to see that the failure of \$$x$ billion in deposits at a single large bank has greater costs for the real economy than a large number of failures at smaller banks that results in the same \$$x$ billion in failed deposits.

This calculation requires plugging all necessary variables into the right hand side of the regression specification in order to compute the predicted economic performance on the left hand side. This is shown generally in the following equation for any percentile *p*:

$$Forecast = \widehat{\alpha_p} + \widehat{\beta_p}\,\overline{\log(Stress_p)} + \widehat{\gamma_p}\overline{AR(1)}$$

Presenting the results in this way requires two additional assumptions. First, we must make an assumption regarding the value of the bank stress measure. As a demonstration, we choose $50 billion, which we then convert into natural logarithm units. This is $\overline{\log(Stress_p)}$. Second, we make an assumption regarding the average value of lagged GDP growth, which we designate $\overline{AR(1)}$. We use the average GDP growth rate of the regression sample, which is 0.747.[6]

Using these inputs, our results suggest that the failure of a single bank—above the 99.5th size percentile and with an assumed $50 billion in deposits—would result in approximately a 42 percent decline in quarterly real GDP growth, while failures of five banks—each above the 99th size percentile and with an assumed $10 billion in deposits—would result in approximately a 14 percent decline in quarterly real GDP growth. While both scenarios assume $50 billion in total deposits, the negative impact is greatest when larger banks fail. Indeed, the relative impact in this scenario is a multiple of three. These results are qualitatively similar for a change in the unemployment rate.

[6] The *1-p* version of the stress measure is not here because, in this hypothetical scenario, we are assuming that only banks above size threshold *p* fail. Thus, there are no failed banks in the *1-p* set.

IV. Robustness Checks

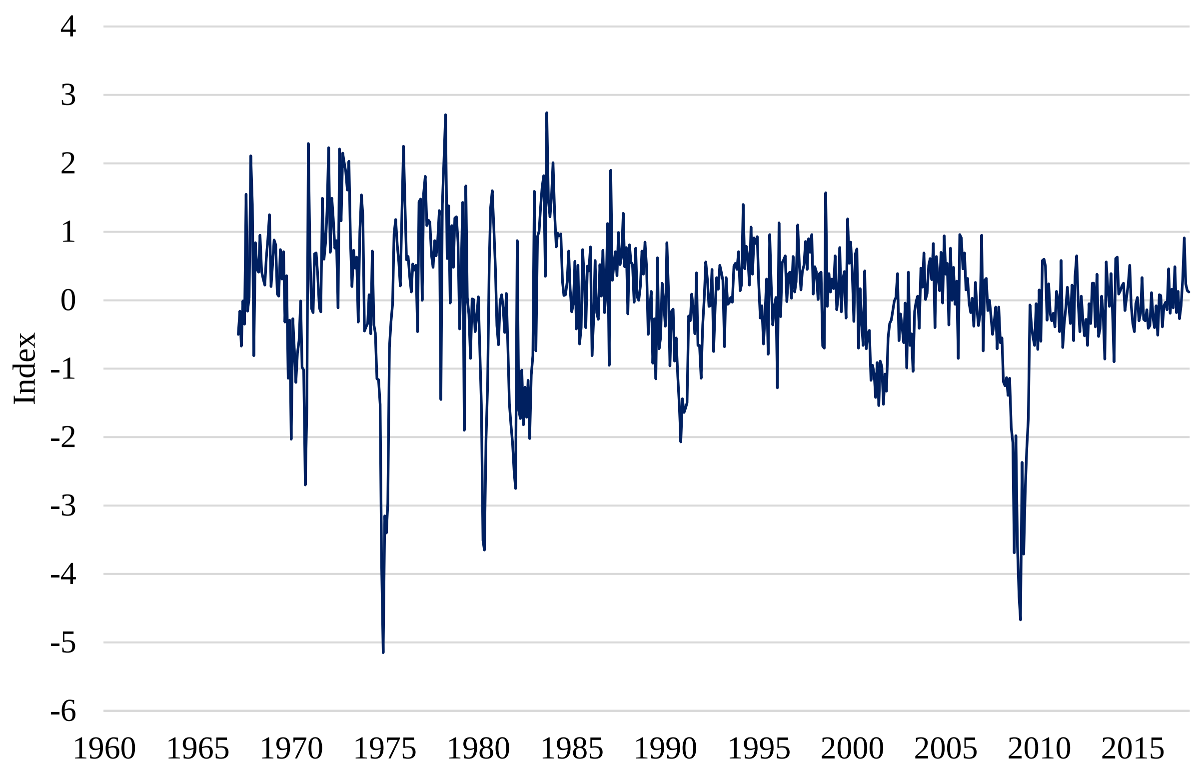
The purpose of this section is to subject our baseline results to a battery of tests in order to check for robustness. We work through five robustness checks, though there could surely be more. First, we examine the assumption of contemporaneous impact in our baseline model by analyzing monthly economic data. Next, we run a simple Granger test to answer the question: How do we know bank stress is causing a decline in economic performance, as opposed to a decline in economic performance causing bank stress? Third, we re-run our baseline model with a shorter time series—stopping at the end of 2006 to remove the recent financial crisis—because the severity of the recent financial crisis could overstate the impact of stress at large banks. Fourth, we re-run our baseline model with data from banks that have only failed as opposed to those that have failed or received assistance. Finally, we conduct our analysis using the assets of failed banks as our financial stress proxy instead of using the deposits of those banks. In some of these robustness tests, the estimated point estimates have larger standard errors than those in our baseline case; this is because we are dropping a nontrivial number of observations to conduct those robustness checks. Nevertheless, our main results survive—the impact of bank stress on the real economy is negative, and the impact is greater for stress at larger banks than at smaller banks.

