Stress Testing Community Banks

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Abstract: The Dodd-Frank Act requires stress testing for U.S. banks with assets in excess of $10 billion. Smaller community banks are not required to participate in this important information generating exercise. While community banks are clearly too small to generate systemic shocks to the U.S. economy, they are exposed to the recessions caused by systemic shocks. Because hundreds of community banks failed in the aftermath of the 2008-2009 financial crisis, the sensitivity of these banks to systemic shocks poses a concern for both policymakers, community banks, and the job-creating small businesses that depend on a healthy community banking sector. In this paper we estimate a top-down stress testing model built upon the work of Hirtle et al. (2015), but we focus our modeling specifically on community banks. Because our model uses standard econometric techniques and relies solely on publicly available data, it can be used to provide community banks access to otherwise prohibitively expensive macroprudential risk analysis, and may help further stabilize this important financial sector.

1 Introduction

The financial crisis of 2008-2009 exposed the systemic fragility of the worldwide financial system. Intermediaries and markets had become interconnected to the point that a negative shock in one market quickly spread to other markets. While a highly interconnected financial system can allocate resources more efficiently and deliver faster economic growth, it also exposes the financial system to systemic failure (Billio et al., 2010). The crisis of 2008-2009 was characterized by shocks that propagated rapidly and seemed to amplify in the process. Policymakers would proclaim that shocks were “contained", but it would soon become clear that they were not. In the end, policymakers provided taxpayer-financed bailouts - a combination of equity capital injections, loans, and debt guarantees - for damaged financial institutions deemed too-big-to-fail (TBTF), because it judged that bailing them out would be less costly (at least in the short-run) than the systemic damage that would result from allowing them to fail.

A large portion of financial policy responses taken both during and after the financial crisis can be categorized as macroprudential policy. The goal of macroprudential policy is to reduce the likelihood and severity of systemic events, while preserving as much as possible the positive externalities that come from highly interconnected financial intermediaries and markets. One of the main tools for implementing macroprudential policy is stress testing. The first stress test of the post-crisis era was the Supervisory Capital Assessment Program (SCAP), conducted by the Federal Reserve System (the Fed) in 2009. The SCAP was applied to the 19 largest U.S. banking companies. The results of these tests were made available to the public, and were largely credited with reducing market uncertainty and reassuring financial markets that the tested banks were, for the most part, financially solvent and operationally sound.

Stress testing was formalized for the post-crisis era by the Dodd-Frank Wall Street Reform and Consumer Protection Act, which was signed into law in July 2010. It contained a requirement that banks with assets greater than $10 billion of assets perform annual stress tests. Rules for these stress tests - which became known as the Comprehensive Capital Analysis and Review (CCAR) for larger more complex banks above $50 billion, and the Dodd Frank Annual Stress Testing (DFAST) for smaller and less complex banks above $10 billion - were announced by U.S. bank regulatory agencies in 2012.

Under Dodd-Frank, the Fed is responsible for conducting these stress tests on an annual basis. The Fed announces a set of stressful hypothetical macroeconomic scenarios each year, instructs banks to use their own internal risk models to generate a set of standardized stress test outputs, and then publicly discloses these results. A bank passes the stress test if the results show that it would emerge from the hypothetical stress scenarios having absorbed large losses but still having a financially sound balance sheet. A bank that fails the stress test is usually prohibited from paying dividends, is directed to make operational and financial changes that reduce its exposure to systemic risk, and must operate under these restrictions until it passes a future stress test. In either case, public disclosure of the stress test results reduces financial market uncertainty and increases general public confidence in the U.S. banking system (Gick and Pausch, 2012).

Although regulatory stress testing has focused exclusively on large banks, in this paper we innovate by applying stress tests to smaller, more locally focused “community banks". Community banks are by no means systemically important financial institutions - hundreds of small banks can fail without launching a systemic event or contagion - but they are exposed to systemic shocks to the macro-economy and the financial system. For example, the typical community bank in the U.S. significantly reduced its supply of business credit during the global financial crisis (DeYoung et al., 2015). Nevertheless, the financial health of the community banking sector is critical to long-run U.S. macroeconomic growth. Community banks are the main source of bank financing for most small firms in the U.S. (Berger et al., 2005), and in turn, small firms create approximately two-thirds of new private sector jobs and provide approximately one-half of total private sector jobs in the U.S. (Small Business Administration 2012). Yet little if any work has been done to study the application of macroprudential analytic tools to community banks.

It is reasonable to ask whether applying some features of macroprudential policy to community banks would be socially beneficial, but policymakers in the U.S. have so far avoided doing so. In large part due to industry and political pressure, U.S. bank regulators are more reticent than their European counterparts to loading additional regulatory burden onto small banks. Community banks lack the staff expertise to build customized stress testing models, and hiring outside experts to build such models would be prohibitively costly for many of these small banks.

But while it may not be feasible for individual community banks themselves to build customized stress testing models, non-customized stress tests models based on publicly available information are far less costly and may provide a potential second-best approach. The customized internal stress test models used by large commercial banks use a so-called “bottom-up" approach in which the loss sensitivities (i.e., probability of default, loss given default) of tens of thousands of unique loan and derivatives exposures within large bank portfolios are evaluated in response to macroeconomic stress scenarios; the stress test then compares the aggregated projected losses within these portfolios to the bank's loss absorbing equity capital. In contrast, a "top-down" stress testing approach simply observes the historic correlations between macroeconomic conditions and various items on a bank's financial statements (e.g., net interest income, loan charge-offs); it is then straightforward to use these correlations to project how far any bank's net income would fall in response to macroeconomic stress scenarios.

Hirtle et al. (2015) developed a top-down stress testing model - the Capital and Loss Assessment under Stress Scenarios (CLASS) model - and estimated the model for the largest 200 U.S. commercial banks. We carefully replicate the CLASS model for these 200 banks, but more importantly, we re-estimate the model for "large" community banks with between $500 million and $10 billion in assets, and also for "small" community banks with between $50 and $500 million in assets.

When we stress the simple Leverage ratios of the "large" community banks using the Fed's "Supervisory Severely Adverse" scenario - a set of macroeconomic conditions meant to mimic the Great Recession of 2008-2009 - the expected value of the projected leverage ratio falls below adequately capitalized for only about 7% of these banks, with only a small handful of these banks projected to fail. These relatively benign stress test outcomes likely reflect the reliance of community banks - very few of which have access to public capital markets, and most of which lack the financial expertise to hedge risk with financial derivatives - on holding high stores of equity capital as their primary risk management tool. Nevertheless, our model generates a wide distribution of potential outcomes around these expectations, and a non-trivially large number of these banks fare poorly in the lower tails of the distributions. For example, we find a one-in-twenty chance that the leverage ratio falls below adequately capitalized for

30% of these banks and falls below below zero (failed) for 1% of these banks, and a one-in-one hundred chance that the leverage ratio falls below adequately capitalized for 84% of these banks and falls below zero for 11% of these banks.

Our projections for the Tier 1 Risk-based Capital ratios for the “large" community banks are somewhat more negative. For example, the expected risk-based capital ratio falls below adequately capitalized for about 57% of these banks, but still falls below zero for very few of these banks. Risk-based capital ratios essentially deflate book equity by the credit risk of the loans and securities backed by that equity, and these results suggest that community banks may be more exposed to macroeconomic shocks than suggested by their more robust leverage capital ratios.

In contrast, our projections find much stronger performance-under-stress for the “small" community bank subsample. For example, we project that the risk-based capital ratios will fall below adequately capitalized at only about 15% of these banks under the severely adverse stress scenario. This strong performance is consistent with the risk-management practices of these very small banks, which relies primarily on holding large cushions of equity capital.

Generating these kinds of risk assessments is beyond the internal expertise of most community banks. Thus, our overriding objective of informing individual community banks of their positions on these stress test distributions would provide them with otherwise inaccessible information to consider during their internal risk management deliberations. In addition to the possibility of making such information available to community banks, our study also contributes to a small but growing academic literature on bank stress testing. As mentioned above, Hirtle et al. (2015) focus on the largest 200 U.S. banks. Similarly, Kapinos and Mitnik (2015) study only banks with assets in excess of $10 billion. They forecast aggregate pre-provision net revenue

(PPNR), net charge-offs, and capital for each bank in their sample. An important feature of their paper is model selection in the identification of macroeconomic drivers and individual bank characteristics that drive capital levels. Covas et al. (2014) apply fixed effects quantile autoregression to 15 of the largest U.S. banks, and generate density forecasts for future bank capital levels for each of these banks. Fisher et al. (2017) apply a top-down approach to both large and small banks, but they limit their stress testing analytics to mortgage loans.

The remainder of the paper proceeds as follows: In section 2 we present the fundamental structure of our stress testing model, which follows closely the methodology developed in Hirtle et al. (2015). In section 3 we describe the data that we use to estimate the model parameters. In section 4 we present the estimated parameters of the model, report the results of the stress tests for community banks, and conduct a robustness test in which we replace the Federal Reserve's nationwide economic stress conditions with state-level economic stress conditions that should be more relevant for locally focused community banks. Section 5 concludes.

2 Bank Stress Testing Model

The objective of the annual Dodd-Frank Act stress tests (DFAST) and the Comprehensive Capital Analysis and Reviews (CCAR) is to determine whether U.S. banks with assets over $10 billion have sufficient capital to absorb losses and continue operating through times of economic and financial stress. The overall methodology for stress testing is straightforward. First, historical data are used to estimate a multi-equation financial performance model for a bank (or a set of banks). The model includes a separate equation for each element in the bank's financial statements (interest margins, loan charge-offs, etc.) that impacts its earnings and equity capital. Importantly, each equation specification includes macroeconomic conditions variables, so that the model captures the sensitivity of bank financial performance to external business conditions. Second, the parameterized model is used to project the financial performance of the bank into the future, conditional on recession-like values for the macroeconomic variables. Finally, the projected results are used to assess the adequacy of the bank's current equity capital levels. If the bank's projected end-of-recession equity capital remains above minimum regulatory standards, then the bank has "passed" the stress test. If not, then the regulator instructs the bank to raise additional equity capital (or equivalently, shrink its assets) in order to decrease its vulnerability to economic shocks.

2.1 Equity Capital at U.S. Commercial Banks

To get a sense of how the equity capital levels of U.S. banking companies were affected by the 2008-2009 financial crisis, Figure 1 plots the average capital ratios (in this case, Tier 1 equity capital divided by gross total assets) in each quarter from 1996 through 2015 for two very different sets of banks: Community banks with assets between \$500 million and \$10 billion and Systemically Important (SIFI) banks with assets in excess of \$250 billion. The data reflect the impact of the 2008-2009 financial crisis on bank equity capital levels. In the years leading up to the crisis, bank borrowers began defaulting on their (mainly real estate) loans in large numbers. While the losses associated with those loan defaults destroyed equity capital at both sets of banks, the losses were far more severe at the larger banks, many of which continued to increase their exposure to real estate loans and real estate-backed securities well into the mid-2000s, and financed that loan growth with increased financial leverage.[1]

[1] As Charles Prince, chairman and CEO of Citigroup, said at the time, "When the music stops, in terms of liquidity, things will be complicated. But as long as the music is playing, you've got to get up and dance. We're still dancing." Quote taken from interview with the Financial Times on

The resulting credit losses were especially problematic at large banks because, as is clearly evident in Figure 1, they tended to operate with relatively small equity capital cushions relative to smaller banks. The figure shows that the average bank in each size group remained above the minimum regulatory level of 4.0% for the capital ratio in question, below which a bank is no longer considered by regulators to be adequately capitalized. But the loss distributions around these mean averages widened during the crisis years; many banks were unable to maintain equity capital above the regulatory minimum, and some banks became insolvent. For example, approximately 10.52% of individual community banks in our data fell below the 4.0% threshold during the recession and its aftermath. The number of SIFI banks that would have suffered similar outcomes in the absence of government support is less easily calculated.

The post-crisis increase in average capital ratios shown in Figure 1 are both instructive in general and help explain the ultimate results of our analysis. Bank regulators in nearly all developed economies tightened their minimum equity capital rules in the aftermath of the financial crisis, chiefly under that auspices of the international Basel III Accords. Higher equity capital standards were announced in 2010 and were phased in during 2013-2015. As can be seen in Figure 1, equity capital levels increased substantially at both community banks and SIFI banks, and the historic gap between these two sets of banks disappeared. On average, bank capital ratios had reached historically high levels by the end of 2015, providing much larger loss-absorbing cushions. Thus, while the stress tests that we carry out in this paper generate large amounts of loan losses and equity capital destruction, only a very small handful of banks are projected to become insolvent.

July 9, 2007.

2.2 Stress Testing Equity Capital at U.S. Commercial Banks

In this paper, we essentially replicate the top-down CLASS stress testing model of Hirtle et al. (2015). The main difference is that, while the original CLASS model focused on the 200 largest U.S. banking companies, we estimate separate versions of the model for seven different subsamples of banks, from small community banks with assets of only $500 million, to large systemically important banking companies with assets in excess of $250 billion. Once estimated, we use these models to apply a Federal Reserve-type stress test to each individual commercial bank included in our models. Our chief interest is the community banks with assets between $500 million and $10 billion that have been left out of previous stress testing research.

The CLASS model is comprised of 16 separate regression equations, each of which takes the following general form:

$$Y_{j,t} = \beta_{j,0} + \beta_j' X_{j,t} + \gamma_j' Z_t + \varepsilon_{j,t} \tag{1}$$

The data are observed at the individual bank level; we suppress the bank-specific index i for convenience. $Y_{j,t}$ is the j^{th} income statement item (e.g., net interest margin) or balance sheet item (e.g., net loan charge-offs) in quarter t. To control for bank size effects, all of the $Y_{j,t}$ are expressed as ratio values, using either book value bank assets or the appropriate category of book value loans. $X_{j,t}$ is a vector of bank-specific characteristics, such as bank size, loan portfolio mix, and geographic (bank headquarters state) fixed effects. Z_t is a vector of macroeconomic and financial market variables. Following the CLASS model, we constrain the Z_t variables to be the same for all banks regardless of their geographic location; in robustness tests, we show that allowing the Z_t variables to vary across states improves the statistical fit for most of the equations. (We provide complete definitions and summary statistics for all of the Y, X, and Z variables in the Data section below.) The $\varepsilon_{j,t}$ are zero-mean innovations.

Each of the 16 Y variables in (1) correspond conceptually to a separate element in the commercial bank income statement:

1. Net interest income
2. + Noninterest income
3. − Noninterest expense (Compensation)
4. − Noninterest expense (Fixed Assets)
5. − Noninterest expense (All Other)
6. − Loan loss provisions (Commercial & Industrial)
7. − Loan loss provisions (Construction & Development)
8. − Loan loss provisions (Agricultural Production)
9. − Loan loss provisions (Farm Land)
10. − Loan loss provisions (Credit Cards)
11. − Loan loss provisions (Other Consumer)
12. − Loan loss provisions (Residential Real Estate)
13. − Loan loss provisions (Home Equity Lines of Credit)
14. − Loan loss provisions (Multi-family Real Estate)
15. − Loan loss provisions (Nonfarm Nonresidential Real Estate)
16. − Loan loss provisions (All Other)

Each of the Y elements 1 through 16 is estimated in a separate regression using historical data - in our case, quarterly data for all U.S. commercial banks with assets greater than $500 million from 1991:Q1 through 2015:Q4. The estimated parameters of these equations are then used to project 9 quarters of future values (2016:Q1 through 2018:Q4) for each of the Y variables; this is done by holding the bank-specific X values constant at their 2015:Q4 values, and then iterating the model forward based on the values for the Z variables that correspond to the Federal Reserve macroeconomic stress scenario (we refer to these values as the $Z\text{-}forward$ vector). By summing the projected values of 16 Y values for each bank in each quarter, we generate a 9-quarter projection of per-tax net income in real 2015 dollars. (Note: To control for size effects in the regression equations, we specify the Y and X variables as ratios, where the denominator in each ratio is either total assets or the appropriate value for total loans. Before we perform the above summation, we convert each of the 16 projected Y ratios back into dollar values by multiplying through by the most recent values of the denominators.) Projected net income is then calculated in each future quarter by applying a common tax rate for all banks.[2]

With a 9-quarter projection of net income under macroeconomic stress in-hand for each bank, we are ready to forecast bank capital levels. Assuming that time t is the final quarterly observation in the data used to estimate (1), so that $t+1$ is the first quarter for which we are making projections, we forecast capital for each bank as follows:

$$capital_{t+1} = capital_t + net\_income_{t+1} - dividends_{t+1} \tag{2}$$

where $capital_t$ is the bank's final equity capital from the historical estimation time period, projected $dividends_{t+1}$ are the bank's historical quarterly dividend payouts, and net_income_{t+1} is projected quarterly net income as described above. Similarly,

[2] We use a 35% corporate tax rate in this paper. In future iterations we will use the new 21% corporate tax rate instituted in the Tax Cuts and Jobs Act of 2017. One of the overlooked implications of this tax reform is its potential impact on the stability of the banking system: By potentially increasing retained earnings, banks will be better able to generate internal capital to add to their equity capital cushions.

we use equation (2) to make forecasts for $capital_{t+2}$, $capital_{t+3}$, ..., based on one-period updated values for $capital_{t+\tau}$ and $net\_income_{t+\tau+1}$. (Note: These capital forecasts are in real 2015 dollars. Prior to reporting these results in tables or figures, we convert the capital forecasts back into ratio values.)

Following Hirtle et al. (2015), we make three important technical adjustments. First, U.S. bank regulators constrain dividend payments at banks with low levels of equity capital. In our calculations, we constrain the variable $dividends_{t+1}$ accordingly.[3]

Second, we assume a constant annual growth rate for real bank assets (in our case, 0%) throughout the future capital forecast period. Third, in regressions 6 through 16 above, we replace the dependent variable *Loan loss provisions* with *Net loan charge-offs*. Banks have substantial discretion regarding the timing and size of provisions expenses, but much less flexibility in charging off actual loan losses; hence, the timing and magnitudes of loan charge-offs track macroeconomic conditions much more closely than do the timing and magnitudes of loan loss provisions. We convert the projected estimates of *Net loan charge-offs* into equivalent *Loan loss provisions* expenses using the "tunnel" algorithm explained in Hirtle et al. (2015, pages 27, 43 and 44), which we then use to calculate net income in the 16-element summation illustrated above in Section 2. Because loan loss provisioning is a forward-looking activity designed to anticipate loan charge-offs over the next four quarters, we are only able to project bank net income (and hence bank capital) for the first 9 quarters of the 12-quarter Federal Reserve's macroeconomic stress scenarios.

[3]Under Basel III, banks are expected to hold 250 basis points of equity capital over-and-above the level that qualifies a bank as adequately capitalized. This extra capital is referred to as the capital conservation buffer. As a bank's conservation buffer declines below 250 basis points, U.S. regulators constrain the percentage of its (four-quarter averaged) net income that it can pay out to shareholders, as follows:

Capital conservation buffer (basis points)	>250	187.5-250	125-187.5	62.5-125	<62.5
Dividend maximum (% of net income)	No limit	60%	40%	20%	0%

A fundamental concern in stress testing models is that the underlying structural time series processes on the $Y_{j,t}$ can be highly nonlinear. A good example of this are the default options embedded in real estate loans: When house prices fall below a certain level, the principle balance still owed on a home mortgage loan becomes greater than the market value of the home (i.e., the borrower becomes "under water"). Because home mortgages tend to be non-recourse loans in the U.S., this gives the borrower a financial incentive to default on the loan. Moreover, house prices are highly correlated within geographic regions; as home prices decline, default options for multiple loans go into-the-money simultaneously, resulting in discontinuous movements in time series data for loan charge-offs.[4] Stress test researchers have dealt with these nonlinearities in various ways - for example, Covas et al. (2014) use a dynamic panel quantile regression approach. We deal with this issue by placing no structure on the distribution of the $\varepsilon_{j,t}$ in our pooled bank-quarter data, and then diagnosing bank expected losses by sampling from the error distribution. This simple approach allows the asymmetric and/or fat-tailed shocks to which some banks are more susceptible to accumulate on top of the average sample trajectory during a stressful scenario.[5]

For an illustration of this potential effect, consider large systemically important financial institutions (SIFIs, or banks with assets greater than $250 billion) over the crisis. It is well known that banks in this sector tended to be long default options on their portfolios of home equity lines of credit (HELOCs) as the crisis approached. Figure 2a displays the distribution of the pooled residuals from equation (1) estimated for

[4] It is important to note that banks can hedge these losses, but only imperfectly. For example, banks typically require mortgage borrowers with loan-to-value ratios greater than 80% typically to purchase default insurance, and banks can purchase mortgage credit default swaps to hedge against their exposures in mortgage-backed securities. But during the financial crisis a number of mortgage insurers and reinsurance companies became insolvent, the largest of which was American Insurance Group (AIG).

[5] For more detail on this approach, see Koenker (2005).

these large banks over the 1991:Q1-2015:Q4 sample period, using net charge-offs on HELOCs as the dependent variable Y. The fat right-hand tail generated by increased charge-offs during the crisis years clearly stands out. In contrast, for other equations in our model and/or for different groups of banks, fat tails would be less likely. Figure 2b displays the residual distribution for community banks using net interest margin as the dependent variable. Clearly, these small banks have little option exposure in their net interest margin operations.

3 Data

A key advantage of top-down models is that they can usually be estimated using publicly available data. For U.S. commercial banks organized in holding company structures, we obtain the Y variables and the X variables in equation (1) from the Federal Reserve Y9-C reports, which are downloadable from the Federal Reserve Bank of Chicago website. For stand-alone commercial banks not organized as holding companies, we obtain these variables from the Statements of Condition and Income (call reports), which are downloadable from the Federal Reserve Bank of Chicago website prior to 2011, and from the Federal Financial Institutions Examination Counsel (FFIEC) Central Data Repository Public Data Distribution website from 2011 onward. (We shall refer to both the stand-alone banks and the bank holding companies as “banks" or “banking companies" without distinction throughout the remainder of the paper.) We obtain the Z variables in equation (1) from the Federal Reserve website. We observe all of these variables with quarterly frequency. We express all variables in terms of real 2015 dollars.

