Are Bank Mergers Bad for Financial Stability?*

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Abstract

Using a novel forward-looking measure of resiliency, we show that U.S. banks become, on average, less resilient after mergers. In other words, they are more likely to fail during a crisis. This finding, however, varies significantly by bank size. In particular, large bank mergers drive our result, which suggests the presence of increased moral hazard. We also observe that diversification plays an important role in an unexpected way. While the literature has overwhelmingly demonstrated that geographic diversification is beneficial, less is known about diversification across business models. We show that mergers between certain large banks that are too dissimilar can actually reduce resiliency, likely because of increased complexity from the merger.

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1. Introduction

Do mergers between banks harm their resiliency during times of stress? The 2023 panic involving large regional banks—and JPMorgan's subsequent acquisition of First Republic's assets—has reignited the debate. Treasury Secretary Janet Yellen and Acting Comptroller of the Currency Michael Hsu have issued remarks suggesting an openness to certain bank mergers. Conversely, Senator Elizabeth Warren has proposed a stricter framework around merger and acquisition (M&A) deals, citing financial stability concerns. In this paper, we examine the consequences of bank mergers on financial stability. Findings show banks become, on average, less resilient after mergers. In other words, they are more likely to fail during a crisis.

The underlying concern among policymakers is not unwarranted. During the 2007-2008 Global Financial Crisis (GFC), several of the banks that were bailed out by the U.S. government through the Capital Purchase Program were mega-banks created through a series of mergers. Indeed, many have argued that "too-big-to-fail" (TBTF) banks engage in excessive risk-taking in normal times due to moral hazard, believing that the government will rescue them in times of distress (Strahan, 2013; Kaufman, 2014). The TBTF phenomenon implies that large entities created through mergers and acquisitions can become less safe and sound in the face of an economic shock.

However, the relationship between bank mergers and resiliency is far from clear. While concerns over creating TBTF banks suggests some large mergers may detract from resiliency, other mergers may help strengthen resiliency due to potential benefits from diversification. In fact, there is substantial evidence suggesting that banks with diversified portfolio or geographic profiles fare better during economic downturns (Estrella, 2001; Carlson and Mitchener, 2006; Shim, 2019; Doerr and Schaz, 2021). If bank mergers can successfully contribute to the diversification, then merged banks should be able to navigate through a crisis without incurring greater losses.

Despite the importance of this question, there is a lack of empirical evidence directly illustrating the relationship between bank mergers and resiliency. Does the benefit derived from portfolio diversification after a merger lead to greater resiliency, or does the increase in size and corresponding moral hazard do more harm than good? The lack of empirical evidence likely reflects the fact that several identification challenges exist in evaluating bank resiliency after mergers. First, to measure resiliency, one needs to look at banks' performance under stress. However, in contrast to bank merger deals which take place from time to time, major crises occur far less frequently, making it challenging to assess bank merger outcomes associated with resiliency. Even if one were to utilize the GFC to calculate merged banks' resiliency, that measure would only be available for a small subset of banks which experienced the GFC and *also* engaged in a merger not long before the crisis. Indeed, if one observes the deteriorating performance of a bank during the GFC, it would still be implausible to attribute that performance to a merger that the bank engaged in during the 1990s. Furthermore, the measure would only reflect resiliency at that particular point in time around 2007-2010. Given the constant change in economic environment as well as in the portfolios and business strategies of banks engaging in mergers, it is important to develop a measure that can be broadly applied to assess the financial stability implication of various deals over time. In addition, assessing the effects of bank mergers requires careful apples-to-apples comparisons between the resiliency of merged banks and similar ones that did not engage in a merger, under similar economic stress.

To overcome these identification challenges, we develop a novel, forward-looking approach to measure financial resiliency outcomes associated with bank mergers over time. In particular, we review the historical relationship between banks' loan losses and economic situation and calculate *projected* loss rate from banks' loan portfolios under a stress test scenario designed to mimic crisis dynamics. With this measure, we employ a stacked difference-in-differences framework to assess the effects of bank mergers on resiliency. We compare the changes in resiliency of treated banks that engage in mergers with similar ones that do not, before and after the merger takes place. We include a rich menu of variables to capture characteristics of banks and economic status that may have contributed to changes in banks' resiliency. To further account for potentially differences in bank characteristics, we use propensity score matching to match merged banks with comparable banks along key dimensions such as size, profitability, and business model using pre-merger characteristics but did not engage in mergers (Gormley and Matsa, 2011).

Combining the above strategy with a comprehensive dataset of bank mergers in the United States from 1984 to 2013, we find that banks become, on average, less resilient after mergers. In other words, their likelihood of default increases during a crisis, as estimated losses increase significantly. What explains our main finding? Here, we return to our initial discussion on the interplay between costs associated with moral hazard and benefits gained from diversification.

The TBTF label goes back decades—even before the failure of Continental Illinois in 1984 (Omarova, 2019). The underlying idea is that the government will rescue an organization that is in trouble if the organization is sufficiently important for the economy, if it is too big to fail. This, of course, leads to a classic case of moral hazard in which the organization can then behave in a riskier manner during normal times, knowing that it will not bear the full cost during a downturn. Consistent with this moral hazard channel, we observe that the estimated impact on resiliency varies across size thresholds. While mergers involving large banks with combined assets of $50 billion or more are expected to book an additional $600 million in loan losses per quarter during a severe economic downturn, smaller mergers under $1 billion barely move the needle on financial resiliency. In other words, our main empirical finding of worsened resiliency is driven entirely by mergers involving big banks that become even bigger, even more systemically important. If these banks believe that they are indeed too big to fail—and are becoming even bigger—they are more likely in engage in risky lending practices. Thus, our analysis is consistent with moral hazard weakening resiliency.

Next, we turn our attention to diversification, which is typically viewed in an unequivocally positive light—expanding into new product lines or new geographic markets can improve risk-return trade-offs, thereby strengthening a bank's resiliency and reducing its probability of failure. For instance, geographic diversification may reduce a bank's idiosyncratic risk of adverse economic shocks (Deng and Elyasiani, 2008; Goetz, Laeven, and Levine, 2016; Chu, Deng, and Xia, 2020; Doerr and Schaz, 2021). However, we find that not all diversification is created equal when it comes to mergers and crisis resiliency. In fact, we find that having *too much* diversification can reduce resiliency among certain large banks that engage in mergers, as they are likely creating a business model that is overly complex.

With a focus on portfolio diversification (i.e., business models), we construct the "distance" between the acquirer and target banks' loan portfolios. A greater portfolio distance represents a merger of two more distinct banks with respect to their business models. We find that portfolio diversification does not play a significant role in mergers below $50 billion. Interestingly, for mergers between $50 billion and $100 billion, greater diversification—that is, the combination of more dissimilar business models—actually leads to *reduced* resiliency. Finally, portfolio diversification among banks with more than $100 billion in assets has no impact on resiliency, likely because the moral hazard channel dominates. In other words, portfolio diversification only matters for bank mergers between $50 billion and $100, and it matters in a way that is negative. Too much of it can be a bad thing.

We then examine diversification along the geographic dimension, which the literature has examined in great detail. Interestingly, we discover that geographic diversification does not materially affect the crisis resiliency of merged banks relative to their counterparts. Portfolio diversification matters more in our analysis. In other words, when contemplating a proposed merger from a financial stability perspective, it's more important for regulators to focus on how different the two banks' lending lines are from each other as opposed to the areas in which they are conducting their business.

For completeness, we also examine whether merged banks' liquidity and regulatory capital help preserve resiliency during times of stress (Berger and Bouwman, 2013). Consistent with the literature, we find that higher levels of liquidity and regulatory capital indeed strengthen resiliency. Altogether, our results provide a framework to differentiate good mergers from bad mergers in the context of financial stability. Our article engages with at least three bodies of literature. First, it speaks to the literature focused on the costs and benefits of bank mergers. Many papers examining the consequences of bank consolidation have focused on the costs and benefits to banks (Cornett and Tehranian, 1992; Houston and Ryngaert, 1994; Berger, Demsetz, and Strahan, 1999; Cornett et al., 2003; Carletti, Hartmann, and Spagnolo, 2007). Some studies find positive effects on economic activity resulting from financial integration and expansion (Avkiran, 1999; Penas and Unal, 2004) while other studies find bank mergers can have negative implications in terms of higher interest rates, diminished lending, and lower productivity gains (Berger et al., 1998; Garmaise and Moskowitz, 2006; Erel, 2011). Previous analysis has shown effects vary by merger size: large bank mergers lead to slower loan growth, while small, community bank mergers are associated with higher loan growth (Sapienza, 2002; Avery and Samolyk, 2004; Bonaccorsi Di Patti and Gobbi, 2007; Jagtiani, 2008). Despite an abundance of literature investigating the economic consequences of bank mergers, few papers have focused on the financial stability implications of bank mergers. We seek to bridge that gap by showing that bank M&A leads to increased riskiness of banks and worsened financial resiliency outcomes.

Second, we contribute to the literature on diversification and bank resiliency. The extant literature documents the importance of diversification for banks (Demsetz and Strahan, 1997; Acharya, Hasan, and Saunders, 2006; Goetz, Laeven, and Levine, 2016; Chu, Deng, and Xia, 2020; Doerr and Schaz, 2021). Our paper adds to the literature by dissecting the role of portfolio diversification and geographic diversification in bank mergers.