A. Monthly Frequency

In our baseline model, we investigate the contemporaneous impact of bank stress on quarterly real GDP growth and the quarterly change in the unemployment rate. To check the robustness of our contemporaneous modeling assumption—that is, to test whether the impact does indeed materialize within the same quarter—we now re-run the GDP and unemployment regressions using monthly economic performance indicators. Note that the unemployment rate series is available at a monthly frequency, but the GDP series is not. We therefore replace real

GDP growth with the Chicago Fed National Activity Index (CFNAI), which closely tracks real GDP growth.

Figure 8: Monthly Chicago Fed National Activity Index (CFNAI)



The regression specifications are modified to include more lags, as there are three months in a quarter. Otherwise, the two specifications are unchanged from the baseline model discussed previously:

$$CFNAI_t = \alpha + \sum_{i=0}^{2} \beta_i \log\left(Stress_{t-i,p}\right) + \sum_{i=0}^{2} \phi_i \log\left(Stress_{t-i,1-p}\right) + \sum_{i=1}^{2} \gamma_i \, CFNAI_{t-i} + \varepsilon_t$$

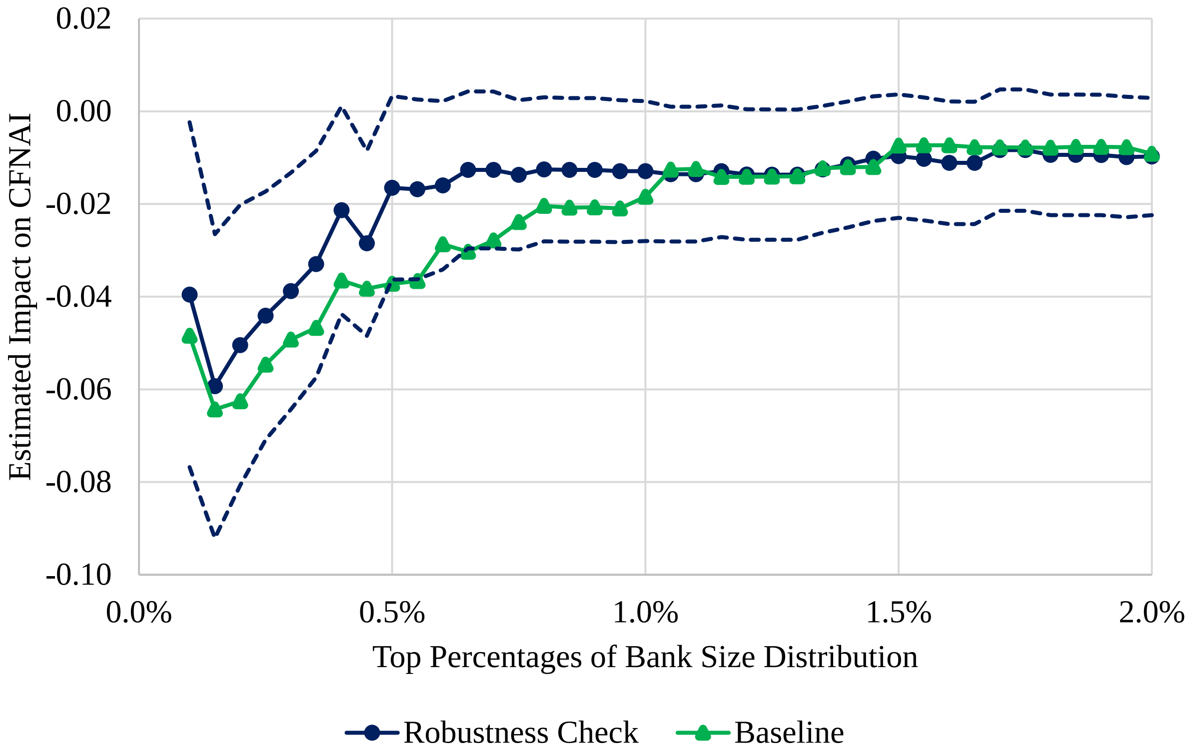
$$(UR_t - UR_{t-1}) = \alpha + \sum_{i=0}^{2} \beta_i \log\left(Stress_{t-i,p}\right) + \sum_{i=0}^{2} \phi_i \log\left(Stress_{t-i,1-p}\right)$$