To be included in our unbalanced quarterly data panel, all banks had to be at least five years old, issue insured deposits, have positive amounts of loans, transactions deposits, and book equity, and have controlling domestic ownership. Applying these filters to all 19,144 banks that were present in the regulatory databases for at least one quarter during our 1991-2015 sample period reduced the sample to 9,481 unique banks. The initial quarter of our data (1991:Q1) includes 4,580 banks (1,336 bank holding companies and 3,244 stand-alone banks) and the final quarter of our data (2015:Q4) includes 2,052 bank holding companies (612 bank holding companies and 1,440 stand-alone banks).

We estimate equation (1) using 100 quarters of data, from the first quarter of 1991 through the fourth quarter of 2015. Using those estimated parameters, we project the performance of each bank under stressful economic conditions for the next 9 quarters. For ease of exposition, we assert that these 9-quarter projections occur from the first quarter of 2016 through the first quarter of 2018, although no actual data from those quarters are used in the projections.

One main innovation in our study is that we estimate and implement a top-down stress testing model not only for subsamples of large U.S. commercial banks that are required under Dodd-Frank to undergo annual stress testing, but also for subsamples of smaller commercial banks that do not currently face that regulatory requirement. We estimate our model separately for the following four size-based subsamples of U.S. commercial banks:

- Assets in excess of $250 billion (SIFI)
- Assets in excess of $5 billion (CLASS)
- Assets between $500 million and $10 billion (Large Community)
- Assets between $50 million and $500 million (Small Community)

Asset size is used extensively in the empirical bank research literature as a proxy for institution characteristics such as business strategy, funding mix, and risk management. Hence, one would expect bank sensitivity to macroeconomic shocks to vary across bank size. By estimating our model separately for each of these subsamples of banks, we allow the parameters of the model to be freely flexible across the groups.

Our two community bank definitions are crude, but they suffice for the purposes of this study. Going back at least 30 years, researchers and regulators have used a simple $1 billion upper size threshold to define a community bank. This ad hoc threshold has not been adjusted upward for inflation, nor for changes in bank regulations and banking technologies that have allowed larger banks to use a community bank business strategy. Our higher $10 billion upper size boundary for community banks reflects these developments. We split the community bank population into a subset of larger banks with assets greater than $500 million and a subset of smaller community banks with assets less than $500 million for two main reasons. First, the lion's share of banking industry exits over the past 40 years (mainly via acquisition by other banks) has been banks with assets less than $500 million. These smaller, scale inefficient banks are much less likely to survive in the long-run regardless of periodic macroeconomic stress events. Second, smaller banks tend to be undiversified and manage insolvency risk chiefly by holding larger amounts of equity capital; hence, they are likely to perform differently when exposed to stressful economic conditions, and placing these banks into a separate subsample allows the parameters of our stress test models to better capture these differences.

The SIFI and CLASS subsamples contain banks that are for the most part too large to qualify (by our definition) as community banks. The SIFI subsample corresponds roughly to the set of U.S. financial holding companies that regulators consider to be "systemically important financial institutions" or "too-big-to-fail", i.e., the banks for which stress testing is most important. The CLASS corresponds closely to the largest 200 banks in each year of the data, i.e., the banks upon which Hirtle et al. (2015) focused in their initial CLASS model. We estimate our stress test models for these non-community banks in order to (a) replicate the results of Hirtle, et al. and (b) to compare and contrast the estimated performance-under-stress of large banks with community banks.

Table 1 contains definitions, and Table 2 contains summary statistics, for (a) the Y, X, and Z variables that we use to estimate our model, and (b) all additional variables that we use to make capital projections and perform the actual stress tests. To save space, the table displays statistics for only three subsamples: Large Community banks, CLASS banks, and SIFI banks. While we follow this convention throughout most of the paper, we produce a full set of stress scenario capital projections for both the Large Community Bank and the Small Community Bank subsamples. We make these capital projections for two regulatory definitions of bank equity capital: the Leverage capital ratio and the Tier 1 Risk-weighted capital ratio.

Because stress testing is about studying and forecasting the dynamic behavior of banks over time and especially during times of stress, it is illustrative to examine some of these data in graphical formats that show their sometimes severe time series variation. Accordingly, we present time series plots of the annual cross-sectional means for a sampling of these variables in Figures 3a through 3e. The figures indicate that both the levels and the variations in the community bank time series differ substantially from those of the larger banks. Loan charge-offs tend to be lower and less volatile at community banks. This likely reflects the nature of lending at community banks, which depends more on bank-borrower relationships that allow community banks to better screen and better monitor their borrowers. As a result, these banks may be less sensitive to macroeconomic stress scenarios. Net interest margins (the main source of income for both large and small commercial banks) are higher and more stable at community banks. This is because community banks are able to charge higher interest rates on relationship loans (i.e., exploiting the switching costs of their borrowers) and benefit from paying low interest rates on relationship deposit funding. The relative stability of the net interest margin over time is also reflective of the relationship-based business model, which once again suggests that community banks may be less sensitive to stress scenarios, remaining profitable and hence generating internal capital during recessions. Noninterest income is low but very stable at community banks, consistent with prior research showing that fee income at these banks is earned largely from fees charged to depositors (DeYoung and Roland, 2001).

4 Results

We estimate each of the 16 versions of equation (1) using ordinary least squares techniques and bank-quarter data from 1991:Q1 through 2015:Q4. Each of the 16 regression equations uses a slightly different right-hand side specification for the X and Z vectors, which we borrow directly from Hirtle et al. (2015). To allow for flexibility in the parameters, we estimate the system of 16 equations separately for each of the four size-based data subsamples described in the Data section above. As in Hirtle et al. (2015) we use a pooled panel approach. We include geography fixed effects in each equation, and we cluster the standard errors by bank.

4.1 Model Parameters

The parameter estimates are displayed in the first three columns of Tables 3.1 through 3.16. The coefficients on the macroeconomic stress scenario variables are highlighted. To save space, we only show these results for the Large Community banks ($500 million to $10 billion) in which we are most interested in this study; the larger CLASS banks (greater than $5 billion) upon which Hirtle et al. (2015) were most interested; and the very large SIFI banks (greater than $250 billion) that construct their own highly detailed and costly in-house stress test models. (When we use the estimated parameters to stress test community banks in Section 4.2, we do so for both the Large Community and Small Community bank subsamples.)

There are clear and systematic differences in the sensitivity of bank performance to the macroeconomic stress variables across these three sets of banks. The coefficients on the macroeconomic variables tend to have the same signs and tend to be statistically significant. However, the absolute magnitudes of these coefficients increase monotonically and substantially (often by an order of magnitude) for the larger bank subsamples. This is consistent with our conjectures above that community bank business models should be less sensitive than large bank business models to negative macroeconomic shocks.

In general, the right-hand side regression specifications provide substantially weaker statistical fits for the Large Community Bank subsample compared with the two subsamples of larger banks. The adjusted R-squared averages 0.559 across the 16 SIFI bank regressions, but averages only 0.329 across the 16 Large Community bank regressions. This is not surprising, given that Hirtle et al. (2015) chose these specifications with large banks in mind. For our purposes, this may also indicate that the national macroeconomic conditions measured by the variables the Fed specifies in its stress test scenarios may be less meaningful for smaller banks that are exposed mainly to local or at most regional macroeconomic conditions. We pursue this possibility below in Section 4.3 of the paper.

4.2 Capital Forecasts

Table 4 displays the "adverse" and "severely adverse" scenarios announced by the Federal Reserve for use by large U.S. commercial banks in their 2016 CCAR and DFAST stress tests. Following Hirtle et al. (2015), we use these eight macroeconomic conditions variables to create $Z\text{-}forward$ variables for use as regressor values in the capital projection exercise. The definitions used to make these transformations are shown in Table 1.

Each bank within a given size-based subsample of banks will have a different performance forecast, because each bank in a given subsample has a different set of starting values for its X vector. Performance forecasts will also differ across size-based subsamples because we estimate the model (1) parameters separately for each subsample.

We can get a sense of the severity of the scenario forecasts by examining some of the projected Y trajectories for the average bank in each of the subsamples, as illustrated in Figures 4a through 4e. These figures show clear and systematic differences in stress performance across the Large Community, CLASS, and SIFI subsamples. When placed under macroeconomic stress, community banks experience far fewer loan performance problems than larger banks (Figures 4c, 4d, 4e); community bank net interest income is less disrupted under under macroeconomic stress (Figure 4a); and community bank noninterest income remains more stable (Figure 4b). These are expected results: The relationship-based nature of small bank loan portfolios, and the fact that most small banks derive the bulk of their noninterest income from service charges on their core depositors, drive these results.

It is instructive to note the strong associations between (a) the projected loan charge-offs under the Severely Adverse scenario and (b) the historical experience of loan charge-offs observed during the financial crisis. For example, in Figures 4d and 4e, the projected charge-off paths for Residential Real Estate and Home Equity Lines of Credit at the SIFI banks peak at about 1.5% and 2.5%, respectively; these levels are very similar to the historical net charge-off data which peaked at about 1.4% and 2.6% (Figures 3d and 3e). These results offer some important reassurance that our estimated parameters are accurately capturing the impact of macroeconomic stress on bank performance.

Figure 5a displays the Severely Adverse projected capital path of the Tier 1 Risk-based capital ratio for an individual bank: UMB Financial Corporation, a $20 billion asset bank headquartered in Kansas City, Missouri. The dashed line labeled "Mean" is the expected path for UMB's Tier 1 Risk-based capital ratio. Our model projects this capital ratio would fall below its 8.5% capital conservation level approximately 9 months after the onset of macroeconomic stress, which would trigger limits on UMB's dividend payments to about 5.5% after three years. The solid line labeled "1% lower bound" shows the one-in-one hundred worst case outcome for UMB, in which the Tier 1 Risk-based capital ratio would fall to almost 4% after three years.

An important question is how far away from insolvency would UMB be after three years? Figure 5b displays the Severely Adverse projected capital path of UMB's book value Leverage capital ratio. Based on our projections, we expect that UMB would remain well short of insolvency at the end of three years, with a Leverage ratio just slightly below 5.0%, the threshold which bank regulators use to distinguish a “well capitalized" from a merely “adequately capitalized" bank. Even in the 1% worst case outcome, we project that UMB’s book equity would still be substantially positive at about 3.75% of book value assets.

We find similar capital paths for most of the banks in our analysis: The vast majority of banks suffer substantial loan losses, their capital levels fall below “well capitalized" standards, but they remain financially solvent. Figures 5c through 5d show one of the rare exceptions. Comenity Capital Bank of Utah is projected to experience losses and become insolvent under the severely adverse stress scenario.

Tables 6(i) and 6(ii) collect and summarize the results of the community bank capital projection exercises. Our model projects substantial reductions in equity capital for community banks under the Federal Reserve’s “severely adverse" stress scenario, i.e., the scenario that mimics the levels of economic stress faced by U.S. commercial banks during the Great Recession of 2008-2009. For Large Community banks (Table 6(i)), the Tier 1 Risk-based Capital ratio is projected to fall to “undercapitalized" or lower for about 58% of these banks; in the one-in-one hundred worst-case outcome this increases to about 94%. For Small Community banks (Table 6(ii)), these numbers are only 23% and 45%, respectively, consistent with our expectation that very small banks “which tend to hold high levels of equity capital as their primary risk management tool" will be less exposed to macroeconomic stress on average. For both Large and Small Community banks, the simple Leverage capital ratio is substantially less likely to fall below adequately capitalized levels.[6] We display the kernel density functions for all of the Large and Small Community Bank capital projections in Figures 6a

[6]This difference is systematic but has nothing to do with the underlying financial health of the banks. This difference is strictly due to (a) the way that regulators have defined these two equity capital ratios and (b) the levels at which regulators have placed the thresholds between capital adequacy definitions.

through 6d.

The most striking result in Tables 6(i) and 6(ii) is the virtual absence of projected bank insolvencies (the "% Banks Bankrupt" row). There are three reasons for this. First, our 2016:Q1-2018:Q4 projection time period allows only three years for banks to run through their equity capital. As we know, many of the failed banks in our data (from which the model parameters are estimated) managed to stay alive for more than three years before finally capitulating. Second, and perhaps most importantly, our data contain a very specific survivor bias: The population of U.S. banks in 2015 is comprised entirely of banks that survived the financial crisis, and the Fed's "severely adverse" stress scenario is meant to mimic that macroeconomic episode. Naturally, one would expect that these banks would experience losses should such a scenario re-occur 2015, but one would not expect many of these banks to fail. Third, U.S. banking companies increased their capital levels to historically high levels after the financial crisis (see Figure 1). This de-levering was largely a response to the tighter minimum capital regulations imposed on banks. As a result, banks were holding much larger amounts of loss-absorbing capital at year-end 2015, and hence they perform better in our stress tests based on their year-end 2015 balance sheets.

To better assess the accuracy of our model, we re-run the equity capital stress tests with a single difference: We begin the 2016-2018 projection period with each bank at its year-end 2008 equity capital levels (i.e., their capital near the beginning of the crisis) rather than its actual year-end 2015 equity capital levels. The results are displayed in Tables 6(iii) and 6(iv), and they are telling. Under the severely adverse scenario, the Tier 1 Risk-based Capital ratio now falls to "significantly undercapitalized" or lower for over half (53%) of the Large Community banks. An expected 1% of these banks are now projected to fail, and the failure rate increases to 51% (!!!) in the one-in-one hundred worst-case outcome. The results for the Small Community Bank subsample are less affected, which is not at all surprising given that these very small banks were holding large cushions of equity capital even before the post-crisis regulatory reforms.

Overall, these results suggest that the U.S. banking industry is now less exposed to a financial crisis-like shock now than it was a decade ago. To a large extent, this is due to the tighter post-crisis capital regulations. Nevertheless, our results are not all good news for community banks or for the economy. Our projections suggest that a large portion of these banks will experience large (albeit non-fatal) losses during a severe macroeconomic disruption, and as a result will incur substantial costs as they recover from the shock. Regulators require banks that fall below adequately capitalized levels to increase their capital ratios, and this can be difficult under weak economic conditions. Building capital internally via retained earnings is a slow process unless net income quickly recovers from recessionary levels, and most community banks do not have access to external equity capital markets. Absent new internal or external injections of equity capital, banks must rebuild their Leverage capital ratios by reducing asset growth and must rebuild their Risk-based capital ratios by shifting away from risky loans and toward lower risk securities; in turn, these changes reduces the expected investment returns to bank equity holders. Regardless of the Modigliani and Miller theorem, higher bank capital ratios do not come for free. A growing number of studies - some based on natural experiments and exogenous shocks related to country-specific capital regulations after the financial crisis - are discovering that increases in bank capital ratios result in reductions in bank loan supply (e.g., Aiyar, Calomiris, Wieladek 2014, Gropp, Mosk, Ongena, and Wix 2016, Jimenéz, Ongena, Peydró, and Saurina 2016, Kisin and Manela 2016). Unless reduced bank lending is fully replaced by increased lending by non-bank financial institutions, total credit supply in the economy will decline and, all else equal, macroeconomic growth will be dampened.

4.3 A Robustness Test

The Federal Reserve designs the Adverse and Severely Adverse macroeconomic scenarios for its CCAR and DFAST stress tests with large commercial banks in mind. Because these banks operate either nationwide or across large geographic portions of the country, it is appropriate to (a) estimate the parameters of their stress testing models using historical economy-wide macroeconomic conditions data and then (b) apply stress to these models using economy-wide macroeconomic scenarios. But the activities of community banks by definition are limited mainly to local counties, cities or MSAs. The true parameters of their stress test models are likely to differ from those of banks that operate nationally. They make business loans predominantly to local firms, many of which are more sensitive to the waxing and waning of local, as opposed to national, economic conditions. Because local firms tend to hire local workers, economic stress at local firms will spillover to local households; hence, loan defaults at business, consumer, and residential real estate loans will tend to be more closely correlated for community banks than for large banks. Moreover, local economies can differ from each other in systematic ways. For example, in some local economies business firms tend to be especially capital intensive, while in other areas business firms tend to have especially long production processes, in both cases making local business firms (and spillovers to the local economy) especially sensitive to changes in financial markets. For these as well as many other similar reasons, it makes logical sense to include local economic conditions, in addition to national economic conditions, in our community bank stress testing models.

Huge volumes of macroeconomic data are collected and processed within the U.S. Department of Labor (e.g., the Bureau of Labor and Statistics), the U.S. Department of Commerce (e.g., the Bureau of Economic Analysis), the U.S. Federal Reserve System, the Federal Home Finance Agency, and other federal offices. In comparison, only a very limited number of macroeconomic data series are uniformly constructed and regularly collected for U.S. states and/or U.S. counties. We re-estimate our stress test models using information from the only three such time series that are publicly available: State-level household income, state-level unemployment insurance claims, and state-level residential real estate prices. We link each community bank in our data to these data, using the state in which each bank's headquarters office is located.

We transform the information in these state-level time series into a vector F of state-level economic conditions variables using principal components analysis (Stock and Watson 1999, 2002a, and 2002b). Following Bai and Ng (2002, 2008), we extract the first five principal components from the 3-by-50-by-100 data matrix (3 state-level economic conditions variables, 50 states, 100 quarters from 1991:Q1 through 2015:Q4). This vector of 5 factors, F, captures approximately 70% of the variance in the three state-level variables. We augment equation (1) as follows:

$$Y_{j,t} = \beta_{j,0} + \beta_j' X_t + \gamma_j' Z_t + \alpha' F_t + \varepsilon_{j,t} \tag{3}$$

and estimate the 16 separate Y regressions as before. The results are displayed in the final three columns of Tables 3.1 through 3.16. In general, the F state-level economic conditions variables complement rather than offset or replace the Z macroeconomic conditions variables, which remain statistically significant as in the original regressions. Adding the state-level principal components increases the explanatory power (adjusted R-squared) of the two models by 4.61% on average across the community bank regressions, and by 2.34% on average across the SIFI regressions.[7] Hence, local economic conditions in a bank's headquarters state are non-trivial performance factors not only for banks that operate mainly or solely inside that state, but also for banks that operate far outside that state.

To generate projected future values of net income and equity capital for each bank, we need to generate *F-forward* values for each of the five state-level (principal components) variables. To do so, we follow the dynamic factor model literature (Stock and Watson, 1999, 2002a, 2002b) and estimate a vector autoregression (VAR) model. The VAR model generates the mean baseline trajectory of *F-forward*, and we use the 5.0% and 2.5% quantiles of the VAR residual distribution to create Adverse and Severely Adverse analogues around the baseline.

The capital projections are presented in Tables 7(i) through 7(iv). Relative to the our initial model that did not include state-level economic conditions (see Table 6), this augmented model projects larger financial losses. Based on the year-end 2015 capital levels, we project non-trivially larger numbers of Large Community banks to become Undercapitalized or Significantly Undercapitalized. Based on the year-end 2008 capital levels, we project non-trivially larger numbers of these banks to become Significantly Undercapitalized, Critically Undercapitalized, or Bankrupt. As above, our projections for the Small Community Bank subsample are relatively unaffected.

4.4 Summary and Conclusions

It is our intention to refine, expand, and update the community bank stress testing model presented above, and then make arrangements to provide each individual com-

[7] These are percent increases, not percentage point increases, and are calculated across 14 of the 16 regressions after removing the largest and smallest changes in adjusted R-squared.

munity bank in the U.S. with its projected capital levels, both in absolute terms as well as relative to its community bank peers and competitors. While we find little insolvency exposure for community banks in our models at this time, many of these banks have non-trivial loss exposures. Should a recession occur that is similar to the length, depth, and scope of the Great Recession of 2008-2009, we project that a large percentage of community banks would experience loan losses leaving them either undercapitalized or significantly undercapitalized by regulatory standards.

The typical U.S. community bank has grown larger and more sophisticated over the past several decades. Many of these banks have become more capable modelers of credit risk, interest rate risk, repayment risk, and other risks - either by expanding or training their internal staff, or by purchasing turnkey risk management tools from outside vendors. Neither of these solutions, however, is viable for individual community bank stress testing. Macroeconomic stress testing requires education and training seldom if ever found within the staffs of small banks, and the marketplace is not yet offering a vended product that is affordable for community banks. Although small U.S. banks are not required to perform annual stress test exercises (as are small banks in Europe), our results illustrate clearly that stress tests can deliver potentially useful information for risk management at community banks. Our ultimate goal is to provide U.S. community banks with an affordable outside option that would make them aware of their loss exposures. Avoiding these losses would add value beyond community bank shareholders, bank managers, and bank employees. To the extent that the community banking sector remains stable and continues to make credit available during periods of economic stress, it will be providing important negative financial feedback to shorten those recessionary periods.

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Table 1: This table displays definitions for the main variables used in our analysis.

	Variable Definition
Dependent variables (Y)	
Net Interest Income	(Interest income - interest expense)/interest-bearing assets
Noninterest Income	Noninterest income/assets
Compensation Expense	Compensation expenses/assets
Fixed Assets Expense	Fixed assets expenses/assets
Other Noninterest Expense	Other noninterest expenses/assets
NCO Commercial & Industrial Loans	Net % of Commercial & Industrial Loans charged-off
NCO Construction & Development Loans	Net % of Construction & Development Loans charged-off
NCO Agriculture Production Loans	Net % of Agriculture Production Loans charged-off
NCO Farmland Loans	Net % of Farmland Loans charged-off
NCO Credit Card Loans	Net % of Credit Card Loans charged-off
NCO Other Consumer Loans	Net % of Other Consumer Loans charged-off
NCO Residential Real Estate Loans	Net % of Residential Real Estate Loans charged-off
NCO Home Equity Lines of Credit	Net % of Home Equity Lines of Credit Loans charged-off
NCO Multifamily Real Estate Loans	Net % of Multifamily Real Estate Loans charged-off
NCO Nonfarm Nonresidential Loans	Net % of Nonfarm Nonresidential Loans charged-off
NCO All Other Loans	Net % of All Other Loans charged-off
Bank characteristics (X)	
ln(Assets)	Natural log of gross total assets
CI mix	Commercial & Industrial Loans/assets
MFRE mix	Multifamily Real Estate Loans/assets
RRE mix	NCO Residential Real Estate Loans/assets
CCRE mix	Construction and Land Development Loans/assets
NFNR mix	Nonfarm Nonresidential Loans/assets
CC mix	NCO Credit Card Loans/assets
OC mix	NCO Other Consumer Loans/assets
HELOC mix	Home Equity Lines of Credit/assets
Macroeconomic stress variables (Z-$forward$)	
Slope	% 10yr treasury yield(t) - % 3mo treasury yield(t)
Equity Market Return	dl_dow = [ln(dow(t)) - ln(dow(t-1))]*100
RGDP Growth	[ln(RGDP(t)) - ln(RGDP(t-1))]*400
Unemployment Rate	[% unemployment(t) - % unemployment(t-1)]*4
3-mo UST Rate	% 3mo treasury yield(t)
BBB Spread	% bbb bond yield(t) - % 10yr treasury yield(t)
BBB Spread Change	bbb_spread(t) - bbb_spread(t-1)
10-yr UST Rate	% 10yr treasury yield(t) - % 10yr treasury yield(t-1)
House Prices	[ln(hpi(t)) - ln(hpi(t-4))]*400
Commercial Real Estate	[ln(cppi(t) - ln(cppi(t-4)]*400
House Price Momentum	1{min[h<0,0]}
Commercial Real Estate Momentum	1{min[cp<0,0]}

Table 2: This table displays means (standard deviations) for the 16 different dependent variables used to estimate equation (1). Data are for year-end observations from 1991:Q4 through 2015:Q4, and are displayed three of the subsamples of U.S. commercial banking companies that we use in our analysis: Large Community Banks with assets between $500 million to $10 billion, CLASS banks with assets greater than $5 billion, and SIFI banks with assets greater than $250 billion.