Third, we contribute to the literature by proposing a forward-looking measure to assess the financial stability outcomes of banks and financial institutions. Regulators, researchers, and practitioners have long been relying on measures based on banks' financial reporting and thus is mostly backward-looking in nature. These metrics includes the classic measures of the Loan-to-Value Ratio (LTV), Debt Service Coverage Ratio (DSCR) and Non-Performing

Loans (NPLs) ratio, as well as indices calculated using other credit rating models, such as Altman's Z-Score (Altman, 1968). Our approach, similar to the forward-looking stress tests, aims to evaluate how banks' loan portfolios perform under hypothetical adverse economic scenarios. We argue that this method could be widely applied in assessing the merger outcomes of banks and financial institutions under hypothetical stress scenarios, and thereby help regulators and policymakers to understand the financial stability implications from these deals.

The rest of our paper is organized as follows: In Section 2, we provide institutional background and a brief review of bank mergers from the regulatory perspective. In Section 3, we discuss the data and sample used in our analysis. In Section 4, we explain the identification strategy and empirical design. In Section 5, we present the main results. Section 6 concludes.

2. Regulatory Background

During the GFC, the United States witnessed the failure or near-failure of many large financial institutions. Politicians, regulators, and academics began to repeat the mantra of TBTF. The articles written on that theme, or some variation of that theme, are well known. But how did the U.S. banking ecosystem produce so many TBTF institutions? The U.S. banking sector experienced tremendous consolidation via mergers and acquisitions in the 1980s, 1990s, and 2000s. Some of those mergers transformed regional banks into the global mega-banks that we saw during the GFC.

Not surprisingly, following the GFC, Congress decided to act by amending the laws that affected the merger process. For example, Congress modified section 3 of the Bank Holding Company Act to require the Federal Reserve to consider "the extent to which a proposed acquisition, merger, or consolidation would result in greater or more concentrated risks to the stability of the United States banking or financial system." Congress also added "risk to the stability of the United States banking or financial system" to the list of possible adverse effects that the Federal Reserve must weigh against any expected public benefits in considering a proposal under section 4 of the Bank Holding Company Act. Moreover, the Federal Reserve was required to consider "the extent to which the proposed acquisition would result in greater or more concentrated risks to global or United States financial stability or the United States economy" in reviewing a notice submitted pursuant to section 163(b) of the Dodd-Frank Act.[1]

Against this backdrop, regulators do not possess an analytically rigorous framework to evaluate the financial stability consequences of bank mergers. This is a glaring shortcoming, particularly when one compares the financial stability analysis to the competition analysis, which features robustness analysis that leverages the Herfindahl-Hirschman Index (HHI).[2] Simply put, where is the quantitative analysis on financial stability that examines the trade-offs between, say, the costs of moral hazard and the benefits of diversification?

In recent years, the Federal Reserve has examined metrics like the size of the merging entities, their interconnectedness with the financial sector, and their cross-border activities. (These metrics line up with those that constitute the GSIB 1 Method Score.) In the BB&T-SunTrust merger, for example, the Federal Reserve clearly reviewed the combined size as a financial stability problem but did not view it as disqualifying.[3] The analysis, however, lacked a formal framework to tie it all together in a systematic way. And, without a formal framework, it is almost impossible to know which combined size threshold threatens financial stability or what degree of interconnectedness threatens financial stability. Regulators like

[1] In addition to evaluating the financial stability consequences of a merger, the Bank Merger Act and its companion statute, the Bank Holding Company Act, direct the federal banking agencies to consider the proposal's anticompetitive effects, transaction's probable effect on the public interest, and (4) the companies' financial and managerial resources. The statutes authorize the agencies to reject a merger proposal if any one of these factors weighs against approval. For a detailed description of the merger review process, see Kress (2020).

[2] To be sure, the HHI component of anticompetitive analysis is not perfect. But it is a formal framework that allows for more than just ad hoc review.

[3] In the Federal Reserve's Order Approving the Merger of BB&T and Suntrust, the Federal Reserve states: "Although the proposed transaction would increase BB&T's overall size and result in Truist Bank becoming the sixth largest commercial bank in the United States based on U.S. deposits, the combined organization's larger size must be viewed in conjunction with other metrics. Accordingly, the Board has considered other factors, both individually and in combination with size, to evaluate the likely impact of this transaction on the stability of the U.S. banking or financial system."

the Federal Reserve are left with making a series of ad hoc decisions.[4]

Notably, the Federal Reserve also holds the position that "[merger] proposals involving an acquisition of less than $10 billion in total assets, or that result in a firm with less than $100 billion in total assets, generally are not likely to pose systemic risks. Accordingly, the [Federal Reserve] presumes that a proposal does not raise material financial stability concerns if the assets involved fall below either of these size thresholds, absent evidence that the transaction would result in a significant increase in interconnectedness, complexity, cross-border activities, or other risk factors." Here, the Federal Reserve provides a safe harbor based on two quantitative cut-offs. While safe harbors can be useful, it is not clear how these two asset thresholds were derived. Moreover, we observe that the words resiliency or probability of default do not show up in these discussions. The focus is on size and systemic footprints, which only paint a partial picture of the financial stability consequences.

It is therefore our ambition to address this shortcoming by providing a rigorous analytical framework to assess changes in resiliency during a crisis. While we do not assert that our framework must be *the* framework used by regulators, our framework does, at the very least, provide a useful proof of concept that regulators can use to build a less ad hoc framework going forward. Given that we are now over 15 years from the GFC and over a year removed from the SVB banking panic, the need for a formal financial stability merger review framework is pressing.

3. Data

We focus our empirical analyses on commercial banks and obtain data from several sources. Specifically, we obtain data on bank merger transactions from the Federal Financial Institutions Examination Council's (FFIEC) National Information Center (NIC). We collect information on all commercial bank mergers and acquisitions (M&As) spanning 1984 to

[4] As argued by Kress (2020), "In the decade since Congress added the financial stability factor to the bank merger statutes, the agencies have relied on ad hoc assessments of a merged bank's size, complexity, interconnectedness, and activities to determine whether a proposal would increase systemic risks."

2018. This dataset identifies the acquired bank, acquiring bank, and merger date for each merger transaction. Furthermore, we collect data on bank financial data from quarterly Call Reports filed through the FFIEC from 1984 to 2018. These data include variables on bank loan portfolio performance and other balance sheet, income sheet, and regulatory capital ratio information.[5]

We construct our primary sample using these two datasets. The merger transaction data allow us to identify the "treatment" group of banks that engaged in M&A activity. We form a control group by propensity score matching banks that did not engage in M&A activity to banks that did using observable characteristics from the bank financial data.

In assessing changes in financial resiliency before and after mergers, we require a measure for financial resiliency. We use net charge-off (NCO) rates, which represent the percentage of a lender's outstanding loans that is classified as delinquent or bad debt, as our primary measure of bank financial resiliency.[6] Data on NCO rates are available through the quarterly Call Reports.

Implementing our forward-looking approach to estimate bank financial resiliency outcomes associated with bank mergers is a two-step process. First, we obtain historical data on various macroeconomic variables, available through FRED and the Bureau of Labor Statistics, that are indicative of business cycles and are closely linked to loan portfolio performance (e.g., BBB spread, unemployment rate, VIX) from 1975 to 2018. These data allow us to estimate the historic sensitivity of bank financial resiliency to macroeconomic variables. Specifically, we estimate the sensitivity of bank NCO rates to macroeconomic variables across a five-year period before and after the M&A transaction. Second, using the estimated historical relationship, we project banks' financial resiliency under adverse economic conditions. To model these conditions, we follow the "severely adverse scenario" laid out in the 2019 Dodd-Frank Act Stress Test (DFAST). This hypothetical scenario is

[5] See Appendix A for details on the variables used in the analyses.

[6] NCO rates are widely used in the context of risk management and provide insights into the quality of a bank's loan portfolio given broader economic conditions.

characterized by an unemployment rate that climbs to 10 percent and a corresponding real GDP decline of 8 percent. Accompanying the severe decline in real activity, the interest rate for 3-month Treasury bills falls 2.25 percentage points and remains near zero through the end of the scenario. The 10-year Treasury yield falls by a smaller amount, resulting in a mildly steeper yield curve. Specifically, the 10-year Treasury yield bottoms out at approximately 0.75% then gradually rises to 1.5-1.75%. Correspondingly, the spread between yields on investment-grade corporate bonds and long-term Treasury securities widens to 5.5%.[7]

Our final sample consists of 7,947 mergers that occurred between the first quarter of 1984 and the fourth quarter of 2013. While we collect data from 1980 to 2018, the starting and ending year of our sample corresponds to the five-year estimation window before and after the merger.[8] Figure 1 shows the distribution of mergers in our sample by combined merger size. As evidenced by the significantly right skewed distribution, the majority of bank mergers are small in size. Indeed, in our sample, more than 80% of commercial bank mergers are less than $1 billion in combined assets. Table 1 presents descriptive statistics of key variables for merged (i.e., treated) banks in our sample.

4. Empirical Strategy

We next explain our empirical approach. We first walk through the construction of the forward-looking measure of financial resiliency that captures banks' loan losses during economic stress. Then, we apply the difference-in-differences framework and compare the changes in financial resiliency in merged banks to one with similar characteristics that did not engage in a merger.

