An Historical Loss Approach to Community Bank Stress Testing*

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We develop a macro stress testing model that can be used systematically by community banks and supervisors to assess the ability of banks 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 rate by loan type for each year between 2008 and 2012. We apply the stress test to 105 Arkansas community banks at year-end 2014 and find that all but three would survive the shock. We also use the model to evaluate the benefits from diversifying within loan types. Beginning in 2007, the call reports separately tracked residential construction loans and owner-occupied nonfarm nonresidential loans. These loan categories were perceived to have lower default risk, which could provide risk-reduction benefits to a bank that diversified into these loan categories. In fact, the defaults within the loan types were similar during the 2008-2012 period and therefore provided few performance benefits.

Keywords: Community banks; Stress testing; Loan diversification; Commercial real estate, Arkansas banks

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I. Introduction

Since 2009, the Federal Reserve has greatly expanded the role of stress testing at banking organization with assets greater than $10 billion. The Comprehensive Capital Analysis and Review (CCAR) is an annual exercise to assess whether the largest bank holding companies (BHCs) have sufficient capital to continue operations through periods of economic and financial stress. The Dodd-Frank Act stress test (DFAST) is a forward-looking component to assess whether institutions have sufficient capital to absorb losses and support operations during adverse economic conditions.[2] Results from these tests have effectively become the binding minimum capital requirements on large banking organizations, more onerous than the Basel III Capital Accord.

To date, community banks, which we define as those with $10 billion or less in total assets, are not required or expected to conduct the enterprise-wide stress tests required of larger organizations. However, all banking organizations, regardless of size, are expected to analyze the potential impact of adverse outcomes on their financial condition.[3]

One area where community banks are expected to utilize stress testing is in their exposure to commercial real estate (CRE). Since the early 1990s, loan portfolios at community banks have become increasingly concentrated in CRE lending. By 2007 CRE loans comprised more than half of all loans at banks with inflation-adjusted assets less than $10 billion (in 2009 dollars). The booming housing market contributed to the rapid growth in CRE as community banks financed much of the residential housing construction fueled by subprime originations.

Recognizing this growing concentration, the federal bank regulators in 2006 issued joint guidance warning banks that exposure to CRE was an area of high risk and that banks with

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[2] Federal Reserve Board of Governors, "Stress Tests and Capital Planning," http://www.federalreserve.gov/bankinforeg/stress-tests-capital-planning.htm.

[3] Board of Governors of the Federal Reserve System, "Statement to Clarify Supervisory Expectations for Stress Testing by Community Banks," May 14, 2012.

especially high concentrations of CRE lending would be subject to higher risk management standards (Board of Governors, 2006), including an expectation that banks would put their loan portfolios through stress tests.

The primary objective of this study is to introduce a stress-testing model that assesses a community bank's ability to withstand severely adverse credit conditions. We developed this "macro" stress test to meet three conditions. First, it must provide realistic worst-case forecasts at a high confidence level. Second, the model must pose no additional regulatory burden on banks, which implies that it is simple to use and relies on data currently being collected. Third, the model can be run quarterly by banks and/or regulators similar to the Economic Value Model, the Federal Reserve's interest rate risk stress test (Houpt and Embersit, 1991).

Our model is realistic and severe in that each adverse loan shock imposed on banks is drawn from the 90th percentile of geographically clustered community bank chargeoffs for the years 2008-2012, a period encompassing the financial crisis and Great Recession. The confidence interval for the *portfolio* loan shock imposed on banks is closer to the 95th percentile. Our model is simple in that it does not require explicit mapping from hypothetical economic conditions to bank performance; rather, the model contains a handful of assumptions about how provision expense and dividends adjust to the shock. In addition, the model relies exclusively on existing call report data and can be run quarterly.

Given the availability of a host of risk metrics for community banks such as CAMELS ratings, periodic examinations, and failure probability scores, it is reasonable to question the value from yet another metric. The key advantage of a stress test is its ability to model abrupt changes in economic and banking conditions. Traditional early warning signals such as failure probability scores and equity ratios provide static and relative risk measures. They allow for comparisons with other banks and time periods, but they provide no context for how bank risk will change in the future, nor do they provide a reasonable worst case estimate. On the eve of the financial crisis in 2007, it was reasonable to assume that banks with Tier 1 Leverage ratios of 7.0% were sufficiently capitalized. The crisis made clear that 7% was inadequate for the majority of banks. Indeed, traditional early warning signals were not designed to anticipate rapid and sharp deterioration in banks' conditions. The implementation of CCAR and DFAST are direct testaments to the Federal Reserve's belief that stress testing adds significant value for the larger banks. Our model expands this approach to community banks.