	Community	CLASS	SIFI
Net Interest Margin	0.0355	0.0337	0.0263
	(0.0056)	(0.0070)	(0.0098)
Noninterest Income	0.0092	0.0165	0.0247
	(0.0048)	(0.0090)	(0.0067)
Compensation Expense	0.0154	0.0149	0.0154
	(0.0036)	(0.0040)	(0.0033)
Fixed Assets Expense	0.0040	0.0041	0.0037
	(0.0012)	(0.0013)	(0.0013)
Other Noninterest Expense	0.0099	0.0122	0.0124
	(0.0033)	(0.0053)	(0.0035)
Home Equity Lines of Credit	0.0012	0.0020	0.0074
	(0.0025)	(0.0031)	(0.0098)
Commercial & Industrial	0.0049	0.0055	0.0064
	(0.0069)	(0.0061)	(0.0057)
Residential Real Estate	0.0016	0.0018	0.0050
	(0.0026)	(0.0026)	(0.0067)
Construction & Land Development	0.0049	0.0080	0.0142
	(0.0122)	(0.0175)	(0.0277)
Multifamily Real Estate	0.0008	0.0017	0.0015
	(0.0026)	(0.0040)	(0.0033)
Farmland	0.0001	0.0008	0.0012
	(0.0006)	(0.0026)	(0.0029)
Nonfarm Nonresidential	0.0016	0.0025	0.0017
	(0.0029)	(0.0042)	(0.0033)
Credit Cards	0.0234	0.0326	0.0474
	(0.0179)	(0.0199)	(0.0169)
Other Consumer	0.0065	0.0085	0.0162
	(0.0066)	(0.0073)	(0.0112)
All Other	0.0036	0.0027	0.0024
	(0.0106)	(0.0049)	(0.0026)
Agriculture	0.0003	0.0013	0.0025
	(0.0012)	(0.0034)	(0.0050)
Quarterly Observations	78,568	14,753	785

Table 3.1: Regression Results: Net Interest Margin

	Dependent variable:					
	d_nim					
	(COMM)	(CLASS)	(SIFI)	(COMM)	(CLASS)	(SIFI)
lag(d_nim)	0.742***	0.592***	0.665***	0.734***	0.588***	0.641***
	(0.010)	(0.025)	(0.056)	(0.011)	(0.025)	(0.065)
slope	0.023***	0.053***	0.070***	0.029***	0.048***	0.043*
	(0.003)	(0.010)	(0.021)	(0.003)	(0.009)	(0.025)
cmt3mo	0.024***	0.044***	0.033*	0.022***	0.037***	0.028
	(0.003)	(0.009)	(0.019)	(0.003)	(0.008)	(0.020)
PC1				0.007***	0.007***	−0.006**
				(0.0003)	(0.001)	(0.002)
PC2				−0.002***	−0.0004	−0.006***
				(0.0003)	(0.001)	(0.002)
PC3				−0.002***	−0.007***	−0.0001
				(0.0004)	(0.001)	(0.004)
PC4				0.009***	0.012***	−0.032***
				(0.001)	(0.004)	(0.012)
PC5				0.016***	0.021***	0.002
				(0.001)	(0.003)	(0.009)
heloc_mix	0.261*	0.516	0.066	0.436***	0.866**	−0.472
	(0.134)	(0.401)	(1.140)	(0.136)	(0.427)	(1.399)
ci_mix	0.516***	1.238***	0.910*	0.505***	1.158***	1.426**
	(0.062)	(0.165)	(0.539)	(0.064)	(0.165)	(0.656)
mfre_mix	0.078	0.951***	−2.590	0.017	0.918***	1.631
	(0.067)	(0.208)	(5.470)	(0.069)	(0.199)	(5.231)
rre_mix	0.247***	0.709***	0.224	0.232***	0.641***	−0.226
	(0.036)	(0.106)	(0.489)	(0.037)	(0.109)	(0.406)
ccre_mix	0.222***	−0.035	−2.324	0.591***	0.776***	−2.446
	(0.061)	(0.255)	(4.155)	(0.065)	(0.272)	(4.011)
nfnr_mix	0.550***	1.768***	10.198***	0.588***	1.706***	9.635***
	(0.047)	(0.249)	(2.637)	(0.048)	(0.249)	(2.756)
cc_mix	1.218***	2.616***	4.907***	1.257***	2.639***	6.065***
	(0.137)	(0.258)	(1.257)	(0.130)	(0.252)	(1.472)
oc_mix	0.819***	2.012***	4.333***	0.813***	1.995***	3.759***
	(0.099)	(0.306)	(1.277)	(0.095)	(0.300)	(1.405)
log(gta)	−0.032***	−0.020*	0.045	−0.031***	−0.017	0.006
	(0.004)	(0.012)	(0.055)	(0.004)	(0.013)	(0.053)
Constant	1.096***	0.455**	−1.077	1.091***	0.456**	−0.191
	(0.112)	(0.202)	(1.182)	(0.107)	(0.202)	(1.160)
Observations	73,334	13,771	726	73,334	13,771	726
R^2	0.770	0.784	0.942	0.775	0.788	0.945
Adjusted R^2	0.770	0.783	0.940	0.775	0.786	0.942
Note:	*p<0.1; **p<0.05; ***p<0.01					

Table 3.2: Regression Results: Noninterest Income

	Dependent variable:					
	d_nonii					
	(COMM)	(CLASS)	(SIFI)	(COMM)	(CLASS)	(SIFI)
lag(d_nonii)	0.828***	0.867***	0.686***	0.827***	0.865***	0.690***
	(0.011)	(0.022)	(0.060)	(0.011)	(0.022)	(0.061)
dl_sp500	−0.00002	0.001	0.010**	0.00001	0.001	0.008*
	(0.0002)	(0.001)	(0.005)	(0.0002)	(0.001)	(0.004)
PC1				0.001***	0.004***	−0.007
				(0.0003)	(0.001)	(0.007)
PC2				−0.001***	−0.001	0.010***
				(0.0003)	(0.001)	(0.004)
PC3				0.00002	−0.003**	−0.021***
				(0.0004)	(0.001)	(0.005)
PC4				−0.003***	−0.008**	0.001
				(0.001)	(0.004)	(0.015)
PC5				0.004***	0.009***	−0.001
				(0.001)	(0.003)	(0.016)
heloc_mix	0.788***	0.187	−0.290	0.808***	0.234	0.123
	(0.135)	(0.328)	(1.585)	(0.134)	(0.328)	(1.710)
ci_mix	0.112**	−0.192*	−1.792	0.108**	−0.192*	−1.368
	(0.045)	(0.113)	(1.192)	(0.045)	(0.115)	(0.971)
mfre_mix	−0.151***	−0.412***	−14.918*	−0.161***	−0.466***	−16.111**
	(0.051)	(0.139)	(8.210)	(0.051)	(0.142)	(7.900)
rre_mix	0.063*	−0.082	−2.067***	0.053	−0.114	−2.095***
	(0.035)	(0.120)	(0.582)	(0.035)	(0.120)	(0.783)
ccre_mix	−0.135***	−0.167	−7.480	−0.100**	0.003	−10.339
	(0.043)	(0.190)	(6.245)	(0.048)	(0.221)	(7.807)
nfnr_mix	−0.029	−0.460***	7.810	−0.045	−0.489***	7.894
	(0.033)	(0.169)	(6.035)	(0.034)	(0.165)	(5.701)
cc_mix	0.557***	0.686***	−0.651	0.562***	0.713***	−1.453
	(0.119)	(0.255)	(1.785)	(0.119)	(0.258)	(1.539)
oc_mix	0.038	−0.197	6.431***	0.044	−0.180	6.118***
	(0.052)	(0.136)	(1.677)	(0.053)	(0.133)	(1.708)
log(gta)	0.023***	0.029***	−0.002	0.023***	0.028***	0.025
	(0.004)	(0.007)	(0.068)	(0.004)	(0.007)	(0.068)
Constant	−0.150**	−0.291***	0.504	−0.135*	−0.285***	0.049
	(0.073)	(0.106)	(1.602)	(0.074)	(0.108)	(1.668)
Observations	72,956	13,705	723	72,956	13,705	723
R^2	0.756	0.856	0.667	0.757	0.856	0.675
Adjusted R^2	0.756	0.855	0.657	0.756	0.856	0.663
Note:	*p<0.1; **p<0.05; ***p<0.01					

Table 3.3: Regression Results: Compensation Noninterest Expense

	Dependent variable:					
	d_nonie					
	(COMM)	(CLASS)	(SIFI)	(COMM)	(CLASS)	(SIFI)
lag(d_nonie)	0.818***	0.809***	0.693***	0.818***	0.807***	0.697***
	(0.009)	(0.019)	(0.071)	(0.009)	(0.020)	(0.071)
dl_sp500	0.0001	−0.0001	0.005***	0.00005	−0.001*	0.005***
	(0.0001)	(0.0003)	(0.002)	(0.0001)	(0.0003)	(0.002)
PC1				0.001***	0.003***	−0.002
				(0.0001)	(0.0004)	(0.002)
PC2				−0.001***	0.001*	0.002
				(0.0002)	(0.0004)	(0.001)
PC3				−0.0005**	−0.003***	−0.007***
				(0.0002)	(0.001)	(0.002)
PC4				−0.002***	0.001	−0.004
				(0.001)	(0.002)	(0.006)
PC5				0.005***	0.006***	0.002
				(0.0005)	(0.001)	(0.004)
heloc_mix	0.801***	0.406**	0.110	0.828***	0.528***	0.206
	(0.087)	(0.166)	(0.480)	(0.087)	(0.176)	(0.639)
ci_mix	0.154***	0.053	0.604**	0.147***	0.027	0.750**
	(0.033)	(0.065)	(0.278)	(0.033)	(0.064)	(0.299)
mfre_mix	−0.064	−0.330***	0.459	−0.075*	−0.345***	0.213
	(0.041)	(0.075)	(3.202)	(0.041)	(0.073)	(3.431)
rre_mix	0.069***	0.053	−0.768**	0.058**	0.035	−0.831**
	(0.023)	(0.052)	(0.346)	(0.023)	(0.053)	(0.373)
ccre_mix	−0.040	−0.117	3.820**	0.011	0.091	3.472*
	(0.029)	(0.092)	(1.888)	(0.032)	(0.114)	(1.794)
nfnr_mix	0.147***	0.055	−2.397*	0.136***	0.069	−2.389*
	(0.022)	(0.071)	(1.399)	(0.023)	(0.074)	(1.434)
cc_mix	0.033	−0.063	−1.453**	0.035	−0.066	−1.539**
	(0.052)	(0.069)	(0.618)	(0.050)	(0.068)	(0.659)
oc_mix	0.190***	0.030	2.695***	0.189***	0.009	2.403***
	(0.041)	(0.087)	(0.807)	(0.041)	(0.083)	(0.922)
log(gta)	−0.010***	0.011***	0.007	−0.010***	0.014***	0.013
	(0.002)	(0.004)	(0.019)	(0.002)	(0.004)	(0.022)
Constant	0.392***	−0.010	0.194	0.401***	−0.043	0.059
	(0.051)	(0.061)	(0.422)	(0.052)	(0.063)	(0.494)
Observations	73,390	13,775	730	73,390	13,775	730
R^2	0.768	0.795	0.762	0.769	0.796	0.767
Adjusted R^2	0.768	0.794	0.755	0.769	0.795	0.759
Note:	*p<0.1; **p<0.05; ***p<0.01					

Table 3.4: Regression Results: Fixed Assets Expense

	Dependent variable:					
	d_fae					
	(COMM)	(CLASS)	(SIFI)	(COMM)	(CLASS)	(SIFI)
lag(d_fae)	0.837***	0.808***	0.718***	0.838***	0.804***	0.696***
	(0.006)	(0.018)	(0.056)	(0.006)	(0.019)	(0.051)
g	0.001***	0.002***	0.002**	0.0005***	0.002***	0.003***
	(0.0001)	(0.0004)	(0.001)	(0.0001)	(0.0004)	(0.001)
PC1				0.0002***	0.0003***	−0.0004
				(0.00005)	(0.0001)	(0.0003)
PC2				−0.0002***	0.0002	−0.0002
				(0.0001)	(0.0002)	(0.0003)
PC3				−0.0001	−0.001***	−0.002*
				(0.0001)	(0.0002)	(0.001)
PC4				0.0002	0.001**	−0.004**
				(0.0002)	(0.001)	(0.002)
PC5				0.001***	0.002***	0.001
				(0.0001)	(0.0004)	(0.001)
heloc_mix	0.220***	0.091	0.323	0.227***	0.132**	0.326
	(0.022)	(0.055)	(0.244)	(0.022)	(0.059)	(0.213)
ci_mix	0.034***	0.023	0.302***	0.033***	0.013	0.389***
	(0.008)	(0.020)	(0.087)	(0.008)	(0.020)	(0.119)
mfre_mix	−0.026**	−0.074***	1.438	−0.029**	−0.074***	1.678*
	(0.012)	(0.026)	(0.902)	(0.012)	(0.027)	(0.951)
rre_mix	0.010	0.003	−0.134	0.008	−0.002	−0.204*
	(0.006)	(0.017)	(0.108)	(0.006)	(0.017)	(0.115)
ccre_mix	0.012	0.008	0.504	0.024***	0.076**	0.743
	(0.008)	(0.032)	(0.664)	(0.009)	(0.036)	(0.661)
nfnr_mix	0.031***	0.002	−0.533**	0.030***	−0.0004	−0.603**
	(0.006)	(0.022)	(0.234)	(0.007)	(0.023)	(0.255)
cc_mix	0.004	−0.029	0.030	0.004	−0.031*	0.096
	(0.013)	(0.018)	(0.159)	(0.013)	(0.018)	(0.180)
oc_mix	0.072***	0.026	0.619***	0.072***	0.019	0.504**
	(0.009)	(0.029)	(0.222)	(0.009)	(0.028)	(0.256)
log(gta)	−0.003***	0.0002	−0.017**	−0.003***	0.001	−0.018**
	(0.001)	(0.001)	(0.008)	(0.001)	(0.001)	(0.009)
Constant	0.114***	0.017	0.386**	0.116***	0.011	0.403**
	(0.018)	(0.020)	(0.178)	(0.018)	(0.020)	(0.195)
Observations	73,338	13,752	733	73,338	13,752	733
R^2	0.779	0.784	0.884	0.779	0.786	0.888
Adjusted R^2	0.779	0.783	0.880	0.779	0.784	0.883
Note:	*p<0.1; **p<0.05; ***p<0.01					

Table 3.5: Regression Results: Other Noninterest Expense

	Dependent variable:					
	d_onie					
	(COMM)	(CLASS)	(SIFI)	(COMM)	(CLASS)	(SIFI)
lag(d_onie)	0.659***	0.620***	0.717***	0.647***	0.618***	0.714***
	(0.015)	(0.049)	(0.108)	(0.017)	(0.050)	(0.108)
d_bbb_spread	0.007*	0.098***	0.130**	0.025***	0.106***	0.127*
	(0.004)	(0.027)	(0.060)	(0.004)	(0.027)	(0.069)
PC1				−0.001***	−0.001	−0.003
				(0.0003)	(0.001)	(0.002)
PC2				0.002***	0.003*	0.005
				(0.0004)	(0.002)	(0.004)
PC3				−0.003***	0.00003	0.005
				(0.001)	(0.002)	(0.006)
PC4				0.013***	0.004	−0.006
				(0.001)	(0.004)	(0.011)
PC5				0.011***	0.012***	0.010
				(0.001)	(0.003)	(0.016)
heloc_mix	0.775***	0.626	−1.042	0.929***	0.800*	−0.926
	(0.143)	(0.401)	(1.985)	(0.148)	(0.430)	(1.999)
ci_mix	0.148**	−0.049	−1.116	0.137**	−0.090	−1.021
	(0.066)	(0.184)	(0.703)	(0.069)	(0.188)	(0.854)
mfre_mix	−0.047	−0.603***	−14.500**	−0.066	−0.575***	−13.900**
	(0.059)	(0.160)	(6.041)	(0.061)	(0.156)	(6.209)
rre_mix	0.012	−0.276**	0.007	0.014	−0.289**	0.024
	(0.038)	(0.118)	(0.529)	(0.039)	(0.118)	(0.592)
ccre_mix	0.013	0.124	−6.683**	0.228***	0.319	−7.401**
	(0.050)	(0.226)	(3.312)	(0.056)	(0.276)	(3.768)
nfnr_mix	−0.001	−0.562***	12.790***	0.043	−0.611***	12.471***
	(0.037)	(0.174)	(4.369)	(0.040)	(0.175)	(4.474)
cc_mix	1.369***	2.195***	2.582**	1.392***	2.190***	2.300*
	(0.149)	(0.451)	(1.055)	(0.155)	(0.455)	(1.174)
oc_mix	0.291***	−0.226	0.051	0.258***	−0.250	0.352
	(0.067)	(0.189)	(1.707)	(0.066)	(0.186)	(1.906)
log(gta)	0.002	−0.0004	0.047	0.004	0.001	0.038
	(0.004)	(0.012)	(0.044)	(0.004)	(0.012)	(0.045)
Constant	0.388***	0.233	−1.069	0.342***	0.253	−0.819
	(0.122)	(0.200)	(0.987)	(0.115)	(0.191)	(0.975)
Observations	73,032	13,724	725	73,032	13,724	725
R^2	0.546	0.661	0.693	0.550	0.661	0.696
Adjusted R^2	0.545	0.659	0.684	0.550	0.660	0.684
Note:	*p<0.1; **p<0.05; ***p<0.01					

Table 3.6: Regression Results: NCO HELOC Loans

	Dependent variable:					
	d_heloc					
	(COMM)	(CLASS)	(SIFI)	(COMM)	(CLASS)	(SIFI)
lag(d_heloc)	0.291^{***}	0.521^{***}	0.789^{***}	0.275^{***}	0.516^{***}	0.778^{***}
	(0.013)	(0.020)	(0.042)	(0.013)	(0.020)	(0.050)
h	-0.001^{***}	-0.001^{***}	-0.004^{***}	0.002^{***}	-0.0005^{**}	-0.003^{**}
	(0.0001)	(0.0001)	(0.001)	(0.0002)	(0.0002)	(0.002)
h_d	0.105^{***}	0.021^{***}	0.101^{***}	0.118^{***}	0.005	0.054
	(0.009)	(0.007)	(0.038)	(0.011)	(0.008)	(0.063)
PC1				-0.011^{***}	-0.002^{***}	-0.007
				(0.001)	(0.001)	(0.005)
PC2				0.005^{***}	-0.0002	-0.004
				(0.001)	(0.0005)	(0.003)
PC3				0.005^{***}	0.002^{***}	0.001
				(0.001)	(0.001)	(0.006)
PC4				0.008^{***}	-0.002^{**}	-0.009
				(0.001)	(0.001)	(0.009)
PC5				0.016^{***}	0.001	0.002
				(0.001)	(0.001)	(0.008)
Constant	0.090^{**}	0.008	0.239^{***}	0.060	0.021^{***}	0.258^{***}
	(0.044)	(0.009)	(0.041)	(0.054)	(0.008)	(0.052)
Observations	65,979	11,357	464	65,979	11,357	464
R^2	0.113	0.351	0.788	0.123	0.353	0.792
Adjusted R^2	0.112	0.348	0.782	0.122	0.350	0.784
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$					

Table 3.7: Regression Results: NCO C & I Loans

	Dependent variable:					
	d_ci					
	(COMM)	(CLASS)	(SIFI)	(COMM)	(CLASS)	(SIFI)
lag(d_ci)	0.229***	0.476***	0.707***	0.205***	0.443***	0.646***
	(0.008)	(0.029)	(0.035)	(0.008)	(0.033)	(0.048)
g	0.021***	0.008**	0.016**	0.041***	0.025***	0.016*
	(0.003)	(0.004)	(0.007)	(0.003)	(0.004)	(0.008)
d_iu	0.121***	0.154***	0.152***	0.038***	0.084***	0.137***
	(0.006)	(0.012)	(0.028)	(0.007)	(0.011)	(0.021)
PC1				−0.030***	−0.024***	−0.006
				(0.001)	(0.003)	(0.005)
PC2				0.018***	0.009***	−0.0004
				(0.001)	(0.002)	(0.003)
PC3				−0.012***	−0.008***	−0.005
				(0.001)	(0.002)	(0.004)
PC4				−0.004	−0.026***	−0.031***
				(0.003)	(0.004)	(0.008)
PC5				0.012***	0.017***	0.032***
				(0.003)	(0.004)	(0.008)
Constant	0.538**	0.242***	0.098***	0.430*	0.213***	0.142***
	(0.223)	(0.007)	(0.020)	(0.225)	(0.011)	(0.036)
Observations	70,334	13,260	724	70,334	13,260	724
R^2	0.074	0.305	0.689	0.089	0.319	0.702
Adjusted R^2	0.073	0.302	0.684	0.088	0.315	0.694
Note:	*p<0.1; **p<0.05; ***p<0.01					

