# An Historical Loss Approach to Community Bank Stress Testing

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We develop a top-down macro stress test that assesses a community bank's ability to withstand a severe and prolonged period of high credit losses. The model groups banks by geography and subjects them to the 90th percentile chargeoff rates that banks experienced between 2008 and 2012. Our historical loss approach better reflects patterns of community bank stress than econometric approaches that estimate the relationship between macroeconomic conditions and bank performance. We put all U.S. community banks at year-end 2017 through the test and highlight two results. First, banks are much better prepared to withstand an adverse shock than they were on the verge of the financial crisis because banks have shifted away from the riskiest loan types. Second, the Tax Cuts and Jobs Act of 2017 has increased bank insolvency risk from an adverse shock in 2018 because the higher bank capital is more than offset by the weaker automatic stabilizer effect from operating losses.

Keywords: Community banks, Stress testing, Financial Crisis, Loan diversification, Tax Cuts and Jobs Act

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## 1. Introduction

A macro bank stress test dynamically assesses a bank's insolvency risk and capital adequacy given an abrupt change in economic and financial conditions. Since 2009, the Federal Reserve has greatly expanded the importance of stress testing at the largest banking organizations. Annual results from the Dodd-Frank Act Stress Test (DFAST) and Comprehensive Capital Analysis and Review (CCAR) have effectively become the binding minimum capital requirements on large banking organizations, more onerous than the Basel III Capital Accord (Covas, 2017). Presently, community banks (banks with less than $10 billion in assets) are not required to conduct enterprise-wide stress tests required of larger organizations. However, each banking organization, regardless of size, is expected to analyze the potential impact of adverse outcomes on its financial condition (Board of Governors, 2012). Community banks, for example, are expected to stress test exposure to commercial real estate (CRE) lending (Board of Governors, 2006).

The primary objective of this paper is to introduce an historical-loss macro stress-testing model that assesses a community bank's ability to withstand a severely adverse yet plausible shock over a five-year horizon.[1] Although our historical-loss model differs from the more common econometric approach, it is more accurate in projecting patterns of distress at community banks similar to what they experienced in the years 2008-2012. The increased accuracy results from bypassing statistical approaches that introduce model error. Most stress-test models use econometric analysis to map historical changes in macroeconomic variables onto bank performance; however, researchers have shown that the predictive content of macroeconomic variables in forecasting large bank performance is weak, introducing a wide confidence band around point estimates (Guerreri and Welch, 2012;

[1] The stress test generates reports for every U.S. community bank and thrift and is freely available at [removed]. The model is run in Microsoft Excel and updated annually.

Grover and McCracken, 2014). This problem is exacerbated for community banks because they operate in state and local markets where economic data are relatively poor (Barth et al., 2018).

Our historical-loss stress test bypasses the econometric mapping process by exposing each community bank to the 90$^{th}$ percentile chargeoff rates experienced by banks in the local geographic market of its headquarters in the years 2008-2012, a period encompassing the financial crisis and Great Recession.[2] This approach directly links each bank's projected stressed chargeoffs to its local market, and it naturally captures nonlinear outcomes that confound standard econometric procedures. The relative simplicity of our model is also a helpful feature for community banks because it is easy to use and interpret (Schmieder, Puhr, and Hasan, 2014). We assess the in-sample validity of the model by putting all U.S. community banks through the stress test based on their financial conditions at year-end 2007. Three-fourths of the community banks that failed between 2008 and 2012 also fail or experience dangerously low capital levels during the stress test.

A second objective of this paper is to assess the ability of present-day banks to weather a severely adverse shock. We run our stress tests on bank condition at year-end 2017 and find that banks are much better positioned for a severe downturn in 2017 than they were in 2007 because the riskiest banks are no longer in business, and construction and land development (CLD) loan concentrations are lower. In the extreme, substituting all CLD loans with nonfarm nonresidential (NFR) commercial real estate loans brings large diversification benefits; the number of community banks projected to fail declines by 68%. We also show that the Tax Cuts and Jobs Act of 2017 (TCJA) has diminished the

[2] A variety of evidence shows that community banks lend and take deposits locally. The 2018 FDIC Small Business Lending Survey shows that 82.3 percent of small banks (less than $10 billion in assets) selected the city, county, or MSA as their relevant trade area. In addition, the FDIC Summary of Deposits data show that as late as 2018, banks with less than $500 million in assets held more than three-quarters of their deposits in their headquarters county. Similarly, urban banks of the same size held 92 percent of their deposits in their headquarters MSA. Finally, Petersen and Rajan (2002) show that although the distance between bank lender and small business borrower increased between the early 1970s and 1990s, the median distance increased from just 2 miles to 5 miles. Agarwal and Hauswald (2010) analyze a confidential sample of small business loans from a large U.S. bank and find a median (mean) distance of 2.62 (9.9) miles for accepted loans.

ability of banks at year-end 2018 to survive an adverse shock because the higher capital is more than offset by weakened automatic stabilizers from net operating losses. Among other things, the TCJA forces banks to recover tax benefits from operating losses through deferred tax assets (DTAs), which are excluded from Tier 1 capital.

The paper proceeds as follows. Section 2 discusses weaknesses of an econometric approach for community bank stress testing, and Section 3 explains our historical loss methodology. Section 4 assesses the performance of U.S. community banks after subjecting them to the stress tests in 2007, 2017, and 2018. Section 5 conducts in-sample model testing. Section 6 evaluates the potential diversification benefits from bank reallocation of loan portfolios, and Section 7 concludes.

## 2. Weaknesses of the Econometric Approach

A macro stress test projects the effects of an adverse macroeconomic scenario onto bank performance. Because credit risk is the central focus, the critical assumption is the projection of multi-period bank chargeoffs. Most researchers and practitioners use econometric techniques to estimate the historical relationship between macroeconomic variables and bank performance (Covas, 2014; Hirtle et al., 2016; Kapinos and Mitnik; 2016). The econometrician regresses bank net income components and net chargeoffs by loan type on economic variables such as real estate prices, GDP growth, and unemployment rates. The coefficients on the variables (or principal component indices) are then used to project the average changes in chargeoffs, net income, and capital for each bank given the hypothetical change in the economy. A related methodology is a vector autoregression (VAR) where bank performance is projected from an interdependent system of regressions on banking and economic variables (Hall et al., 2011; Jacobs, 2016). The key benefit is that a VAR captures predictable variations based on dynamic correlations. VARs, however, require relatively long time series to produce statistically reliable results, and the minimum sample size grows with the number of variables in the system.

Econometric approaches to macro stress testing pose two significant challenges. First, standard techniques maintain an assumption of conditional normality, making nonlinearities and tail events difficult to capture. Researchers have adopted different techniques for large bank models to address this challenge. Covas et al. (2014) use a quantile regression approach to capture nonlinearities. Jacobs (2016) shows that a Markov Switching VAR is better suited to capture extreme events than the standard VAR model, and Kapinos and Mitnik (2016) use an optimal grouping strategy where slope coefficients differ among dynamic groups of banks. These procedures, however, potentially introduce more model error and add complexity that must be weighed against a simpler approach necessary for community banks.

A second more serious challenge is that the empirical connection between macroeconomic data and bank performance is tenuous. Guerreri and Welch (2012) find for a sample of large BHCs that macroeconomic variables have little predictive power in forecasting banking variables; confidence bands around the forecasts are too wide to distinguish between adverse and severely adverse macroeconomic scenarios. Grover and McCracken (2014) investigate the usefulness of factor-based methods for assessing industry-wide bank stress. They find that none of their factor models forecasts net chargeoffs better than a random walk. The authors then use the factors to measure the degree of stress faced by the banking industry in each of the 2014 CCAR baseline, adverse, and severely adverse scenarios. Consistent with Guerreri and Welch (2012), they find little difference in projected bank outcomes between the adverse and severely adverse scenarios. In fact, net chargeoffs are often higher after one year under the adverse scenario than the severely adverse scenario.

The empirical relationship between macroeconomic data and net chargeoffs is even more tenuous for community banks. Because these banks are geographically concentrated, local and state economic data may be more relevant than national economic data, yet data availability is relatively sparse, and the quality relatively poor. Moreover, the connection between bank performance and local economic conditions is unclear. Yeager (2004) finds small differences in the performance of community banks in counties that suffered spikes in unemployment rates in the early 1990s relative to similar banks in counties that did not suffer such spikes. Barth et al. (2018) test the relative importance of 364 macro and banking variables in predicting chargeoffs for two large banks and two community banks. They find that bank predictors dominate all macro predictors in forecast accuracy, and state macro predictors slightly outperform national macro predictors, both for large banks and community banks.

DeYoung and Fairchild (2018) develop a community bank stress test using an econometric methodology based on the large-bank model of Hirtle et al. (2016), which estimates the relationship between bank performance and macro conditions by regressing bank performance metrics on bank-specific characteristics and national macroeconomic variables for the years 1991-2015. As robustness, they supplement regressions with principal components derived from state-level economic data. The contribution of state-level data to the $R^2$ of the regressions, however, is modest. The authors run stress tests separately on community banks with assets above and below $500 million, and they find the smaller community banks are essentially unaffected by the adverse scenarios. This result is troubling because 74% of community banks that failed from 2008-2012 had less than $500 million in assets, suggesting that the regression approach poorly captures the relationship between macroeconomic conditions and bank performance.

In addition to nonlinearities and model error, econometric approaches have difficulty replicating the cyclical chargeoff patterns of banks observed through a business cycle. For example, as the economy deteriorated in 2008, bank chargeoffs rose slowly, peaked in 2009 and 2010, and tapered off thereafter. In contrast, econometric approaches typically impose shocks that taper off immediately.

## 3. Historical Loss Stress Test Methodology

We adopt an historical-loss stress-test methodology that bypasses regression estimation and the ensuing model error, naturally incorporates tail events and local economic conditions, requires only five years of annual data, and intrinsically incorporates cyclical shocks to credit quality that build and taper through time. We group community banks into geographic markets and run a five-year simulation that subjects each bank to its market's 90th percentile net chargeoff rates by loan type for each year from 2008-2012. This five-year horizon is chosen because it captures the deterioration and recovery of bank balance sheets from the financial crisis and Great Recession.[3] A limitation of the historical loss approach is that, unlike CCAR and DFAST, it is not adaptable to changing adverse economic scenarios. However, the severe stress that banks experienced from 2008-2012 is a plausible and reasonable scenario benchmark even in today's healthier banking climate. Indeed, reducing the severity of the shock as banking conditions improve can introduce additional sources of procyclicality.[4] The loss rate in the model is easily customized, however, so users can apply lower loss rate percentiles to run less severe scenarios.

### 3.1. Geographic Banking Markets

Each community bank is assigned to one market based on the location of its headquarters. We define geographical market boundaries to ensure that a reasonably large number of banks exists in each market. Banks headquartered in an MSA (urban banks) with at least 30 banks headquartered in that MSA comprise their own market. Banks in MSAs with less than 30 banks are grouped by state to form a market if there are at least 20 such banks across the state. All rural banks (not headquartered

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[3] As robustness, we use loss rates from 1991-1995 and the results show, as expected, that the number of banks that undergo severe stress decline between 64% and 78%. Consequently, we do not view that time period representative of a severely adverse scenario.

[4] Some large banks subject to CCAR and DFAST commented to the Federal Reserve that the scenarios should be less severe to be more in line with historical post-war recessions. The Federal Reserve responded that, by design, the severity of the scenarios increases as economic conditions improve to limit sources of procyclicality in the stress tests. See "Amendments to Policy Statement on the Scenario Design Framework for Stress Testing," Federal Register, February 28, 2019: 84(40) 6654.

in MSAs) in a state form a market if there are at least 20 rural banks. If there are fewer than 20 urban banks from the smaller MSAs in the state or fewer than 20 rural banks in the state, those urban and rural banks are combined into one market. In all, there are 46 unique markets for community banks headquartered in rural markets. For most years, 32 of those markets consist only of rural community banks headquartered in the same state, and 14 markets consist of rural and urban community banks in the same state. Similarly, there are 66 unique urban markets for community banks headquartered in urban markets. For most years, 16 markets consist of banks in the same MSA, 33 markets consist of urban banks in the same state, and 17 markets consist of rural and urban community banks in the same state.[5]

### 3.2. Loss Rates at the 90th Percentile

After establishing markets, we impose on each bank the 90$^{th}$ percentile net chargeoff rate for each loan type experienced by banks in its respective market for each of the five years 2008-2012. Table 1 lists by loan type mean 90$^{th}$ percentile net chargeoff rates experienced by rural and urban markets, respectively, for each year 2008-2012. Annualized chargeoff rates for each bank are computed quarterly, averaged by year, and winsorized at the top and bottom 1% to eliminate outliers. The 90$^{th}$ percentile chargeoff rates from each market are then averaged by year and MSA status. In general, urban markets experience far higher chargeoff rates than rural markets, and loss rates for 'other' CLD (CLD-OTH) loans are particularly high, peaking at 12% in 2010.