$$+ \sum_{i=1}^{2} \gamma_i \left(UR_{t-i} - UR_{t-1-i}\right) + \varepsilon_t$$

We begin our estimation at the 99.9th percentile and progress down in intervals of 0.05. The coefficient of interest is still β, except we now have three of them. The first one β_0 corresponds to the contemporaneous effect; β_1 captures the impact with a one-month lag; and β_2 captures the impact with a two-month lag.

Figure 9 presents the estimated β_0 coefficients of the CFNAI regressions in the solid blue line. The magnitude of the monthly point estimates is smaller than that of the baseline GDP results, though it is still true that the largest point estimate is more than three times the point estimate at the top 1 percent threshold. In addition, the shape of the solid blue line is slightly different. The solid blue line begins to flatten out—and lose its statistical significance—below the top 0.5 percent, whereas the baseline green line flattens out below the top 1 percent.

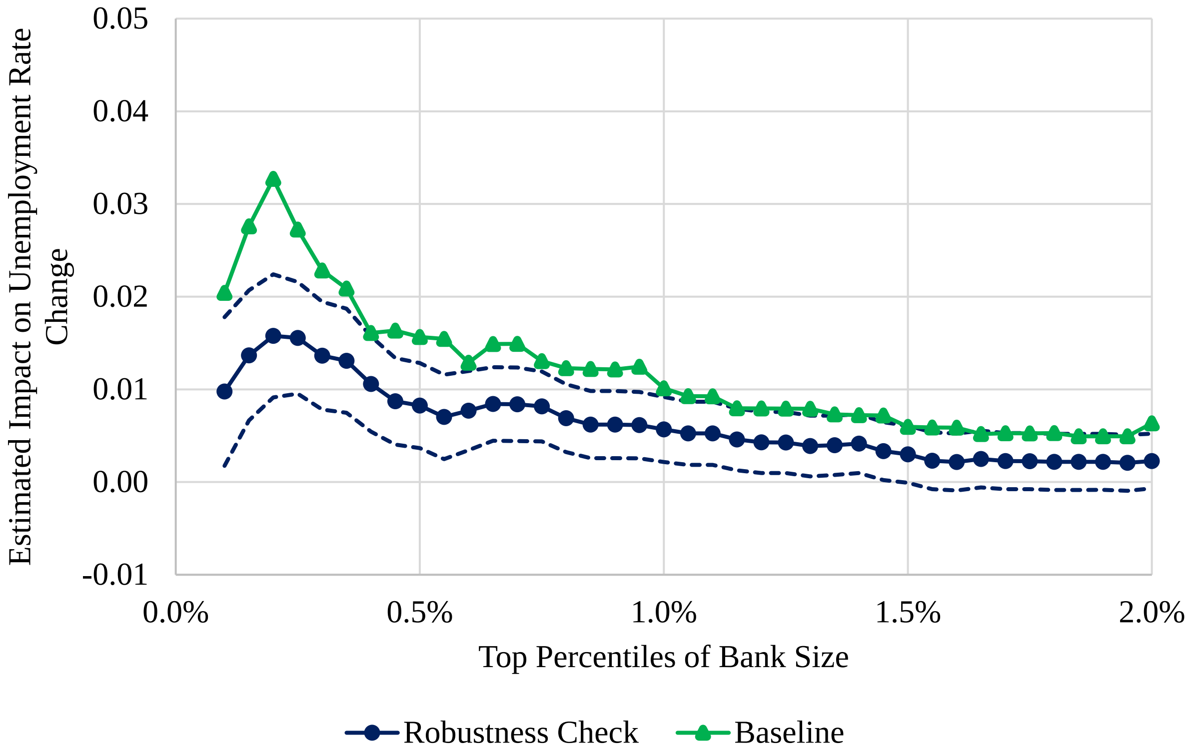
Figure 9: Impact on Monthly CFNAI



Notes: This figure shows the estimated β_0 coefficients for the monthly CFNAI regressions in the top 2 percent of the bank size distribution. The estimated β_0 coefficients are depicted by the solid blue line with circular markers, and the dashed lines represent the 95th percent confidence interval around the point estimates. The point estimates from the baseline quarterly GDP regressions are depicted by the solid green line with triangular markers. Each point on the two solid lines represents an estimated coefficient.

The results using the unemployment rate are similar, but with a couple of notable differences. First, the contemporaneous impact β_0 is not the main driver of the results, but rather the lags, β_1 and β_2. Second, as shown in Figure 10, while the monthly point estimates are smaller in magnitude than the baseline ones, the monthly point estimates are statistically significant up to the top 1.5 percent of the bank size distribution. In contrast, the baseline estimates lose their statistical significance earlier, below the top 1.3 percent.

Figure 10: Impact on Monthly Unemployment Rate



Notes: This figure shows the estimated β_1 coefficients for the monthly unemployment rate regressions in the top 2 percent of the bank size distribution. The estimated β_1 coefficients are depicted by the solid blue line with circular markers, and the dashed lines represent the 95^{th} percent confidence interval around the point estimates. The point estimates from the baseline quarterly unemployment rate results are depicted by the solid green line with triangular markers. Each point on the two solid lines represents an estimated coefficient.