Table 3.8: Regression Results: NCO Residential Real Estate Loans

	Dependent variable:					
	d_rre					
	(COMM)	(CLASS)	(SIFI)	(COMM)	(CLASS)	(SIFI)
lag(d_rre)	0.398***	0.694***	0.872***	0.377***	0.672***	0.874***
	(0.012)	(0.021)	(0.027)	(0.012)	(0.022)	(0.027)
h	−0.001***	−0.001***	−0.003***	0.002***	−0.0001	−0.004***
	(0.0001)	(0.0002)	(0.001)	(0.0002)	(0.0004)	(0.001)
h_d	0.137***	0.082***	−0.012	0.148***	0.050***	−0.024
	(0.009)	(0.013)	(0.069)	(0.010)	(0.016)	(0.074)
PC1				−0.012***	−0.008***	0.001
				(0.001)	(0.001)	(0.002)
PC2				0.006***	0.002*	−0.011**
				(0.001)	(0.001)	(0.005)
PC3				0.003***	0.002*	−0.005**
				(0.001)	(0.001)	(0.002)
PC4				0.007***	−0.006***	−0.011*
				(0.001)	(0.002)	(0.006)
PC5				0.015***	0.010***	−0.001
				(0.001)	(0.001)	(0.004)
Constant	0.040	0.035***	0.189***	−0.001	0.018**	0.195***
	(0.030)	(0.006)	(0.063)	(0.036)	(0.008)	(0.062)
Observations	71,726	13,246	718	71,726	13,246	718
R^2	0.211	0.561	0.798	0.223	0.568	0.802
Adjusted R^2	0.211	0.559	0.795	0.222	0.566	0.797
Note:	*p<0.1; **p<0.05; ***p<0.01					

Table 3.9: Regression Results: NCO Construction and Land Development Loans

	Dependent variable:					
	d_ccre					
	(COMM)	(CLASS)	(SIFI)	(COMM)	(CLASS)	(SIFI)
lag(d_ccre)	0.312^{***}	0.506^{***}	0.727^{***}	0.281^{***}	0.466^{***}	0.712^{***}
	(0.010)	(0.021)	(0.085)	(0.010)	(0.020)	(0.089)
cp	-0.003^{***}	-0.005^{***}	-0.004^{*}	-0.002^{***}	-0.004^{***}	-0.003
	(0.0002)	(0.001)	(0.002)	(0.0002)	(0.001)	(0.002)
cp_d	-0.030^{**}	0.093^{**}	0.269	-0.078^{***}	0.022	0.204
	(0.012)	(0.037)	(0.198)	(0.012)	(0.038)	(0.215)
PC1				-0.020^{***}	-0.035^{***}	-0.016^{**}
				(0.001)	(0.003)	(0.008)
PC2				0.009^{***}	0.018^{***}	0.010
				(0.001)	(0.003)	(0.013)
PC3				0.011^{***}	0.020^{***}	-0.005
				(0.001)	(0.003)	(0.020)
PC4				-0.010^{***}	-0.019^{***}	-0.009
				(0.001)	(0.004)	(0.018)
PC5				0.015^{***}	-0.001	-0.056^{**}
				(0.001)	(0.005)	(0.022)
Constant	0.040	0.179^{***}	0.165^{*}	0.101^{**}	0.243^{***}	0.034
	(0.031)	(0.017)	(0.090)	(0.045)	(0.021)	(0.159)
Observations	65,533	12,096	649	65,533	12,096	649
R^2	0.136	0.361	0.593	0.160	0.384	0.598
Adjusted R^2	0.135	0.358	0.585	0.159	0.381	0.586
Note:	*p<0.1; **p<0.05; ***p<0.01					

Table 3.10: Regression Results: NCO Multifamily Real Estate Loans

	Dependent variable:					
	d_mfre					
	(COMM)	(CLASS)	(SIFI)	(COMM)	(CLASS)	(SIFI)
lag(d_mfre)	0.191***	0.331***	0.471***	0.183***	0.310***	0.439***
	(0.014)	(0.025)	(0.064)	(0.014)	(0.024)	(0.060)
cp_d	0.093***	0.246***	0.231***	0.002	0.086***	0.171*
	(0.010)	(0.027)	(0.083)	(0.012)	(0.029)	(0.103)
PC1				−0.008***	−0.023***	−0.005
				(0.001)	(0.003)	(0.004)
PC2				0.008***	0.014***	0.017***
				(0.001)	(0.002)	(0.006)
PC3				−0.002**	0.003	−0.014**
				(0.001)	(0.002)	(0.007)
PC4				0.014***	0.006*	0.021
				(0.002)	(0.003)	(0.019)
PC5				0.007***	0.006	−0.007
				(0.002)	(0.004)	(0.018)
Constant	0.289**	−0.120*	−0.000	0.279**	−0.100*	0.073
	(0.138)	(0.070)	(0.00000)	(0.139)	(0.056)	(0.048)
Observations	58,419	12,694	707	58,419	12,694	707
R^2	0.044	0.154	0.345	0.050	0.171	0.364
Adjusted R^2	0.043	0.150	0.334	0.048	0.167	0.348
Note:		*p<0.1; **p<0.05; ***p<0.01				

Table 3.11: Regression Results: NCO Farmland Loans

	Dependent variable:					
	d_farm					
	(COMM)	(CLASS)	(SIFI)	(COMM)	(CLASS)	(SIFI)
lag(d_farm)	0.129***	0.174***	0.119*	0.127***	0.170***	0.110
	(0.015)	(0.028)	(0.071)	(0.015)	(0.028)	(0.067)
h	−0.0002***	−0.001***	−0.0004	0.0002*	0.001	−0.0001
	(0.00004)	(0.0002)	(0.001)	(0.0001)	(0.001)	(0.004)
PC1				−0.002***	−0.010***	−0.002
				(0.0005)	(0.003)	(0.013)
PC2				0.001***	0.003	0.012***
				(0.0003)	(0.002)	(0.004)
PC3				−0.0002	0.003	−0.009
				(0.0004)	(0.003)	(0.012)
PC4				−0.001	0.002	0.002
				(0.001)	(0.004)	(0.020)
PC5				0.002***	0.004	0.003
				(0.001)	(0.003)	(0.013)
Constant	0.002***	0.005*	0.021	−0.002	−0.013	0.033
	(0.001)	(0.003)	(0.045)	(0.003)	(0.015)	(0.097)
Observations	53,028	10,776	551	53,028	10,776	551
R^2	0.025	0.044	0.041	0.027	0.047	0.051
Adjusted R^2	0.024	0.039	0.019	0.026	0.042	0.020
Note:	*p<0.1; **p<0.05; ***p<0.01					

Table 3.12: Regression Results: NCO Nonfarm Nonresidential Loans

	Dependent variable:					
	d_nfnr					
	(COMM)	(CLASS)	(SIFI)	(COMM)	(CLASS)	(SIFI)
lag(d_nfnr)	0.279***	0.430***	0.594***	0.264***	0.410***	0.577***
	(0.009)	(0.019)	(0.031)	(0.010)	(0.020)	(0.027)
cp	−0.001***	−0.002***	−0.002*	−0.001***	−0.002***	−0.002
	(0.0001)	(0.0003)	(0.001)	(0.0001)	(0.0003)	(0.001)
cp_d	−0.014	0.115***	0.107	−0.036***	0.088***	0.095
	(0.009)	(0.026)	(0.131)	(0.009)	(0.025)	(0.138)
PC1				−0.009***	−0.008***	−0.002
				(0.0005)	(0.001)	(0.003)
PC2				0.008***	0.011***	0.015*
				(0.001)	(0.001)	(0.008)
PC3				−0.001*	−0.001	−0.003
				(0.001)	(0.002)	(0.008)
PC4				0.010***	0.013***	0.023
				(0.001)	(0.003)	(0.018)
PC5				0.011***	−0.002	−0.0004
				(0.001)	(0.003)	(0.016)
Constant	0.147***	0.098***	0.069	0.123**	0.121***	0.165**
	(0.055)	(0.011)	(0.055)	(0.057)	(0.013)	(0.083)
Observations	71,363	13,016	720	71,363	13,016	720
R^2	0.098	0.278	0.417	0.108	0.286	0.423
Adjusted R^2	0.097	0.275	0.406	0.107	0.283	0.408
Note:	*p<0.1; **p<0.05; ***p<0.01					

Table 3.13: Regression Results: NCO Credit Card Loans

	Dependent variable:					
	d_cc					
	(COMM)	(CLASS)	(SIFI)	(COMM)	(CLASS)	(SIFI)
lag(d_cc)	0.326^{***}	0.412^{***}	0.781^{***}	0.321^{***}	0.401^{***}	0.683^{***}
	(0.027)	(0.038)	(0.026)	(0.027)	(0.039)	(0.044)
d_iu	0.210^{***}	0.176^{***}	0.391^{***}	0.091^{***}	0.077^{*}	0.191^{***}
	(0.021)	(0.053)	(0.046)	(0.025)	(0.043)	(0.065)
PC1				-0.026^{***}	-0.032^{***}	-0.063^{***}
				(0.006)	(0.011)	(0.017)
PC2				0.006	0.028^{***}	0.036^{***}
				(0.005)	(0.008)	(0.009)
PC3				-0.016^{***}	-0.002	-0.029^{*}
				(0.006)	(0.008)	(0.016)
PC4				-0.078^{***}	-0.026	-0.040^{*}
				(0.012)	(0.024)	(0.021)
PC5				0.040^{***}	0.133^{***}	0.019
				(0.010)	(0.024)	(0.028)
Constant	1.548^{*}	0.005^{***}	1.116^{***}	1.639^{*}	0.147^{***}	1.564^{***}
	(0.906)	(0.001)	(0.140)	(0.958)	(0.050)	(0.216)
Observations	37,368	10,248	565	37,368	10,248	565
R^2	0.160	0.227	0.750	0.163	0.233	0.771
Adjusted R^2	0.159	0.223	0.745	0.162	0.229	0.765
Note:	*p<0.1; **p<0.05; ***p<0.01					

Table 3.14: Regression Results: NCO Other Consumer Loans

	Dependent variable:					
	d_oc					
	(COMM)	(CLASS)	(SIFI)	(COMM)	(CLASS)	(SIFI)
lag(d_oc)	0.398***	0.595***	0.796***	0.393***	0.581***	0.793***
	(0.016)	(0.030)	(0.045)	(0.016)	(0.031)	(0.048)
d_iu	0.072***	0.094***	0.115***	0.036***	0.034***	0.069*
	(0.004)	(0.010)	(0.031)	(0.005)	(0.011)	(0.036)
PC1				−0.010***	−0.016***	−0.012
				(0.001)	(0.003)	(0.010)
PC2				0.003***	0.003	−0.004
				(0.001)	(0.002)	(0.006)
PC3				0.002*	0.0005	0.001
				(0.001)	(0.002)	(0.006)
PC4				−0.017***	−0.025***	−0.013
				(0.002)	(0.005)	(0.024)
PC5				0.012***	0.015***	−0.015
				(0.002)	(0.004)	(0.017)
Constant	0.695***	0.038***	0.031	0.724***	0.030**	−0.005
	(0.227)	(0.001)	(0.023)	(0.246)	(0.012)	(0.069)
Observations	71,800	13,465	716	71,800	13,465	716
R^2	0.195	0.461	0.719	0.198	0.467	0.720
Adjusted R^2	0.195	0.459	0.714	0.197	0.464	0.714
Note:	*p<0.1; **p<0.05; ***p<0.01					

Table 3.15: Regression Results: NCO All Other Loans

	Dependent variable:					
	d_other					
	(COMM)	(CLASS)	(SIFI)	(COMM)	(CLASS)	(SIFI)
lag(d_other)	0.616^{***}	0.486^{***}	0.375^{***}	0.615^{***}	0.485^{***}	0.365^{***}
	(0.022)	(0.036)	(0.047)	(0.022)	(0.036)	(0.047)
slope	-0.080^{***}	0.010	0.062^{**}	-0.007	0.036^{***}	0.044
	(0.015)	(0.011)	(0.027)	(0.017)	(0.012)	(0.039)
cmt3mo	-0.071^{***}	0.012	0.051^{***}	-0.047^{***}	0.026^{***}	0.047^{***}
	(0.011)	(0.008)	(0.014)	(0.012)	(0.009)	(0.018)
bbb_spread	0.090^{***}	0.088^{***}	0.109^{***}	0.080^{***}	0.041^{*}	0.082^{**}
	(0.020)	(0.018)	(0.036)	(0.027)	(0.021)	(0.039)
PC1				0.0004	-0.005^{**}	-0.004
				(0.004)	(0.002)	(0.003)
PC2				-0.009^{***}	-0.006^{***}	0.002
				(0.003)	(0.002)	(0.002)
PC3				0.028^{***}	0.010^{***}	-0.001
				(0.004)	(0.002)	(0.003)
PC4				-0.008	-0.022^{***}	-0.014
				(0.007)	(0.006)	(0.010)
PC5				-0.016^{***}	-0.001	0.002
				(0.006)	(0.005)	(0.009)
Constant	1.581^{**}	-0.199^{***}	0.149	1.407^{*}	-0.203^{***}	0.216
	(0.731)	(0.056)	(0.098)	(0.731)	(0.067)	(0.166)
Observations	64,634	13,173	720	64,634	13,173	720
R^2	0.386	0.305	0.334	0.387	0.308	0.339
Adjusted R^2	0.386	0.302	0.321	0.386	0.305	0.321
Note:	*p<0.1; **p<0.05; ***p<0.01					

Table 3.16: Regression Results: NCO Agricultural Loans

	Dependent variable:					
	d_ag					
	(COMM)	(CLASS)	(SIFI)	(COMM)	(CLASS)	(SIFI)
lag(d_ag)	0.135^{***}	0.187^{***}	0.204^{**}	0.133^{***}	0.182^{***}	0.157^{*}
	(0.013)	(0.024)	(0.100)	(0.013)	(0.024)	(0.092)
d_iu	0.004^{**}	0.022^{***}	0.048^{*}	0.001	−0.013	−0.058
	(0.001)	(0.008)	(0.027)	(0.002)	(0.011)	(0.047)
PC1				-0.001^{*}	-0.009^{***}	-0.026^{***}
				(0.0004)	(0.002)	(0.010)
PC2				0.001^{***}	0.00001	0.007
				(0.0004)	(0.002)	(0.009)
PC3				-0.002^{***}	-0.004^{**}	−0.009
				(0.0004)	(0.002)	(0.008)
PC4				−0.001	-0.013^{***}	-0.064^{***}
				(0.001)	(0.005)	(0.020)
PC5				0.004^{***}	0.014^{***}	0.063^{***}
				(0.001)	(0.004)	(0.014)
Constant	-0.001^{**}	−0.061	0.274^{***}	−0.004	−0.032	0.428^{***}
	(0.0003)	(0.136)	(0.011)	(0.005)	(0.143)	(0.070)
Observations	43,917	10,495	627	43,917	10,495	627
R^2	0.027	0.048	0.059	0.028	0.052	0.099
Adjusted R^2	0.026	0.043	0.040	0.027	0.047	0.074
Note:		*p<0.1; **p<0.05; ***p<0.01				

Table 4: This table shows the Federal Reserve's Adverse and Severely Adverse supervisory stress test scenarios for 2015.

Quarter	Dow Jones Industrial Average	RGDP Growth (annual %)	Unemployment Rate (%)	3-mo UST Rate (%)	10-yr UST Rate (%)	BBB Yield (%)	House Price Index	Commercial Property Index
				Adverse Scenarios				
20160331	20,899.6	-1.5	5.5	0.1	1.3	4.4	181.2	270.6
20160630	18,454.3	-2.8	6.1	0.1	1.4	4.9	178.7	264.2
20160930	16,692.8	-2.0	6.7	0.1	1.5	5.1	175.9	257.7
20161231	15,536.2	-1.1	7.1	0.1	1.7	5.4	172.8	251.8
20170331	15,745.4	0.0	7.4	0.1	1.8	5.4	169.8	246.6
20170630	16,052.6	1.3	7.5	0.1	1.9	5.3	167.0	243.5
20170930	16,396.9	1.7	7.5	0.1	2.2	5.4	164.5	240.5
20171231	17,115.4	2.6	7.5	0.1	2.3	5.4	162.9	240.6
20180331	17,806.7	2.6	7.4	0.1	2.4	5.4	161.7	241.0
20180630	18,645.6	3.0	7.3	0.1	2.6	5.5	161.1	242.2
20180930	19,184.9	3.0	7.2	0.1	2.8	5.5	161	244.4
20181231	19,756.4	3.0	7.1	0.1	2.9	5.6	161.2	246.8
				Severely Adverse Scenarios				
20160331	16,831.9	-5.1	6.0	0.0	0.2	4.8	178.8	264.9
20160630	13,254.9	-7.5	7.2	-0.2	0.4	5.6	173.5	251.0
20160930	11,469.2	-5.9	8.3	-0.5	0.4	6.0	167.4	236.5
20161231	10,395.5	-4.2	9.1	-0.5	0.6	6.4	160.8	223.2
20170331	11,183.3	-2.2	9.7	-0.5	0.7	6.1	154.7	210.4
20170630	12,131.9	0.4	9.9	-0.5	0.8	5.8	148.9	201.3
20170930	13,178.9	1.3	10.0	-0.5	1.0	5.7	144.0	193.4
20171231	14,671.1	3.0	9.9	-0.5	1.1	5.5	140.8	191.2
20180331	16,180.1	3.0	9.8	-0.5	1.2	5.3	138.5	190.1
20180630	17,996.1	3.9	9.6	-0.5	1.4	5.1	137.5	190.5
20180930	19,271.6	3.9	9.4	-0.5	1.5	5.0	137.3	192.6
20181231	20,640.9	3.9	9.1	-0.5	1.6	4.8	137.7	195.4

Table 5: This table shows the values of the macroeconomic stress variables $Z\text{-}forward$ used in the projections of equation (1). These values are converted from the information in Table 4 using the formulas in Table 1.

Quarter	Slope	Equity Market Return	RGDP Growth	Unemployment Rate	3-mo UST Rate	BBB Spread	BBB Spread Change	10-yr UST Rate	House Prices	Commercial Real Estate	House Price Momentum	Commercial Real Estate Momentum
Adverse Scenarios												
2016:Q1	1.20	-0.96	-1.50	2.00	0.10	3.10	0.70	-0.90	8.70	15.98	0	0
2016:Q2	1.30	-12.44	-2.80	2.40	0.10	3.50	0.40	0.10	-1.56	0.30	1	0
2016:Q3	1.40	-10.03	-2.00	2.40	0.10	3.60	0.10	0.10	-12.98	-18.65	1	1
2016:Q4	1.60	-7.18	-1.10	1.60	0.10	3.70	0.10	0.20	-23.16	-32.92	1	1
2017:Q1	1.70	1.34	0.00	1.20	0.10	3.60	-0.10	0.10	-25.99	-37.15	1	1
2017:Q2	1.80	1.93	1.30	0.40	0.10	3.40	-0.20	0.10	-27.09	-32.64	1	1
2017:Q3	2.10	2.12	1.70	0.00	0.10	3.20	-0.20	0.30	-26.80	-27.63	1	1
2017:Q4	2.20	4.29	2.60	0.00	0.10	3.10	-0.10	0.10	-23.60	-18.20	1	1
2018:Q1	2.30	3.96	2.60	-0.40	0.10	3.00	-0.10	0.10	-19.55	-9.19	1	1
2018:Q2	2.50	4.60	3.00	-0.40	0.10	2.90	-0.10	0.20	-14.39	-2.14	1	1
2018:Q3	2.70	2.85	3.00	-0.40	0.10	2.70	-0.20	0.20	-8.60	6.43	1	0
2018:Q4	2.80	2.94	3.00	-0.40	0.10	2.70	0.00	0.10	-4.20	10.18	1	0
Severely Adverse Scenarios												
2016:Q1	0.20	-22.60	-5.10	4.00	0.00	4.60	2.20	-2.00	3.37	7.47	0	0
2016:Q2	0.60	-23.89	-7.50	4.80	-0.20	5.20	0.60	0.20	-13.38	-20.20	1	1
2016:Q3	0.90	-14.47	-5.90	4.40	-0.50	5.60	0.40	0.00	-32.79	-52.99	1	1
2016:Q4	1.10	-9.83	-4.20	3.20	-0.50	5.80	0.20	0.20	-51.95	-81.15	1	1
2017:Q1	1.20	7.30	-2.20	2.40	-0.50	5.40	-0.40	0.10	-57.91	-92.14	1	1
2017:Q2	1.30	8.14	0.40	0.80	-0.50	5.00	-0.40	0.10	-61.16	-88.27	1	1
2017:Q3	1.50	8.28	1.30	0.40	-0.50	4.70	-0.30	0.20	-60.23	-80.480	1	1
2017:Q4	1.60	10.73	3.00	-0.40	-0.50	4.40	-0.30	0.10	-53.13	-61.90	1	1
2018:Q1	1.70	9.79	3.00	-0.40	-0.50	4.10	-0.30	0.10	-44.25	-40.58	1	1
2018:Q2	1.90	10.64	3.90	-0.80	-0.50	3.70	-0.40	0.20	-31.86	-22.06	1	1
2018:Q3	2.00	6.85	3.90	-0.80	-0.50	3.50	-0.20	0.10	-19.06	-1.66	1	1
2018:Q4	2.10	6.86	3.90	-1.20	-0.50	3.20	-0.30	0.10	-8.91	8.69	1	0

Table 6(i): This table shows the projected distribution of the capital ratios for **Large Community Banks** (assets between $500 million and $10 billion) under the Adverse and Severely Adverse stress scenarios.

Community Banks	Mean	5% lower bound	1% lower bound	Mean	5% lower bound	1% lower bound
	Supervisory Adverse					
	Tier 1			*Leverage Ratio*		
% Banks Well Capitalized	4.10	3.01	1.64	55.87	27.46	6.01
% Banks Adequately Capitalized	40.71	20.77	4.51	38.25	43.99	9.97
% Banks Undercapitalized	53.69	63.11	21.17	5.05	23.91	19.67
% Banks Significantly Undercapitalized	1.09	12.02	38.66	0.41	3.42	24.18
% Banks Critically Undercapitalized	0.27	0.27	23.91	0.27	0.41	30.05
% Banks Bankrupt	0.14	0.82	10.11	0.14	0.82	10.11
	Supervisory Severely Adverse					
	Tier 1			*Leverage Ratio*		
% Banks Well Capitalized	3.96	2.87	1.64	54.1	26.78	5.74
% Banks Adequately Capitalized	38.52	19.95	4.23	38.8	43.03	9.97
% Banks Undercapitalized	55.6	63.25	20.63	6.28	25.27	18.44
% Banks Significantly Undercapitalized	1.50	12.7	37.98	0.41	3.69	24.32
% Banks Critically Undercapitalized	0.27	0.27	24.86	0.27	0.27	30.87
% Banks Bankrupt	0.14	0.96	10.66	0.14	0.96	10.66

Table 6(ii): This table shows the projected distribution of the capital ratios for **Small Community Banks** (assets between \$50 and \$500 million) under the Adverse and Severely Adverse stress scenarios.