Given that there are 11 loan types in the model and actual chargeoff rates across loan types within a bank are not perfectly correlated, the joint probability is extremely low that a bank will experience the 90$^{th}$ percentile loss rate in every loan type, which at first glance suggests that we overstate the severity of the shock to the bank. Indeed, the median failed bank between 2008 and

[5] Six states have fewer than 20 community bank headquarters, so we ensured that the 90$^{th}$ percentile loss rates from these markets are consistent with the other markets. On average, the loss rates are lower in the markets with fewer than 20 banks.

2012 had four loan categories that exceeded the threshold prior to failure. However, it is more important for the stress test to accurately represent the actual loan *portfolio* chargeoff rates experienced by banks during the crisis years rather than the chargeoff rates of each loan category. Even if a bank incurs its market's 90$^{th}$ percentile chargeoff rate for each loan type, its chargeoff rate for the portfolio as a whole may be above or below its market's portfolio 90$^{th}$ percentile chargeoff rate depending on the bank's loan composition relative to the market. The 90$^{th}$ percentile chargeoff rates on some loan types (such as construction loans) between 2008 and 2012 were much higher than others, and a bank with a greater share of those loan types could experience a portfolio chargeoff rate above the market's 90$^{th}$ percentile even if loss rates on other loans were well below the 90$^{th}$ percentile.[6]

We show that our simulated portfolio loss rates are reasonable relative to the actual chargeoff rates experienced by community banks. Because we observe the actual distributions of portfolio chargeoff rates in each market and year between 2008 and 2012, we can compute the projected chargeoff rate percentile for each bank from the stress test results. As we show later, in-sample stress test results produce portfolio chargeoff rates that on average range between the 86$^{th}$ and 90$^{th}$ percentiles of actual portfolio chargeoff rates. In addition, imposing the same 90th percentile loss rate on all loan types alleviates the concern that we are choosing loan types ex-ante that will perform better than others.

Although survivorship bias is present in the computation of the 90$^{th}$ percentile loss rates, it is appropriate for our purposes to retain this bias. Survivorship bias arises because all failed banks are excluded from the loss rate calculations in the years after they fail, and because banks that failed during the 1st quarter of a given year are excluded from the loss rate calculations within that same year. Loss rates from banks that failed after the 1st quarter of the year are included in that year's loss rate

[6] As robustness, we tested the model with stress tests ranging from the 85$^{th}$ to 95$^{th}$ percentiles, and we found that no sharp discontinuities existed around the choice of the 90$^{th}$ percentile.

distribution because we compute each bank's annualized net chargeoffs each quarter from the Call Reports and average them over the calendar year. The purpose of selecting the five-year loss rate window from 2008 to 2012 is to capture the deterioration and recovery of banks over a full economic cycle. Including the loss rates of previously failed banks each year alters the loss-rate distributions and amplifies the persistence of the simulated shock, weakening the natural recovery process.[7]

### 3.3. Model Dynamics

For the stress test, the initial condition of each bank is taken from its annualized year-to-date Call Report data as of the fourth quarter of the year being tested. Inputs include loan amounts, average loan yields, loss rates, and other information obtained from publicly available Call Reports. The bank-specific simulation input worksheet for the fictitious "Sample Community Bank" is presented in Appendix A. The simulation then projects financial ratios five years forward after applying the relevant chargeoff rates.

Assets in year *t* consist of securities, federal funds sold, interest-bearing balances, loans (L), and loan loss reserves (LLR).[8] All liabilities are represented as deposits (D), and shareholders' equity (E) is the difference between assets and liabilities. We lump federal funds and interest-bearing balances with securities (S) so that the balance sheet is represented as:

$$S_t + L_t - LLR_t = D_t + E_t \tag{1}$$

We assume that banks reinvest all principal and interest payments in the same asset categories. Consequently, securities grow according to:

$$S_{t+1} = S_t(1 + a) \tag{2}$$

[7] As robustness, we ran simulations that included loss rates from banks that failed in the first quarter of the year by using their final reported loss rates from the fourth quarter of the previous year. Projected bank failures increased by small amounts, easing concerns that same-year survivorship bias has large effects on the results.
[8] Non-earning assets are excluded for ease of exposition. Because the core simulation model is similar to that in Hall et al. (2011), we draw heavily from that approach.

where $\alpha$ is the target growth rate of assets, which we set at 3%. Charged-off loans, however, are not reinvested so that loans (and hence, total assets) decrease by the amount of chargeoffs.[9] The bank's *j* loan categories in its portfolio grow through time as:

$$L_{t+1} = \sum_j \left(1 - c_{j,t+1}\right) L_{jt} (1 + a) \tag{3}$$

where $c_j$ is the annual charge-off rate for loan category *j*. Because the stress test focuses exclusively on credit risk, we do not explicitly change interest rates over the simulation horizon. To the extent that interest rates affected chargeoffs over the 2008-2012 period, some of their dynamics are captured in the historical loss rates.

Banks use provision expense (*P*) to offset exactly net chargeoffs (*LS*) in the current year if net chargeoffs are positive, but provision expense is zero if net chargeoffs are negative. We also cap the loan loss reserve to total loan ratio at 1.5% to allow for banks to draw down high initial loan loss reserves before replenishing them with new provisions.[10] In addition, banks add to provisions an amount equal to the realized loan growth rate as:

$$P_t = \max[0, LS_t] + LLR_{t-1} \cdot (L_t / L_{t-1} - 1) \tag{4}$$

Loan loss reserves, then, change through time according to:

$$LLR_t = LLR_{t-1} + P_t - LS_t \tag{5}$$

Net income is computed each year as:

$$NI_t = r_s S_t + \sum_j r_j L_{jt} - r_d D_t - NNE_t - P_t - T_t \tag{6}$$

[9] Sensitivity analysis of the target growth rate shows that it has large effects on model outcomes. Higher growth rates induce more projected bank failures because more assets reduce the capital ratio. We choose a 3% growth rate because it is similar to the long-run U.S. nominal GDP growth rate so that bank assets and economic growth have similar long-run trends. The actual loan growth rate should fall during a period of stress given the economic decline. Interestingly, the actual community bank growth rate (winsorized at the top and bottom 10%) averaged 3.0% annually between 2008 and 2012, while the 2017 simulated loan growth averaged 1.3%.

[10] Call Report data show that at year-end 2007, the 75th percentile of the ratio of LLR to total loans was 1.5%. Consequently, we assume that most banks would be comfortable drawing down their reserves to that level, but they would add to provisions to rebuild their reserves below that threshold. This assumption has little effect as it prevents just a handful of banks from dropping below critical capital thresholds.

where $r_s$ is the average rate on securities, $r_j$ is the rate on loan *j*, $r_D$ is the average rate on deposits, *NNE* is net noninterest expense (noninterest expense less noninterest income), and *T* represents taxes. Deposit interest expense, noninterest expense and noninterest income are assumed equal to their initial percentages of total assets and they change in proportion to the bank's total assets. Taxes are assumed to be 35 percent of operating income, though we also run the tests using the 2018 corporate tax rates of 21%.

Finally, the dividend payout ratio (*d*) is assumed equal to the initial ratio of dividends to net income (NI); however, dividend payments are set to zero if net income turns negative so that

$$DIV_t = \max\,[0, d \cdot NI_t] \tag{6}$$

Retained earnings (RE) equal net income less dividends, and they boost equity (E) such that

$$E_t = E_{t-1} + RE_t \tag{7}$$

Deposits are assumed to automatically adjust each period to balance the balance sheet, as in Equation (1). Figure 1 provides a flow chart that summarizes the simulation logic.

### 3.4. Capital Thresholds

The most important metric from the stress test results is a bank's Tier 1 Leverage (T1Lev) ratio, or Tier 1 capital divided by Tier 1 average assets. Because the simulation computes equity directly, the T1Lev ratio for each bank each year is derived by subtracting the initial (Y0) Tier 1 capital from equity, and initial (Y0) Tier 1 average assets from total assets, and we hold those differences constant throughout the simulation. For a given simulation, we track the number of banks where the T1Lev ratio falls below 2% and 6%, respectively. The 2% threshold mimics the Prompt Corrective Action (PCA) guidelines that define a bank as "critically undercapitalized" if its tangible equity is equal to or less than 2% of total assets.[11] If the capital deficiency is not corrected, a critically undercapitalized bank must be placed into receivership within 90 days by regulators.

We also track the number of banks where the T1Lev ratio falls below 6% to identify banks falling into a dangerous capital zone that signaled high insolvency risk during the crisis and Great Recession. Although the 6% threshold is above the 5% ratio that PCA defines as "well capitalized," it is abundantly clear that the 5% ratio was too low to flag banks with high insolvency risk. Cole and White (2017) show that the mean equity ratio of banks closed between 2007 and 2014 was 6.4% one year prior to failure, and the mean equity ratio did not fall below 2% until one quarter prior to failure. In addition, the Government Accounting Office (2011) concluded that the PCA framework did not prevent widespread losses to the deposit insurance fund. Consequently, the 6% T1Lev threshold represents a reasonable lower bound ratio signaling insufficient capital even though it exceeds PCA guidelines.

## 4. U.S. Community Bank Stress Test Results

### 4.1. Stress Tests Results for 2017

We run stress tests on all 4,846 community banks at year-end 2017 and simulate results for the years 2018-2022. Aggregate results are presented in Table 2. (The simulation output for a representative bank is shown in Appendix B.) Loan loss rates for a given bank come from the 90th percentile chargeoff rates experienced by banks in the same market between 2008 and 2012, and the initial condition of the banks in Year 0 is taken from financial data at year-end 2017.

[11] "Tangible equity" is defined by the regulators as Tier 1 capital plus outstanding cumulative perpetual preferred stock (including related surplus) not already included in Tier 1 capital. Changes to the Call Report after 2014 do not allow us to precisely measure the cumulative perpetual stock not already in Tier 1 capital, so we use the T1Lev ratio as a proxy for tangible equity.

The top panel of Table 2 shows that the mean bank begins the simulation well capitalized with a T1Lev ratio of 11.5% and a median ratio of 10.4%. Despite the severe shocks that hit the banks, mean capital ratios remain high over the five-year horizon; the mean ratio in Year 5 (2022) is 10.2%. Just 153 of the 4,846 banks (3.2%) T1Lev ratios that fall below 2% during the forecast horizon, implying that they would be closed by regulators in the absence of additional capital injections. Another 563 banks (11.6%) have T1Lev ratios that fall below 6%. Not surprisingly, the stress test results show that bank profitability plummets. The bottom panel of Table 2 lists mean ROA, which reaches its nadir in Year 3 (2020) at -9bp before improving in Years 4 and 5. In Y3, 2,246 banks (46.4%) have negative earnings.

The middle panel of Table 2 reports mean net chargeoff rates from the 2017 stress tests, and they peak in Year 3 at 2.3%. To assess the plausibility of these loss rates, we examine how closely the projected portfolio chargeoff rates are correlated with the actual 90$^{th}$ percentile portfolio chargeoffs community banks experienced between 2008 and 2012. Mean chargeoff rates from the 2017 stress tests are plotted as dark-shaded columns (ST2017) in Figure 2. The light-shaded columns (P90) display means of the actual 90$^{th}$ percentile portfolio chargeoff rates for all U.S. community bank markets between 2008 and 2012. The mean chargeoff rates from the 2017 stress tests are consistently lower than actual 90$^{th}$ percentile chargeoff rates. Figure 2 also plots as a dashed line (ST2017PCTL) the percentiles of mean chargeoff rates from the 2017 stress tests relative to actual chargeoff rate distributions between 2008 and 2012. The right-hand axis represents percentile ranking and shows that mean projected chargeoff rates lie between the 86$^{th}$ and 90$^{th}$ percentiles. In sum, applying the 90$^{th}$ percentile chargeoff rate to each loan category produces simulated loan portfolio chargeoffs at reasonably severe levels.