B. Granger Causality

The interpretive issue in this type of analysis is reverse causality. How do we know bank stress is causing a decline in economic performance, as opposed to a decline in economic performance causing bank stress? We test the robustness of our baseline results by following the time series methods developed in Granger (1969). Specifically, we first run a vector auto-regression ("VAR") using proxies of bank stress and economic performance, with a one-quarter lag. We then compare the p-values of the coefficients on the lagged terms. We are essentially asking which lagged series is a better predictor of the other series—for instance, are lagged failed deposits better at predicting GDP growth, or is lagged GDP growth better at predicting failed deposits? The results are, on balance, favorable to our model.

Consider columns (1) and (2) of Table 3. Up until the top 0.5 percent, the Granger tests suggest that lagged deposits at these large failed banks are better at predicting GDP growth than vice versa, because a smaller p-value corresponds to greater significance. Once the size threshold reaches the top 0.5 percent, however, the story changes: lagged values of GDP growth become a stronger predictor of deposits at failed banks. That implies reverse causality for stress at banks below the top 0.5 percent size threshold. However, the issue does not appear when analyzing changes in the unemployment rate. Columns (3) and (4) of Table 3 show that lagged deposits are uniformly better predictors of changes in the unemployment rate than vice versa.

Thus, while these results provide some evidence that poor economic performance causes bank stress, they provide as much, if not more, evidence that bank stress causes poor economic performance.

Table 3: Comparing p-Values of Granger Tests

Percentile	Lagged Failed Deposits Predict GDP (1)		Lagged GDP Predicts Failed Deposits (2)	Lagged Failed Deposits Predict UR (3)		Lagged UR Predicts Failed Deposits (4)
99.9	0.042	<	0.715	0.001	<	0.502
99.8	0.011	<	0.303	0.003	<	0.345
99.7	0.054	<	0.141	0.006	<	0.051
99.6	0.069	<	0.165	0.010	<	0.081
99.5	0.078		0.028	0.002	<	0.022
99.0	0.035		0.010	0.003	<	0.006
98.0	0.184		0.041	0.080	<	0.137

Notes: This table contains the p-values of Granger tests at select percentiles. A smaller p-value corresponds to greater statistical significance.