Community Banks	Mean	5% lower bound	1% lower bound	Mean	5% lower bound	1% lower bound
	Supervisory Adverse					
	Tier 1			*Leverage Ratio*		
% Banks Well Capitalized	19.98	15.68	10.76	85.96	75.61	51.84
% Banks Adequately Capitalized	64.86	61.58	44.06	12.50	22.03	34.43
% Banks Undercapitalized	14.96	22.13	40.16	1.13	1.74	10.25
% Banks Significantly Undercapitalized	0.20	0.61	4.51	0.41	0.61	2.66
% Banks Critically Undercapitalized	0.00	0.00	0.51	0.00	0.00	0.82
% Banks Bankrupt	0.00	0.00	0.00	0.00	0.00	0.00
	Supervisory Severely Adverse					
	Tier 1			*Leverage Ratio*		
% Banks Well Capitalized	20.59	15.78	10.76	86.07	75.61	51.74
% Banks Adequately Capitalized	64.75	61.48	44.06	12.4	22.03	34.22
% Banks Undercapitalized	14.45	22.13	40.16	1.13	1.64	10.45
% Banks Significantly Undercapitalized	0.20	0.61	4.41	0.41	0.72	2.77
% Banks Critically Undercapitalized	0.00	0.00	0.61	0.00	0.00	0.82
% Banks Bankrupt	0.00	0.00	0.00	0.00	0.00	0.00

Table 6(iii): This table shows the projected distribution of the capital ratios for **Large Community Banks** (assets between $500 million and $10 billion) under the Adverse and Severely Adverse stress scenarios, **based on the Tier 1 capital levels at these banks as of year-end 2008**.

Community Banks	Mean	5% lower bound	1% lower bound	Mean	5% lower bound	1% lower bound
	Supervisory Adverse					
	Tier 1			*Leverage Ratio*		
% Banks Well Capitalized	0.39	0.39	0.39	12.28	5.65	1.36
% Banks Adequately Capitalized	7.41	3.51	0.97	22.42	12.48	3.51
% Banks Undercapitalized	41.33	22.61	6.04	36.26	24.56	6.04
% Banks Significantly Undercapitalized	43.86	50.49	16.37	20.86	29.24	9.16
% Banks Critically Undercapitalized	6.04	18.71	25.54	7.21	23.78	29.24
% Banks Bankrupt	0.97	4.29	50.68	0.97	4.29	50.68
	Supervisory Severely Adverse					
	Tier 1			*Leverage Ratio*		
% Banks Well Capitalized	0.39	0.39	0.39	11.7	5.65	1.36
% Banks Adequately Capitalized	6.82	3.51	0.97	22.03	12.09	3.51
% Banks Undercapitalized	39.57	22.22	5.65	34.7	24.37	6.04
% Banks Significantly Undercapitalized	45.81	48.93	15.98	22.42	28.85	8.77
% Banks Critically Undercapitalized	6.43	20.08	26.12	8.19	24.17	29.43
% Banks Bankrupt	0.97	4.87	50.88	0.97	4.87	50.88

Table 6(iv): This table shows the projected distribution of the capital ratios for **Small Community Banks** (assets between \$50 and \$500 million) under the Adverse and Severely Adverse stress scenarios, **based on the Tier 1 capital levels at these banks as of year-end 2008**.

Community Banks	Mean	5% lower bound	1% lower bound	Mean	5% lower bound	1% lower bound
	Supervisory Adverse					
	Tier 1			*Leverage Ratio*		
% Banks Well Capitalized	10.61	9.20	6.86	54.13	47.11	32.14
% Banks Adequately Capitalized	34.17	28.86	21.37	31.67	29.64	27.3
% Banks Undercapitalized	47.58	49.3	45.87	11.39	17.78	24.02
% Banks Significantly Undercapitalized	6.86	11.23	20.28	2.03	3.74	10.61
% Banks Critically Undercapitalized	0.78	1.25	4.52	0.78	1.56	4.84
% Banks Bankrupt	0.00	0.16	1.09	0.00	0.16	1.09
	Supervisory Severely Adverse					
	Tier 1			*Leverage Ratio*		
% Banks Well Capitalized	10.92	9.20	6.86	53.82	46.96	31.83
% Banks Adequately Capitalized	34.32	28.86	21.37	31.83	29.64	27.3
% Banks Undercapitalized	47.58	49.14	45.55	11.54	17.47	24.02
% Banks Significantly Undercapitalized	6.40	11.39	20.59	2.03	4.21	10.92
% Banks Critically Undercapitalized	0.78	1.25	4.52	0.78	1.56	4.84
% Banks Bankrupt	0.00	0.16	1.09	0.00	0.16	1.09

Table 7(i): This table shows the projected distribution of the capital ratios for **Large Community Banks** (assets between \$500 million and \$10 billion) under the Adverse and Severely Adverse stress scenarios. Model includes state-level economic conditions variables F.

Community Banks	Mean	5% lower bound	1% lower bound	Mean	5% lower bound	1% lower bound
	Supervisory Adverse					
	Tier 1			*Leverage Ratio*		
% Banks Well Capitalized	2.87	2.60	0.96	24.04	18.44	4.78
% Banks Adequately Capitalized	18.99	15.03	3.83	46.86	40.03	6.69
% Banks Undercapitalized	65.30	59.70	14.75	26.78	31.83	13.39
% Banks Significantly Undercapitalized	12.30	21.31	32.92	1.78	7.92	21.17
% Banks Critically Undercapitalized	0.41	0.55	28.28	0.41	0.96	34.70
% Banks Bankrupt	0.14	0.82	19.26	0.14	0.82	19.26
	Supervisory Severely Adverse					
	Tier 1			*Leverage Ratio*		
% Banks Well Capitalized	2.73	2.46	0.96	24.32	15.57	4.78
% Banks Adequately Capitalized	18.31	13.66	3.83	46.72	34.84	6.69
% Banks Undercapitalized	65.16	55.74	14.75	26.50	34.15	13.80
% Banks Significantly Undercapitalized	13.11	25.68	33.74	1.78	12.16	21.17
% Banks Critically Undercapitalized	0.55	1.37	27.87	0.55	2.19	34.70
% Banks Bankrupt	0.14	1.09	18.85	0.14	1.09	18.85

Table 7(ii): This table shows the projected distribution of the capital ratios for **Small Community Banks** (assets between \$50 and \$500 million) under the Adverse and Severely Adverse stress scenarios. Model includes state-level economic conditions variables F.

Community Banks	Mean	5% lower bound	1% lower bound	Mean	5% lower bound	1% lower bound
	Supervisory Adverse					
	Tier 1			*Leverage Ratio*		
% Banks Well Capitalized	17.73	15.47	10.25	82.79	76.02	52.46
% Banks Adequately Capitalized	63.63	62.19	45.70	15.27	21.52	34.02
% Banks Undercapitalized	18.55	21.82	39.65	1.33	1.84	10.35
% Banks Significantly Undercapitalized	0.10	0.51	3.89	0.61	0.61	2.36
% Banks Critically Undercapitalized	0.00	0.00	0.51	0.00	0.00	0.82
% Banks Bankrupt	0.00	0.00	0.00	0.00	0.00	0.00
	Supervisory Severely Adverse					
	Tier 1			*Leverage Ratio*		
% Banks Well Capitalized	18.34	15.16	10.35	83.09	75.00	52.97
% Banks Adequately Capitalized	64.14	61.27	45.80	14.96	22.34	33.71
% Banks Undercapitalized	17.42	23.05	39.55	1.33	2.05	10.35
% Banks Significantly Undercapitalized	0.10	0.51	3.79	0.61	0.61	2.15
% Banks Critically Undercapitalized	0.00	0.00	0.51	0.00	0.00	0.82
% Banks Bankrupt	0.00	0.00	0.00	0.00	0.00	0.00

Table 7(iii): This table shows the projected distribution of the capital ratios for **Large Community Banks** (assets between \$500 million and \$10 billion) under the Adverse and Severely Adverse stress scenarios, **based on the Tier 1 capital levels at these banks as of year-end 2008**. Model includes state-level economic conditions variables F.

Community Banks	Mean	5% lower bound	1% lower bound	Mean	5% lower bound	1% lower bound
	Supervisory Adverse					
	Tier 1			*Leverage Ratio*		
% Banks Well Capitalized	0.39	0.39	0.19	5.65	4.87	1.17
% Banks Adequately Capitalized	3.12	2.73	0.97	11.50	8.58	2.53
% Banks Undercapitalized	23.20	17.93	3.90	24.95	20.27	4.29
% Banks Significantly Undercapitalized	50.49	45.22	13.26	31.58	27.88	7.60
% Banks Critically Undercapitalized	18.32	26.71	22.03	21.83	31.38	24.76
% Banks Bankrupt	4.48	7.02	59.65	4.48	7.02	59.65
	Supervisory Severely Adverse					
	Tier 1			*Leverage Ratio*		
% Banks Well Capitalized	0.39	0.39	0.19	5.65	3.90	1.17
% Banks Adequately Capitalized	3.12	2.73	0.97	11.89	7.99	2.73
% Banks Undercapitalized	22.61	15.20	3.90	24.76	18.13	4.09
% Banks Significantly Undercapitalized	50.49	43.27	13.45	31.58	25.93	8.19
% Banks Critically Undercapitalized	18.91	30.21	22.42	21.64	35.87	24.76
% Banks Bankrupt	4.48	8.19	59.06	4.48	8.19	59.06

Table 7(iv): This table shows the projected distribution of the capital ratios for **Small Community Banks** (assets between \$50 and \$500 million) under the Adverse and Severely Adverse stress scenarios, **based on the Tier 1 capital levels at these banks as of year-end 2008**. Model includes state-level economic conditions variables F, 2008 Tier 1 capital.

Community Banks	Mean	5% lower bound	1% lower bound	Mean	5% lower bound	1% lower bound
	Supervisory Adverse					
	Tier 1			*Leverage Ratio*		
% Banks Well Capitalized	9.98	9.36	6.71	51.33	47.89	33.23
% Banks Adequately Capitalized	32.61	28.55	21.53	30.89	29.17	27.46
% Banks Undercapitalized	48.21	49.30	46.49	14.51	18.10	23.71
% Banks Significantly Undercapitalized	8.42	11.39	19.81	2.34	3.12	9.67
% Banks Critically Undercapitalized	0.62	1.25	4.52	0.78	1.56	4.99
% Banks Bankrupt	0.16	0.16	0.94	0.16	0.16	0.94
	Supervisory Severely Adverse					
	Tier 1			*Leverage Ratio*		
% Banks Well Capitalized	10.45	9.20	6.86	51.79	46.80	33.23
% Banks Adequately Capitalized	32.61	28.08	21.68	30.89	29.33	27.77
% Banks Undercapitalized	47.89	49.45	46.80	14.04	18.72	23.56
% Banks Significantly Undercapitalized	8.27	11.86	19.19	2.34	3.43	9.52
% Banks Critically Undercapitalized	0.78	1.25	4.52	0.94	1.56	4.99
% Banks Bankrupt	0.00	0.16	0.94	0.00	0.16	0.94

Figure 1: This figure shows the mean quarterly values of Tier 1 equity capital-to-gross total assets for U.S. commercial banking companies from 1996:Q1 to 2015:Q4. The “community banks" category includes banks with assets less than $10 billion (in real 2015 dollars). The “SIFI" category includes banks with assets greater than $250 billion (in real 2015 dollars).

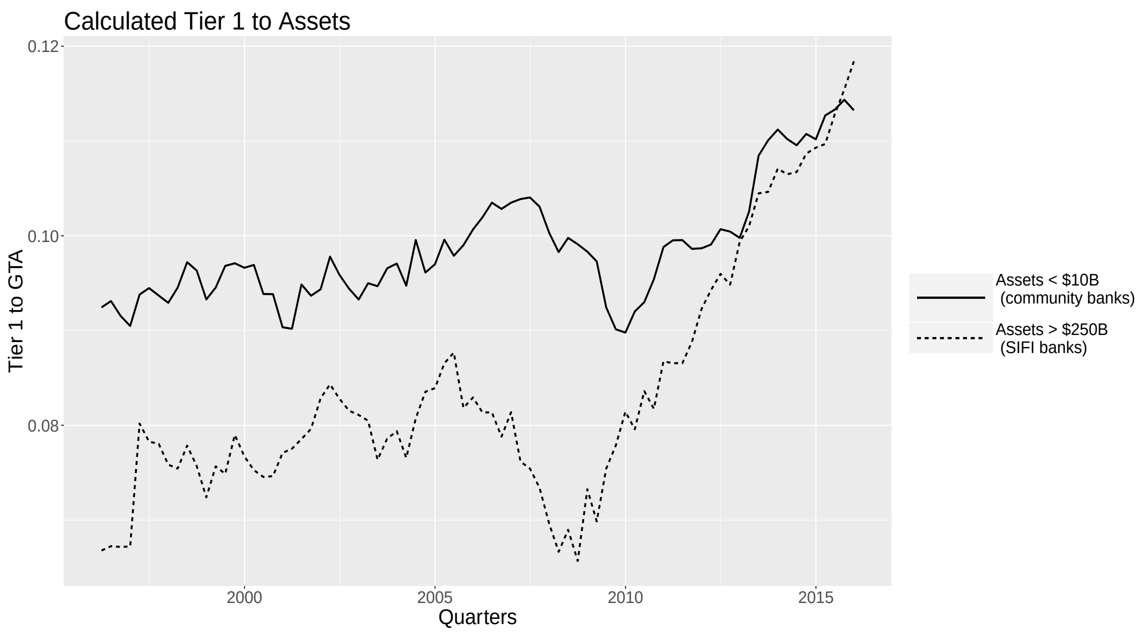


Figure 2a: This figure shows the distribution of the pooled residuals from equation (1) estimated using 541 bank-quarter observations during 1991-2015 data for **SIFI** (assets greater than $250 billion). The dependent variable is charge-offs on home equity lines of credit (HELOCs). The residual distributions are displayed separately for all quarters, and also for crisis (2008-2010) and non-crisis subsamples.

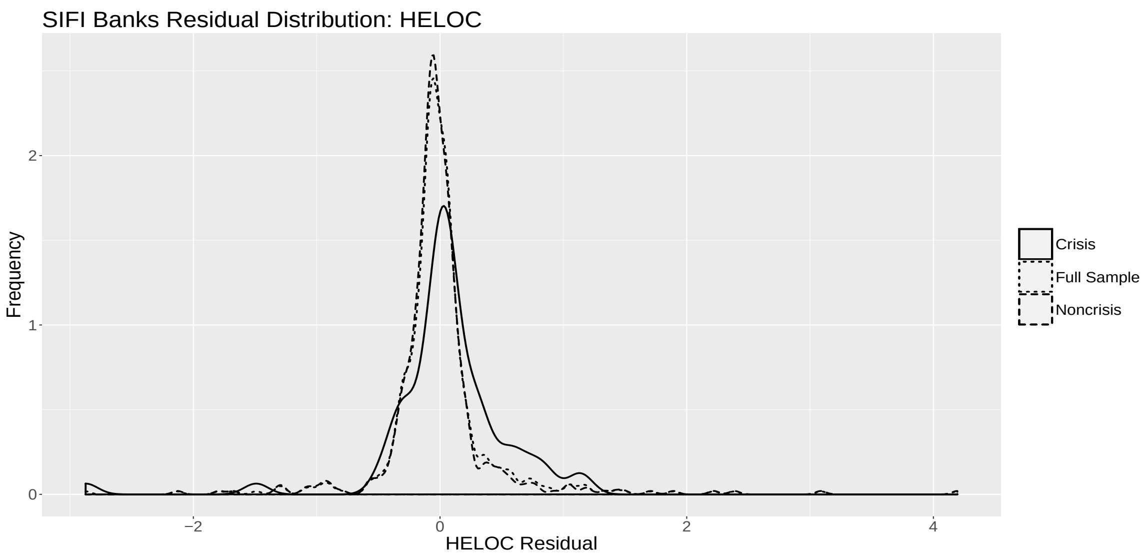


Figure 2b: This figure shows the distribution of the pooled residuals from equation (1) estimated using 77,483 bank-quarter observations during 1991-2015 data for **Large Community Banks** (assets between $500 million and $10 billion). The dependent variable is net interest margin. The residual distributions are displayed separately for all quarters, and also for crisis (2008-2010) and non-crisis subsamples.

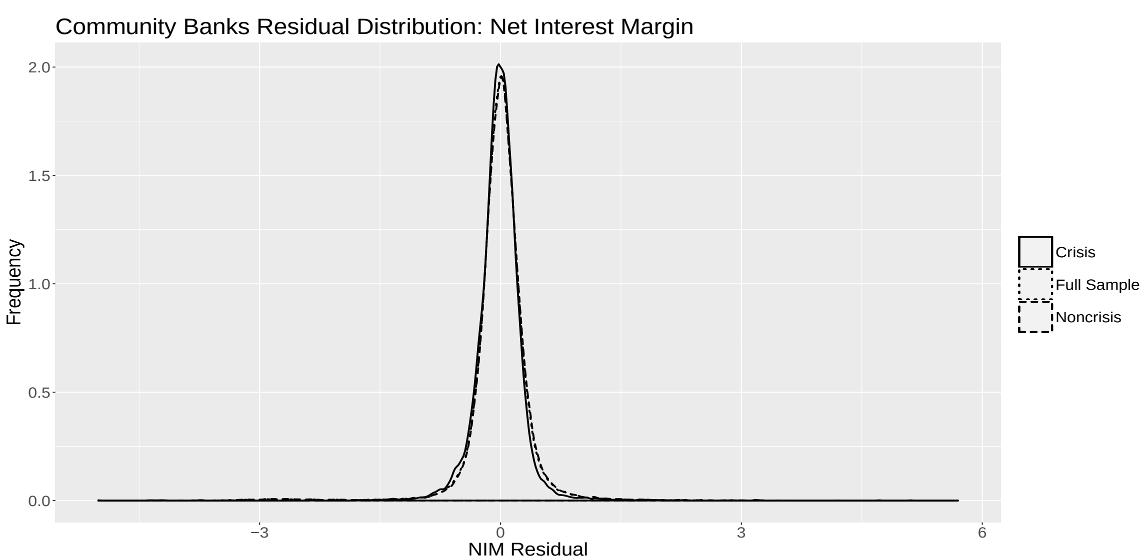


Figure 3a: This figure shows the mean annual values of Net Interest Margin (interest income minus interest expense, divided by assets) for U.S. commercial banking companies in the SIFI, CLASS, and Large Community Bank subsamples from 1991 to 2015.

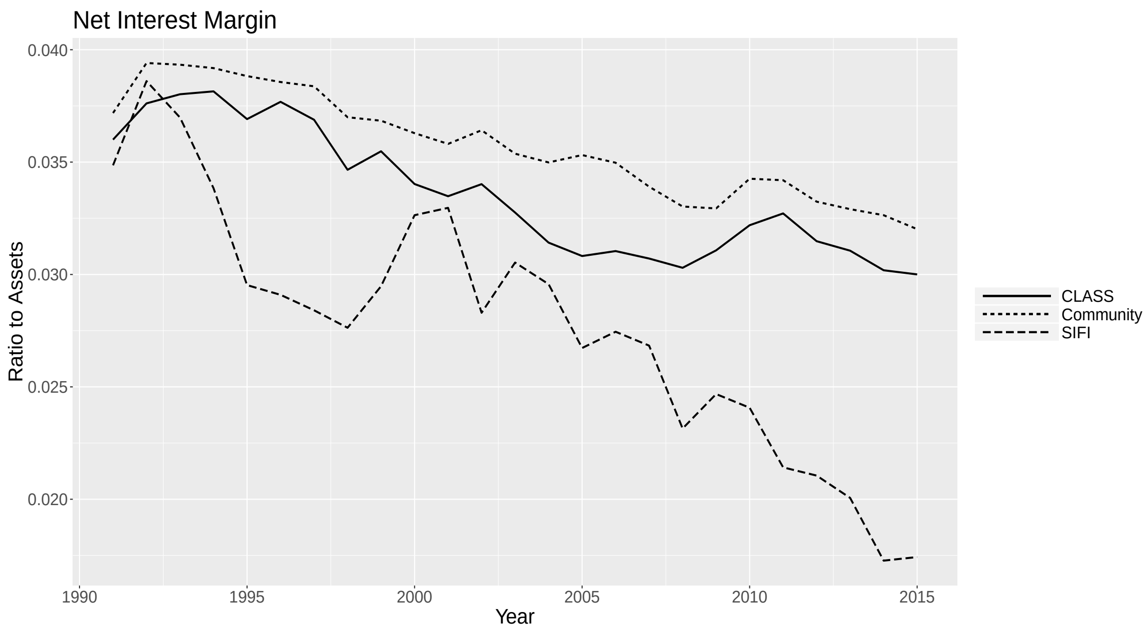


Figure 3b: This figure shows the mean annual values of Noninterest Income (noninterest income divided by assets) for U.S. commercial banking companies in the SIFI, CLASS, and Large Community Bank subsamples from 1991 to 2015.