As a further check, we compare our mean loss rates from 2017 with the mean loss rates from the 2017 DFAST severely adverse scenario taken from Table 7 of the report (Board of Governors, 2017). Given the vast differences in the types of banks and the simulation processes between the two stress tests, our sole objective is to observe whether the loss rates are reasonably similar. To make the comparisons more appropriate, we report loss rates from the 2017 community bank simulation using only urban banks because DFAST banks operate in urban areas. In addition, DFAST loss rates are computed as cumulative losses over the nine-quarter horizon divided by the average loan balances over the same period. In contrast, our loss rates are computed annually, so we recompute them as Y1+Y2+Y3/4. In other words, we sum community bank loss rates from 2008, 2009, and one-fourth of 2010. Table 3 lists the nine-quarter mean loss rates for the 2017 stress tests from both models. DFAST loss rates are 2.4 percentage points higher for CRE loans, but the community bank simulation shows higher loss rates for consumer, C&I, and Agriculture loans.[12] Overall nine-quarter portfolio loss rates are 5.0% for the urban community bank simulation compared with 5.8% for DFAST. We conclude that although loss rates across the loan categories are somewhat different between the models, the overall portfolio chargeoff rates are similar, providing further evidence that the community bank simulation results are reasonable.

### 4.2. Comparison of 2007 and 2017 Stress Test Results

The 2017 stress tests show that most community banks at year-end 2017 can weather a severe downturn and sustain high capital ratios. It is interesting to ask how community banks in 2007 would have fared the stress test.[13] Table 4 displays stress test results for the 7,125 community banks at year-end 2007, and performance is much worse than the 2017 results. The number of projected failed banks

[12] We use the "other consumer" category from DFAST to exclude credit cards because community banks extend few credit card loans.

[13] Because many banks did not report the subdivided NFR and CLD components separately in the 2007 Call Reports, we estimate the component values of loans and chargeoffs at year-end 2007 by applying the percentages from March 2008. See Appendix C for details.

in Y5 is 762, or 10.7% of all community banks relative to 3.2% in 2017. In addition, the percentage of banks with T1Lev ratios projected to fall below 6% is 23.0%, double the 11.6% value in 2017.

We identify two explanations for the more favorable stress test outcomes in 2017 than in 2007.[14] First, many of the riskiest banks in 2007 dropped out of the sample by 2017.[15] Nearly two-thirds of the 762 banks projected to fail the 2007 stress tests were no longer in business in 2017, and these banks had loan portfolios with high default risk. Table 5 summarizes several stress test scenarios by listing the percentage of banks that dropped below the 2% (and 6%) T1Lev threshold. Row 1 shows that in the 2007 baseline stress test, 10.7% of banks dropped below the 2% threshold. Rows 2 and 3, however, show that the number jumps to 19.5% for banks in 2007 that did not exist in 2017, and it falls to 4.9% for banks that existed in both years. This disparity exists because the 2,509 banks that existed in 2007 but not in 2017 had higher inherent credit risk than the 4,616 banks that existed in both years. Figure 3 plots the mean differences in 2007 loan shares by bank status in 2017. Banks that did not exist in 2017 held nearly 7 percentage points more in CLD-OTH and CLD-RES loans, and 3.7 percentage points more in NFR-OTH and NFR-OWN loans than banks still in the sample in 2017.

Removing banks that did not exist in 2017 from the 2007 bank stress test accounts for most but not all the difference in insolvency risk between 2007 and 2017. The projected failure rate from the 2007 stress test that includes only banks that also existed in 2017 is 4.9% (Row 3 of Table 5), still higher than the 3.2% (Row 4) in the baseline 2017 simulation. A second explanation for the improved stress-test performance in 2017 relative to 2007 is that the banks that existed in both years adjusted loan portfolios during the interim 10-year period away from loan types with high default rates such as

[14] One potential explanation is that community banks held more securities and fewer loans in 2017 than 2007. Distributions of loan-to-asset ratios, however, are similar across those years.

[15] Of the 2,509 banks that disappeared from the sample, 18% failed, 2% converted to thrifts or exceeded the $10 billion asset threshold for a community bank, and the remaining 80% were acquired or converted to a bank branch.

CLD. Figure 4 shows this shift. Panel A plots major loan category shares for all banks that existed in both years, but it shows modest changes between 2007 and 2017. The CRE share, for example, increased from 41% to 45% of loans while consumer and commercial and industrial loan shares declined by 3% and 2%, respectively. Panel B of Figure 4, however, shows larger changes within the CRE portfolio. CLD loans declined by 11% from 2007 to 2017, NFR loans increased by 4%, farm loans increased by 4%, and multifamily loans increased by 3%.

To estimate the effects on stress test outcomes from loan portfolio shifts between 2007 and 2017, we first run stress tests on the 4,616 U.S. community banks in 2017 that also existed in 2007. Row 5 of Table 5 shows that 2.5%, or 117 banks are projected to fail. We then adjust the loan shares of each bank in 2017 to equal its loan shares in 2007. Row 6 of Table 5 shows a sharp rise to 4.5%, or 206 projected failures, which explains most of the 4.9% (Row 3) projected failure rate of banks in the 2007 simulation. We conclude that the reduction in CLD loan shares has greatly reduced bank insolvency risk over the last decade.

Taken together, these results show that banks had much lower insolvency risk in 2017 than in 2007 because most of the riskiest banks in 2007 no longer existed in 2017, and because the existing banks in 2017 shifted away over the last decade from loan categories with relatively high default risk.

### 4.3. Effects from the New Tax Law

We also use the stress test to examine effects on community bank insolvency risk from the Tax Cuts and Jobs Act (TCJA) signed into law in December 2017. The new law lowers the corporate tax rate, eliminates net operating loss (NOL) carrybacks, and limits NOL deductions to 80% of taxable income. Each of these changes weakens the automatic stabilizers that banks with negative NOLs received under the previous tax law. We show that TCJA has increased community bank insolvency risk in 2018 relative to 2017 because, although banks boosted capital ratios in response to the tax cuts, the higher capital was insufficient to offset the weakened automatic stabilizers.

The TCJA weakens automatic stabilizers that help offset bank losses in adverse conditions. Imagine a bank that has net operating income during the years Y1 through Y3 of -$100, -$100, and +$100. Relative to the previous tax law, automatic stabilizers are weakened in three ways. First, the new law lowers the corporate tax rate to 21% from 35%, which reduces the NOL tax benefit in Y1 and Y2 to $21 ($100 x 0.21) from $35 ($100 x 0.35). Second, TCJA eliminates NOL carrybacks so banks must exclusively use carryforwards, which has implications for cash flow and regulatory capital. Under the previous tax rules, a bank with a $100 NOL in Y1 and again in Y2 could have applied carrybacks for taxes paid in the previous two years to receive a cash-based tax benefit of $35 each year, which reduces annual after-tax loss to $65.[16] Under the new rules, a bank would receive an accrual-based tax benefit each year of $21 called a deferred tax assets (DTA), which represents a claim on reduced cash-based tax payments in future profitable years. Importantly, the Basel III Capital Accord excludes those DTAs from Tier 1 capital because severely distressed banks may be unable to generate future positive operating income to utilize the DTAs. Although the DTA asset increases equity in the year of the NOL, regulatory capital ratios are unaffected until the DTAs are utilized. Third, TCJA limits carryforwards to 80% of taxable income. When the bank in our example earns net operating income of +$100 in Y3, it can utilize the accumulated DTAs ($42 over Y1 and Y2) to offset the taxable income. Previously, a bank using carryforwards could utilize $35 in DTAs to offset the full Y3 tax obligation. Under TCJA, the bank can offset only 80% of the taxable income, or $16.80 (80% x $100 x 21%) with DTAs, leaving a tax obligation of $4.20.

We compare the effects from the 2017 stress test on T1Lev ratios under the current and previous tax laws. Under the new tax law, DTAs that result from NOLs during the simulation are subtracted from the T1Lev ratio. Row 7 of Table 5 shows the sharp increase in insolvency risk from the new tax

[16] Although the previous tax law limited NOL carrybacks to two years, in November 2009 Congress extended carrybacks to five years for most banks for losses in 2008 and 2009. Consequently, banks could offset losses in 2008 or 2009 with tax payments made from 2003 to 2007.

law relative to the 2017 baseline (Row 4). The percentage of banks with T1Lev ratios below 2% more than doubles from 3.2% to 6.8%. The increased projected bank insolvency arises for two reasons. First, as discussed above, the lower tax benefit from operating losses combined with the exclusion of DTAs from Tier 1 capital reduce regulatory capital ratios. The effect on regulatory capital can be seen in Row 7 of Table 5 as just 4.5% of banks cross the 2% equity-to-asset threshold compared with 6.8% for the T1Lev ratio. Second, the stress test run in 2017 affords banks no time after the change in the tax law to accumulate more capital even though net income should increase due to reduced tax payments. The fixed dividend payout ratio built into the model may also slow capital build-up because banks are assumed to keep payout ratios constant for all years with positive earnings rather than decreasing them as net income rises. But even if payout ratios remain unchanged, higher industry operating income would increase capital over time. It is an empirical question as to whether banks will accumulate more capital in the low-tax environment to offset the weaker automatic stabilizers.

To answer this question for the year 2018, we first examine the effects of TCJA on banks' capital in 2018 relative to the prior two years. Figure 5 plots ROA, the dividend payout ratio, and the T1Lev ratios for community banks between the 10$^{th}$ and 90$^{th}$ percentiles. We average the values for banks in 2016 and 2017 to reduce the likelihood that banks already began to adjust their behavior in anticipation of the tax cuts (Wagner, Zeckhauser and Ziegler, 2018). Panel A shows, as expected, that bank earnings increased consistently in 2018 along the distribution. Panel B shows that dividend payout ratios are slightly higher in 2018 for banks with payout ratios less than 20%, but they decline for banks with payout ratios above 20%. The net result is that higher income combined with lower dividend payout ratios for most banks boosted the median Tier 1 leverage ratio in 2018 by 17bp, which we observe in Panel C of Figure 5.

Even given that community banks responded to the TCJA by increasing capital ratios in 2018, we examine whether the increase is sufficient to offset the weakening automatic stabilizers. We run stress tests in 2018 that include only banks that existed both in 2017 and 2018. Row 8 of Table 5 presents the stress test results of the 4,598 community, and it projects that 5.9% of banks fall below the 2% T1Lev ratio threshold. The projected failures are below the 6.8% of banks projected to fail in the 2017 simulation under TCJA reported in Row 7, which indicates that the higher T1Lev ratios have reduced insolvency risk relative to what it would have been without an increase in capital. The relevant comparison, however, is with the much lower 3.2% of banks that failed the baseline 2017 stress test reported in Row 4. At year-end 2018, TCJA has increased community bank insolvency risk from a severely adverse scenario because the increased capital ratios are not sufficient to offset the weakened automatic stabilizers.

## 5. In-Sample Model Performance

The value added from a stress test is the ability to identify banks that are the most vulnerable to a sudden adverse shock. Out-of-sample testing of our model is not yet possible because the parameters are based on recent experience and, fortunately, banks have not experienced another shock like the 2007-2009 financial crisis. However, we can conduct in-sample tests by comparing stress-test projections with the actual performance of community banks at year-end 2007 that were not acquired in the years 2008-2012. We expect the stress tests to detect most banks that failed during the period (low Type I error). However, because we apply the 90$^{th}$ percentile loss rates to all banks, the model should identify more banks as distressed than those that actually became distressed (high Type II error).

The stress test identifies a failed bank as one that has a T1Lev ratio below 2% at some point during the simulation. A Type 1 error occurs when the stress test fails to identify a failed bank. Of the 386 community banks from year-end 2007 that failed between 2008 and 2012, the stress test identifies 215 of those banks, resulting in a Type 1 error of 171 banks (45%). Book capital ratios were commonly overstated at many banks that failed during this period because banks were reluctant to recognize losses in a timely manner (Garcia, 2010; GAO, 2011). If we assume that banks with simulated T1Lev ratios less than 6% also were likely to fail, the stress test flags an additional 72 failed banks, reducing the Type I error to 99 banks (26%). For these remaining Type I banks, the average minimum simulated T1Lev ratio is 10.4% and the average minimum ROA is -1.1%.

A Type II error occurs when the model incorrectly identifies a healthy bank as distressed. The 2007 stress tests forecasts a total of 762 banks with T1Lev ratios below 2%. Of those banks, 215 failed and 160 were closed or acquired between 2008 and 2012, resulting in 387 banks projected to fail that did not fail. Among those, 80 banks were enrolled in the TARP program, which may have been used to recapitalize the banks to avoid failure. Excluding those 80 banks, the Type II error is 307 banks (40%). For Type II banks, the average minimum simulated T1Lev ratio is -2.1% and the average minimum ROA is -3.7%.