For tractability, we limit our stress testing to Arkansas community banks, though the approach is applicable to all community banks. We put the 105 Arkansas community banks through the stress test based on their financial condition at year-end 2014, and forecast the profitability, chargeoffs, and capital ratios of each bank over a five-year horizon. We find that Arkansas banks are well positioned to suffer through a severe downturn. All but three of them would be able to survive a reasonable worst-case shock as severe as the one experienced between 2008 and 2012.

At the same time that the 2006 CRE joint guidance was issued, call reports were updated to provide more detail on CRE loan types. Beginning in 2007, the call reports separated nonfarm nonresidential loans (NFR) into owner-occupied (NFR-OWN) and other (NFR-OTH) loans. In addition, construction and land development (CLD) loans were separated into loans for residential construction (CLD-RES) and loans for all other construction (CLD-OTH). One motivation for these changes was the belief that owner-occupied and residential construction loans had relatively lower default risks and therefore provided important diversification benefits to banks (Federal Register, 2005).

A second objective of our study is to examine the stress-test outcomes from diversifying loan portfolios across CRE loan types, especially within the newly defined CRE loan categories.

We find that ex-post diversification outcomes are small within the CLD and NFR loan categories mainly because the historical loss rates for these loan classifications' subcategories were similar.

We proceed as follows. Section 2 documents the increasing concentration of CRE loans at community banks and describes the call report changes for CRE loan types. Section 3 provides a deeper motivation for a community bank stress test and describes the model in detail. Section 4 describes the performance of Arkansas banks after subjecting them to the stress test, and it compares their performance in 2014 with their performance in 2007. Section 5 conducts in-sample model testing, and Section 6 evaluates the performance benefits to banks if they were to focus more heavily on residential construction and/or owner-occupied real estate. Section 7 concludes.

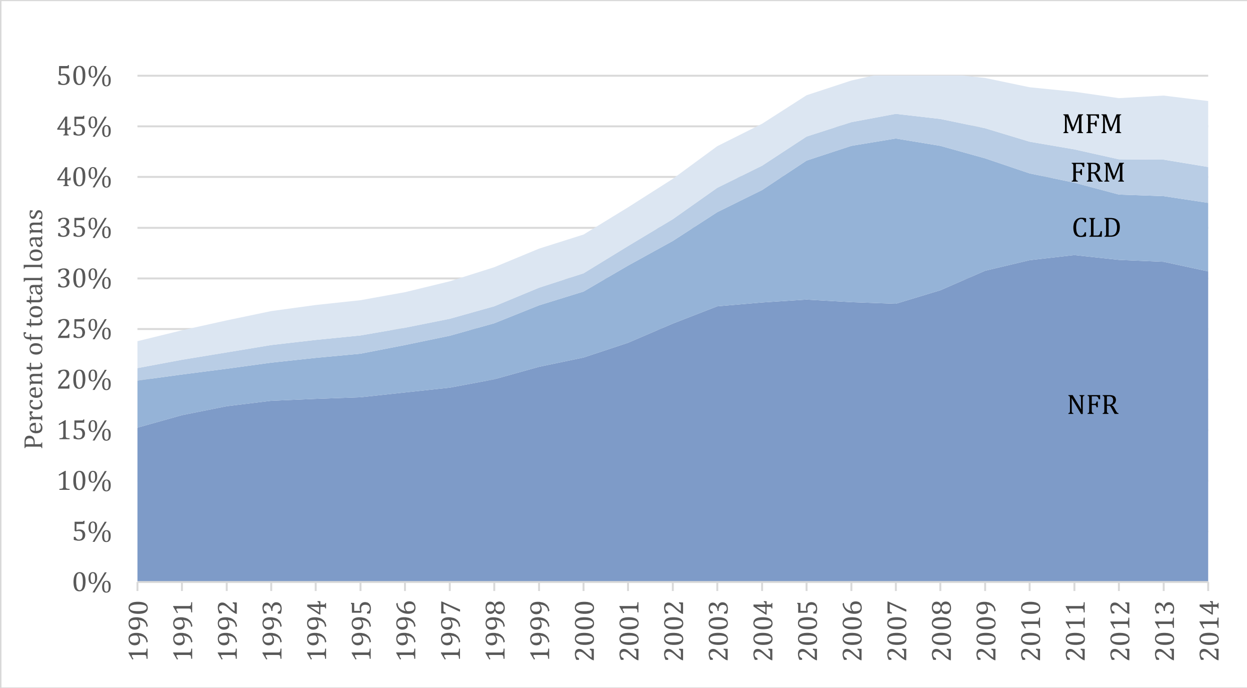
II. CRE Concentration, Regulatory Guidance, and Call Report Changes