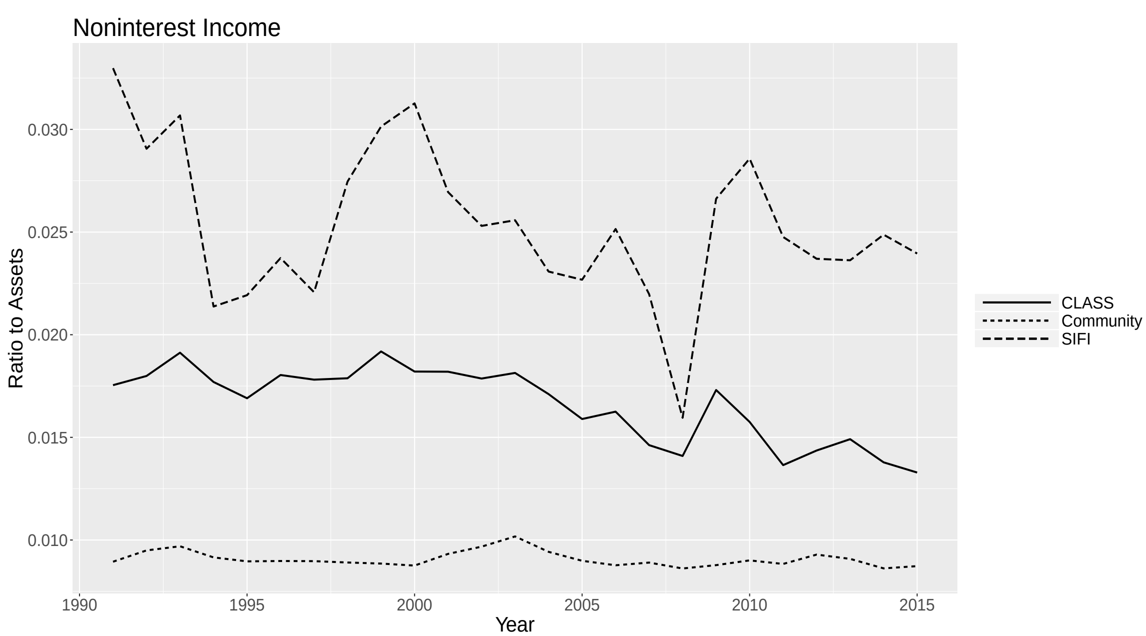


Figure 3c: This figure shows the mean annual values of Net Charge-offs of Commercial and Industrial Loans (C&I net charge-offs divided by assets) for U.S. commercial banking companies in the SIFI, CLASS, and Lage Community Bank subsamples from 1991 to 2015.

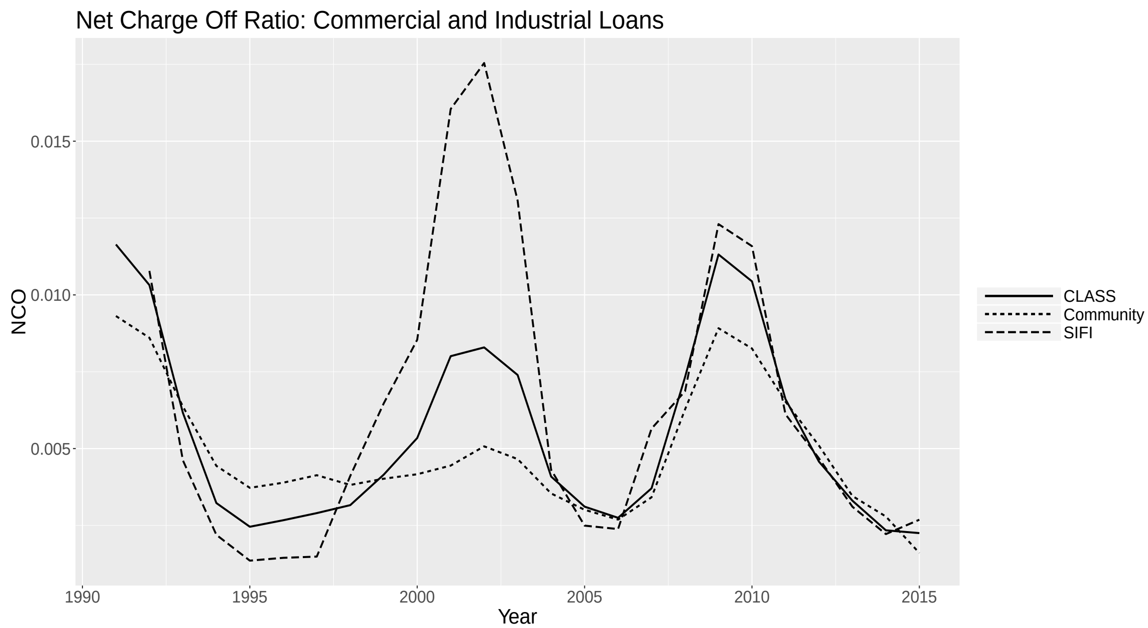


Figure 3d: This figure shows the mean annual values of Net Charge-offs of Residential Real Estate Loans (RRE net charge-offs divided by assets) for U.S. commercial banking companies in the SIFI, CLASS, and Large Community Bank subsamples from 1991 to 2015.

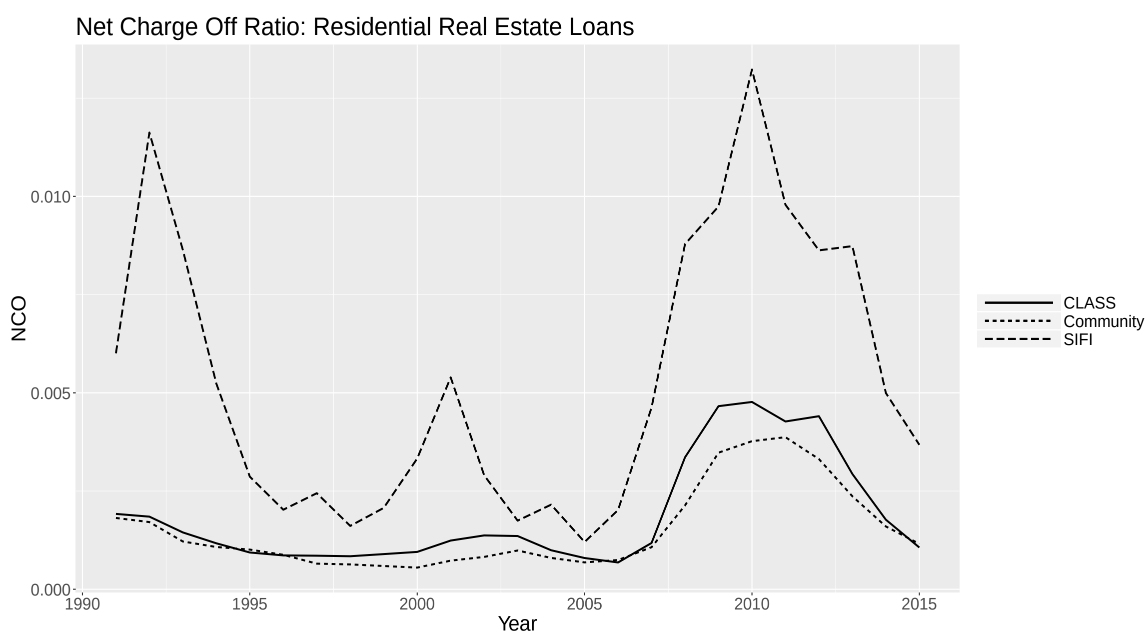


Figure 3e: This figure shows the mean annual values of Net Charge-offs of Home Equity Lines of Credit (HELOC net charge-offs divided by assets) for U.S. commercial banking companies in the SIFI, CLASS, and Community subsamples from 1991 to 2015.

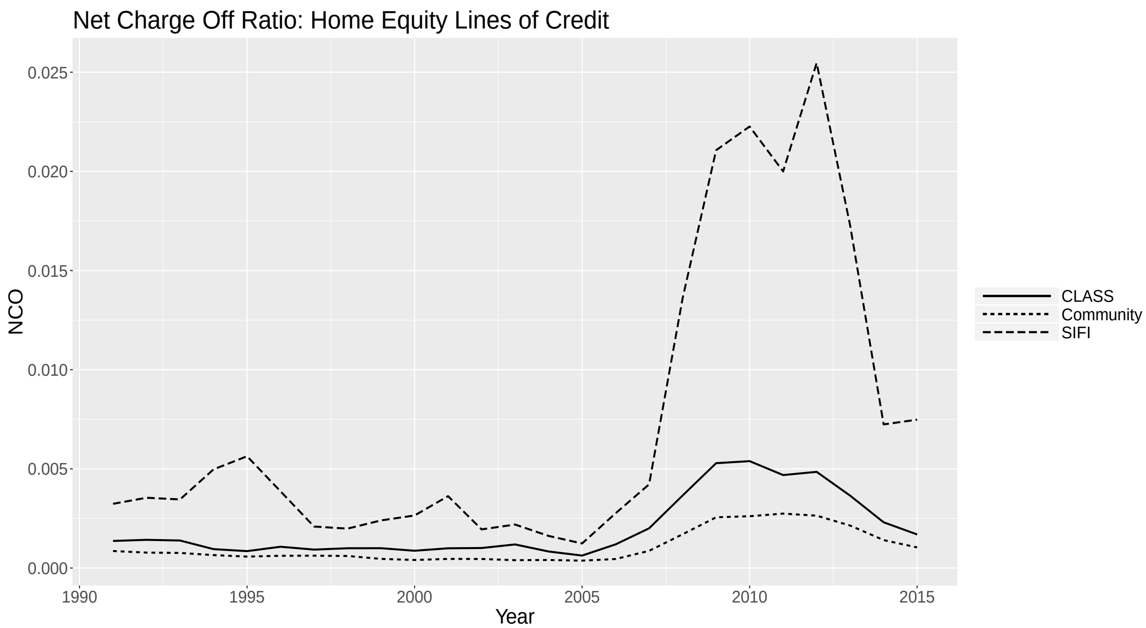


Figure 4a: This figure shows the (smoothed) quarter-by-quarter average projected values for *Net Interest Margin* across all banks in our data.

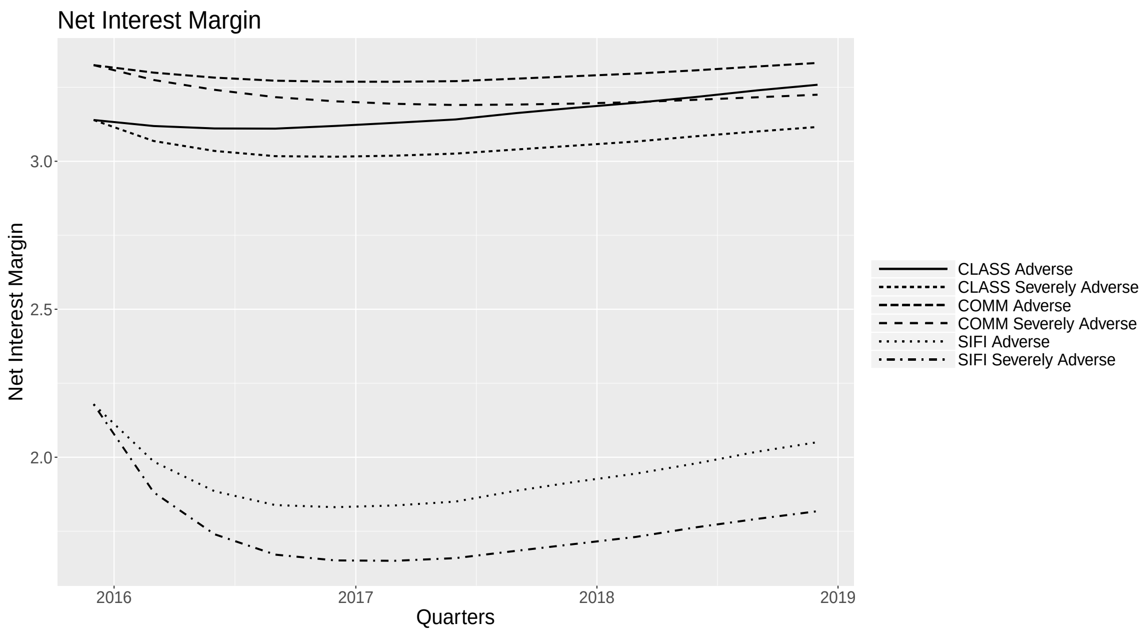


Figure 4b: This figure shows the (smoothed) quarter-by-quarter average projected values for *Noninterest Income* across all banks in our data.

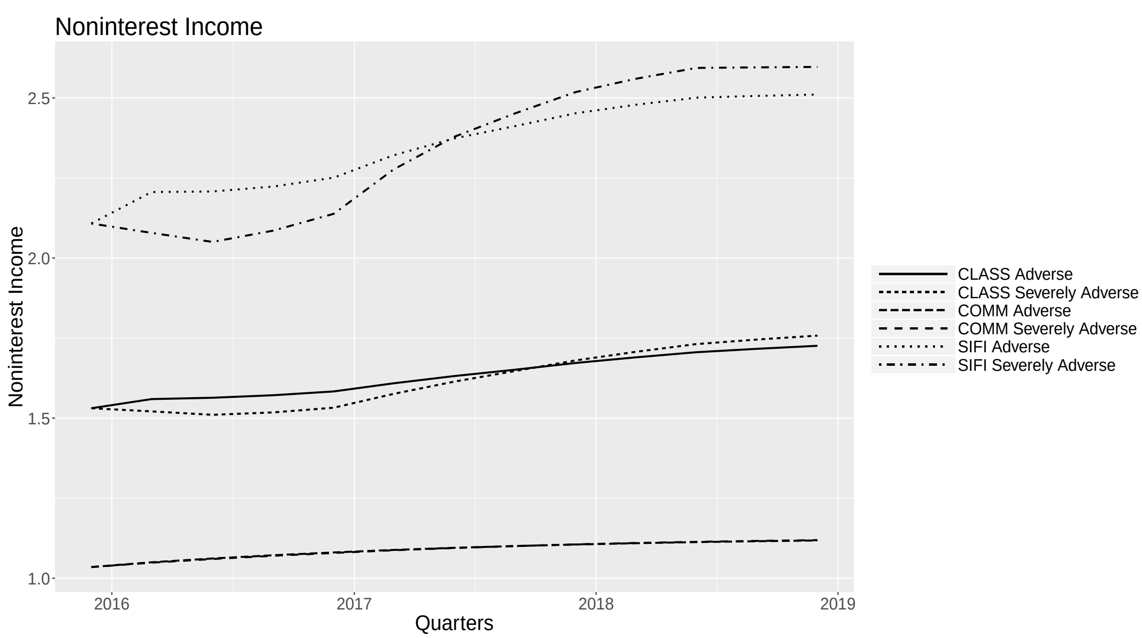


Figure 4c: This figure shows the (smoothed) quarter-by-quarter average projected values for *Commercial & Industrial Net Charge-offs* across all banks in our data.

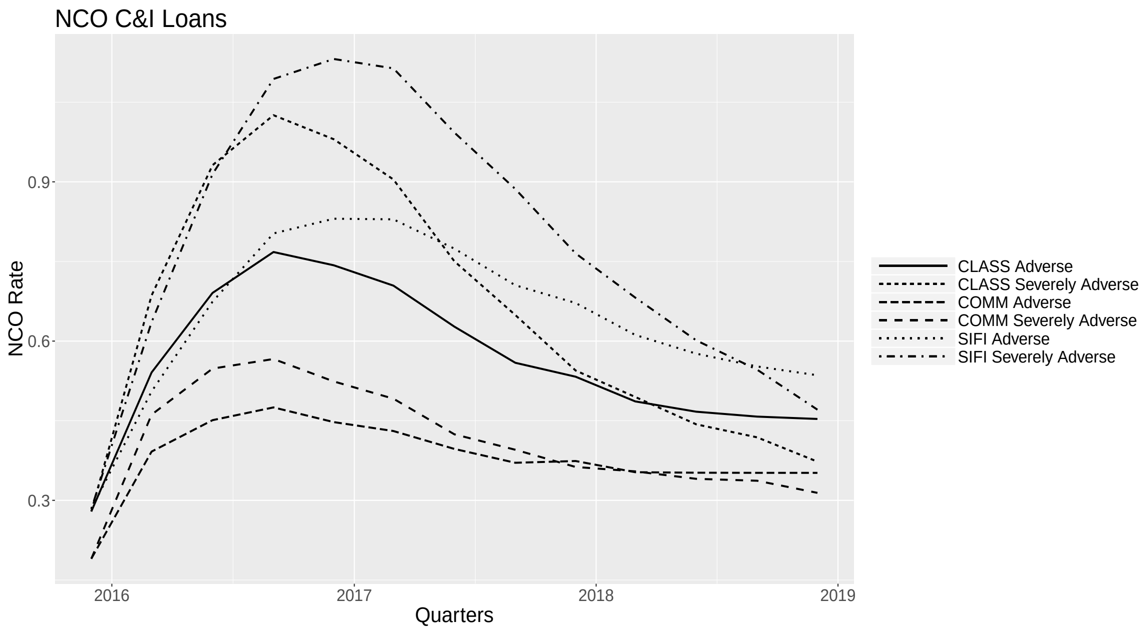


Figure 4d: This figure shows the (smoothed) quarter-by-quarter average projected values for *Residential Real Estate Net Charge-offs* across all banks in our data.

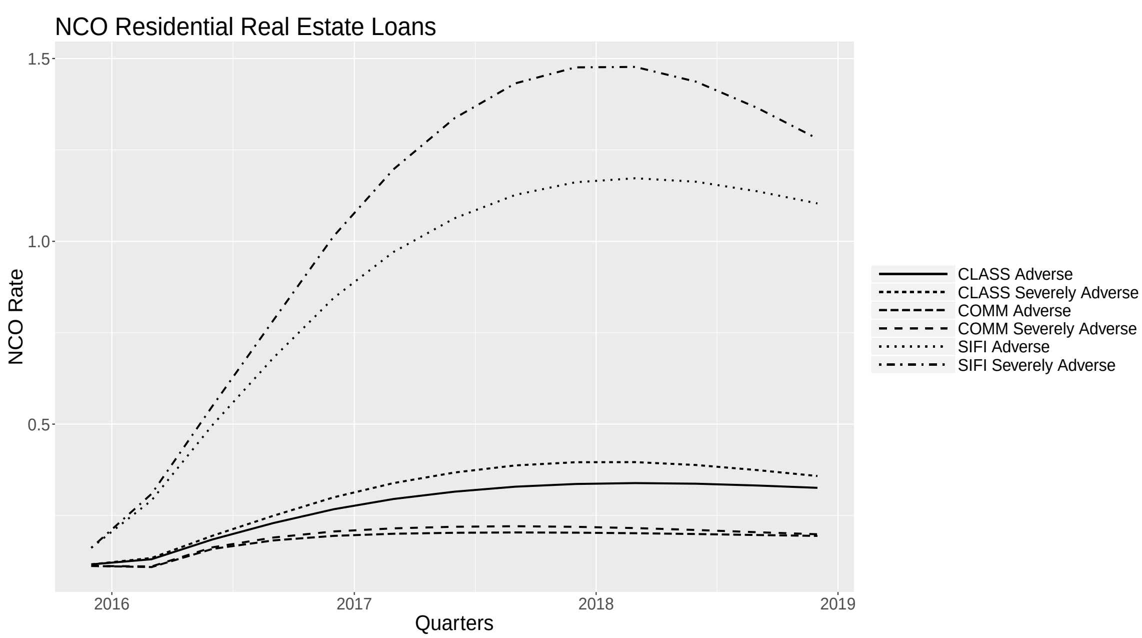


Figure 4e: This figure shows the (smoothed) quarter-by-quarter average projected values for *Home Equity Lines of Credit Net Charge-offs* across all banks in our data.

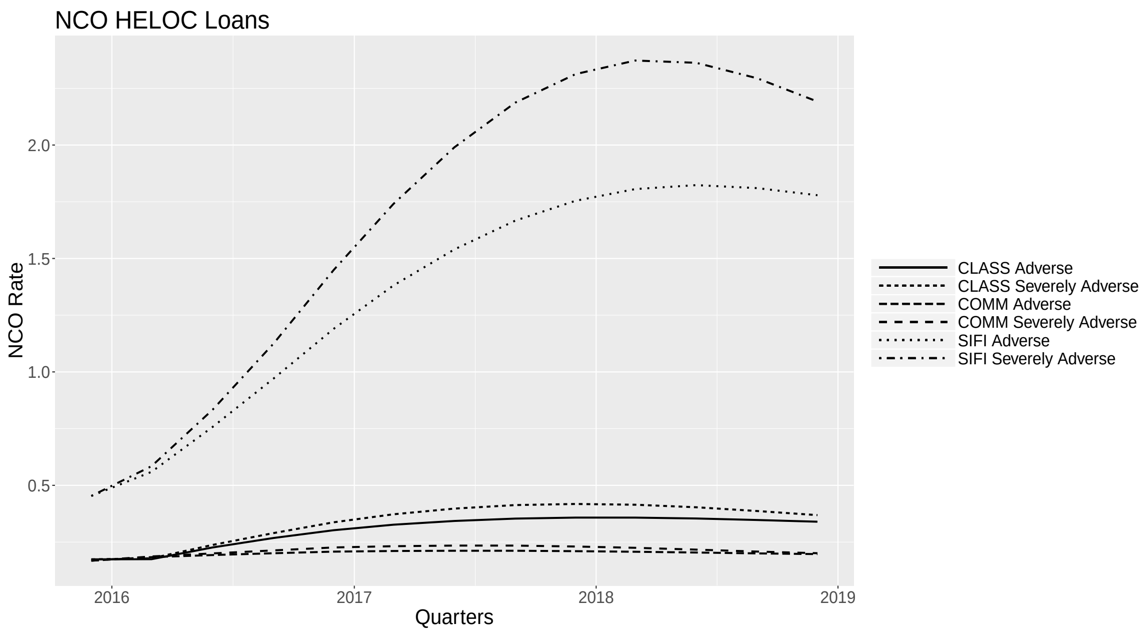


Figure 5a: This figure shows the (smoothed) quarter-by-quarter projected values of the Tier 1 Risk-based capital ratio for UMB Financial Corporation under the Severly Adverse stress scenario.