Our 2007 stress test results accurately project failure risk by community bank size. Recall that 74% of community banks that failed from 2008-2012 had less than $500 million in assets. Fully 79% of banks that our model projects to fail had assets in 2007 less than $500 million.

Another approach to measuring in-sample performance of our stress test is to compare the model's results with traditional early warning signals of bank distress. Stress tests differ from early warning signals because they subject all banks to adverse shocks while early warning signals are static indicators designed to detect banks with high default risk at a point in time. Nevertheless, it is reasonable to expect overlap between the banks flagged by early warning signals and those that perform poorly in stress tests.

A simple and potentially powerful early warning signal is the T1Lev ratio. Banks with higher capital cushions, all else equal, can absorb more losses before failure. How likely is the stress test to project banks with the lowest leverage ratios in Year 0 to fail? Using year-end 2007 Call Report data as Year 0, Table 6 shows that the spearman rank correlation coefficient between actual Y0 T1Lev ratios and projected Y5 T1Lev ratios is 0.64. The same correlation for the 2017 simulation is 0.75. In both years, a strong correlation exists between the initial Tier1 leverage ratio and the projected capital ratio in Year 5.

A more robust early warning signal is the Federal Reserve's SEER failure probability model, designed to predict the likelihood of bank failure over the subsequent two years (Cole, Cornyn, and Gunther, 1995). Each bank's failure probability is derived from a multinomial probit regression of bank failures in the mid-1980s through the early 1990s. The coefficients from this model are confidential, but Miller et al. (2015) replicate the model and show that the so-called dated failure probability (DFP) signal was the most accurate of a host of early warning signals for detecting bank failures from 2009 through 2012.[17] We rank banks by failure probability from highest to lowest (riskier banks have lower ranks) and compare those rankings with Year 5 T1Lev ratio stress test projections. As shown in Table 6, the rank correlation coefficient of failure probability with the 2007 simulation is 0.51, and the correlation coefficient with the 2017 simulation is 0.41.

Finally, we compare T1Lev ratio rankings in Year 5 with CRE rankings—banks ranked by their proportion of CRE loans to total loans. Because the recession hit CRE loans particularly hard, we might expect a strong correlation between banks with high CRE loan concentrations and banks with poor performance in the stress tests. Again, banks are ranked from highest to lowest risk. The spearman rank correlation coefficient is 0.40 for the 2007 simulation and 0.16 for the 2017 simulation, much lower than the other correlations.

In sum, projections from our stress test model built on historical loss rates are highly correlated in sample during the 2008-2012 period with banks that failed or had early warning indicators with

[17] The variables in the early SEER model and DFP are the log of total assets, ROA, equity to assets, other real estate owned to assets, loans 30-89 days past due to assets, loans 90 or more days past due to assets, nonaccrual loans to assets, securities to assets, and jumbo CDs to assets. Interestingly, this model performed better than a model estimated on bank failures between 2006 and 2009.

heightened risk in 2007. Depending on the capital threshold, stress test projections identify between 54% and 74% of the banks that failed between 2008 and 2012, and the projections are correlated with banks that had relatively low T1Lev ratios and high failure probabilities in 2007.

## 6. Benefits from Loan Portfolio Reallocations

In this section, we use our stress tests to quantify the benefits to insolvency risk from loan portfolio reallocations. Exposure to commercial real estate (CRE) loans increased sharply at community banks between 1990 and 2006, which prompted supervisors to issue guidance that defined CRE concentration thresholds and encouraged banks to stress test loan portfolios (Board of Governors. 2006.) Figure 6 shows that CRE lending as a percent of total loans more than doubled from 23% in 1991 to 50% in 2007. NFR and CLD loans grew the fastest, while farmland (FRM) and multifamily (MFM) remained relatively small portions of CRE loans throughout the period. Interestingly, CRE concentration has remained high since the financial crisis pinnacle in 2008. Even as late as 2017, CRE lending comprised 48.6% of total loans.

The financial crisis and subsequent recession revealed the substantial risk to community banks resulting from high CRE concentrations. Indeed, 23% of banks that exceeded both CRE thresholds established in the 2006 guidance failed during the ensuing economic downturn (Friend, Glenos and Nichols, 2013). Banks with high concentrations of CLD loans were particularly vulnerable to the economic downturn and collapse of real estate prices. Figure 7 plots mean chargeoff rates by CRE loan type for community banks between 2008 and 2017. Of the four categories, CLD incurred the highest chargeoffs. The mean chargeoff rate for CLD in 2009 was 2.7%; in contrast, mean chargeoffs for NFR loans never exceeded 0.6%.

At the same time the CRE guidance was finalized, changes to the Call Report were introduced that refined CRE loan categories. Beginning in 2007 (and finalized in 2008), the Call Reports separated nonfarm nonresidential loans into owner-occupied (NFR-OWN) and "other" non-owner occupied

(NFR-OTH) loans. It also split construction and land development loans into 1-4 family construction loans (CLD-RES) and "other" construction loans (CLD-OTH). Appendix C describes these changes in detail. The presumption by bankers and regulators was that owner-occupied properties would be relatively less risky because the tenants had more skin in the game. Similarly, residential construction loans were presumably less risky than other construction loans because defaults on residential construction were historically low (Federal Register, 2005). As shown in Figure 8, between 2007 and 2017, an average 47% of NFR loans were owner occupied, and 25% of CLD loans were residential construction. Since 2012, the share of NFR loans that are owner occupied has decreased, and the share of CLD loans that are residential has increased.

We use the community bank stress test to assess risk-reduction benefits from hypothetical loan portfolio adjustments. We focus initially on portfolio adjustments between residential CLD loans (CLD-RES) and "other" CLD loans (CLD-OTH), and between owner-occupied NFR (NFR-OWN) loans and "other" NFR (NFR-OTH) loans. Figure 9 plots mean chargeoff rates by these four loan categories for all U.S. community banks between 2007 and 2017. Chargeoff rates for residential construction loans were lower than other construction loans after 2009, though the chargeoff rates were similar before then. In addition, chargeoff rates for owner-occupied NFR loans were slightly lower than for other NFR loans for most the period. More importantly, defaults on NFR loans were much lower than defaults on CLD loans. These patterns suggest that community banks can achieve significant risk reduction from shifting lending from CLD to NFR rather than shifting lending within CLD and NFR.

We construct five hypothetical balance sheets for the 7,125 U.S. community banks at year-end 2007, each time restarting with the actual 2007 data so that the changes are not cumulative. We first place all CLD-OTH loans into the CLD-RES category and run the stress test. We then transfer all CLD-OTH loans into CLD-RES. We repeat the exercise for NFR loans, placing all of them in NFR-

OWN and NFR-OTH, respectively. Finally, we shift all CLD loans to NFR loans by jointly transferring all CLD-RES loans into NFR-OWN, and all CLD-OTH loans into NFR-OTH. In all, we create five distinct datasets with hypothetical loan portfolios using 2007 as Y0 for the stress tests.

Stress test results in Table 7 show that just one portfolio reallocation results in large differences in the number of banks that cross the capital thresholds relative to the base case. Shifting loans from CLD to NFR as shown in Row 6 of the table leads to a reduction from 762 to 262 in the number of banks with a T1Lev ratio below 2%, and a reduction from 1638 to 925 in the number of banks with a T1Lev ratio below 6%. Of course, this hypothetical loan reallocation is an extreme example where banks make no construction loans, but even modest shifts from CLD into NFR bring risk reduction benefits.

Table 7 also shows that within-NFR portfolio reallocation from NFR-OTH into NFR-OWN (Row 4) results in a modest reduction in the number of banks that cross the capital thresholds, and reallocation from NFR-OWN to NFR-OTH (Row 5) results in a modest increase. This result is consistent with Figure 9 that shows slightly lower chargeoff rates for NFR-OWN. For within-CLD loan reallocations, however, we observe unexpected results. The shift from CLD-OTH to CLD-RES (Row 2) increases the number of banks with less than 2% capital, perhaps because chargeoff rates for CLD-RES are slightly higher than chargeoff rates for CLD-RES in 2008 and 2009. Nevertheless, portfolio reallocations within CLD and NFR lead to modest changes in stress test outcomes relative to portfolio shifts from CLD to NFR.

## 7. Conclusion

We develop an historical loss macro stress test that can be used by U.S. community banks and supervisors. Each bank undergoes a severely adverse five-year scenario where the bank experiences a chargeoff rate on a given loan type equal to the 90$^{th}$ percentile chargeoff rate experienced by community banks in its geographical market each year between 2008 and 2012. The model naturally captures tail risk and avoids model error inherent in econometric approaches. We show that it more accurately projects patterns of actual community banks distress in the years surrounding the financial crisis and Great Recession.

More than ten years after the 2007-2009 financial crisis, community banks are well prepared to weather a similar shock. Stress tests results beginning with bank condition in 2017 show significantly lower insolvency risk than stress tests run on community banks in 2007 primarily because banks in 2017 have much lower concentrations in construction and land development loans. The Tax Cut and Jobs Act of 2017, however, offset some of these improvements for banks in 2018 because it weakens the automatic stabilizer effect from net operating losses and makes it more difficult for banks to convert accrued tax benefits to Tier 1 capital. Finally, loan portfolio diversification within each of the construction land development and nonfarm nonresidential loan categories results in little improvement in stress test outcomes because chargeoff rates within each of those categories are similar, but replacing construction land development loans with nonfarm nonresidential loans can lead to a substantial reduction in bank insolvency risk from a severely adverse shock.

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**Figure 1. Five-Year Simulation Flow Chart**

Flow chart summarizes the logic of the five-year community bank stress test. From the initial condition at Y0, the bank incurs in Y1 the 90th percentile loan chargeoff rates of its market from 2008 and sets aside provision expense equal to the net chargeoffs plus realized loan growth targeted at 3%. After-tax net income (35% tax rate) not paid as dividends (Min($0, Payout $\text{Ratio}_{2007}$)) add to or subtract from the bank's retained earnings and capital. The bank then incurs the 90th percentile chargeoff rates from 2009 in Y2, and the pattern repeats through Y5.

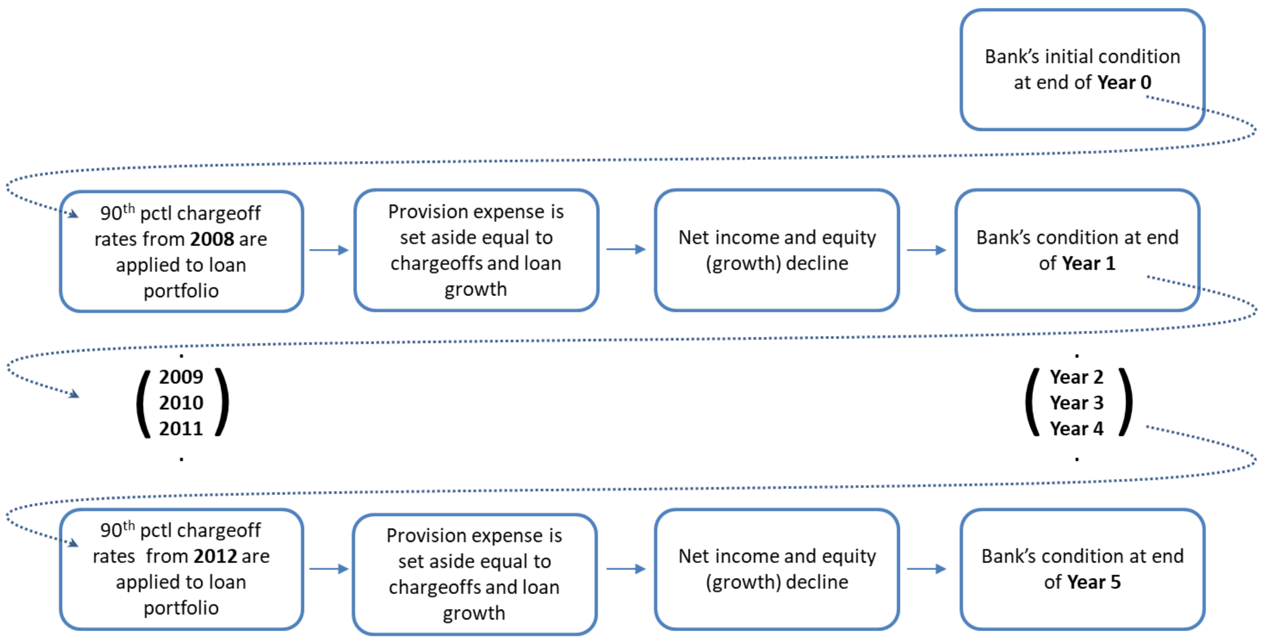


**Figure 2. Actual and Simulated Portfolio Chargeoff Rates**

Figure compares means of community bank projected net chargeoff rates with actual net chargeoff rates. *ST2017* plots the mean projected net chargeoff rate for each year 2018-2022 based on banks' initial conditions at year-end 2017. *P90* plots the mean actual 90th percentile net chargeoff rate across all markets for each year 2008-2012. *ST2017PCTL* (right axis) plots the percentile of the projected net chargeoff for the years 2018-2022 relative to actual mean 90th percentile net chargeoff rates from the years 2008-2012.