Exposure to commercial real estate (CRE) loans increased sharply at community banks between 1990 and 2007. As seen in Figure 1, CRE lending as a percent of total loans more than doubled from 24% in 1991 to 50.5% in 2007. The growth was the most rapid in NFR and CLD. Farm loans (FRM) and multifamily (MFM) remained relatively small components throughout the period. Interestingly, the CRE concentration level has not fallen significantly since the financial crisis pinnacle in 2008. Even as late as 2014, CRE lending comprised 47.5% of all loans.

Recognizing the increasing CRE concentration and federal bank regulators released formal guidance in 2006 to encourage banks to focus more resources on risk management. The guidelines defined CRE concentration thresholds that would serve as indicators of high risk:

1) "Total reported loans for [CLD] represent 100 percent or more of the institution's total capital; or

Figure 1: CRE Loan Concentration at Community Banks 1991-2014



Source: FDIC Statistics on Depository Institutions Report

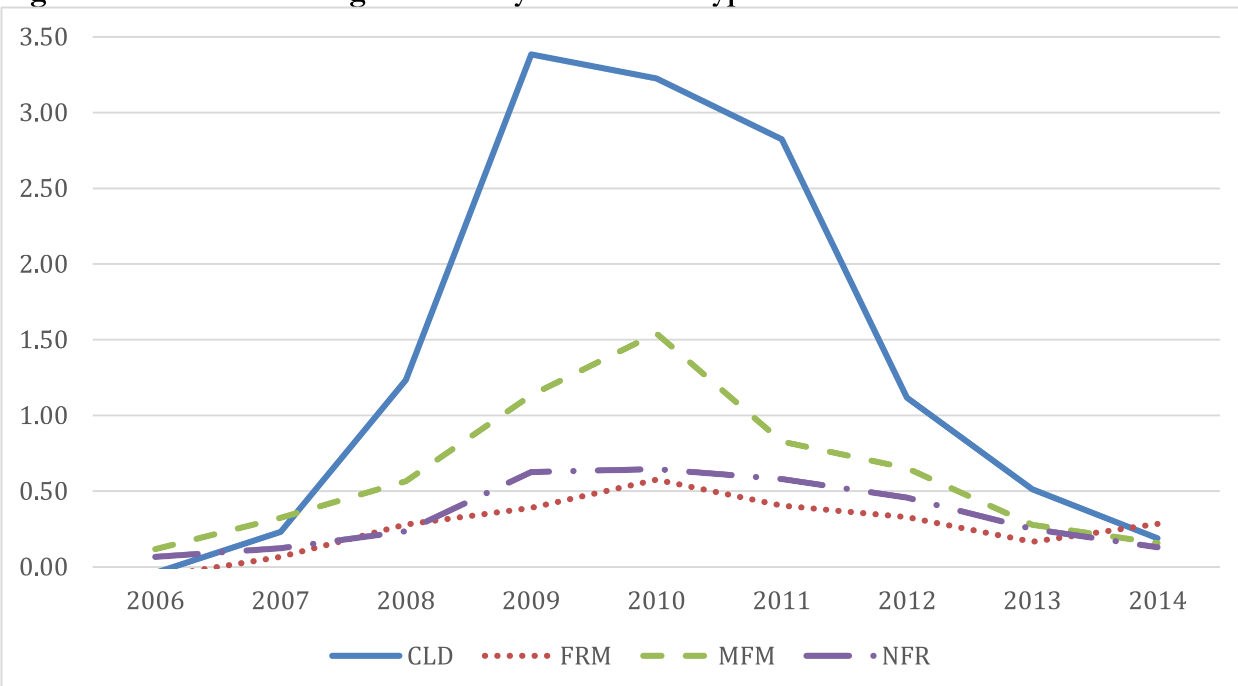
> 2) Total [CRE] loans as defined in this Guidance represent 300 percent or more of the institution's total capital, and the outstanding balance of the institution's [CRE] loan portfolio has increased by 50 percent or more during the prior 36 months" (Board of Governors, p. 18).