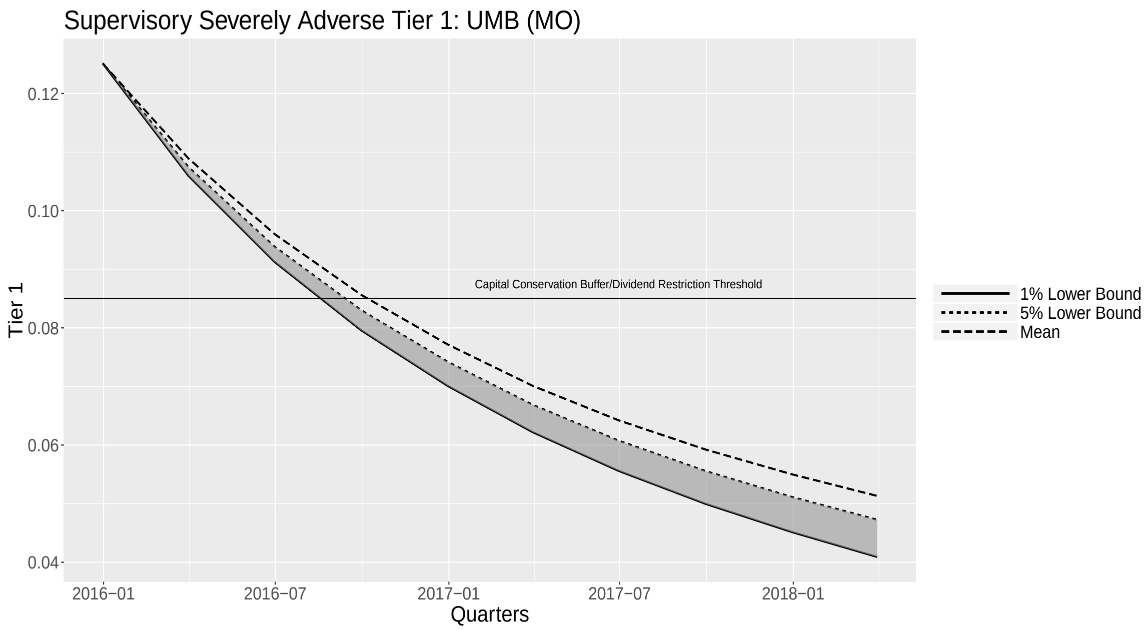


Figure 5b: This figure shows the (smoothed) quarter-by-quarter projected values of the book value Leverage capital ratio for UMB Financial Corporation under the Severly Adverse stress scenario.

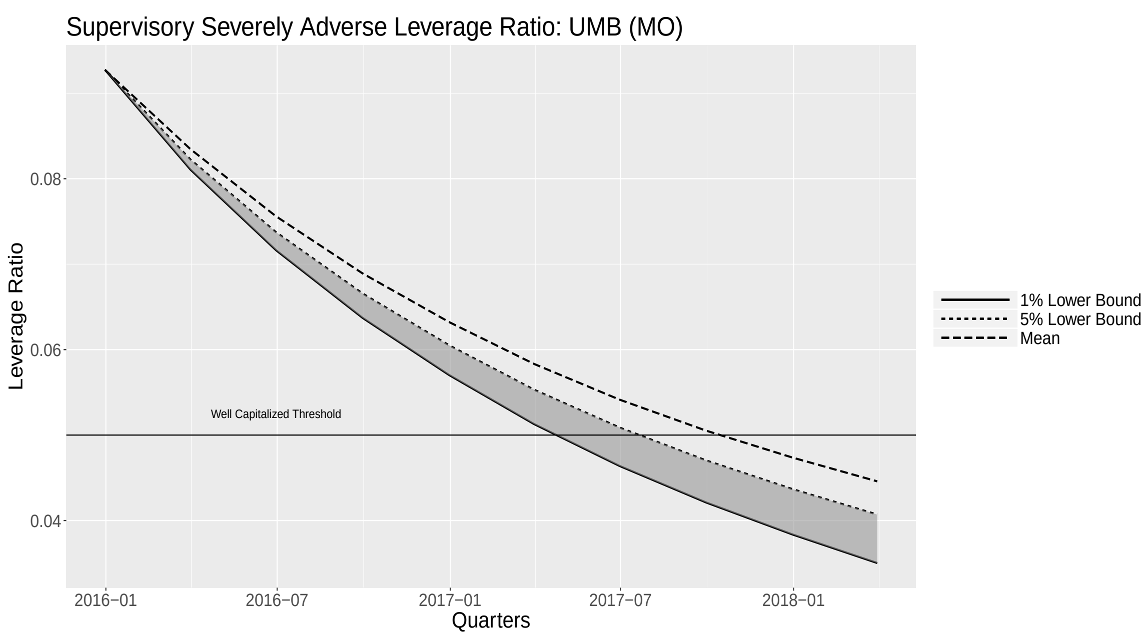


Figure 5c: This figure shows the (smoothed) quarter-by-quarter projected values of the Tier 1 Risk-based capital ratio for Comenity Capital Bank of Utah under the Severly Adverse stress scenario.

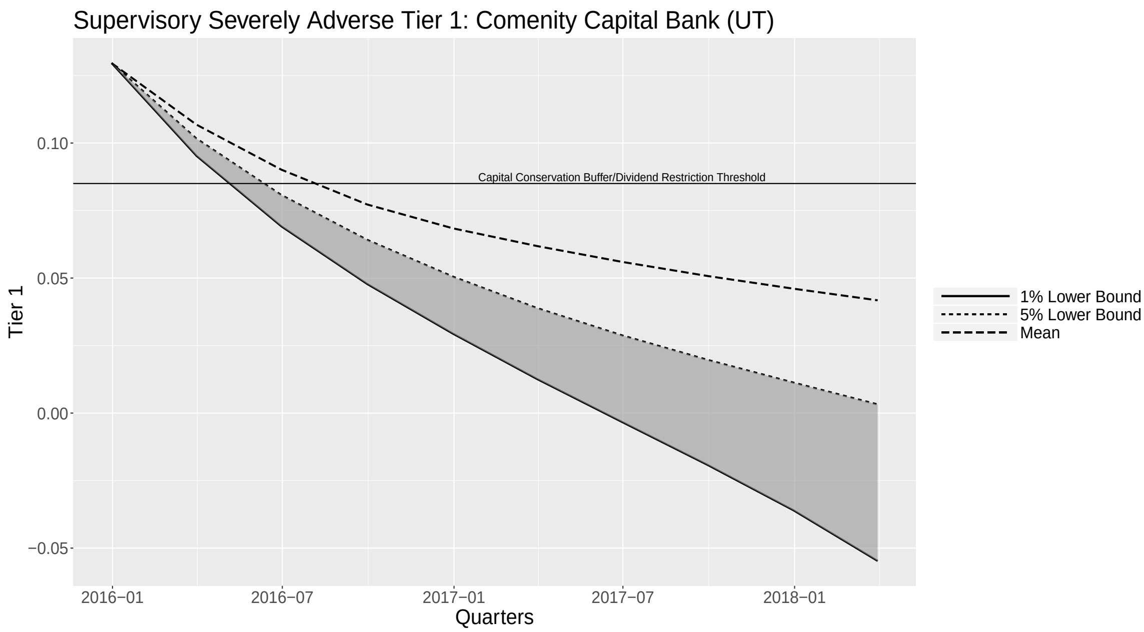


Figure 5d: This figure shows the (smoothed) quarter-by-quarter projected values of the book value Leverage capital ratio for Comenity Capital Bank of Utah under the Severly Adverse stress scenario.

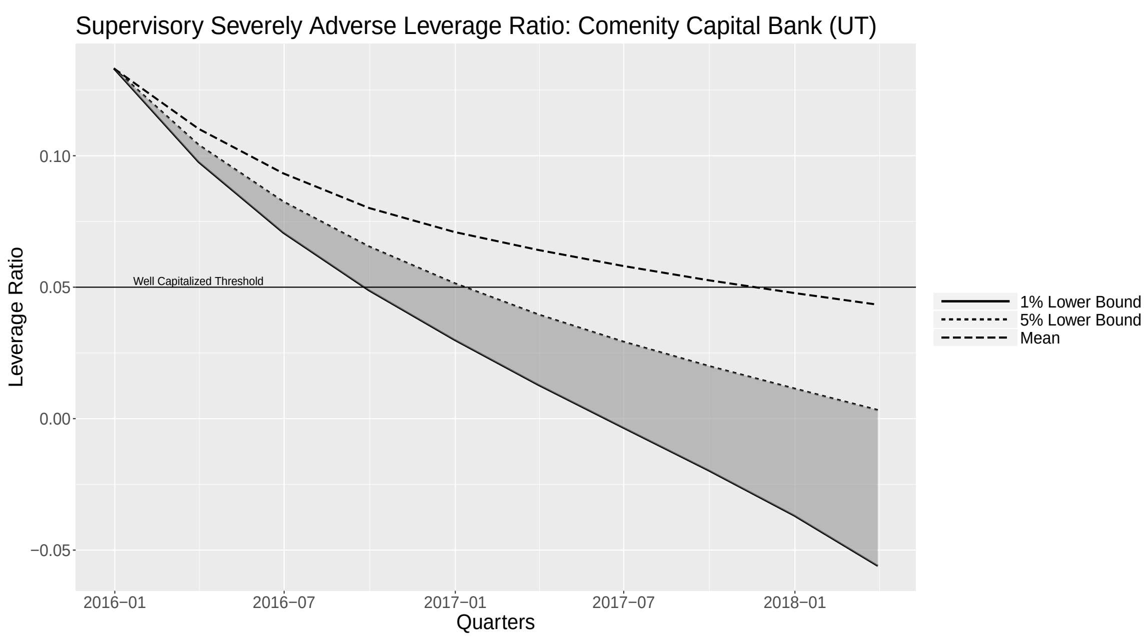
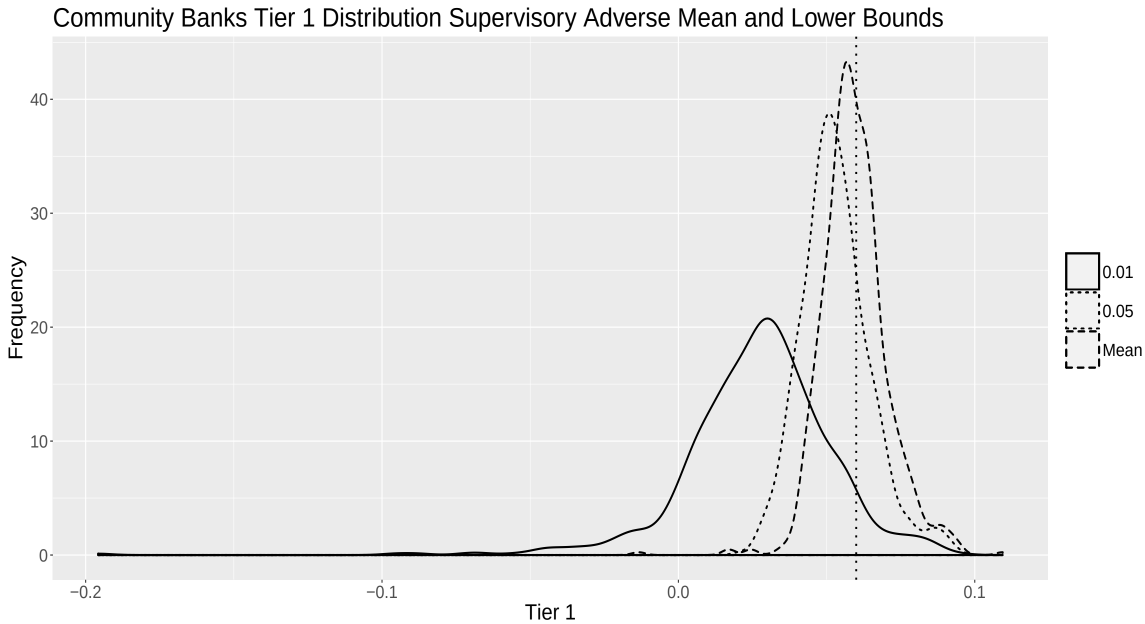


Figure 6a(i and ii): These figures show the kernel density distributions of the mean and projected 5% and 1% lower bounds of the **Tier 1 Risk-based Capital ratio** for **Large Community Banks** (Assets between \$500 million and \$10 billion) under the **Adverse** stress scenario. Top panel is based on Tier 1 capital levels at these banks **as of year-end 2015**. Bottom panel is based on the Tier 1 capital levels at these banks **as of year-end 2008**.



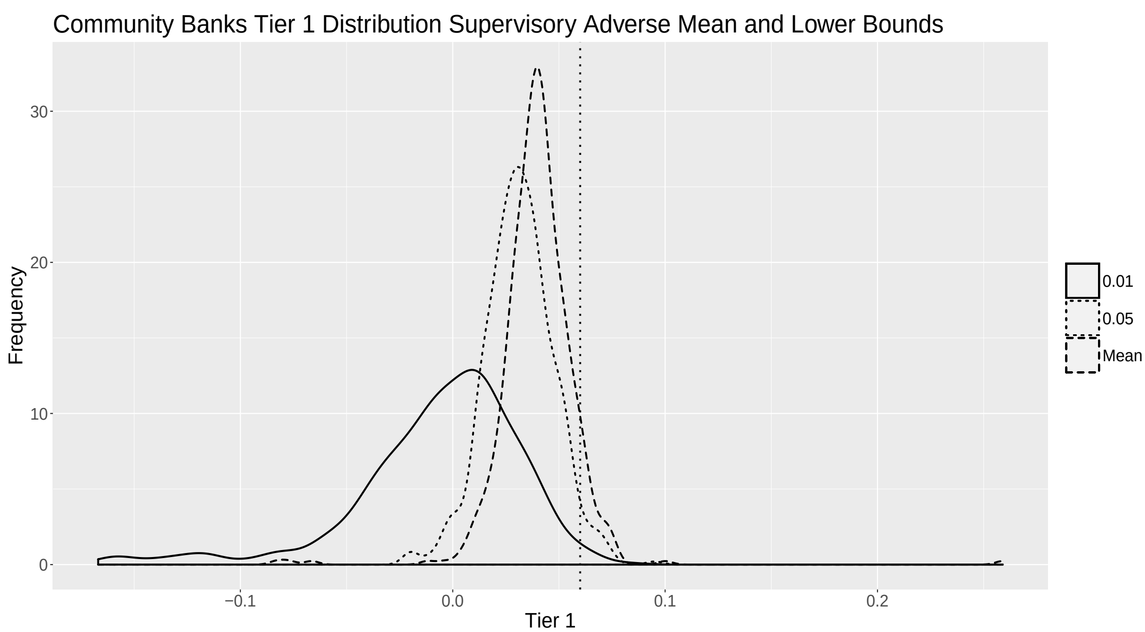
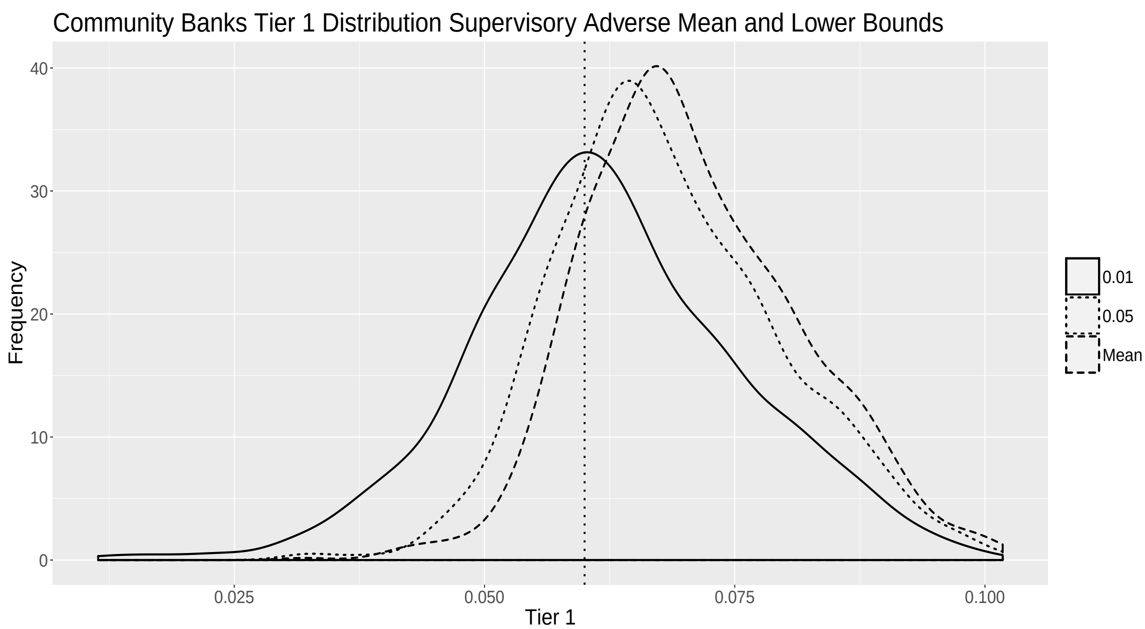


Figure 6a(iii and iv): These figures show the kernel density distributions of the mean and projected 5% and 1% lower bounds of the **Tier 1 Risk-based Capital ratio** for **Small Community Banks** (Assets between \$50 million and \$500 million) under the **Adverse** stress scenario. Top panel is based on Tier 1 capital levels at these banks **as of year-end 2015**. Bottom panel is based on the Tier 1 capital levels at these banks **as of year-end 2008**.



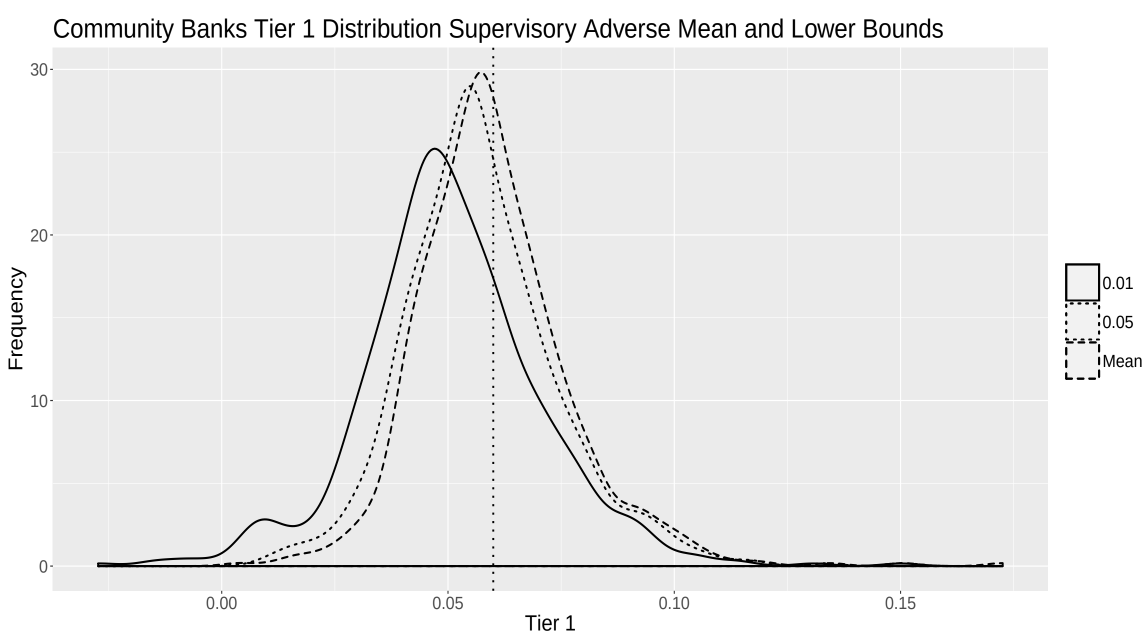
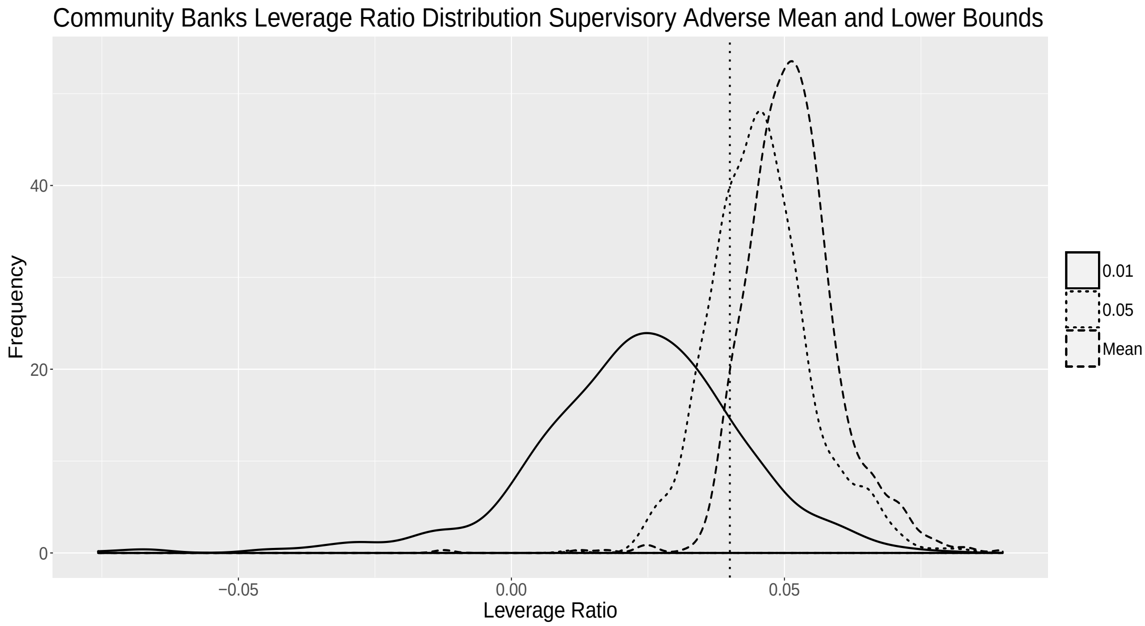


Figure 6b(i and ii): This figure shows the kernel density distributions of the mean and projected 5% and 1% lower bounds of the book value **Leverage Capital ratio** for **Large Community Banks** (Assets between \$500 million and \$10 billion) under the **Adverse** stress scenario. Top panel is based on leverage capital levels at these banks **as of year-end 2015**. Bottom panel is based on the Tier 1 capital levels at these banks **as of year-end 2008**.