[7] More details on the stress scenario can be found in the 2019 Supervisory Scenarios for Annual Stress Tests Required under the Dodd-Frank Act Stress Testing Rules and the Capital Plan Rule.
[8] More details about this estimation process is provided in the Section 4.

4.1. Measuring Resiliency in a Forward-Looking Loan Loss Framework

To assess a bank's financial resiliency, we must estimate the performance of its loan portfolio during economic stress. To this end, we first calculate the sensitivity of the bank's loan portfolio performance to economic conditions across time using historical data. Once we have estimated this historical sensitivity, we combine the estimates with the standard set of hypothetical economic stress scenarios used in Federal Reserve's DFAST exercise and the characteristics of the banks measured at the time of assessment to obtain the forward-looking financial resiliency—a measure reflecting how the bank's loan portfolio performs under economic stress.

We proxy bank loan portfolio performance with the net charge-off (NCO) ratio, representing the percentage of a lender's outstanding loans that is classified as delinquent or bad debt. The measure is widely used in the risk management context. By evaluating this rate, bank analysts and supervisors obtain insights into the quality of banks' loan portfolio given broader economic conditions. A lower NCO ratio during economic distress suggests stable portfolio quality and strong resilience for the bank during adverse economic conditions. In other words, the NCO ratio is an indicator of a bank's portfolio quality and loan performance.[9] In prior literature, NCO ratios have been widely used by scholars and policymakers as a key variable to measure bank loan quality and performance (Berger and Udell, 1990; Bhat, Ryan, and Vyas, 2019).[10]

We use a standard set of scenario variables developed by the Federal Reserve to capture "economic stress." Specifically, we employ the Federal Reserve's 2019 "severely adverse"

[9] When borrowers fail to pay the interest on their loans on time, banks will first mark the loan as "delinquent." Eventually, these non-performing loans will be "charged off" if the bank fails to collect payment from the borrower. In other words, "charge off" reflects the terminal state of a loan when it defaults. The net charge-off the dollar amount representing the difference between gross charge-offs and any subsequent recoveries of delinquent debt.

[10] The NCO ratio is the primary parameter used in the Federal Reserve's Supervisory Stress Testing Programs to assess the capital adequacy of the country's largest banks. See further: https://www.federalreserve.gov/publications/2023-june-supervisory-stress-test-methodology-descriptions-supervisory-models.htm

economic scenario to capture economic stress. The set of hypothetical economic parameters was developed for the Federal Reserve's supervisory stress tests. According to the guidelines put forth by the Federal Reserve, the severely adverse scenario encompasses a comprehensive set of macroeconomic and financial variables covering a 13-quarter recessionary period that mimics the status of the economy during the most severe downturns in the post-war era. Projecting bank loan performance during this "severely adverse" economic scenario allows us to understand how bank portfolios of different characteristics perform under the same commonly-defined hypothetical economic stress.[11]

Putting everything together, our approach projects banks' loan portfolio losses as measured by the NCO ratio over the 13-quarter horizon of the "severely adverse scenario" based on the historical relationship between net charge-off ratios, macroeconomic and financial market conditions, and loan portfolio characteristics. By projecting merged banks' potential losses under economic distress—and comparing those losses to projected losses of banks that did not merge—we can answer the question of whether bank mergers impact financial resiliency.

The model is developed in a parsimonious fashion, with the goal of capturing loan losses through business cycles while providing an intuitive explanation of how NCO ratios move in response to different macroeconomic variables. Specifically, we estimate each bank's loan performance (reflected in the NCO ratio) as a function of the 1-quarter lagged charge-off ratio, BBB spread, and 2-quarter lagged change in unemployment in the five years before and after a bank's merger transaction.

A general concept of the approach can be illustrated as:

$$NCO_{b,t} = f(NCO_{b,t-1},\, BBB_t,\, \Delta UE_{t,t-2}) \tag{1}$$

[11] To ensure that the results are comparable and not driven by changes in the hypothetical scenarios used, we employ the DFAST 2019 scenario in the projection across all M&A events. Using a different scenario does not change the result.

where $NCO_{b,t}$ indicates the NCO ratio of bank b in quarter t and $NCO_{b,t-1}$ is the NCO ratio recorded by bank b in quarter $t-1$. The autoregressive term reflects the loan performance of the previous period $t-1$. The coefficient estimate on this term captures the transition from one state to the other. BBB_t is the BBB spread over the 10-year T-bill rate at quarter t, and $\Delta UE_{t,t-2}$ captures the change in the unemployment rate from quarter $t-2$ to quarter t. We include the BBB spread as a fast-moving economic indicator that reflects the amount of credit risk in the system from the investors' or market participants' point of view. The two-quarter change in the unemployment rate proxies for the overall macroeconomic conditions. The choice of two quarters is justified as the unemployment rate is a slow-moving macro variable. It takes time for a macro shock to transition to the labor market, affecting corporate loan payment capacity and, ultimately, banks' charge-off decisions on non-performing loans.

To validate our choice of macroeconomic variables, we conduct a LASSO regression for variable selection. We begin by including a broader set of six potential variables: (1) 1-quarter lagged actual NCO rate; (2) BBB spread; (3) real GDP growth; (4) nominal GDP growth; (5) 1-quarter difference in unemployment rate; and (6) 2-quarter difference in unemployment rate. From this set of variables, we perform the cross-validation technique to find a "proper" λ value that predicts the NCO rate value with the highest accuracy. Values of λ that are too small lead to overfitting while λ values that are too large lead to underfitting. Figure 3 plots the cross-validated estimates of the mean squared prediction error for the LASSO analysis. The one-standard-error value of λ shrinks the real GDP growth, nominal GDP growth, and 1-quarter difference in unemployment rate variables to zero. As a result of the LASSO regression, we are left with the same set of variables as in Equation 1, bolstering the validity of our variable selection.

The model is estimated using a time series of historical NCO ratios at a certain bank (or a group of banks) across a five-year period. Based on the sensitivity of the NCO ratios to macroeconomic variables, we then estimate the sensitivity in order to project banks' NCO ratios consistent with the evolution of macroeconomic conditions under severely adverse scenarios. To estimate projected losses, the projected NCO ratio is applied to banks' loan balances, giving us a forward-looking measure of the bank's financial resiliency under stress.

To validate our empirical NCO ratio estimation, we conduct an in-sample and out-of-sample test comparing our predicted NCO ratios with the actual realized NCO ratios. Panel A of Figure 4 plots the in-sample test of quarterly projected NCO rates after estimating the sensitivity of banks' to the macroeconomic variables described in Equation 1 from 1990 Q1 to 2018 Q4. The in-sample test provides validation for the chosen model parameters. As shown in the figure, our predicted NCO rates are closely aligned with the realized NCO rate values across the sample period. Panel B of Figure 4 presents the results of the out-of-sample test. In this test, we first estimate banks' sensitivity to the macroeconomic variables from 1990 Q1 to 2005 Q1, then we estimate the NCO ratio from 2005 Q2 to 2018 Q4. The out-of-sample test provides further validation for the forecasting power of our model. Again, we see the projected NCO rates follow the actual NCO rate trend well.

4.2. Stacked Difference-in-Differences Regressions

With the resiliency measure in place, we investigate whether banks become more or less resilient after mergers with a stacked difference-in-differences (DID) methodology. In particular, we compare how resiliency changes across banks that engaged in mergers to similar banks that did not. For each merger event, we calculate the changes in resiliency for the treated (i.e., merged) and control banks by collecting data on banks' performance five years before and five years after the merger quarter to form an event subsample. Critically, the five-year window before and after the merger event allows us to estimate resiliency based on the relationship between loan performance and economic conditions. The empirical strategy we employ is similar to the stacked DID approach for multiple events first used in Gormley and Matsa (2011) and later in Cengiz et al. (2019), Deshpande and Li (2019), Baker, Larcker, and Wang (2022). We stack all merger event subsamples together and employ the DID framework to examine the impact of mergers on resiliency.

We identify control firms using propensity score matching based on observable bank characteristics prior to each bank merger event subsample for the DID analysis, as discussed in the next subsection; and we use the following ordinary least squares DID regression setup:

$$\Delta Resiliency_{b,t} = \beta_1 Treat_b + \beta_2 Post_t + \beta_3 Treat_b \times Post_t + \beta_4 X_{b,t-1} + \gamma_b + \theta_t + \varepsilon_{b,t}. \quad (2)$$

where $Treat_b$ is an indicator variable that takes the value of 1 if bank b is involved in a merger transaction and 0 otherwise. Similarly, $Post_t$ equals 1 if quarter t is within 20 quarters after the merger transaction and 0 otherwise. The outcome variable, $\Delta Resiliency_{b,t}$, captures the changes in financial resiliency for bank b in quarter t under a hypothetical severely adverse economic scenario. As *Resiliency* is constructed using projected NCO ratios under economic stress, a higher value indicates increased NCO ratios under stress, signaling a weakening of bank financial resiliency. $X_{b,t-1}$ is a vector of bank-level control variables that include 1-quarter lagged bank assets, ROA, liquidity ratio, and T1 capital ratio. Bank fixed effects γ_b are included to absorb the potential influence of any time-invariant bank heterogeneity. Year-quarter fixed effects θ_t are included to absorb the potential influence of any macro trends in loan loss activities. Robust standard errors are clustered at the bank and year-quarter levels.