The 2008 financial crisis and subsequent recession revealed the substantial risk to community banks resulting from high CRE concentrations. In 2006, 31% of all commercial banks exceeded at least one of the thresholds, and those banks were far more vulnerable to failure during the Great Recession. Indeed, 23% of banks that exceeded both thresholds failed during the ensuing economic downturn (Friend, Glenos and Nichols, 2013).

Figure 2 plots the mean chargeoff rates by CRE loan type for community banks between 2006 and 2014. Of the four categories, CLD incurred the highest chargeoffs. The mean chargeoff rate for CLD in 2009 was 3.4%; in contrast, mean chargeoffs for NFR loans never exceeded 0.65%.

Banks with high concentrations of CLD loans were particularly vulnerable to the economic downturn and collapse of real estate prices.

Figure 2. Mean Net Chargeoff Rate by CRE Loan Type



At the same time that the CRE guidance was finalized, changes to the call report were introduced that refined the CRE loan categories. Beginning in 2007 (and finalized in 2008), the call report divided 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 A describes these changes in detail. The presumption by bankers and regulators was that owner-occupied properties would be relatively less risky because the tenants would have 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. Between 2007 and 2014, approximately 47% of NFR loans were owner occupied, and 25% of CLD loans were for residential construction.

III. Stress Test Rationale and Methodology

Over the years, supervisors and economists have developed several robust early warning signals to detect banks with relatively high default risk. However, these signals failed to detect the impending risk prior to the onset of the financial crisis primarily because they are static in nature, unable to account for sudden and severe changes in economic and financial conditions.

The early warning signals were especially misleading for the largest banks. Indeed, as late as 2007, U.S. banking regulators were on the verge of implementing Basel II, which would have *reduced* minimum capital requirements for the dozen or so largest U.S. banking organizations. (BIS, 2006) The onset of the financial crisis delayed Basel II implementation, and international regulators quickly followed with plans for Basel III that significantly boosted minimum capital requirements. Miller, Olson, and Yeager (2015) show that for publicly traded banks, every traditional market-based and book-based early warning signal had high Type I error rates prior to 2009. Milne (2014) also shows that distance to default for the 41 largest global banking institutions poorly predicted failure risk.

For community banks, econometric failure probability models have served as the main off-site surveillance tools for community banks since the early 1990s (Cole and Gunther, 1995). Several papers have compared the failure probability model parameters from the 1980s and early 1990s with model parameters from the more recent wave of failures beginning in 2008. Cole and White (2012) argue that the key drivers of bank failures—those that revolve around the CAMELS componens--were quite similar across the two episodes. However, they show that for 2009, banks with higher loan allocations to construction-and-development loans, commercial mortgages, and multi-family mortgages were especially likely to fail. Shaffer (2012) shows that logit regression coefficient estimates of failure probability shifted in important ways between the 1980s and 2008, most notably the sign on bank asset size flipped. Miller et al. (2015) find similar results, though they document that the model estimates from the 1980s were more reliable after 2008 than a model estimated on the 2006-2009 period because bank failures shifted back towards smaller banks in 2009, more closely resembling the 1980s failure patterns. A limitation is that these models can only be updated ex-post, after a wave of bank failures. The failure probability models did not reveal, for example, that construction loans were particularly risky or that large banks were more at risk at failing than in previous crises until after the fact.

For large and small banks alike, regulatory capital ratios woefully underestimated banks' capital adequacy on the eve of the financial crisis. Schuermann (2015) argues that the cascading of defaults by supposedly well-capitalized banking organizations led to a loss of credibility in regulatory capital ratios, and regulators turned to stress testing beginning in 2009 to measure capital adequacy in a more credible manner. For this reason, stress-testing has become an integral part of risk – management for the regional and large banks. If implemented correctly, a stress-testing model could also assist community bankers and supervisors by giving them a dynamic tool that can account for sudden changes in the banking environment.

The critical assumption in a community bank macro stress test is the projection of future chargeoffs. Various options are available. One approach is to define a detailed economic scenario and then map the economic data such as real estate prices and unemployment rates into chargeoffs. The Federal Reserve uses this framework to conduct the Dodd-Frank Act Stress Tests (DFAST) for large banking organizations. This approach, however, requires the user to make a number of subjective decisions about how the scenario will affect a particular bank. Presumably each bank would respond uniquely to the hypothetical scenario, making this methodology unsuitable for application to a large number of community banks.