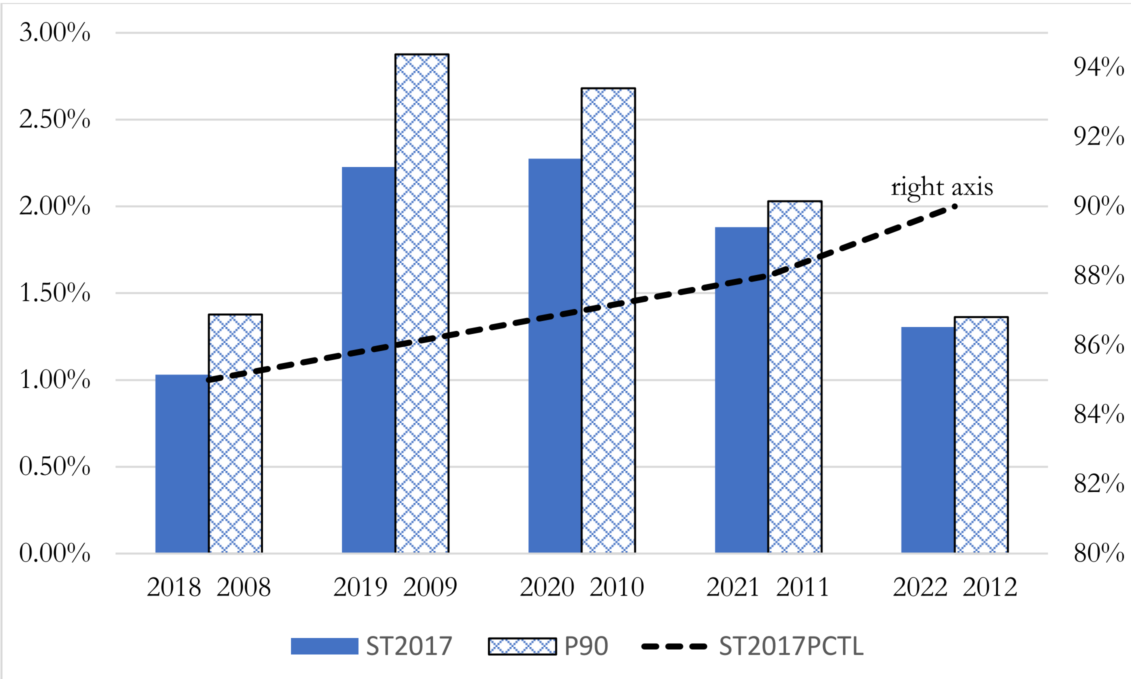


**Figure 3. Differences in mean loan shares in 2007 by bank existence in 2017**
Figure plots the differences in mean loan shares (loan category amount scaled by total loans) in 2007 by bank status in 2017. Differences are computed as mean loan share of banks that did not exist in 2017 less banks that did exist in 2017. See Table 1 for loan category definitions.

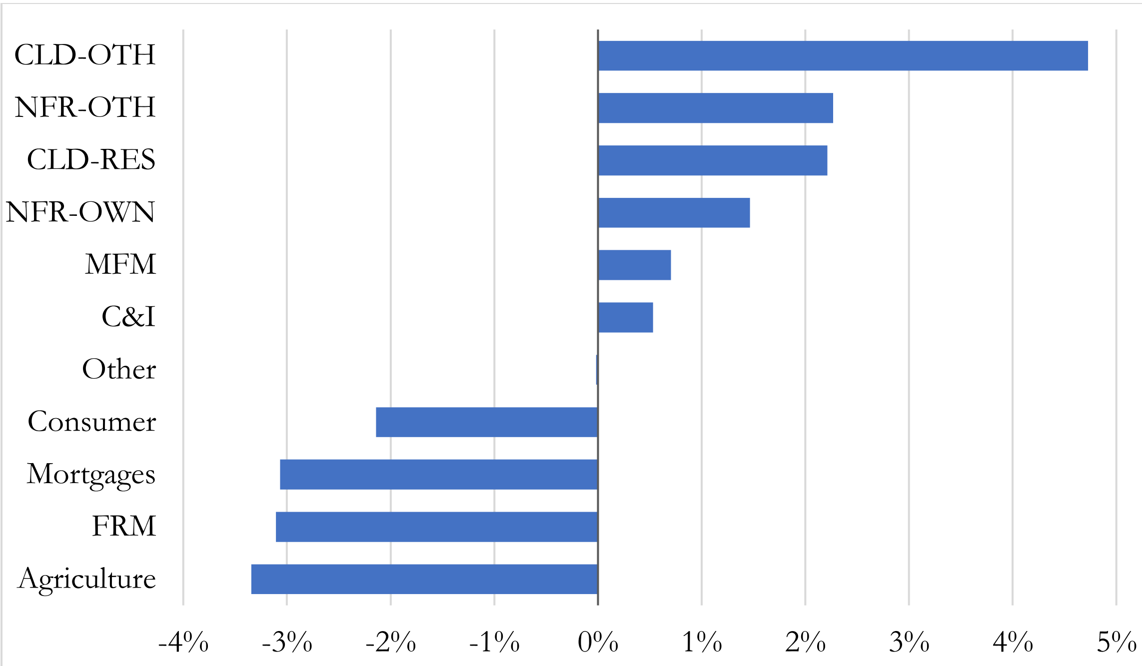
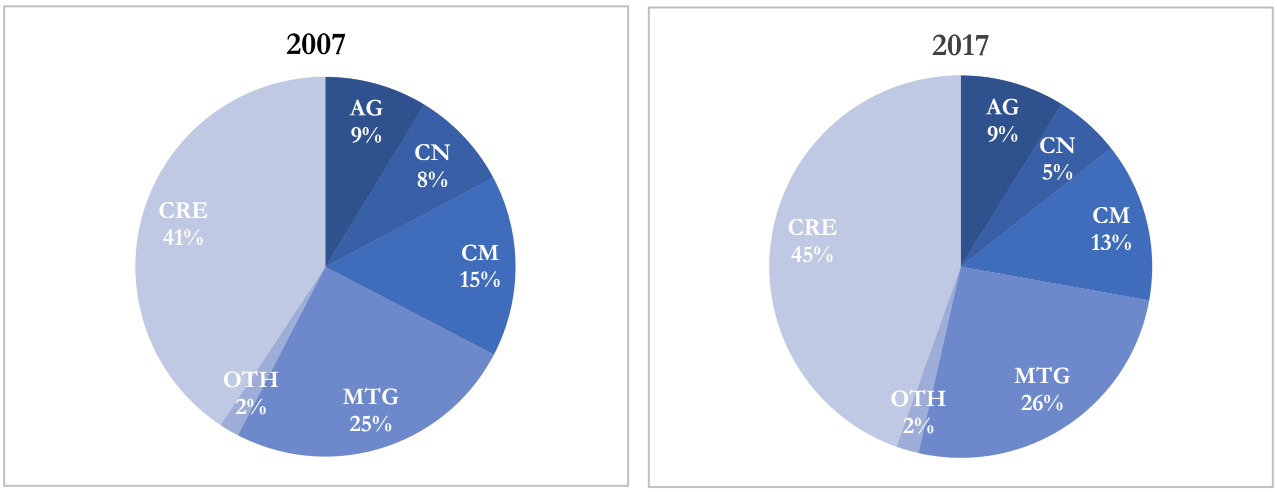


**Figure 4. Mean Community Bank Loan Portfolio, 2007 and 2017**

Figures in Panel A plot mean loan share by major loan category for all community banks that existed in both 2007 and 2017. *CRE* is commercial real estate loans, *AG* is agricultural loans, *CN* is consumer loans, *CM* is commercial and industrial loans, *MTG* is residential mortgage loans, and *OTH* is all other loans. The left-hand chart plots loan shares at year-end 2007, and the right-hand chart, at year-end 2017. Figures in Panel B plot for all community banks that existed in both 2007 and 2017 the loan share by CRE category. *CLD-RES* and *CLD-OTH* are, respectively, residential and other construction and land development loans, *FRM* is loans secured by farmland, *MFM* is multifamily loans, and *NFR-OWN* and *NFR-OTH* are, respectively, owner-occupied and other nonfarm nonresidential loans. The left-hand chart plots CRE loan shares at year-end 2007, and the right-hand chart, at year-end 2017.

Panel A. Major Loan Categories




Panel B. Commercial Real Estate Categories

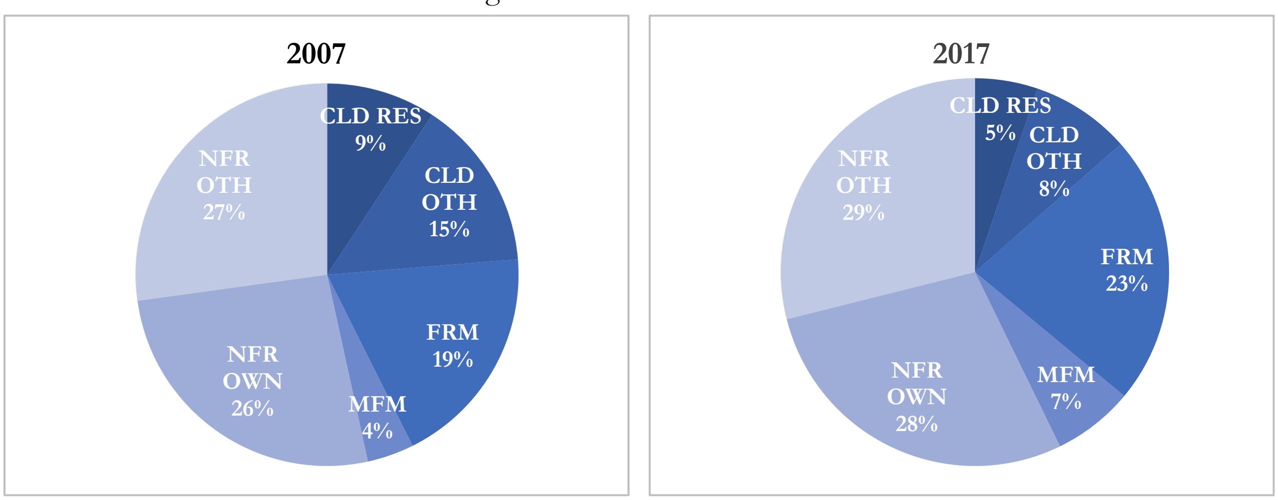
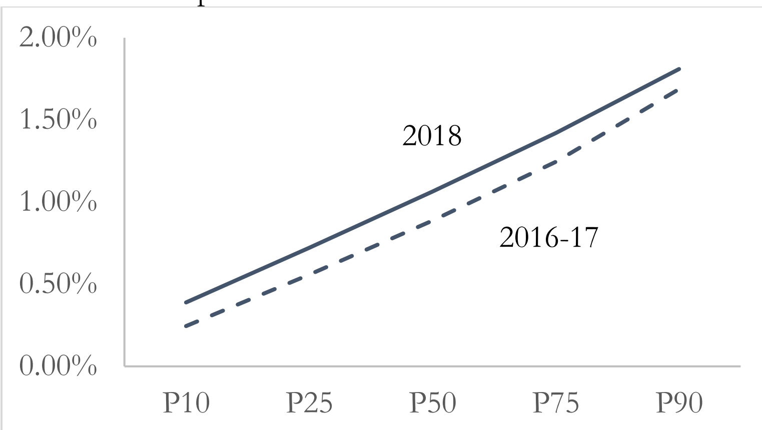
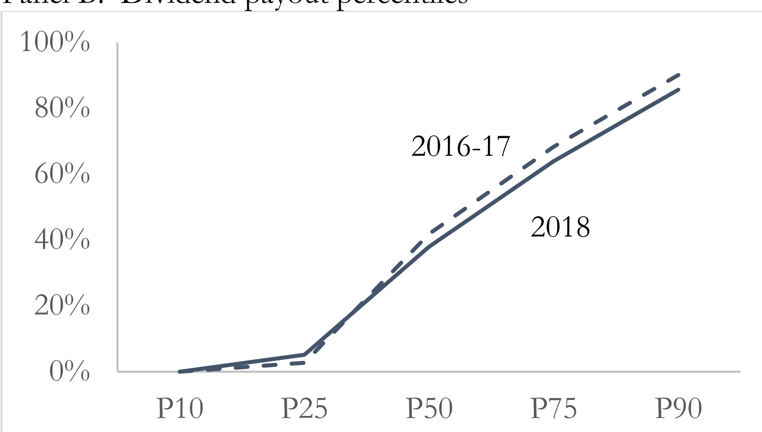


**Figure 5. Bank earnings, dividend payouts, and capital ratios**
Figure plots the 10th through 90th percentiles for select community bank ratios. Ratios for 2016-17 are the average of the two years. Panel A plots return on assets (ROA); Panel B, the dividend payout ratio; and Panel C, the Tier 1 leverage ratio.