The coefficient of interest β_3 represents the change in financial resiliency for bank b pre- and post-merger compared to similar but unmerged banks. Theories regarding bank mergers and financial resiliency provide ambiguous predictions. As such, ex-ante, the sign for β_3 is unclear. A positive β_3 indicates lower resiliency after M&A, possibly suggesting an increased risk-taking behavior and systemic risk exposure. Conversely, a negative β_3 means greater resiliency under stress, signaling that bank mergers may promote synergies, diversification, or efficiency gains, decreasing the overall sensitivity of loan performance to macroeconomic shocks.

4.3. Matching Exercise in Constructing the Stacked DID Sample

The stacked DID approach requires the construction of a treatment group and a comparable control group for each merger event. To achieve this goal, we use a propensity score matching algorithm to find a set of banks that are similar to the merged bank along observable characteristics to serve as the control group. We match treatment to control banks based on total assets (to proxy size), noninterest income (to proxy business model), return on assets (to proxy profitability), and Tier 1 capital ratio (to proxy regulatory capital).

Figure 2 depicts our research design in stylized form. We observe the M&A transaction between Banks 1 and 2—these banks form the treatment group. To have a credible comparison group, we must identify "Bank 3" (or a set of banks that mimic Bank 3) that is similar to Banks 1 and 2 except it did not undergo M&A activity. To identify control banks, we first explore the universe of banks in our dataset and remove the banks that engaged in M&A activity five years prior or one year after the date of the merger of interest. Second, we apply the propensity score matching algorithm on the variables specified above to identify the ten nearest neighbor matches. These ten banks form the control group for Banks 1 and 2.

To see our approach from a slightly different angle, Table 2 presents another stylized example. Suppose Bank A, with \$100 billion in total assets, seeks to acquire Bank B, with \$15 billion in total assets. After the merger goes through, the resulting Bank AB has \$115 billion in total assets. When searching by total assets, we choose candidates with assets closest to \$115 billion (\$100 billion + \$15 billion); when searching by ROA, we choose candidates with ROA that most closely match the weighted average of Bank A's ROA and Bank B's ROA—specifically, (100/115) x Bank A's ROA + (15/115) x Bank B's ROA; so on and so forth.

Table 3 presents summary statistics on the matching variables used in the propensity score match. As expected, there is little discernible difference between the control and treated groups along the dimensions we have selected. To be sure, the treated group is larger in size, but the other three ratios are almost identical.

5. Empirical Results

We begin by examining the effect of bank mergers on financial resiliency using our forward-looking approach. Table 4 reports our main results estimated from Equation 2. The positive interaction term in Column (1) indicates that relative to banks of similar characteristics that did not undergo M&A activity, merged banks, on average, exhibit higher projected loan losses during severely adverse economic conditions. In other words, merged banks have weakened financial resiliency, on average.

In terms of economic magnitude—using the median loan portfolio of $90 million for banks in our sample—a 0.2 p.p. increase in projected NCO ratio translates to an additional $2.3 million in projected loan losses over 13 quarters.[12] For the subset of loan portfolios in the top 75th, 90th, and 95th percentiles, the estimated loan losses are $10.0 million, $49.6 million, and $146.6 million over 13 quarters, respectively.[13]

5.1. Bank Size

Next, we investigate whether the effect of bank mergers on financial resiliency varies by bank size. Bank size is an important parameter to consider when it comes to studying financial stability as banks of differing sizes are under different regulatory scrutiny and may have different implications on financial stability (e.g., too big to fail banks). To examine this dynamic, we split the sample around major regulatory thresholds used by bank supervisors based on the size of the combined merged entity as well as the acquiring bank. For example, the Dodd-Frank Act imposes more stringent capital and liquidity requirements on banks with $50 billion or more in assets. To this end, we examine the financial resiliency implications for banks above and below the $50 billion size threshold and ask whether the effect varies significantly across regulatory size thresholds. Compared to mergers between smaller banks

[12] Estimated loan losses under the severely adverse economic scenario calculated are as $90 million $\times$ 0.2% $\times$ 13 quarters = $2.3 million

[13] Total loan portfolios for the 75th, 90th, and 95th percentiles are $384.8 million, $1.9 billion, and $5.6 billion, respectively. The calculation for the estimated loan losses under the severely adverse economic scenario follows from the previous footnote.

(i.e., less than $50 billion in combined assets), we find larger mergers significantly increase banks' projected losses under stress. Larger transactions with combined assets of at least $50 billion, as shown in Column (2) of Table 4, exhibit a 0.4 p.p. increase which results in approximately $1.5 billion in additional projected loan losses over 13 quarters. On the other end of the spectrum, when we analyze mergers with a combined asset size of under $50 billion, we estimate a coefficient of 0.1 p.p., which translates to $1.1 million in loan losses. This result is shown in Column (3). From these findings, we conclude larger mergers drive our headline result of weakened financial resiliency after bank mergers.

In Columns (4) and (5) of Table 4, we consider whether our findings differ based on the composition of the merger. For instance, it might be the case that a very different pairing of banks in a merger transaction yields worse (or better) results on the resiliency front. Indeed, a "merger of equals" might result in greater changes to the management of the combined bank (and, hence, more turbulence and less resiliency) whereas a large bank buying a small bank might result in more "business as usual." What we see is that size matters for the buyer. In Column (4), mergers with a buyer greater than $50 billion in assets were associated with an estimated coefficient of 0.3 p.p., which translates to $1.3 billion in cumulative loan losses over 13 quarters ($117 million in loan losses per quarter). In Column (5), smaller buyers (i.e., those under $50 billion in assets) had the smallest impact on resiliency, in line with our main findings.

As described previously, the Federal Reserve provides a safe harbor for "[merger] proposals involving an acquisition of less than $10 billion in total assets, or that result in a firm with less than $100 billion in total assets." We examine these thresholds as well. Figure 5 presents more granular breakdowns: under $1 billion, $10 billion, $25 billion, $50 billion, $100 billion, and greater than $100 billion. While mergers involving large banks with combined assets of $100 billion or more are expected to book significantly more losses in loan losses per quarter during a severe economic downturn, smaller mergers under $1 billion barely affect financial resiliency. This result suggests that size matters in evaluating the resiliency outcomes of bank mergers—a story consistent with the TBTF label and the rise of moral hazard.

5.2. Diversification

We now pivot to exploring the role of diversification in our findings. Typically, one hears that expanding into new product lines or into new geographic markets has the potential to improve risk-return trade-offs. However, analysis of diversification in past studies has proved ambiguous. On the one hand, portfolio diversification or geographic diversification may reduce a bank's idiosyncratic risk of adverse economic shocks (e.g., Doerr and Schaz, 2021). On the other hand, too much diversification could lead to higher losses due to the potential failure to integrate risk management and governance processes, thereby causing inefficiency from highly dissimilar and seemingly unfamiliar lines of business.[14] Inspired by this trade-off, we empirically test if and how resiliency differs across levels of diversification between acquirer and acquired banks.

We first examine the effect of loan portfolio diversification by calculating "portfolio distance," which captures the dissimilarity in loan portfolios (including, for example, wholesale loans, mortgages, and consumer loans) between the acquirer and the target bank. Our measure for portfolio distance is constructed as the sum of the squared differences between the acquiring and acquired banks' wholesale, mortgage, and consumer loan portfolios. The resulting portfolio distance score takes values ranging from 0 to 3, with higher values indicating larger portfolio distances.[15] Using this measure, we split the sample into quartiles and estimate the regression specification laid out in Equation 2 for each subsample. Results from this subsample analysis are reported in Table 5. The interaction term capturing the change in financial resiliency remains positive and statistically significant across all quartile splits. As such, the estimates suggest, across the entire sample of mergers, there is no evidence that

[14] For example, many studies examining the implications of corporate M&A deals document negative effects on shareholder returns and firm value when firms of irrelevant industries engage in mergers and acquisitions (Gormley and Matsa, 2011).
[15] By construction, banks in the control group always have a portfolio distance score of 0 since there is "acquiring" and "acquired" bank.

portfolio diversification mitigates the adverse effects on financial resiliency.

Given the differing effects by bank size documented Table 4, we examine whether there are differential effects of portfolio diversification that interact with bank size. We repeat the analysis from above, splitting our sample by combined bank assets around common regulatory thresholds. Subsample analyses using mergers under $10B, between $10B and $50B, between $50B to $100B, and above $100B are presented on Table 6 through Table 9. We find portfolio diversification does not move the needle for smaller bank mergers (i.e., under $50 billion) and the largest bank mergers (i.e., over $100 billion). This is likely because mergers between small banks do not have a noticeable impact on resiliency whereas mergers involving the largest banks create too much moral hazard to offset. Interestingly, we do find a differential impact for bank mergers between $50 billion and $100 billion, but one that is not beneficial. Indeed, the union of two banks that are too different (i.e., in the top quartile of portfolio distances) actually result in worse post-merger resiliency. This implies that there can be too much of a good thing, as mergers between banks with significantly different business models may face integration frictions.

Next, we turn our attention to geographic diversification. The literature has long documented benefits related to geographic diversification in bank risk mitigation (e.g., Doerr and Schaz, 2021). To measure geographic diversification, we calculate the distance (in miles) between the acquirer and the acquired bank using the reported ZIP code of the two bank headquarters. Similar to our portfolio diversification analysis, we split the sample into quartiles based on this distance and estimate the effect of bank mergers on financial stability outcomes for each subsample. Results shown in Table 10 suggest geographic diversification does not affect the baseline effects on bank resiliency. Across all quartile sample splits, the interaction term capturing the change in resiliency post-merger is still positive and statistically significant.