A more promising methodology is a vector autoregression (VAR) that projects future chargeoffs from historical loss rates. Hall et al. (2011) develop such a portfolio stress test. The key benefit is that a VAR captures predictable variation in loss rates based on dynamic correlations. In addition, confidence intervals can be computed from the standard errors embedded in the impulse response functions. Finally, the VAR stress test can be automated and applied quickly and consistently to a large number of banks.

The VAR approach, however, suffers from four weaknesses. First, reliance on historical data makes it inherently backward looking so that the future is assumed to look like the past. Second, the forecasts maintain an assumption of conditional normality, making nonlinearities and tail events difficult to capture. Third, VARs require a relatively long time series to produce statistically reliable results, and the minimum sample size grows with the number of variables in the system; consequently, VAR estimates are often unstable. Finally, it is difficult for a VAR forecast to replicate the chargeoff patterns of banks 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. The linear estimation and stationarity requirements of a VAR imply that shocks tend to taper off immediately. A more realistic VAR forecast requires that the user input exogenous multi-period shocks, making the exercise more subjective and complex.

We propose an historical loss methodology where each community bank is subject to (net) chargeoff rates based on the years 2008-2012. This five-year horizon is chosen because it fully captures the deterioration and recovery of bank balance sheets from the Great Recession. The historical loss approach avoids all of the weaknesses of the VAR methodology except for the backward looking bias. Indeed, the backward bias is even more severe because it relies explicitly on past loss rates rather than estimates of their dynamic correlations. Historical losses naturally capture nonlinearities, require only five years of annual data for each bank, and intrinsically incorporate multi-period shocks to credit quality that build and taper through time.

We group community banks together by the metropolitan statistical area (MSA) of their headquarters and then impose the 90th percentile chargeoff rate for each loan type on all banks in that area.[4] Given that community banks have geographically concentrated operations, the MSA is representative of their lending markets. Banks within a given state not in an MSA are grouped together. This grouping is a bit arbitrary because banks should ideally be grouped based on their exposure to unique economic and real estate conditions. The forecaster is free to group banks as desired.

The 90th percentile chargeoff rate is also a bit arbitrary, and the forecaster is free to use different values. The percentile (p) chosen, however, should be based on the distribution of banks across MSAs and the *effective* desired confidence interval. The minimum size of each geographic bank group is $1/\Delta p$ where Δp is the distance between percentile intervals where unique values can be discerned. For example, to uniquely identify each 10th (Δp=0.10) percentile in the distribution requires at least 10 observations. Higher confidence intervals can be set in MSAs where there are large numbers of community banks. More importantly, the chosen chargeoff percentile for each loan type should lead to a realistic effective confidence interval for the chargeoff rate of the entire loan portfolio. Our model includes 11 loan types. Even given that the actual chargeoff rates across loan types are positively correlated within a bank (i.e. if one loan type has high loss rates, other loan types are likely to have high loss rates as well), the probability that several chargeoff rates at a given bank *jointly* exceed their respective 90th percentile values is extremely low. Consequently, imposing a

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[4] There are several alternatives for deriving future chargeoff rates for each bank. The simplest approach is to use the actual chargeoff rates of each bank. Forecasts would take the current balance sheet of the bank as the starting point and replicate each bank's loss experience. This approach is not very fruitful because there are no confidence intervals around the forecast to compute a reasonable worst-case analysis. Moreover, the backward-looking bias is extreme because it assumes that each bank's credit risk is unchanged from the Great Recession period.

90th percentile chargeoff rate on each loan type results in a higher portfolio confidence interval. Because the historical data determine the distributions of the loss rates, we can only determine ex-post by how much the effective confidence interval exceeds the chosen percentile for individual loan types.

We limit our sample to the 105 Arkansas community banks at year-end 2014. Because Arkansas is a relatively unpopulated state, just one MSA has more than 10 community banks. The Little Rock MSA (LR) has 14 banks. The Fayetteville MSA and the Fort Smith MSA (which are geographically contiguous) jointly have a sufficient number of banks (13) to group them into what we call the Northwest Arkansas MSA (NWA). All other banks (78) are in the no-MSA group. Table 1 lists the 90th percentile net chargeoff rates for each of the 11 loan types at Arkansas community banks by MSA and year. Annualized chargeoff rates are computed quarterly and averaged by year, and the data are Windsorized at the top and bottom 1% to eliminate extreme outliers. Except for 2010, banks in NWA experienced the highest overall chargeoffs; banks not in MSAs consistently experienced the lowest chargeoffs.

For the stress test, the initial condition of each bank is taken from its annualized year-to-date call report data as of the 4th quarter of 2014. 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 illustrated in Appendix B. The simulation then projects financial ratios five years forward after applying the relevant chargeoff rates.