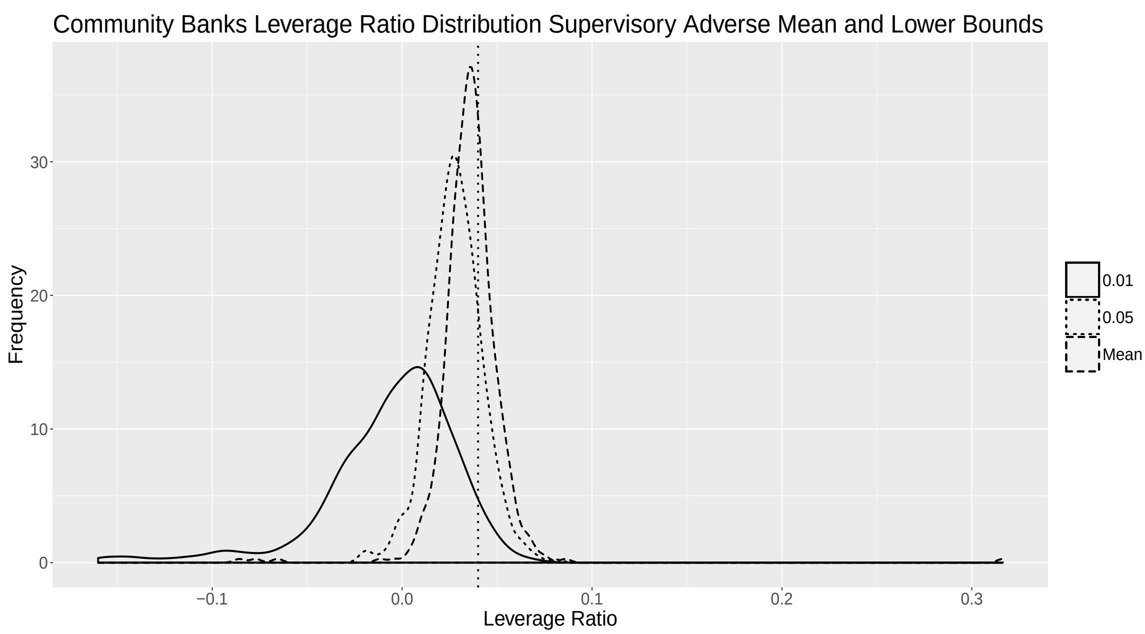
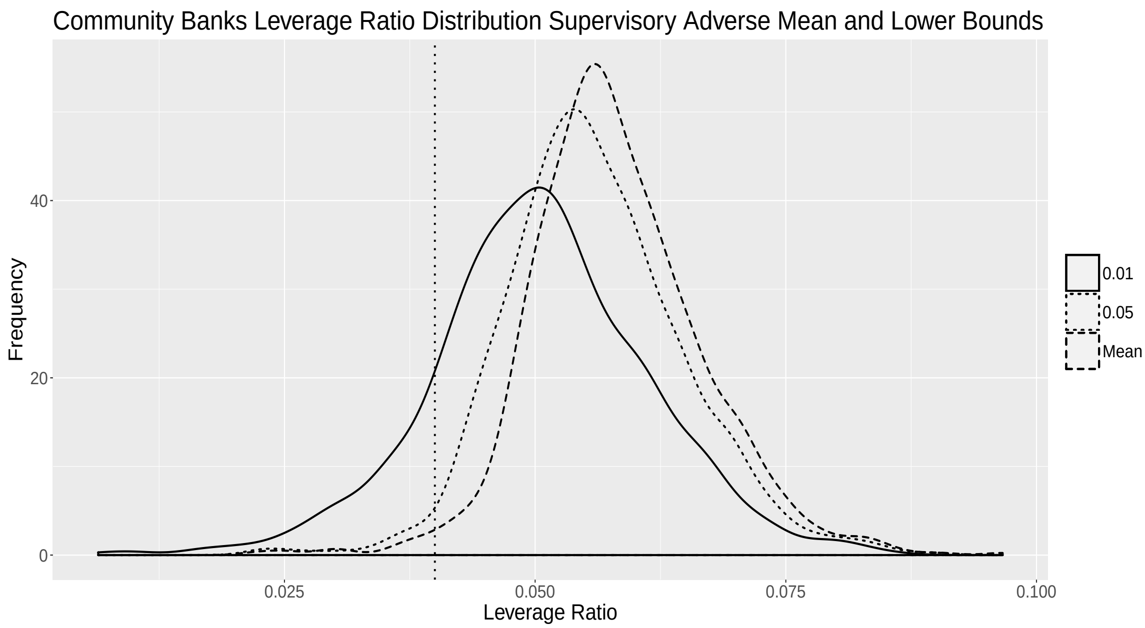


Figure 6b(iii and iv): This figure shows the kernel density distributions of the mean and projected 5% and 1% lower bounds of the book value **Leverage Capital ratio** for **Small Community Banks** (Assets between \$50 million and \$500 million) under the **Adverse** stress scenario. Top panel is based on leverage capital levels at these banks **as of year-end 2015**. Bottom panel is based on the Tier 1 capital levels at these banks **as of year-end 2008**.



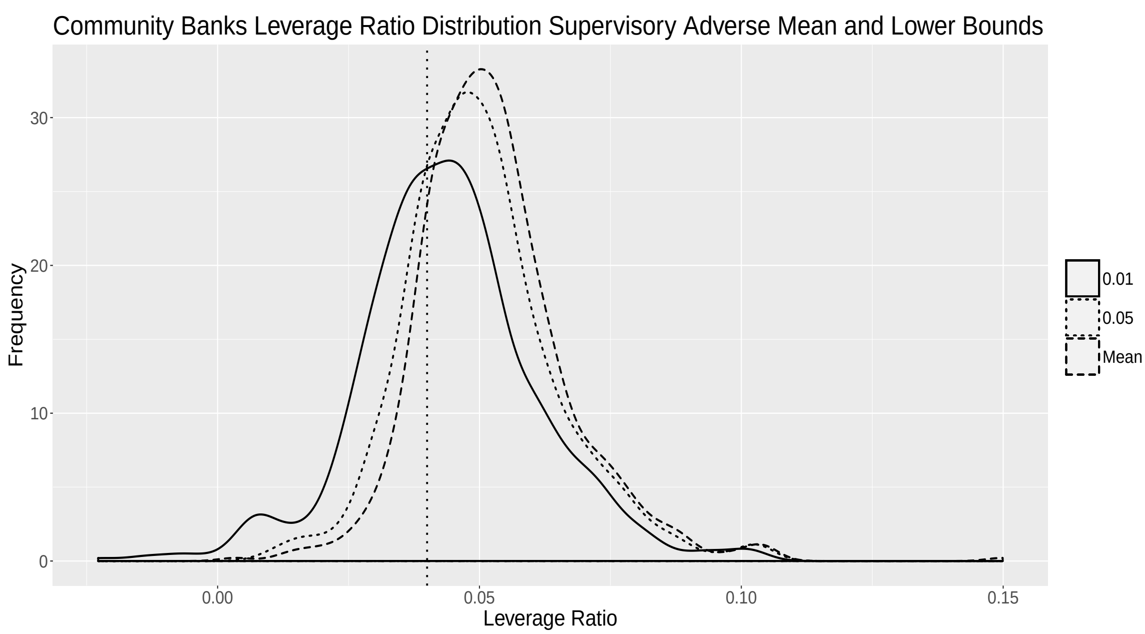
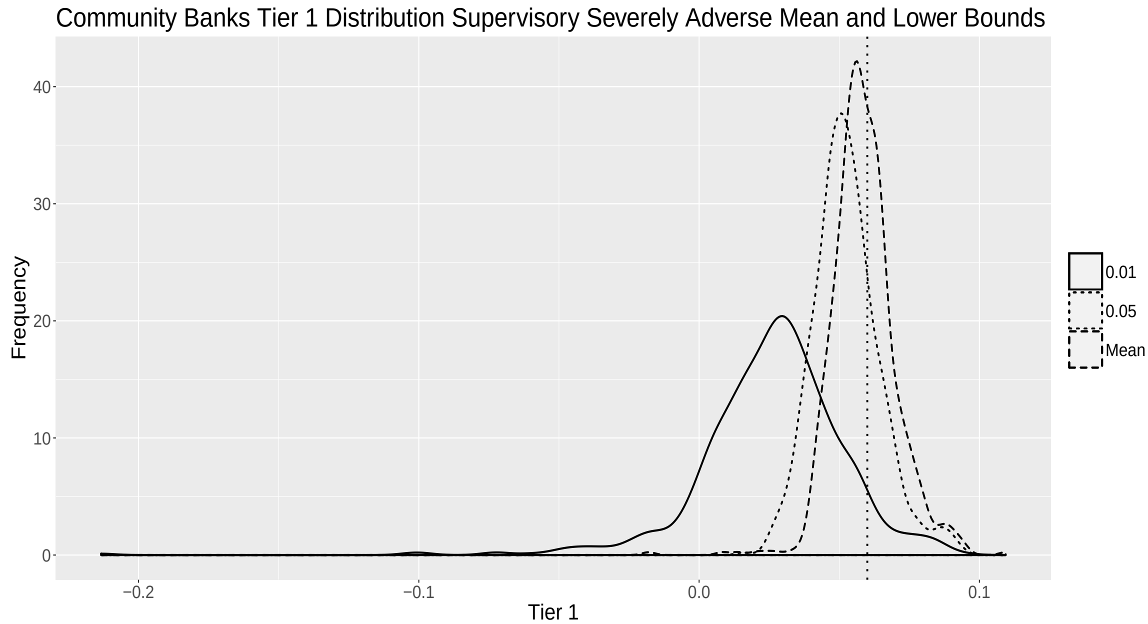


Figure 6c(i and ii): These figures show the kernel density distributions of the mean and projected 5% and 1% lower bounds of the **Tier 1 Risk-based Capital ratio** for **Large Community Banks** (Assets between \$500 million and \$10 billion) under the **Severely Adverse** stress scenario. Top panel is based on Tier 1 capital levels at these banks **as of year-end 2015**. Bottom panel is based on the Tier 1 capital levels at these banks **as of year-end 2008**.



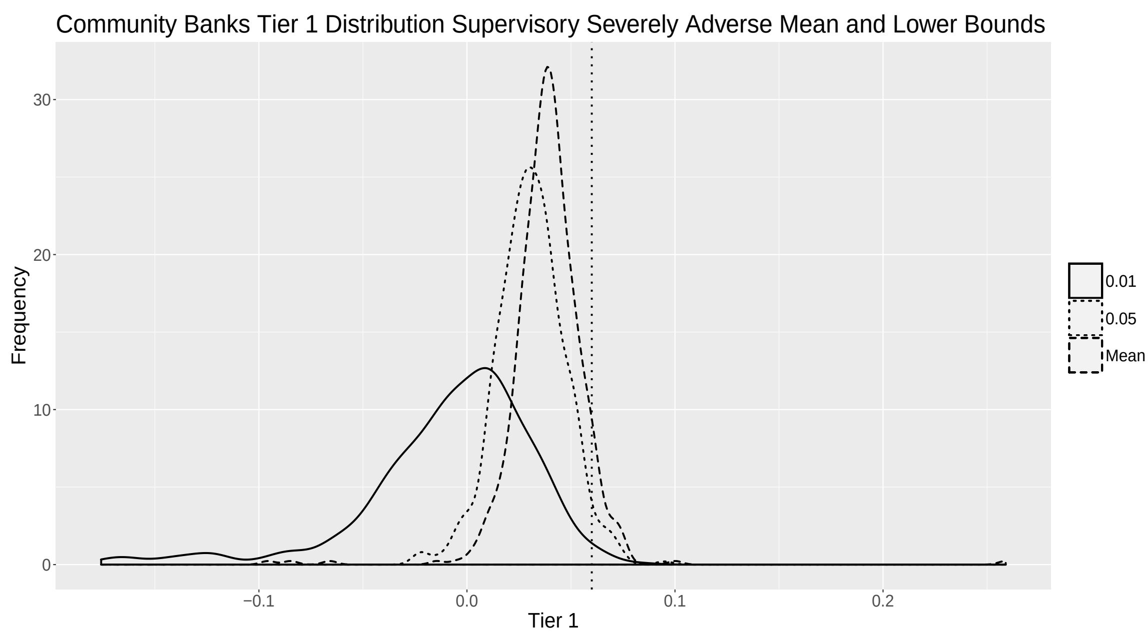
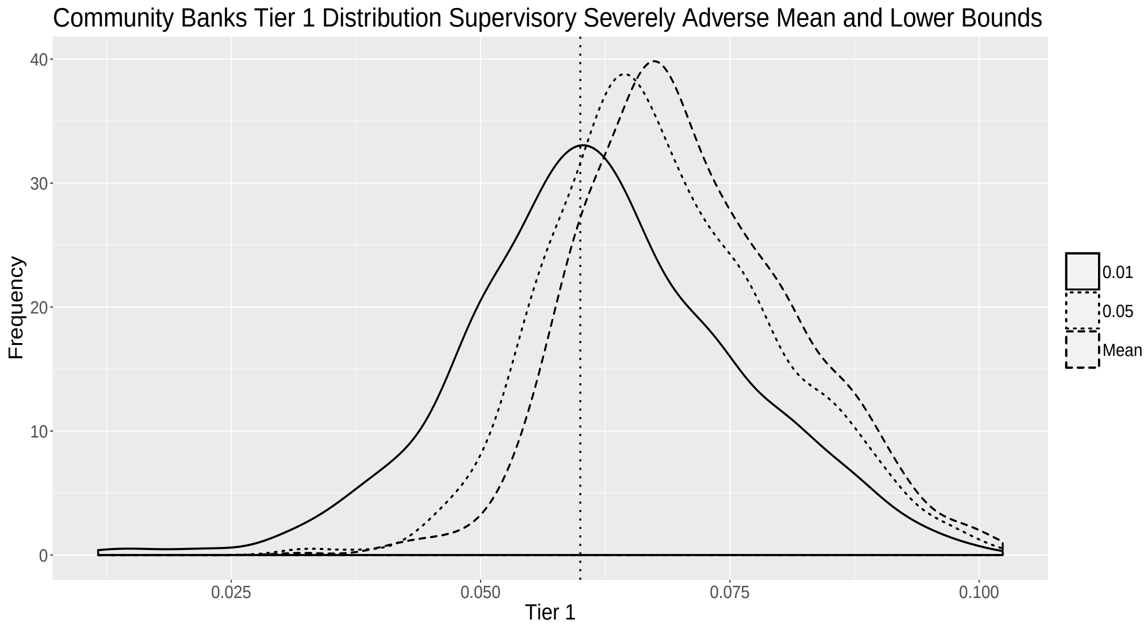


Figure 6c(iii and iv): These figures show the kernel density distributions of the mean and projected 5% and 1% lower bounds of the **Tier 1 Risk-based Capital ratio** for **Small Community Banks** (Assets between \$50 million and \$500 million) under the **Severely Adverse** stress scenario. Top panel is based on Tier 1 capital levels at these banks **as of year-end 2015**. Bottom panel is based on the Tier 1 capital levels at these banks **as of year-end 2008**.



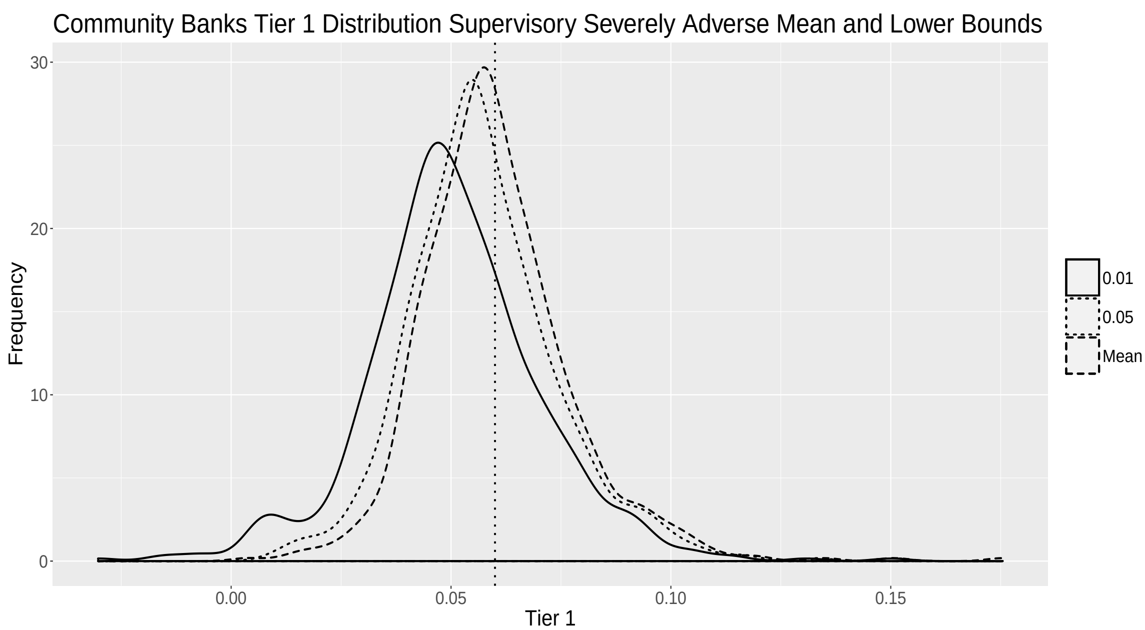
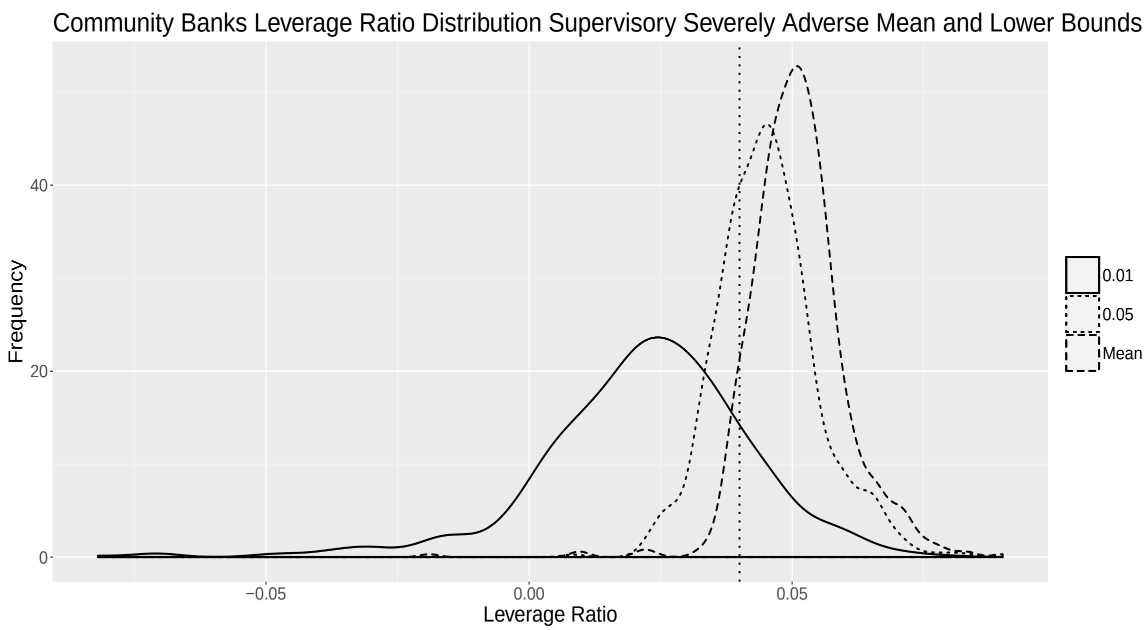


Figure 6d(i and ii): This figure shows the kernel density distributions of the mean and projected 5% and 1% lower bounds of the book value **Leverage Capital ratio** for **Large Community Banks** (Assets between \$500 million and \$10 billion) under the **Severely Adverse** stress scenario. Top panel is based on leverage capital levels at these banks **as of year-end 2015**. Bottom panel is based on the Tier 1 capital levels at these banks **as of year-end 2008**.



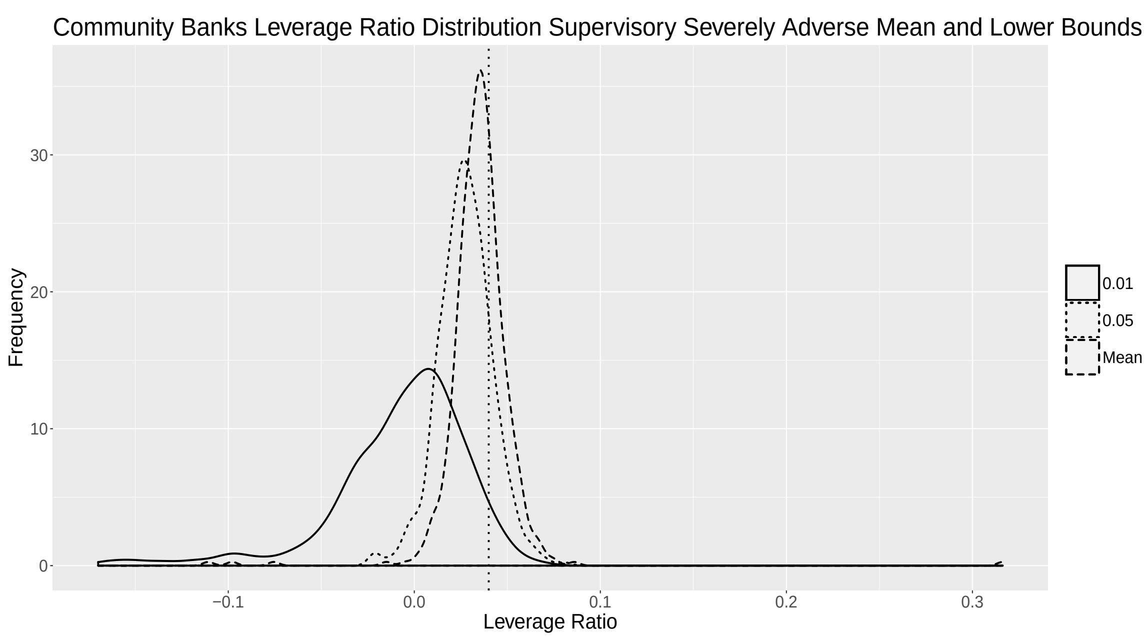


Figure 6d(iii and iv): This figure shows the kernel density distributions of the mean and projected 5% and 1% lower bounds of the book value **Leverage Capital ratio** for **Small Community Banks** (Assets between $50 million and $500 million) under the **Severely Adverse** stress scenario. Top panel is based on leverage capital levels at these banks **as of year-end 2015**. Bottom panel is based on the Tier 1 capital levels at these banks **as of year-end 2008**.