5.3. *Liquidity and Regulatory Capital*

Prior literature also highlights the importance of banks' liquidity and regulatory capital buffers in preserving financial resiliency during crisis time (Berger and Bouwman, 2013). With that in mind, we investigate whether banks with higher liquidity and regulatory capital buffers as well as better portfolio quality might help them mitigate the worsening of resiliency after mergers. To estimate the effect of these characteristics on financial resiliency, we augment our initial regression specification to include a triple interaction term:

$$\begin{aligned}\Delta Resiliency_{b,t} &= \beta_1 Treat_b + \beta_2 Post_t + \beta_3 Bank\ Characteristic_{b,t} \\ &\quad + \beta_4 Treat_b \times Post_t \times Bank\ Characteristic_{b,t} + \beta_5 X_{b,t-1} + \gamma_b + \theta_t + \varepsilon_{b,t}.\end{aligned} \tag{3}$$

We first estimate this regression using a variety of different measures to capture bank liquidity. Table 11 presents the results where the liquidity measure is defined as either the liquidity ratio, cash ratio, or Treasury bond plus mortgage-backed security (MBS) ratio.[16] Results indicate that the increased losses under stress post-merger is attenuated by liquidity. Stated differently, the more liquid assets the combined banks hold, the more resilient the merged entities are to severely adverse shocks. This result is consistent with economic intuition. The more liquid a bank is, the more likely it can withstand poor economic conditions. Moreover, this finding is robust to both alternative definitions of liquidity.

Next, we conduct a similar analysis is conducted using three measurements of regulatory capital: the leverage ratio, Tier 1 capital ratio, and total capital ratio. The findings reported in Table 12 indicate higher levels of the leverage ratio do not materially reduce the losses under stress among merged banks. However, both the Tier 1 capital ratio and the total capital ratio show negative coefficients that are statistically significant. These coefficients suggest higher levels of regulatory capital reduce the losses under stress for merged banks. Similar to the liquidity measure, these results are intuitive. Regulatory capital provides a

[16] Variable definitions are provided in Appendix A.

buffer for banks during economic downturns. Thus, we should expect banks that maintain higher levels of regulatory capital to be more resilient to macroeconomic shocks.

6. Conclusion

The question of whether bank mergers harm financial stability has been frequently debated by scholars and policymakers for almost two decades now, yet we still do not have a clear answer. To move the debate forward, we use a novel forward-looking resiliency measure and a stacked difference-in-differences design to identify the impact of mergers under adverse macroeconomic conditions. Overall, we find that mergers are associated with a decline in resiliency. In other words, merged banks are more likely to fail during a crisis. But we are careful to note that this effect varies considerably with bank size. For mergers under $1 billion in combined assets, there is little-to-no change in resiliency. However, for merged entities of greater than $50 billion in combined assets, there is a sharp decrease in resiliency. This main finding is consistent with a hypothesis of rising moral hazard and TBTF institutions.

We also conduct a number of additional tests to explain and strengthen our main finding. We learn that *too much* portfolio diversification can actually worsen of the post-merger resiliency of certain banks, while geographic diversification does not move the needle at all. We also observe that having higher levels of liquidity or regulatory capital can mitigate the negative impact of mergers.

As regulators and supervisors review the current bank merger framework, they should consider different measures for evaluating the impact on financial resiliency. Doing so would lead to a few implications. First, it is unclear whether any merger should be given a favorable presumption on financial stability grounds. On average, mergers worsen the financial resiliency of merged banks relative to their non-merged counterpart banks. Each merger should, therefore, be reviewed based on a case-by-case basis. Second, the stringency of the regulators' review should increase with the size of the proposed merger. As shown, the increase in loan losses under stress is almost monotonic. In other words, larger banks seeking to merge should face a heavier burden of proof. Third, regulators should consider the role of portfolio diversification and prudent risk management.

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Appendix A. Variable Definitions

Variable	Definition	Source
Bank Characteristics		
Assets	Total bank assets (variable used in analyses are log transformed)	Call Report
Loan / assets	Total bank loans divided by assets	Call Report
Noninterest income / assets	Noninterest income as reported on Call Report divided by bank assets	Call Report
T1 ratio	Total Tier 1 regulatory capital	Call Report
Liquidity ratio	Total cash divided by total deposits	Call Report
Cash ratio	Total cash divided by total assets	Call Report
Treasury + MBS ratio	Total Treasury bonds plus total mortgage-backed securities (MBS) divided by total assets	Call Report
Leverage ratio	Tier 1 capital divided by total assets	Call Report
Tier 1 capital ratio	Tier 1 capital ratio divided by risk-weighted assets	Call Report
Total capital ratio	Sum of Tier 1 capital and Tier 2 capital divided by risk-weighted assets	Call Report
Loan loss provisions	Loan loss provisions divided by total loans	Call Report
Charge-off ratio	Total loan charge-offs divided by total loans	Call Report

Variable	Definition	Source
Control Variables		
Bank size	Natural logarithm of total assets	Call Report
Bank liquidity	Bank liquidity ratio calculated as total cash divided by total loans	Call Report
Bank ROA	Return on assets calculated as net income divided by assets	Call Report
Bank capital ratio	Tier 1 capital ratio calculated as tier 1 capital divided by assets	Call Report
Dependent Variables		
Δ Resiliency	Projected net charge-off ratio for banks under the 2019 Dodd-Frank Act Stress Test (DFAST) Severely Adverse Scenario. Risk sensitivity estimates are calculated following Equation (1)	Call Report; 2019 DFAST Scenario
Demand deposits	Percentage of the sum of demand deposits of all bank branches to total assets	Call Report
Brokered deposits	Percentage of brokered deposits to total assets	Call Report
Total deposits	Percentage of total deposits to total assets	Call Report
Loan loss provisions	Percentage of allowance for loan and lease loss to loans and leases held for sale of banks	Call Report
Charge-off ratio	Ratio of total amount of loan charge-offs to loans and leases held for sale of banks	Call Report
Cash ratio	Percentage of total amount of cash to deposits	Call Report
T-bond + MBS ratio	Percentage of Treasury and agency debt plus mortgage-backed securities to bank total assets	Call Report
Leverage ratio	Tier 1 capital divided by total assets	Call Report
T1 capital ratio	Tier 1 capital divided by risk-weighted assets	Call Report

Variable	Definition	Source
Portfolio diversification	$\left(\frac{Wholesale\ loans_{acquirer}}{Total\ loans_{acquirer}} - \frac{Wholesale\ loans_{acquired}}{Total\ loans_{acquired}}\right)^2 + \left(\frac{Mortgages_{acquirer}}{Total\ loans_{acquirer}} - \frac{Mortgages_{acquired}}{Total\ loans_{acquired}}\right)^2 + \left(\frac{Consumer\ loans_{acquirer}}{Total\ loans_{acquirer}} - \frac{Consumer\ loans_{acquired}}{Total\ loans_{acquired}}\right)^2$	Call Report
Geographic diversification	Distance (in miles) between acquirer and acquired bank calculated using ZIP codes	Call Report
Independent Variables		
Treat	Indicator variable for banks engaged in merger and acquisition activity	NIC
Post	Indicator variable for quarters after bank merger occurred	Call Report; NIC
Treat x Post	Interaction variable between treat and post indicator variables	Call Report; NIC
Liquidity measure	Variable representing liquidity ratio (cash / deposits), cash ratio (cash / assets), or Treasury + MBS ratio (Treasury bonds + MBS / assets)	Call Report
Regulatory capital measure	Variable representing leverage ratio (Tier 1 capital / assets), Tier 1 capital ratio (Tier 1 capital / risk-weighted assets), or total capital ratio (Tier 1 + Tier 2 capital / risk-weighted assets)	Call Report

Figure 1: Distribution of Bank Mergers by Size in Sample

This figure shows the distribution of bank mergers by combined asset size. In total, there are 7,947 mergers in our sample. The majority of mergers (over 5,000) in our sample are below $1 billion in combined assets. A handful of mergers in our sample are over $100 billion (11 total mergers).