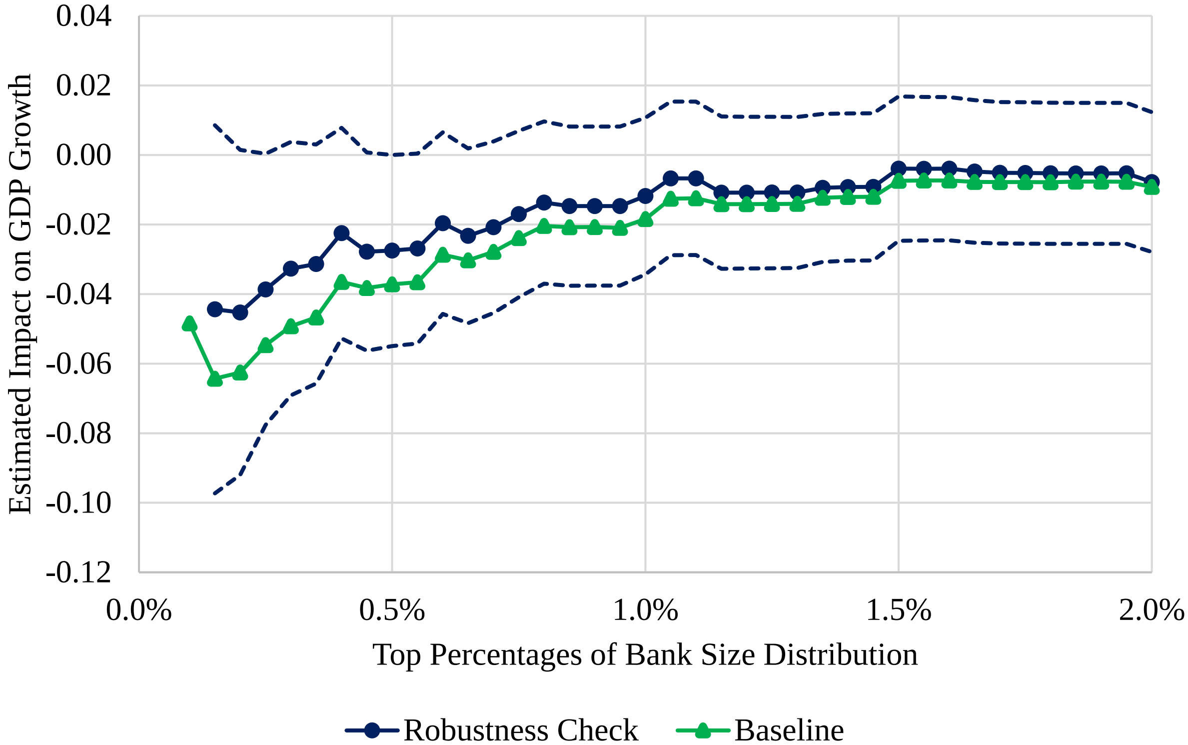
C. Sample Period: Financial Crisis

The recent financial crisis was a period of extreme bank stress compared to most periods in our full sample period. In addition, the crisis resulted in a large amount of assistance and acquisitions, such as the Troubled Asset Relief Program (TARP), that were the result of government initiatives. To assess the impact of the financial crisis on our baseline results, we run our baseline regressions from 1960 through 2006, removing the financial crisis entirely.

Figure 11 compares the results of our GDP regression for the full and non-crisis samples. The shape of the estimated series is the same and the point estimates are uniformly negative, which suggest that the impact is still more severe for stress at the largest banks. The magnitude of the estimated impact is slightly smaller in this no-crisis sample, and the standard errors are larger (as shown by the wider confidence intervals), especially for the point estimates at the top of the bank size distribution.[7] Note, however, that these point estimates are still significant at the 10 percent level. The results are qualitatively similar for the unemployment rate—the shape of the estimated series is the same, the point estimates are uniformly positive, and the standard errors are larger.

[7] Figure 12 omits the point estimate at the 99.9th percentile because of small sample size.

Figure 11: Shorter Sample Period and Quarterly GDP



Notes: This figure shows the estimated β_g coefficients in the top 2 percent of the bank size distribution. The sample period ends in the fourth quarter of 2006, before the financial crisis. The estimated β_g coefficients are depicted by the solid blue line with circular markers, and the dashed lines represent the 95^{th} percent confidence interval around the point estimates. The point estimates from the baseline results are depicted by the solid green line with triangular markers. Each point on the two solid lines represents an estimated β_g coefficient.