Panel A. ROA percentiles




Panel B. Dividend payout percentiles




Panel C. T1Lev ratio percentiles

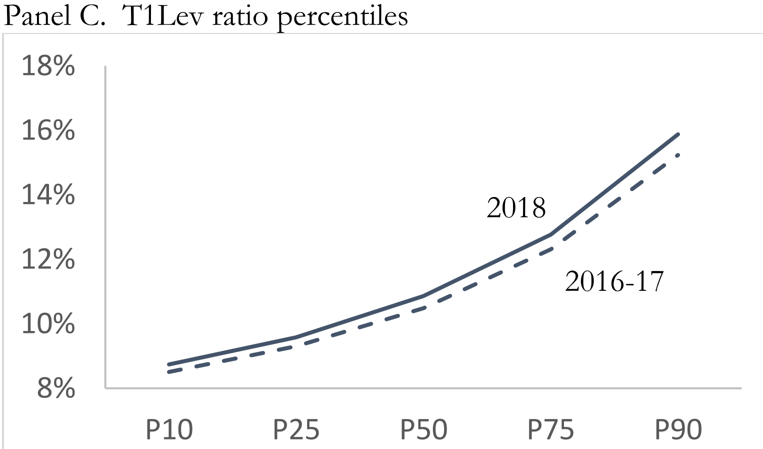


**Figure 6: CRE Loan Concentration at Community Banks 1990-2017**
Figure plots for all community banks between 1990 and 2017 asset-weighted loan shares of the four primary commercial real estate loan categories: nonfarm nonresidential (*NFR*), construction and land development (*CLD*), farmland (*FRM*), and multifamily (*MFM*).

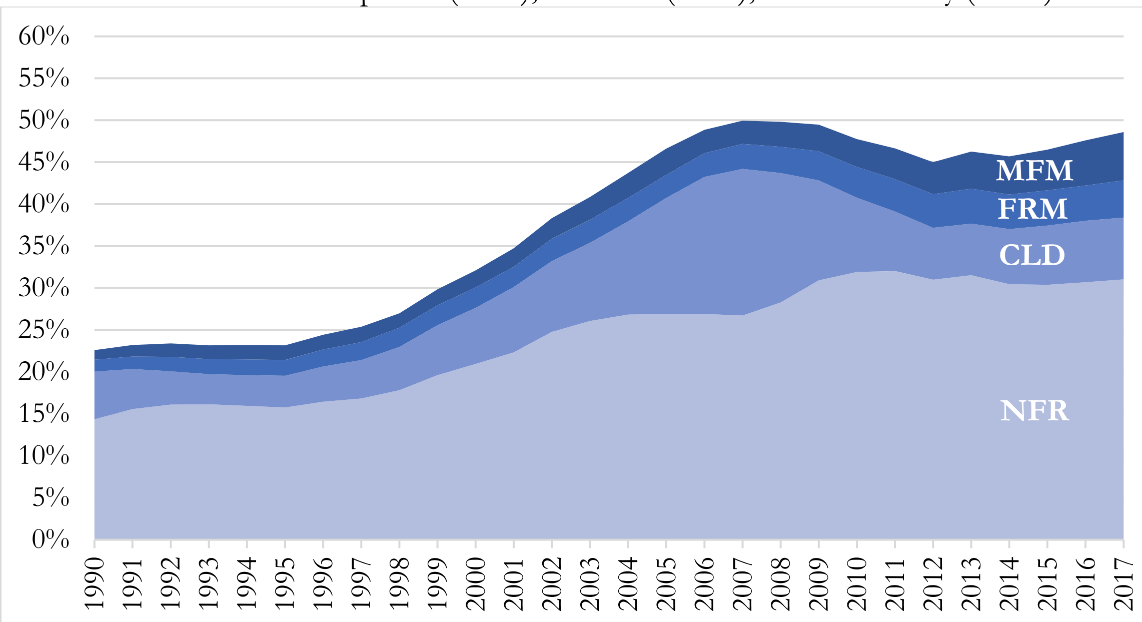


**Figure 7. Mean Chargeoff Rates by CRE Loan Type**

Figure plots community bank mean net chargeoff rates between 2007 and 2017 for construction and land development (*CLD*), farmland (*FRM*), multifamily (*MFM*), and nonfarm nonresidential (*NFR*).

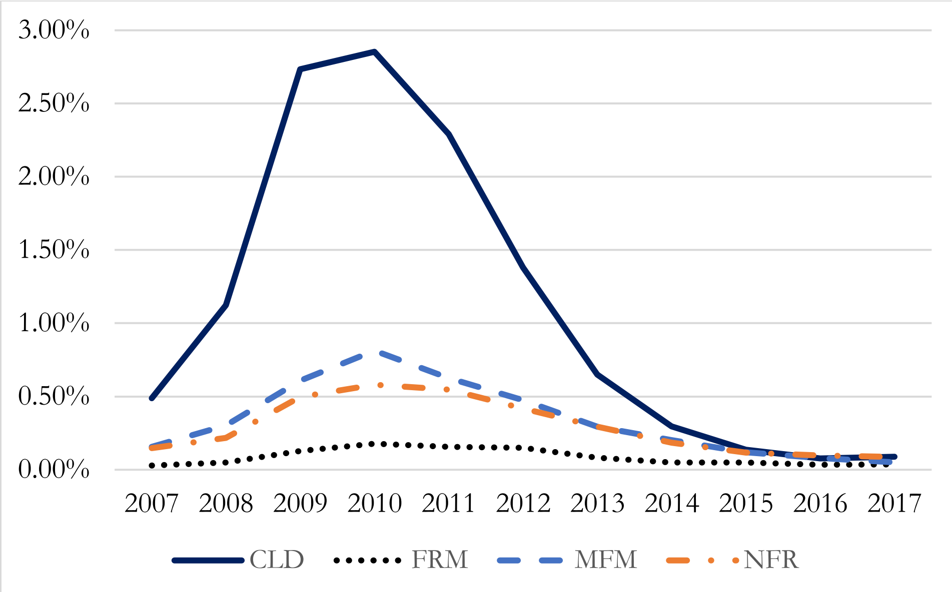


**Figure 8. Relative Shares of CLD and NFR Loans**
Figure plots for all community banks from 2007-2017 the share of total nonfarm nonresidential loans that are owner occupied (NFR-OWN), and the share of total construction and land development loans that are residential (CLD-RES).

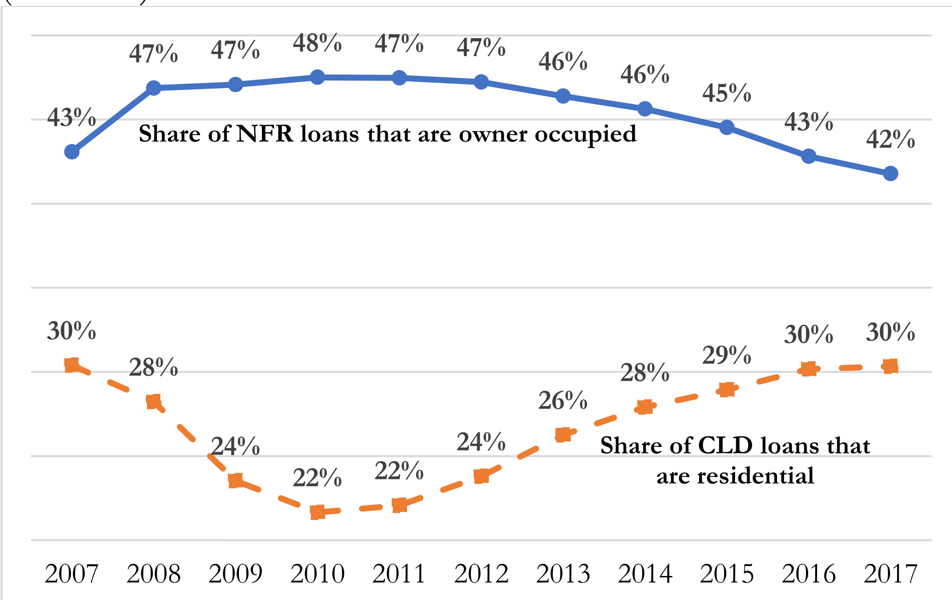


**Figure 9. Mean Chargeoff Rates for CLD and NFR Subcategories**
Figure plots community bank mean net chargeoff rates between 2007 and 2017 for residential (*CLD-RES*) and 'other' (*CLD-OTH*) construction and land development loans. It also plots net chargeoff rates for owner-occupied (NFR-OWN) and 'other' (NFR-OTH) nonfarm nonresidential loans.

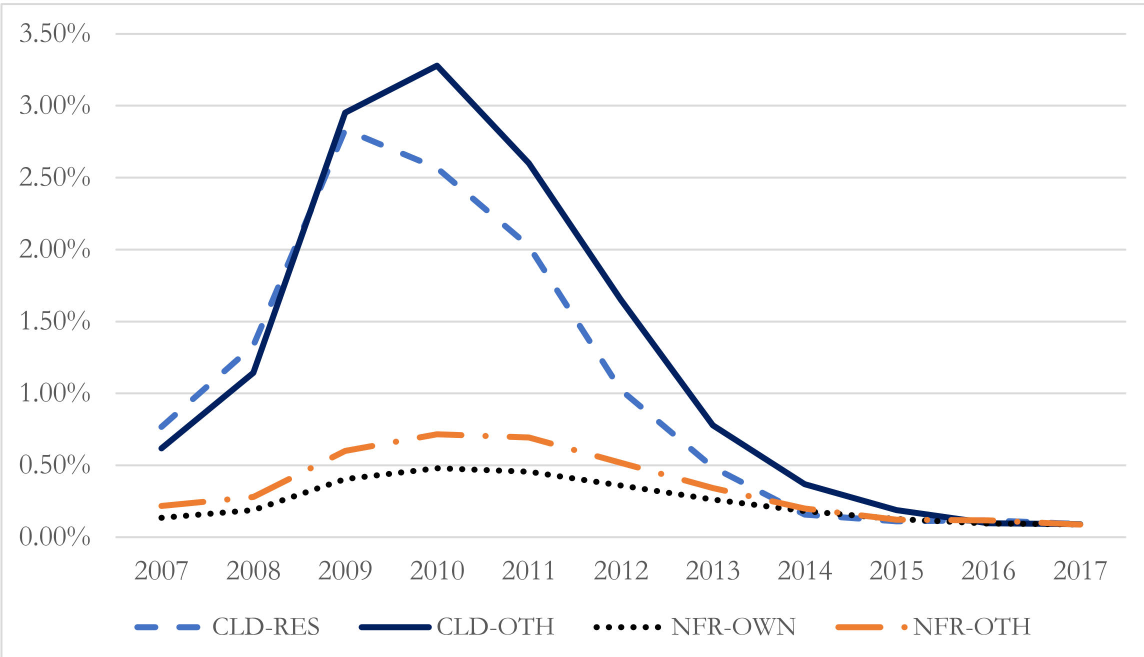


**Table 1. Mean 90th percentile chargeoff rates across U.S. community bank markets**

Table displays mean 90th percentile net chargeoff rates across U.S. community bank markets for the years 2008-2012. Panel A lists values for rural banks (headquartered in counties not in MSAs), and Panel B lists values for urban banks (headquartered in MSAs). Call Reports specify six types of commercial real estate (*CRE*) loans. Multifamily (*MFM*) loans are secured by properties with five or more units. Nonfarm nonresidential (*NFR*) loans are secured by business real estate and they are divided into other (*NLR-OTH*) and owner-occupied *(NFR-OWN*). Farmland (*FRM*) loans are secured by farm real estate. Construction and land development (*CLD*) loans are divided into residential (*CLD-RES*) and other (*CLD-OTH*). Call Reports specify five other loan types. Consumer (*CN*) loans are to individuals for items such as automobiles and credit cards loans. Mortgage (*MTG*) loans are residential real estate loans secured by property with less than five units. Commercial and Industrial (*C&I*) loans are business loans not secured by real estate. Agricultural (*AG*) loans are loans for agricultural production not secured by farmland. We define *Other* loans as all other loan types.