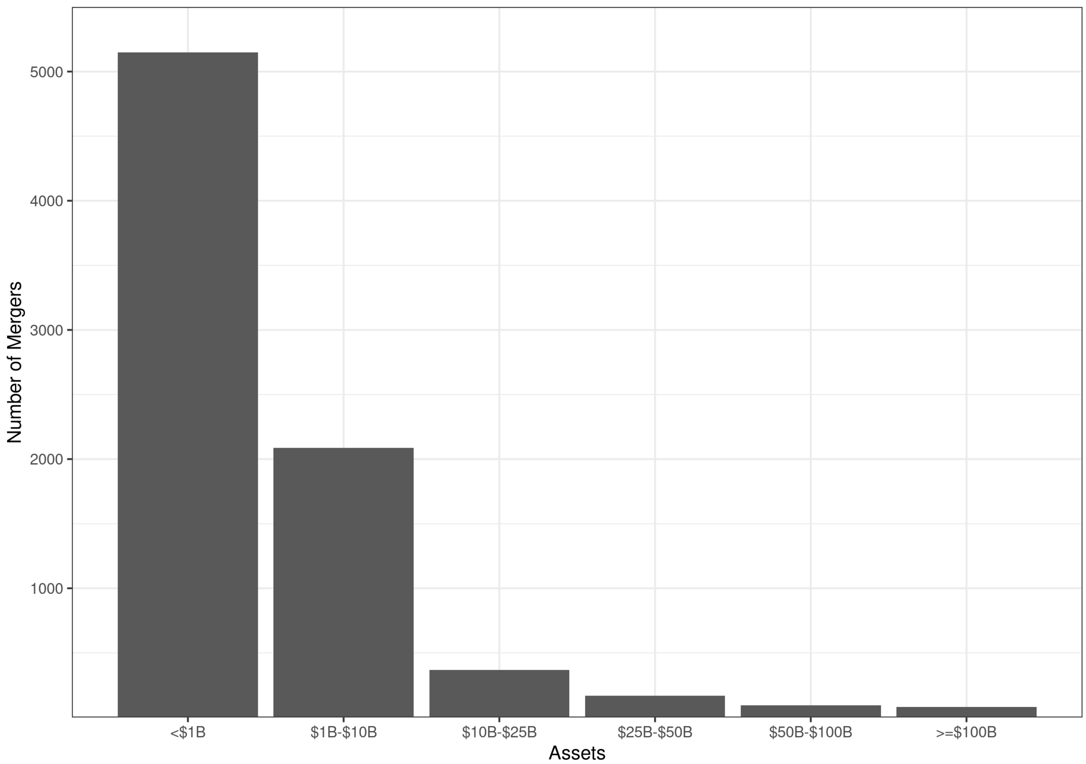


Figure 2: Stylized Methodology

This figure depicts our research design in stylized form. We aim to generate a control group of ten banks that are similar along observable characteristics for each merger transaction, but did not undergo merger and acquisition activity. After identifying the set of control banks, we implement a methodology akin to supervisory stress tests to project banks' net charge-off (NCO) ratio under a severely adverse economic scenario. Comparing the projected NCO ratio for the treatment group (i.e., merged banks) to their corresponding control group allows us to implement a stacked difference-in-differences structure to identify the effect of bank mergers on risk sensitivity.

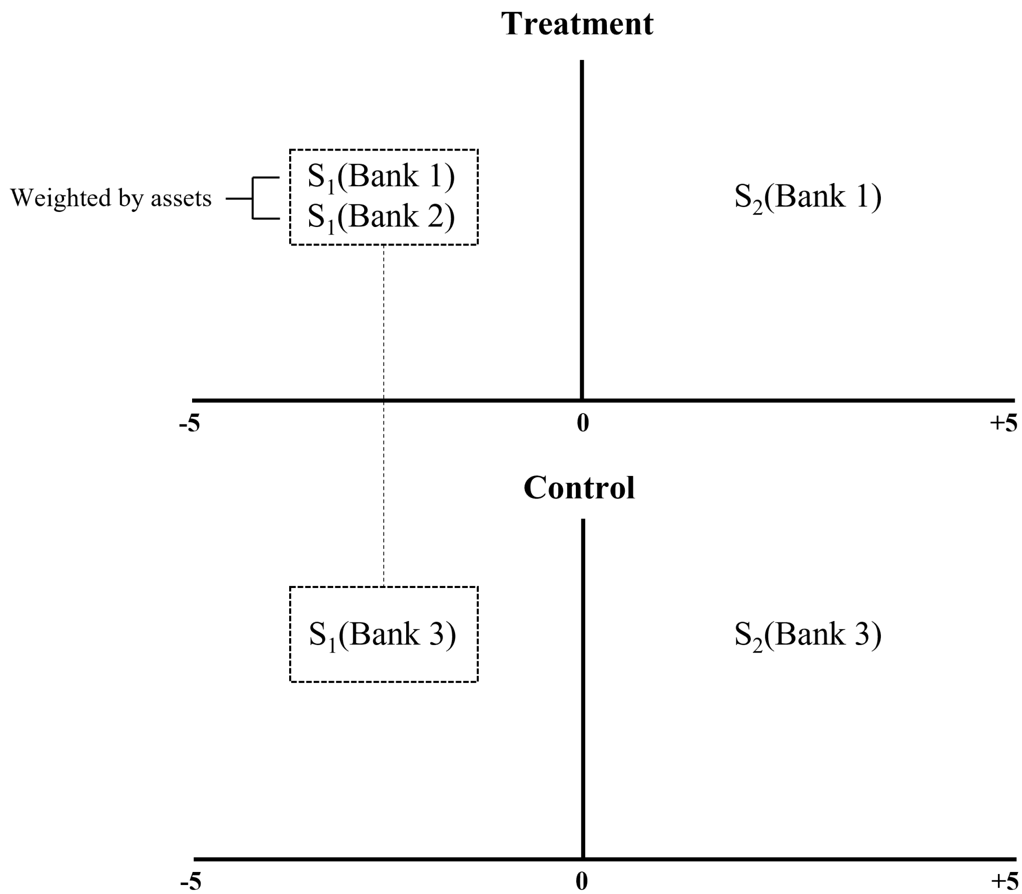


Figure 3: LASSO Analysis

This figure plots the cross-validated estimate of the mean squared prediction error for the LASSO analysis. The upper part of the plot shows the number of non-zero coefficients in the regression model for a given log λ. The dashed lines show the lcoation of the function minimum and the "one-standard-error" location.

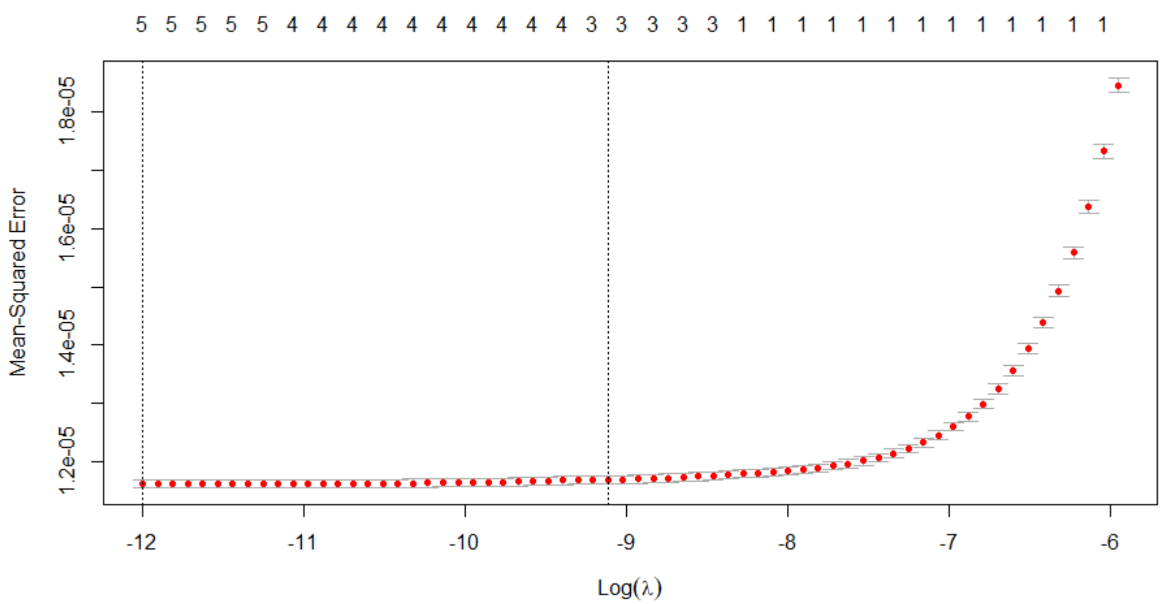
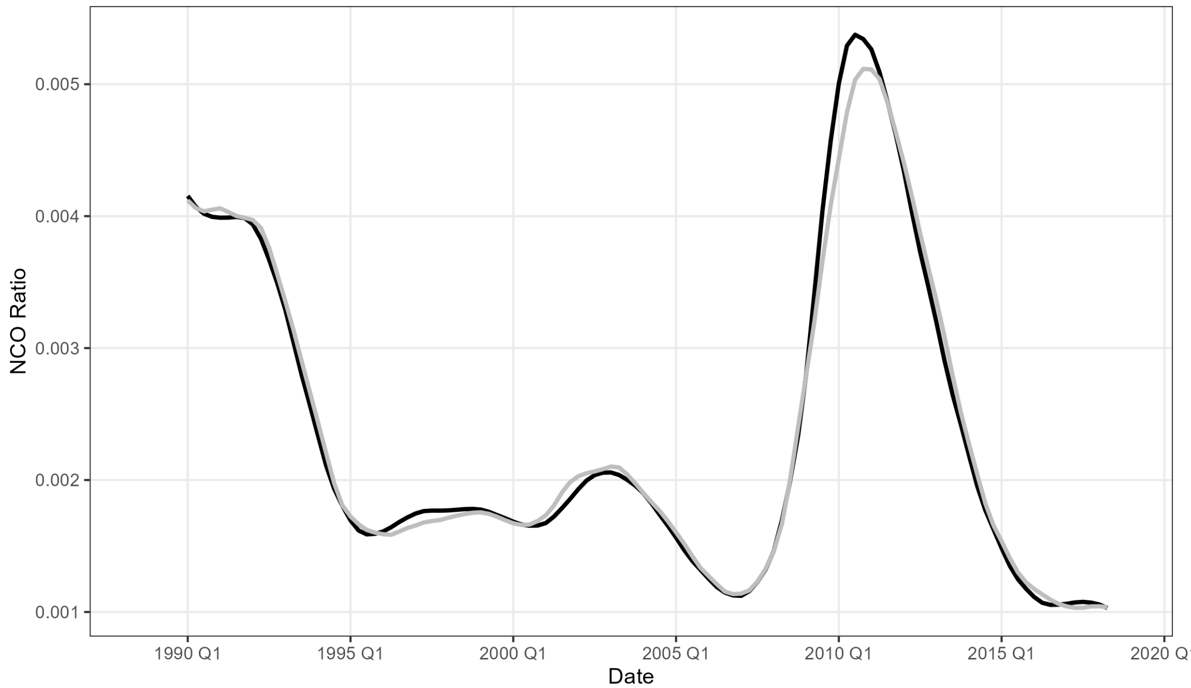
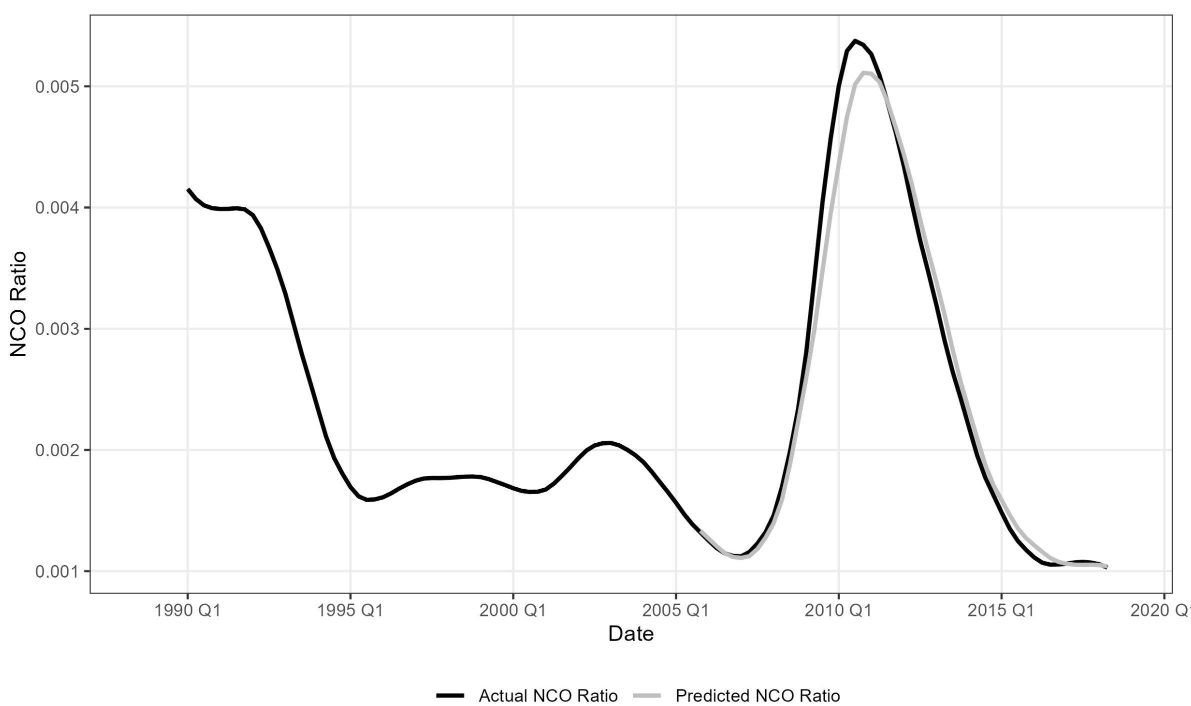