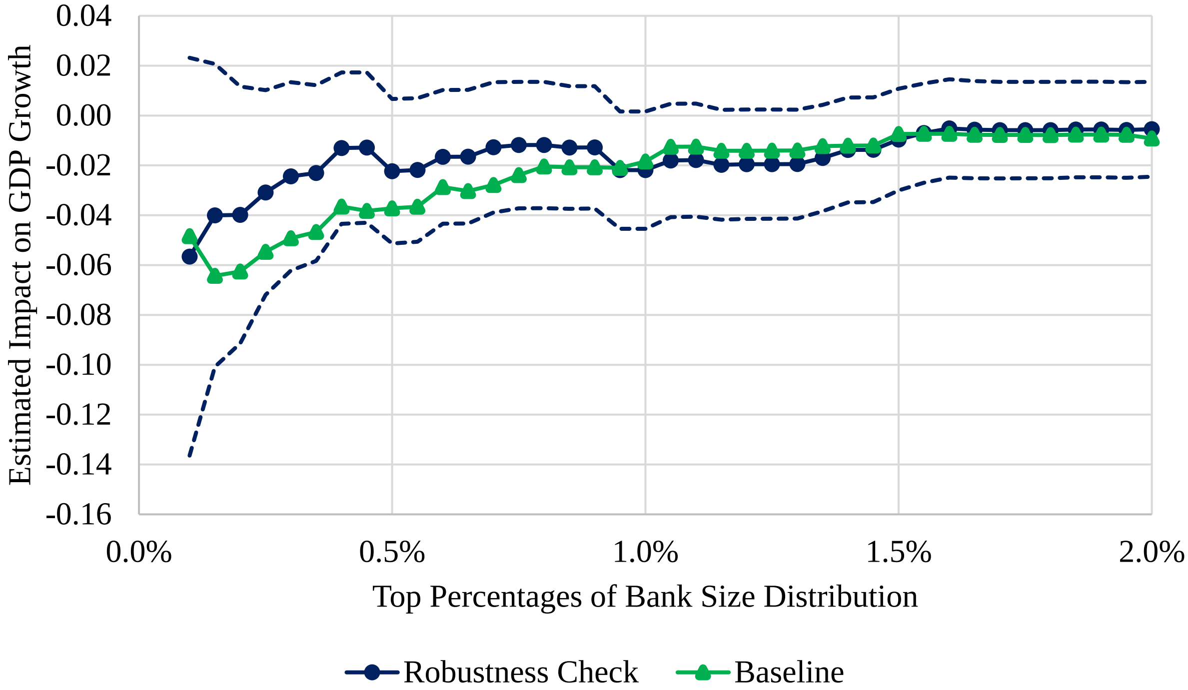
D. Measure of Bank Stress: Failures v. Assistance

The FDIC data used to create our bank stress measure includes both bank failures and assistance. In our baseline model, we considered a bank to have failed either when it failed *or* when it received government assistance. Nearly 600 of the roughly 4,100 observations in the dataset represent assistance. There are differences between the two types of observations because failing is more extreme than receiving assistance. We therefore re-run our regressions using only bank failures data. The result is similar to that of the previous robustness check, though the standard errors are noticeably larger because we are using even fewer observations at the top end of the distribution.

As shown in Figure 12, the shape of this estimated series is similar to that of the baseline and the point estimates are still all negative, which suggest that the estimated impact is still the most severe for stress at the largest banks. However, the magnitude of the point estimates is smaller, and the standard errors are much larger, as shown by the wider confidence intervals.[8] Although the shape of the plotted point estimates roughly matches our baseline, it is clear that removing government assistance observations from our sample has a disproportionate effect on the analysis of banks at the very top of the size distribution. The results are qualitatively similar for the unemployment rate.

[8] Figure 12 omits the point estimate at the 99.9^{th} percentile because of small sample size.