Panel A. Rural banks

| | Loan type | 2008 | 2009 | 2010 | 2011 | 2012 |
|---|---|---|---|---|---|---|
| | MFM | 0.00% | 0.00% | 0.22% | 0.00% | 0.00% |
| | NFR-OTH | 0.45% | 1.35% | 1.81% | 1.83% | 1.18% |
| CRE | NFR-OWN | 0.32% | 1.11% | 1.25% | 1.21% | 0.94% |
| | FRM | 0.00% | 0.00% | 0.02% | 0.03% | 0.00% |
| | CLD-OTH | 1.70% | 6.90% | 8.33% | 6.92% | 3.95% |
| | CLD-RES | 0.99% | 3.48% | 3.19% | 1.31% | 0.15% |
| | Consumer | 1.80% | 2.17% | 1.87% | 1.52% | 1.39% |
| | Mortgages | 0.49% | 0.89% | 1.13% | 1.07% | 0.83% |
| | C&I | 2.57% | 4.26% | 3.58% | 3.02% | 2.04% |
| | Agriculture | 0.13% | 0.38% | 0.25% | 0.10% | 0.02% |
| | Other | 3.43% | 3.65% | 2.79% | 1.99% | 2.17% |

Panel B. Urban banks

| | Loan type | 2008 | 2009 | 2010 | 2011 | 2012 |
|---|---|---|---|---|---|---|
| | MFM | 0.00% | 1.19% | 2.36% | 1.78% | 0.78% |
| | NFR-OTH | 0.44% | 1.99% | 2.55% | 2.42% | 1.67% |
| CRE | NFR-OWN | 0.36% | 1.19% | 1.73% | 1.68% | 1.29% |
| | FRM | 0.00% | 0.00% | 0.09% | 0.03% | 0.01% |
| | CLD-OTH | 3.88% | 10.73% | 12.02% | 9.46% | 5.49% |
| | CLD-RES | 4.85% | 11.15% | 10.02% | 6.73% | 2.03% |
| | Consumer | 2.86% | 3.81% | 3.74% | 2.81% | 2.15% |
| | Mortgages | 1.05% | 2.65% | 2.64% | 2.32% | 1.68% |
| | C&I | 2.71% | 5.85% | 5.49% | 3.83% | 2.85% |
| | Agriculture | 0.07% | 0.18% | 0.20% | 0.03% | 0.00% |
| | Other | 3.43% | 7.66% | 5.81% | 3.14% | 2.37% |

**Table 2. Stress test results for U.S. community banks, 2017-2022**

Summary statistics of stress-test results for the sample of 4,846 community banks based on their financial conditions at year-end 2017 (Y0). *T1Lev*<2%, *T1Lev* <6%, and *ROA*<0% are the number of banks each year with projected Tier 1 leverage ratios and return on assets, respectively, below the threshold.

| | **Year 0** | **Year 1** | **Year 2** | **Year 3** | **Year 4** | **Year 5** |
|---|---|---|---|---|---|---|
| T1Lev Ratio | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 |
| Mean | 11.46% | 11.42% | 11.02% | 10.61% | 10.30% | 10.17% |
| Median | 10.42% | 10.45% | 10.16% | 9.94% | 9.78% | 9.74% |
| Min | 2.66% | -64.92% | -141.77% | -218.17% | -294.09% | -369.51% |
| Max | 98.75% | 100.50% | 102.88% | 105.18% | 110.65% | 116.97% |
| StdDev | 5.85% | 5.93% | 6.39% | 7.08% | 7.87% | 8.71% |
| T1Lev< 2% | 0 | 7 | 21 | 49 | 97 | 153 |
| T1Lev<6% | 31 | 44 | 104 | 295 | 474 | 563 |
| | | | | | | |
| Chargeoffs to Loans | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 |
| Mean | 0.18% | 1.03% | 2.23% | 2.27% | 1.88% | 1.31% |
| Median | 0.05% | 0.85% | 1.63% | 1.71% | 1.43% | 1.04% |
| Min | -1.75% | 0.05% | 0.04% | 0.09% | 0.04% | 0.02% |
| Max | 38.80% | 6.19% | 15.10% | 16.06% | 16.56% | 14.78% |
| StdDev | 0.82% | 0.72% | 1.71% | 1.76% | 1.43% | 1.01% |
| | | | | | | |
| ROA | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 |
| Mean | 0.97% | 0.49% | -0.08% | -0.09% | 0.06% | 0.30% |
| Median | 0.97% | 0.50% | 0.10% | 0.06% | 0.18% | 0.36% |
| Min | -174.42% | -130.32% | -130.32% | -130.32% | -130.32% | -130.32% |
| Max | 45.28% | 32.56% | 32.56% | 32.56% | 32.56% | 32.56% |
| StdDev | 2.88% | 2.18% | 2.26% | 2.26% | 2.21% | 2.17% |
| ROA<0% | 261 | 730 | 2132 | 2246 | 1908 | 1246 |

**Table 3. Comparison of 2017 community bank stress test with DFAST**
Table compares cumulative nine-quarter loan loss rates from the 2017 community bank stress test results for banks headquartered in urban markets with the 2017 Dodd Frank Stress Test (DFAST) adverse scenario results from Table 7 of the report. We compute the community bank loss rates using the same procedure as DFAST where loss rates are accumulated over a nine-quarter horizon and divided by the average loan balances over the same period. Consumer loans under DFAST include only the "other consumer" category. n/a signifies that the loss rate is not available.

| | Cumulative Nine-Quarter Loss Rates | |
|---|---|---|
| Loan type | Urban Community Banks | DFAST |
| CRE | 4.6% | 7.0% |
| Consumer | 7.6% | 5.9% |
| Mortgages | 4.4% | 3.4% |
| C&I | 9.9% | 6.4% |
| Agriculture | 0.3% | n/a |
| Other | 12.5% | n/a |
| Portfolio Loss Rate | 5.0% | 5.8% |

**Table 4. Stress test results for U.S. community banks, 2007-2012**

Summary statistics of stress-test results for the sample of 7,125 community banks based on their financial conditions at year-end 2007 (Y0). *T1Lev*<2%, *T1Lev* <6%, and *ROA*<0% are the number of banks each year with projected Tier 1 leverage ratios and return on assets, respectively, below the threshold.

| | **Year 0** | **Year 1** | **Year 2** | **Year 3** | **Year 4** | **Year 5** |
|---|---|---|---|---|---|---|
| T1Lev Ratio | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 |
| Mean | 12.66% | 11.60% | 10.86% | 10.11% | 9.57% | 9.35% |
| Median | 9.67% | 9.67% | 9.28% | 8.97% | 8.83% | 8.82% |
| Min | 2.23% | -4.14% | -13.02% | -24.85% | -38.79% | -68.83% |
| Max | 1811.14% | 112.35% | 134.95% | 156.82% | 178.00% | 198.50% |
| StdDev | 25.03% | 7.81% | 7.86% | 8.21% | 8.62% | 8.95% |
| T1Lev< 2% | 0 | 50 | 124 | 424 | 648 | 762 |
| T1Lev<6% | 44 | 146 | 674 | 1197 | 1536 | 1638 |
| | | | | | | |
| Chargeoffs to Loans | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 |
| Mean | 0.24% | 1.47% | 3.30% | 3.29% | 2.63% | 1.69% |
| Median | 0.09% | 1.05% | 2.09% | 2.18% | 1.79% | 1.26% |
| Min | -20.41% | 0.00% | 0.00% | 0.10% | 0.08% | 0.04% |
| Max | 13.58% | 41.33% | 35.26% | 93.03% | 31.95% | 17.56% |
| StdDev | 0.66% | 1.33% | 3.07% | 3.17% | 2.31% | 1.38% |
| | | | | | | |
| ROA | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 |
| Mean | 1.08% | 0.42% | -0.46% | -0.45% | -0.16% | 0.25% |
| Median | 1.13% | 0.51% | 0.00% | -0.03% | 0.11% | 0.36% |
| Min | -36.30% | -23.95% | -24.48% | -48.47% | -24.35% | -24.14% |
| Max | 60.52% | 62.83% | 62.83% | 62.83% | 62.83% | 62.83% |
| StdDev | 1.89% | 1.74% | 2.21% | 2.23% | 1.95% | 1.73% |
| ROA<0% | 652 | 1705 | 3589 | 3672 | 3276 | 2333 |

**Table 5. Comparison of hypothetical stress test outcomes**
Table displays the percent of community banks with projected Tier 1 Leverage (T1Lev) and equity-to-asset ratios below the respective threshold. Indented rows beneath the baseline in each panel are stress test results relative to the baseline. Stress tests "under TCJA" include effects from the Tax Cuts and Jobs Act of 2017. *N* is the number of banks in the simulation.

| Row | Stress Test Description | T1Lev <2% | T1Lev <6% | Equity < 2% | Equity < 6% | N |
|---|---|---|---|---|---|---|
| 1 | Baseline 2007 stress test | 10.7% | 23.0% | 9.5% | 20.6% | 7125 |
| 2 | with banks that did not exist in 2017 | 19.5% | 35.4% | 16.8% | 31.3% | 2509 |
| 3 | with banks that also existed in 2017 | 4.9% | 14.7% | 4.4% | 13.4% | 4616 |
| 4 | Baseline 2017 stress test | 3.2% | 11.6% | 2.7% | 11.0% | 4846 |
| 5 | with banks that also existed in 2007 | 2.5% | 10.4% | 2.3% | 9.9% | 4616 |
| 6 | with 2007 loan shares | 4.5% | 14.3% | 4.0% | 13.7% | 4616 |
| 7 | under TCJA | 6.8% | 16.7% | 4.5% | 14.0% | 4846 |
| 8 | Baseline 2018 stress test under TCJA | 5.9% | 14.7% | 3.6% | 11.9% | 4598 |

**Table 6. Spearman rank correlations of early warning signals and projected capital**

Table presents Spearman rank correlations of the actual ranks of each of three early warning signals in Y0 with the projected stress-test Tier 1 Leverage ratio in Y5. Each early warning signal is ranked from highest risk to lowest risk. The correlations in the first column are from 2007 stress tests where Y0 is 2007 and Y5 is 2012, and those in the second column are from 2017 stress tests where Y0 is 2017 and Y5 is 2022. *T1Lev Ratio* is the Tier Leverage ratio, *Failure probability* is a logit model that estimates the likelihood of bank failure in the following two years, and *CRE to assets* is the ratio of commercial real estate loans to assets.

| Actual rank of early warning signal in Y0 | Correlation with projected T1Lev Ratio rank in Y5 | |
|---|---|---|
| | 2007 Stress Test | 2017 Stress Test |
| T1Lev Ratio | 0.64 | 0.75 |
| Failure probability | 0.51 | 0.41 |
| CRE to assets | 0.40 | 0.16 |

**Table 7. Stress test outcomes from hypothetical loan portfolio shifts**
Table displays the number of community banks in 2007 with projected stress-test T1Lev ratios below the respective 2% and 6% thresholds. Row 1 results are the baseline 2007 stress tests. The remaining rows reflect hypothetical stress tests that shift loans from the first loan type into the second loan type. For example, Row 2 reports simulation results after shifting all *CLD-OTH* loans into *CLD-RES* loans. *CLD-OTH* and *CLD-RES* are, respectively, other and residential construction and land development loans. *NFR-OTH* and *NFR-RES* are, respectively, other and residential nonfarm nonresidential commercial real estate loans.

| Portfolio Shifts | T1Lev <2% | T1Lev <6% |
|---|---|---|
| 1. Actual 2007 Loan Portfolio | 762 | 1638 |
| 2. CLD-OTH → CLD-RES | 800 | 1570 |
| 3. CLD-RES → CLD-OTH | 754 | 1672 |
| 4. NFR-OTH → NFR- OWN | 717 | 1577 |
| 5. NFR-OWN → NFR-OTH | 810 | 1697 |
| 6. CLD-RES → NFR- OWN *and* CLD-OTH → NFR-OTH | 262 | 925 |