Figure 4: Net Charge-Off Model Validation

This figure compares the predicted net charge-off (NCO) ratio from the NCO model in **??**. Panel A presents the in-sample test from 1990 to 2018. Panel B presents the out-of-sample test using pre-2005 NCO ratios to predict NCO ratios during the crisis period and beyond.



(a) In-Sample



(b) Out-of-Sample

Figure 5: Δ Resiliency by Merger Size

This figure plots the coefficient of interest in the main regression specification (Treat x Post) by merger size, as measured by combined assets. The horizontal axis represents the asset buckets. For example, \$50 billion captures mergers that are between \$25 to \$50 billion in combined assets. There is little change in the projected NCO ratio for banks below \$1 billion, but the risk sensitivity increases significantly as the size of the merger increases.

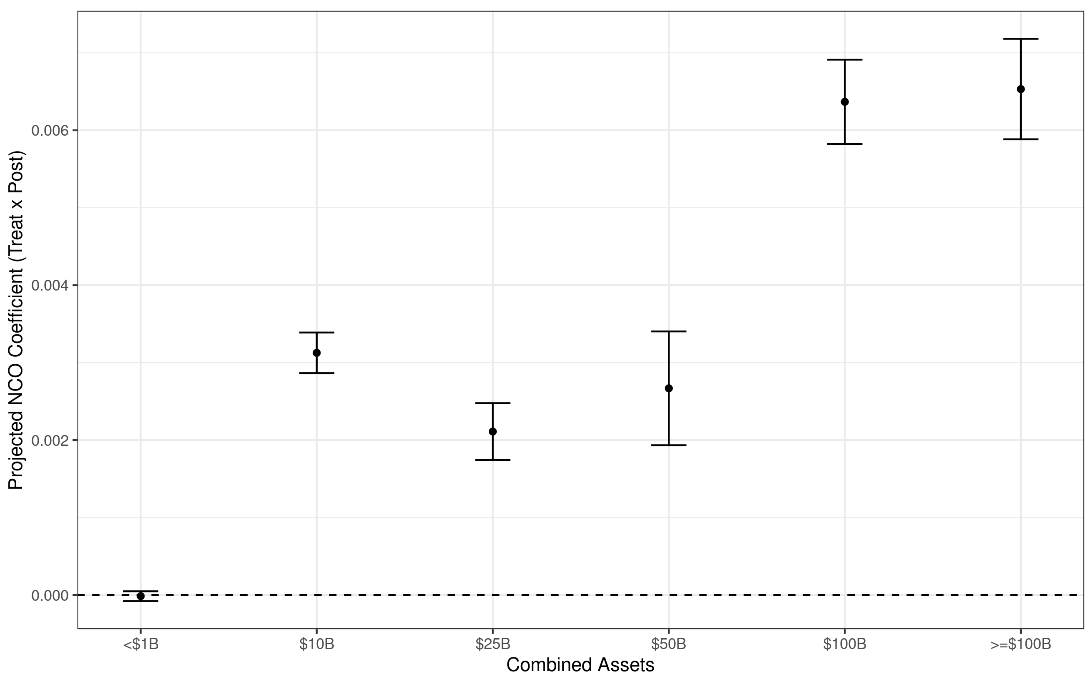


Table 1: Descriptive Statistics

This table presents descriptive statistics for the merged bank sample. The sample covers the period from 1984 Q1 to 2013 Q4. We report the mean, median, standard deviation, 25^{th} percentile, and 75^{th} percentile of each variable. Variables correspond to the definitions in Appendix A.

Variable	Mean	Median	Std. Dev	P25	P75
Net charge-off (NCO) ratio	0.01	0.00	0.44	0.00	0.00
Bank size (in $bn)	3.41	0.14	36.24	0.05	0.59
Bank liquidity	0.09	0.06	1.08	0.04	0.09
Bank ROA	0.00	0.01	0.05	0.00	0.01
Bank capital ratio	0.14	0.11	0.26	0.10	0.14
Demand deposits	0.13	0.12	0.07	0.08	0.17
Brokered deposits	0.01	0.00	0.04	0.00	0.00
Total loans (in $bn)	2.03	0.09	18.38	0.03	0.38
Total deposits (in $bn)	2.27	0.12	23.09	0.04	0.47
Loan-to-deposit ratio	2.03	0.74	88.80	0.60	0.87
Loan loss provision	0.01	0.00	0.48	0.00	0.00
Cash	0.06	0.05	0.06	0.03	0.08
Treasury bonds	0.00	0.00	0.00	0.00	0.00
MBS	0.00	0.00	0.00	0.00	0.00
Securitization	0.00	0.00	0.02	0.00	0.00

Table 2: Stylized Treatment and Control Groups

This table shows a stylized example of our propensity matching procedure. We identify the ten nearest neighbor matches using the weighted average of the pre-merger log(assets), loan / assets, noninterest income / assets, and Tier 1 capital ratio.

	Before Merger	After Merger
Treatment	Bank A ($100B)	Bank AB ($115B)
	Bank B ($15B)	
Control	Bank C	Bank C

Table 3: Propensity Score Matching Summary Statistics

This table presents the averages of the control variables used in the propensity score matching algorithm by treatment group. Treat = 1 represents the banks that merged in our sample while Treat = 0 represents the control group. The control group consists of the ten nearest neighbor matches that did not have M&A activity in the [-5, +1] year window of the merger quarter. For merged banks, the variables reported are the weighted average between acquirer and acquired banks. Variables correspond to the definitions in Appendix A.