Figure 12: Failures Only and Quarterly GDP



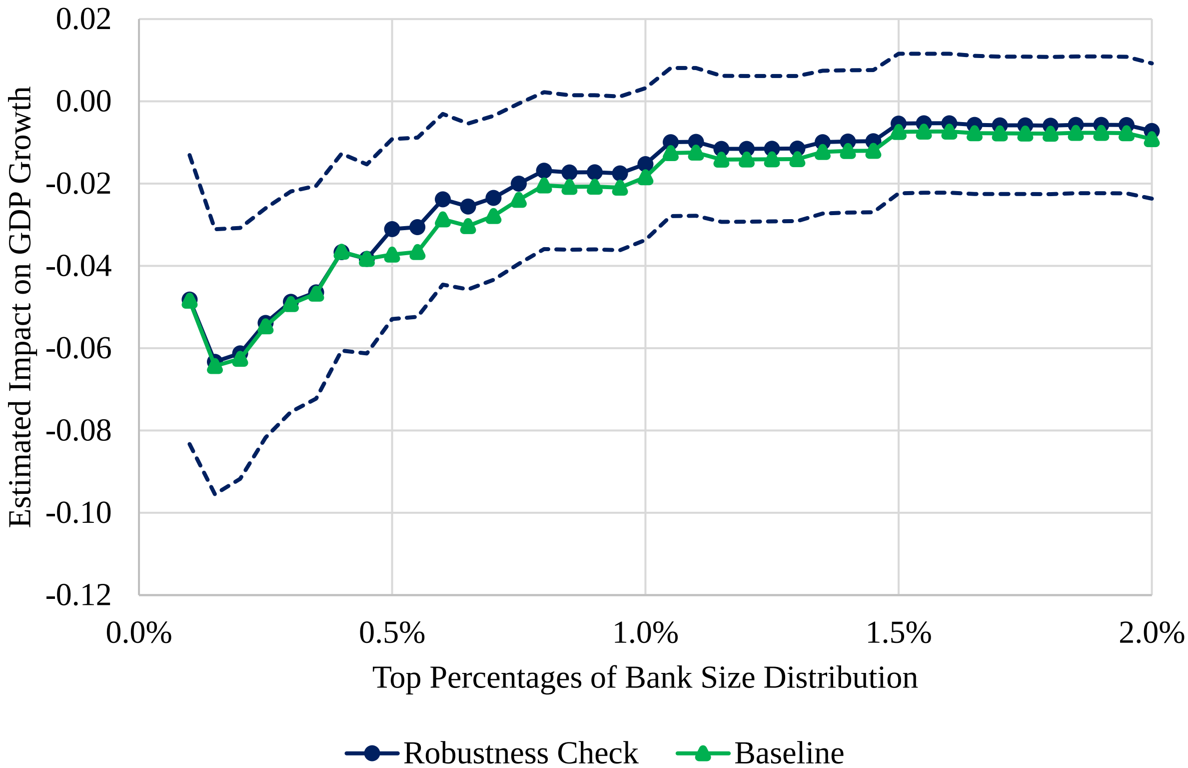
Notes: This figure shows the estimated β_g coefficients in the top 2 percent of the bank size distribution. The estimated β_g coefficients are depicted by the solid blue line with circular markers, and the dashed lines represent the 95$^{\text{th}}$ percent confidence interval around the point estimates. The point estimates from the baseline results are depicted by the solid green line with triangular markers. Each point on the two solid lines represents an estimated β_g coefficient.

E. Measure of Bank Stress: Assets of Failed Banks v. Deposits of Failed Banks

Given the focus on bank liabilities, particularly on bank deposits, one might wonder what would happen if we focused on the asset side of the balance sheet. In our final robustness check, we use the assets of failed banks—instead of the deposits of failed banks—as our numerical proxy for bank stress. The amount of assets is inflation adjusted with the CPI and then converted to natural logarithm units. The results are very similar to our baseline case.

As one can see in Figure 13, the magnitude of the point estimates are almost identical to those in our baseline scenario, which should not be surprising given the strong correlation between deposits and assets at a bank. For both, the largest impact occurs at the 99.85th percentile with β_g equal to -0.063 in the present case and equal to -0.064 in the baseline case. The statistical significance, however, is slightly different in the present case. Under our baseline scenario, the point estimates were statistically significant up to the top 1 percent of the bank size distribution; here, the point estimates lose statistical significance below the top 0.75 percent. Not surprisingly, the results for the unemployment rate are qualitatively identical and robust.

Figure 13: Assets of Failed Banks and Quarterly GDP



Notes: This figure shows the estimated β_g coefficients in the top 2 percent of the bank size distribution. The estimated β_g coefficients are depicted by the solid blue line with circular markers, and the dashed lines represent the 95th percent confidence interval around the point estimates. The point estimates from the baseline results are depicted by the solid green line with triangular markers. Each point on the two solid lines represents an estimated β_g coefficient.

V. Conclusion

This article builds upon the important and early work of Bernanke (1983), which uncovers a link between aggregate bank stress and macroeconomic stress. We document evidence of a link between stress in the banking sector and stress in the economy that varies along the bank-size spectrum. Importantly, we find that stress among larger banks has a greater negative consequence on the economy than does stress at smaller banks.