## Appendix A.  Inputs for Community Bank Stress Test

Microsoft Excel worksheet with the required Call Report inputs to run the stress test.

| Call Report Date: Year 0 | | Metropolitan Statistical Area | |
|---|---|---|---|
| Year: | 2017 | myMSA | |
| Quarter: | 4 | | |
| Cert | COHORT | PCTL Loss Rate | Asset Growth Rate |
| 1 | MSA | 90% | 3.0% |

*Enter dollar amounts as year-to-date*

| Commercial Real Estate | Loan Amount ($000s) | Annual Interest Rate (%) | YTD Net Losses ($000s) |
|---|---|---|---|
| MULTIFAM | 57,296 | 3.50% | 69 |
| NFR-Other | 143,979 | 3.50% | 755 |
| NFR-Owner Occupied | 178,590 | 3.50% | 154 |
| FARM | 0 | 3.50% | 0 |
| CLD-Other | 36,299 | 3.50% | 113 |
| CLD-Residential | 7,875 | 3.50% | 33 |

| Other Loans & Securities | Asset Amount ($000s) | Annual Interest Rate (%) | YTD Net Losses ($000s) |
|---|---|---|---|
| Mortgages | 198,888 | 6.33% | 1,639 |
| Consumer | 233,220 | 2.74% | 437 |
| Commercial & Industrial | 70,071 | 2.99% | 2 |
| Agricultural | 0 | 2.99% | 0 |
| Other Loans | 7,453 | 6.33% | 0 |
| Securities | 217,572 | 2.44% | |
| Federal Funds Sold | 0 | 0.03% | |
| Interest Bearing Balances | 6,215 | 0.02% | |

| Other Items | $000s |
|---|---|
| Interest expense | 4,789 |
| Noninterest expense | 35,090 |
| Noninterest income | 12,999 |
| Provision expense | 3,113 |
| Securities & Extra. gains | -5 |
| Taxes | 3,379 |
| Dividend Payout | 5,300 |
| Loan Loss Reserves (ALLL) | 17,416 |
| Average assets | 1,233,734 |
| Non-earning assets | 95,637 |
| Total Liabilities | 1,106,691 |
| Trading Assets | 0 |
| Tier 1 capital | 107,498 |
| Total assets for leverage ratio | 1,210,128 |

## Appendix B. Stress Test Results for a Sample Community Bank

Microsoft Excel worksheet with the stress test output for a sample community bank.

| Balance Sheet ($000s) | Y0 | Y1 | Y2 | Y3 | Y4 | Y5 |
|---|---|---|---|---|---|---|
| Interest Bearing Balances | 6,215 | 6,401 | 6,593 | 6,791 | 6,995 | 7,205 |
| Federal Funds Sold | 0 | 0 | 0 | 0 | 0 | 0 |
| Securities | 217,572 | 224,099 | 230,822 | 237,747 | 244,879 | 252,226 |
| Total Loans | 933,671 | 950,895 | 960,139 | 968,103 | 978,733 | 992,484 |
| LLR | 17,416 | 17,737 | 17,910 | 18,058 | 18,257 | 18,513 |
| Net Loans | 916,255 | 933,157 | 942,229 | 950,045 | 960,477 | 973,971 |
| Trading Assets | 0 | 0 | 0 | 0 | 0 | 0 |
| Total Earning Assets | 1,140,042 | 1,163,658 | 1,179,645 | 1,194,583 | 1,212,351 | 1,233,402 |
| Non-Earning Assets | 95,637 | 97,618 | 98,959 | 100,212 | 101,703 | 103,469 |
| Total Assets | 1,235,679 | 1,261,276 | 1,278,604 | 1,294,795 | 1,314,054 | 1,336,870 |
| Liabilities | 1,106,691 | 1,131,329 | 1,151,290 | 1,170,984 | 1,192,064 | 1,214,828 |
| Equity | 128,988 | 129,947 | 127,314 | 123,812 | 121,990 | 122,042 |

| Net Chargeoffs (annualized in $000s) | Y0 | Y1 | Y2 | Y3 | Y4 | Y5 |
|---|---|---|---|---|---|---|
| Net chargeoffs | 3,202 | 10,787 | 19,282 | 20,840 | 18,413 | 15,611 |

| Income Statement (annualized in $000s) | Y0 | Y1 | Y2 | Y3 | Y4 | Y5 |
|---|---|---|---|---|---|---|
| Interest income | 41,718 | 42,591 | 43,218 | 43,766 | 44,394 | 45,167 |
| Interest expense | 4,789 | 4,888 | 4,955 | 5,018 | 5,093 | 5,181 |
| Net Interest Income | 36,929 | 37,703 | 38,263 | 38,748 | 39,301 | 39,986 |
| Noninterest expense | 35,090 | 35,817 | 36,309 | 36,769 | 37,316 | 37,964 |
| Noninterest income | 12,999 | 13,268 | 13,451 | 13,621 | 13,823 | 14,064 |
| Provision | 3,113 | 11,108 | 19,455 | 20,989 | 18,611 | 15,868 |
| Securities & Extraordinary gains | -5 | 0 | 0 | 0 | 0 | 0 |
| Operating income | 11,720 | 4,046 | -4,050 | -5,389 | -2,802 | 218 |
| Taxes | 3,379 | 1,416 | -1,418 | -1,886 | -981 | 76 |
| Net income | 8,341 | 2,630 | -2,633 | -3,503 | -1,821 | 142 |
| Dividend Payout | 5,300 | 1,671 | 0 | 0 | 0 | 90 |
| Retained Earnings | 3,041 | 959 | -2,633 | -3,503 | -1,821 | 52 |

| Annualized Net Chargeoffs to Loans (%) | Y0 | Y1 | Y2 | Y3 | Y4 | Y5 |
|---|---|---|---|---|---|---|
| Commercial Real Estate | 0.27% | 0.73% | 1.54% | 1.79% | 2.16% | 1.16% |
| Multifamily | 0.12% | 0.77% | 0.59% | 0.84% | 3.30% | 0.68% |
| NFR-Other | 0.52% | 0.25% | 2.66% | 1.85% | 1.56% | 1.22% |
| NFR-Owner Occupied | 0.09% | 1.25% | 0.99% | 1.26% | 0.97% | 0.91% |
| Farm | 0.00% | 0.00% | 0.00% | 0.00% | 0.02% | 0.00% |
| CLD-Other | 0.31% | 0.00% | 1.25% | 5.70% | 8.00% | 3.14% |
| CLD-Residential | 0.42% | 0.34% | 0.60% | 0.00% | 3.17% | 0.32% |
| Residential Mortgages | 0.82% | 0.63% | 0.78% | 1.39% | 1.26% | 0.98% |
| Consumer | 0.19% | 1.95% | 3.38% | 3.00% | 1.86% | 2.64% |
| Commercial & Industrial | 0.00% | 1.95% | 3.44% | 3.52% | 1.86% | 1.99% |
| Agriculture | 0.00% | 0.66% | 0.36% | 0.09% | 0.02% | 0.05% |
| Other Loans | 0.00% | 3.49% | 1.88% | 1.24% | 1.66% | 3.32% |
| Net chargeoffs to total loans | 0.34% | 1.13% | 2.01% | 2.15% | 1.88% | 1.57% |

## Appendix B. (Cont.)

| **Profitability and Capital (%)** | ***Y0*** | ***Y1*** | ***Y2*** | ***Y3*** | ***Y4*** | ***Y5*** |
|---|---|---|---|---|---|---|
| ROA (annualized) | 0.68% | 0.21% | -0.21% | -0.27% | -0.14% | 0.01% |
| ROE (annualized) | 6.47% | 2.02% | -2.07% | -2.83% | -1.49% | 0.12% |
| Equity to assets | 10.44% | 10.30% | 9.96% | 9.56% | 9.28% | 9.13% |
| T1Lev ratio | 8.88% | 8.78% | 8.45% | 8.06% | 7.80% | 7.67% |

| **Loans by Category ($000s)** | ***Y0*** | ***Y1*** | ***Y2*** | ***Y3*** | ***Y4*** | ***Y5*** |
|---|---|---|---|---|---|---|
| Commercial Real Estate | 424,039 | 433,608 | 439,838 | 445,046 | 448,687 | 456,859 |
| Multifamily | 57,296 | 58,562 | 59,966 | 61,246 | 60,999 | 62,403 |
| NFR-Other | 143,979 | 147,930 | 148,321 | 149,938 | 152,022 | 154,677 |
| NFR-OwnerOccupied | 178,590 | 181,645 | 185,246 | 188,402 | 192,164 | 196,131 |
| Farm | 0 | 0 | 0 | 0 | 0 | 0 |
| CLD-Other | 36,299 | 37,388 | 38,029 | 36,937 | 35,001 | 34,920 |
| CLD-Residential | 7,875 | 8,083 | 8,276 | 8,524 | 8,501 | 8,729 |
| Residential Mortgages | 198,888 | 203,570 | 208,033 | 211,306 | 214,905 | 219,190 |
| Consumer | 233,220 | 235,544 | 234,402 | 234,196 | 236,729 | 237,381 |
| Commercial & Industrial | 70,071 | 70,764 | 70,378 | 69,937 | 70,697 | 71,371 |
| Agriculture | 0 | 0 | 0 | 0 | 0 | 0 |
| Other Loans | 7,453 | 7,409 | 7,488 | 7,617 | 7,716 | 7,683 |
| Loan growth | | 1.84% | 0.97% | 0.83% | 1.10% | 1.40% |

| **Income Statement (YTD in $000s)** | ***Y0*** | ***Y1*** | ***Y2*** | ***Y3*** | ***Y4*** | ***Y5*** |
|---|---|---|---|---|---|---|
| Interest income | 41,718 | 42,591 | 43,218 | 43,766 | 44,394 | 45,167 |
| Interest expense | 4,789 | 4,888 | 4,955 | 5,018 | 5,093 | 5,181 |
| Net Interest Income | 36,929 | 37,703 | 38,263 | 38,748 | 39,301 | 39,986 |
| Noninterest expense | 35,090 | 35,817 | 36,309 | 36,769 | 37,316 | 37,964 |
| Noninterest income | 12,999 | 13,268 | 13,451 | 13,621 | 13,823 | 14,064 |
| Provision | 3,113 | 11,108 | 19,455 | 20,989 | 18,611 | 15,868 |
| Securities & Extraordinary gains | -5 | 0 | 0 | 0 | 0 | 0 |
| Operating income | 11,720 | 4,046 | -4,050 | -5,389 | -2,802 | 218 |
| Taxes | 3,379 | 1,416 | -1,418 | -1,886 | -981 | 76 |
| Net income | 8,341 | 2,630 | -2,633 | -3,503 | -1,821 | 142 |
| Dividend Payout | 5,300 | 1,671 | 0 | 0 | 0 | 90 |
| Retained Earnings | 3,041 | 959 | -2,633 | -3,503 | -1,821 | 52 |

## Appendix C. Call Report Changes

The FFIEC issued FIL-7-2006 "Revisions to the Reports of Condition and Income (Call Report)" on January 27, 2006. The revisions specify that "beginning March 31, 2007, banks with $300 million or more in assets and certain banks with less than $300 million in assets will report two-way breakdowns of their real estate construction loans and their nonfarm nonresidential real estate loans in a number of Call Report schedules. All other banks with less than $300 million in assets will begin to provide these loan breakdowns as of March 31, 2008." [p. 2]

Construction and Land Development (CLD) loans were split into 1-4 family residential construction loans and *other* CLD loans. 1-4 family residential construction loans are "for the purpose of constructing 1-4 family residential properties, which will secure the loan." [p. 10]

Loans previously classified as secured by nonfarm nonresidential properties were split into loans secured by owner-occupied nonfarm nonresidential properties and loans secured by *other* nonfarm nonresidential properties. Loans secured by other nonfarm nonresidential properties are those "where the primary or a significant source of repayment is derived from rental income associated with the property (i.e., loans for which 50 percent or more of the source of repayment comes from third party, nonaffiliated, rental income) or the proceeds of the sale, refinancing, or permanent financing of the property. Thus, the primary or a significant source of repayment for 'Loans secured by owner-occupied nonfarm nonresidential properties' is the cash flow from the ongoing operations and activities conducted by the party, or an affiliate of the party, who owns the property, rather than from third party, nonaffiliated, rental income or the proceeds of the sale, refinancing, or permanent financing of the property." [p. 11]