Treat	log(Assets)	Loan/Assets	Noninterest Income/Assets	T1 Ratio	N
0	13.04	0.63	0.01	0.07	79,470
1	13.35	0.62	0.01	0.07	7,947

Table 4: Bank Merger Effect on Financial Resiliency

This table presents the difference in risk sensitivity as measured by projected net charge-off (NCO) ratio between treatment and control banks, pre- and post-merger. The dependent ratio is the projected NCO ratios under the DFAST 2019 severely adverse stress scenario. Column (1) shows the aggregate results for all mergers in our sample. Columns (2) to (5) stratify the sample by total combined assets in two ways: (1) if combined assets of the acquirer and acquired banks are above or below \$50 billion; and (2) if the acquirer has assets above or below \$50 billion. Δ Resiliency is constructed using projected net charge-off rates under economic stress. A higher value indicates increased net charge-off rates under stress, weakening bank resiliency. Variables correspond to the definitions in Appendix A. Bank controls include 1-quarter lagged bank assets, ROA, liquidity ratio, and T1 capital ratio. Robust standard errors are clustered by bank and year-quarter. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Δ Resiliency				
	All Mergers	Combined $\geq$ \$50B	Combined $<$ \$50B	Acquirer $\geq$ \$50B	Acquirer $<$ \$50B
	(1)	(2)	(3)	(4)	(5)
Treat	0.002***	0.007*	0.002***	0.003***	0.002***
	(0.000)	(0.004)	(0.000)	(0.001)	(0.000)
Post	0.001***	0.000	0.001***	0.000	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Treat x Post	0.002***	0.004**	0.001**	0.003***	0.001**
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Bank Controls	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Observations	1,158,495	39,832	1,118,663	37,856	1,120,639
Adjusted R^2	0.088	0.322	0.089	0.410	0.089

Table 5: Portfolio Diversification

This table presents a subsample analysis of the risk sensitivity measure split by diversification score percentile. The portfolio diversification score corresponds to the definition in Appendix A. The median portfolio diversification score in merged banks is 0.049. Δ Resiliency is constructed using projected net charge-off rates under economic stress. A higher value indicates increased net charge-off rates under stress, weakening bank resiliency. Bank controls include 1-quarter lagged bank assets, ROA, liquidity ratio, and T1 capital ratio. Robust standard errors are clustered by bank and year-quarter. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Δ Resiliency		
	<p25 Div. Score	p25-p75 Div. Score	>p75 Div. Score
	(1)	(2)	(3)
Treat	0.002***	0.002***	0.003***
	(0.001)	(0.000)	(0.001)
Post	0.000**	0.001***	0.001**
	(0.000)	(0.000)	(0.000)
Treat × Post	0.002**	0.001*	0.003**
	(0.001)	(0.001)	(0.001)
Bank Controls	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Observations	283,114	562,887	287,664
Adjusted R^2	0.159	0.098	0.117

Table 6: Effect of Portfolio Diversification in Small Mergers (< \$10B)

Table 6 to Table 9 present subsample analyses of the risk sensitivity measure split by diversification score percentile and bank merger size. The portfolio diversification score corresponds to the definition in Appendix A. The median portfolio diversification score in merged banks is 0.049. Small mergers are defined as mergers with fewer than \$10B in combined assets at the time of the merger. Medium, large, and largest mergers are defined as between \$10B to \$50B, \$50B to \$100B, and above \$100B, respectively. Δ Resiliency is constructed using projected net charge-off rates under economic stress. A higher value indicates increased net charge-off rates under stress, weakening bank resiliency. Bank controls include 1-quarter lagged bank assets, ROA, liquidity ratio, and T1 capital ratio. Robust standard errors are clustered by bank and year-quarter. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Δ Resiliency		
	<p25 Div. Score	p25-p75 Div. Score	>p75 Div. Score
	(1)	(2)	(3)
Treat	0.002***	0.002***	0.003***
	(0.000)	(0.000)	(0.001)
Post	0.000**	0.001***	0.000**
	(0.000)	(0.000)	(0.000)
Treat × Post	0.001	0.001	0.002*
	(0.001)	(0.001)	(0.001)
Bank Controls	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Observations	248,404	493,402	252,941
Adjusted R^2	0.167	0.102	0.119

Table 7: Effect of Portfolio Diversification in Medium Mergers ($10-$50B)

	Δ Resiliency		
	<p25 Div. Score	p25-p75 Div. Score	>p75 Div. Score
	(1)	(2)	(3)
Treat	0.012**	0.005*	0.005
	(0.005)	(0.003)	(0.010)
Post	0.000	0.000	0.001
	(0.000)	(0.000)	(0.002)
Treat × Post	0.004	0.004	0.000
	(0.003)	(0.003)	(0.003)
Bank Controls	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Observations	23,725	49,231	26,130
Adjusted R^2	0.555	0.232	0.258

Table 8: Effect of Portfolio Diversification in Large Mergers (\$50-\$100B)

	Δ Resiliency		
	<p25 Div. Score	p25-p75 Div. Score	>p75 Div. Score
	(1)	(2)	(3)
Treat	0.081***	-0.002	-0.002
	(0.014)	(0.003)	(0.002)
Post	0.003	-0.001	0.001
	(0.004)	(0.001)	(0.001)
Treat × Post	0.007	0.000	0.011**
	(0.006)	(0.002)	(0.005)
Bank Controls	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Observations	5,239	10,257	5,876
Adjusted R^2	0.547	0.483	0.450

Table 9: Effect of Portfolio Diversification in Largest Mergers (≥ \$100B)

	Δ Resiliency		
	<p25 Div. Score	p25-p75 Div. Score	>p75 Div. Score
	(1)	(2)	(3)
Treat	0.003**	0.001	0.004**
	(0.001)	(0.001)	(0.002)
Post	0.001	-0.001*	0.001
	(0.001)	(0.000)	(0.001)
Treat × Post	0.003***	0.004***	0.002**
	(0.001)	(0.001)	(0.001)
Bank Controls	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Observations	4,784	8,970	4,706
Adjusted R^2	0.588	0.535	0.488

Table 10: Geographic Diversification

This table presents a subsample analysis of the risk sensitivity measure split by geographic diversification percentile. The geographic diversification is calculated as the distance between the reported headquarter ZIP codes of the acquirer and acquired bank and corresponds to the definition in Appendix A. The median geographic distance between the merged banks is 43.65 miles. Δ Resiliency is constructed using projected net charge-off rates under economic stress. A higher value indicates increased net charge-off rates under stress, weakening bank resiliency. Bank controls include 1-quarter lagged bank assets, ROA, liquidity ratio, and T1 capital ratio. Robust standard errors are clustered by bank and year-quarter. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Δ Resiliency		
	<p25 Distance	p25-p75 Distance	>p75 Distance
	(1)	(2)	(3)
Treat	0.002***	0.002***	0.005**
	(0.000)	(0.000)	(0.002)
Post	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Treat × Post	0.003**	0.002***	0.005***
	(0.001)	(0.001)	(0.002)
Bank Controls	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Observations	142,610	285,441	141,089
Adjusted R^2	0.360	0.320	0.321

Table 11: Cross-sectional Analysis: Liquidity

Table 11 and Table 12 present the results of our cross-sectional analyses. For all the tables, we use a triple interaction framework to identify how certain bank characteristics drive the change in risk sensitivity. In Table 11, we apply "Liquidity Measure" as our characteristic of interest. Table 12 uses "Regulatory Capital" measures. Δ Resiliency is constructed using projected net charge-off rates under economic stress. A higher value indicates increased net charge-off rates under stress, weakening bank resiliency. Variables correspond to the definitions in Appendix A. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Δ Resiliency		
	Liquidity Ratio	Cash Ratio	Treasury + MBS Ratio
	(1)	(2)	(3)
Treat	0.001***	0.001***	0.002***
	(0.000)	(0.000)	(0.000)
Post	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Liquidity Measure	0.000	-0.001	-0.001***
	(0.000)	(0.001)	(0.000)
Treat × Post	0.004***	0.004***	0.003***
	(0.001)	(0.001)	(0.001)
Treat × Liquidity Measure	0.013**	0.008	-0.071***
	(0.005)	(0.005)	(0.023)
Post × Liquidity Measure	0.000	-0.002*	0.248
	(0.000)	(0.001)	(0.218)
Treat × Post × Liquidity Measure	-0.020***	-0.018**	-0.217
	(0.007)	(0.008)	(0.199)
Bank Controls	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Observations	605,163	605,163	605,163
Adjusted R^2	0.243	0.243	0.242

Table 12: Cross-sectional Analysis: Regulatory Capital

	Δ Resiliency		
	Leverage Ratio	Tier 1 Capital Ratio	Total Capital Ratio
	(1)	(2)	(3)
Treat	0.002***	0.001	0.001
	(0.000)	(0.001)	(0.001)
Post	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Regulatory Capital Measure	-0.002	0.000	0.000
	(0.001)	(0.000)	(0.000)
Treat × Post	0.003***	0.006***	0.006***
	(0.001)	(0.002)	(0.002)
Treat × Regulatory Capital Measure	0.003	0.004	0.004
	(0.003)	(0.010)	(0.010)
Post × Regulatory Capital Measure	-0.001	0.000	0.000
	(0.001)	(0.000)	(0.000)
Treat × Post × Regulatory Capital Measure	0.000	-0.028*	-0.027*
	(0.005)	(0.015)	(0.015)
Bank Controls	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Observations	605,163	605,163	605,163
Adjusted R^2	0.242	0.242	0.242