To this end, our analysis can broadly inform the size threshold at which enhanced standards take effect. There are, however, trade-offs involved with choosing the appropriate level. For instance, one might consider the level at which the impact of bank stress on the economy becomes statistically insignificant. Alternatively, one could choose to calibrate the threshold to a level at which the economic impact of stress is greater than zero and *economically* significant rather than statistically significant. Doing so would result in a higher threshold, and the precise level of economic significance would represent policymakers' views on the trade-off between the costs of enhanced regulation and the benefits associated with more resilient banks.

Our results survive multiple robustness tests, but are nonetheless subject to caveats. First, they are dependent on the particular measures of economic performance and bank stress considered, as well as the sample period employed. Second, an assumption implicit in this approach is that the cost of complying with enhanced standards is the same for banks of varying size. If costs of compliance vary with bank size, then these costs need to be considered in the analysis.

In future research, we would like to explore an alternative measure of bank stress. All analyses to date have used deposits or assets of *failed* banks as a proxy for bank stress. We would like to repeat our analysis using the deposits or assets of banks with *low capital ratios,* which provide a less extreme signal of bank stress than failing or receiving assistance from the FDIC. In addition, deposits of thinly capitalized banks can be adjusted to consider varying degrees of stress or "thinness," whereas failed deposits are binary—a bank has either failed or it has not. Additionally, as mentioned in the introduction, size is not the sole predictor of what impact a bank would have on the economy when under stress. The complexity of a bank's operations also factors into the equation. Future research could explore various ways to measure bank complexity so that size and complexity are analyzed together.

In sum, our results are broadly informative about how the stringency of regulatory standards should vary with bank size, and support the idea that the largest banks should be subject to the most stringent requirements and smaller banks should be subject to successively less stringent requirements.

References

Allen, Linda, Tura G. Bali, and Yi Tang. 2012. "Does Systemic Risk in the Financial Sector Predict Future Economic Downturns?" *The Review of Financial Studies* Vol. 25, No. 10, pp. 3000-3036.

Basel Committee on Banking Supervision. 2014. "The G-SIB Assessment Methodology – Score Calculation."

Bernanke, Ben S. 1983. "Nonmonetary Effects of the Financial Crisis in the Propagation of the Great Depression." *The American Economic Review* Vol. 73, No. 3, pp. 257-276.

Bernanke, Ben S. 2015. *The Courage to Act: A Memoir of a Crisis and Its Aftermath*. Norton.

Calomiris, Charles W. and Joseph R. Mason. 2003. "Consequences of Bank Distress during the Great Depression." *The American Economic Review* Vol. 93, No. 3, pp. 937-947.

Chodorow-Reich, Gabriel. 2014. "The Employment Effects of Credit Market Disruptions: Firm-Level Evidence from the 2008-9 Financial Crisis." *The Quarterly Journal of Economics* Vol. 129, No. 1, pp. 1-59.

Geithner, Timothy F. 2015. *Stress Test: Reflections on Financial Crises*. Broadway Books.

Gorton, Gary B. 2010. *Slapped by the Invisible Hand: The Panic of 2007*. Oxford University Press.

Granger, C. W. J. 1969. "Investigating Causal Relationships by Econometric Models and Cross-Spectral Methods." *Econometrica* Vol. 37, No. 3, pp. 424-438.

Haldane, Andrew G. and Robert M. May. 2011. "Systemic Risk in Banking Ecosystems." *Nature* Vol. 469, pp. 351-355.

Kashyap, Anil K. and Jeremy C. Stein. 2000. "What Do a Million Observations on Banks Say about the Transmission of Monetary Policy?" *The American Economic Review* Vol. 90, No. 3, pp. 407-428.

Kupiec, Paul H. and Carlos D. Ramirez. 2013. "Bank Failures and the Cost of Systemic Risk: Evidence from 1900 to 1930." *Journal of Financial Intermediation* Vol. 22 pp. 285-307.

Office of Financial Research. 2017. "Size Alone Is Not Sufficient to Identify Systemically Important Banks."

Reinhart, Carmen M. and Kenneth S. Rogoff. 2009. *This Time Is Different: Eight Centuries of Financial Folly*. Princeton University Press.

Quarles, Randal K. 2018. "Getting It Right: Factors for Tailoring Supervision and Regulation of Large Financial Institutions." Speech at American Bankers Association Summer Leadership Meeting, Salt Lake City, Utah.

United States Congress. 2018. Economic Growth, Regulatory Relief, and Consumer Protection Act.