Table 1. 90th percentile chargeoff rates for Arkansas community banks by MSA

Panel A. Not in MSA

	Loan type	2008	2009	2010	2011	2012
CRE	Multifamily	0.00%	0.00%	2.12%	0.93%	0.94%
	NFR-Other	0.16%	0.48%	0.71%	0.73%	1.02%
	NFR-Owner Occupied	0.22%	0.46%	0.98%	0.63%	0.48%
	Farm	0.20%	0.17%	0.32%	0.21%	0.63%
	CLD-OTH	1.49%	1.61%	2.21%	4.17%	2.95%
	CLD-RES	1.70%	1.80%	1.90%	2.68%	0.38%
	Consumer	2.50%	2.58%	2.18%	1.53%	1.48%
	Mortgage	0.57%	0.83%	0.73%	0.99%	0.94%
	Commercial & Industrial	1.85%	2.74%	2.61%	2.63%	1.17%
	Agricultural	0.42%	0.64%	0.88%	0.61%	0.69%
	Other	14.56%	5.47%	10.85%	7.30%	16.87%

Panel B. Northwest Arkansas MSA

	Loan type	2008	2009	2010	2011	2012
CRE	Multifamily	4.52%	15.39%	8.66%	0.00%	2.60%
	NFR-Other	0.72%	1.53%	1.03%	5.01%	0.47%
	NFR-Owner Occupied	1.83%	1.94%	6.57%	1.97%	3.70%
	Farm	3.05%	8.92%	4.59%	2.73%	0.35%
	CLD-OTH	3.77%	7.43%	7.13%	6.12%	7.64%
	CLD-RES	7.48%	9.67%	2.57%	3.18%	8.27%
	Consumer	2.66%	2.30%	1.99%	2.67%	1.57%
	Mortgage	2.14%	6.23%	4.16%	2.56%	1.81%
	Commercial & Industrial	5.89%	2.89%	5.44%	6.12%	7.64%
	Agricultural	3.10%	0.51%	1.39%	11.85%	0.00%
	Other	18.39%	15.59%	12.45%	4.48%	9.69%

Panel C. Little Rock MSA

	Loan type	2008	2009	2010	2011	2012
CRE	Multifamily	0.31%	7.92%	6.82%	0.96%	3.07%
	NFR-Other	0.55%	0.25%	1.57%	0.68%	0.56%
	NFR-Owner Occupied	0.18%	0.48%	0.91%	0.29%	0.57%
	Farm	0.00%	1.19%	0.28%	0.80%	0.40%
	CLD-OTH	2.43%	14.50%	9.40%	5.74%	2.53%
	CLD-RES	1.28%	6.33%	4.40%	3.21%	4.42%
	Consumer	1.80%	6.66%	2.42%	3.68%	2.71%
	Mortgage	2.08%	1.87%	6.91%	1.49%	1.38%
	Commercial & Industrial	1.63%	5.95%	10.25%	5.72%	1.81%
	Agricultural	1.32%	1.94%	8.67%	0.87%	2.70%
	Other	7.10%	10.80%	12.85%	8.77%	5.42%

Assets in year *t* consist of securities, federal funds sold, interest bearing balances, loans (L), and loan loss reserves (LLR).[5] All liabilities are represented as deposits (D), and shareholders' equity is defined as (E). We lump federal funds and cash 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:

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

where α is the user-specified annual target growth rate of assets. Charged-off loans, however, are not reinvested so that loans (and hence, total assets) decrease by the amount of chargeoffs. 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 we are interested in credit risk for the purposes of this model, we do not explicitly allow interest rates to change over the simulation horizon. (Of course, to the extent that interest rates affect chargeoffs, some of their dynamics are captured by the historical loss rates.)

Banks use provision expense (*P*) to offset exactly net chargeoffs (*LS*) in the current year, as long as net chargeoffs are positive. In addition, banks add to provisions an amount equal to the realized loan growth rate:

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

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

$$LLR_t = LLR_{t-1} + P_t - LS_t \tag{4}$$

Net income is computed each year as:

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[5] Non-earning assets are excluded for ease of exposition. Because the core simulation model is nearly identical to that in Hall et al. (2011), we draw heavily from that article in this section.

$$NI_t = r_s S_t + \sum_j r_j L_{jt} - r_d D_t - NNE_t - P_t - T_t \tag{5}$$

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), P represents provision expense, 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 equal to 33 percent of operating income.

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

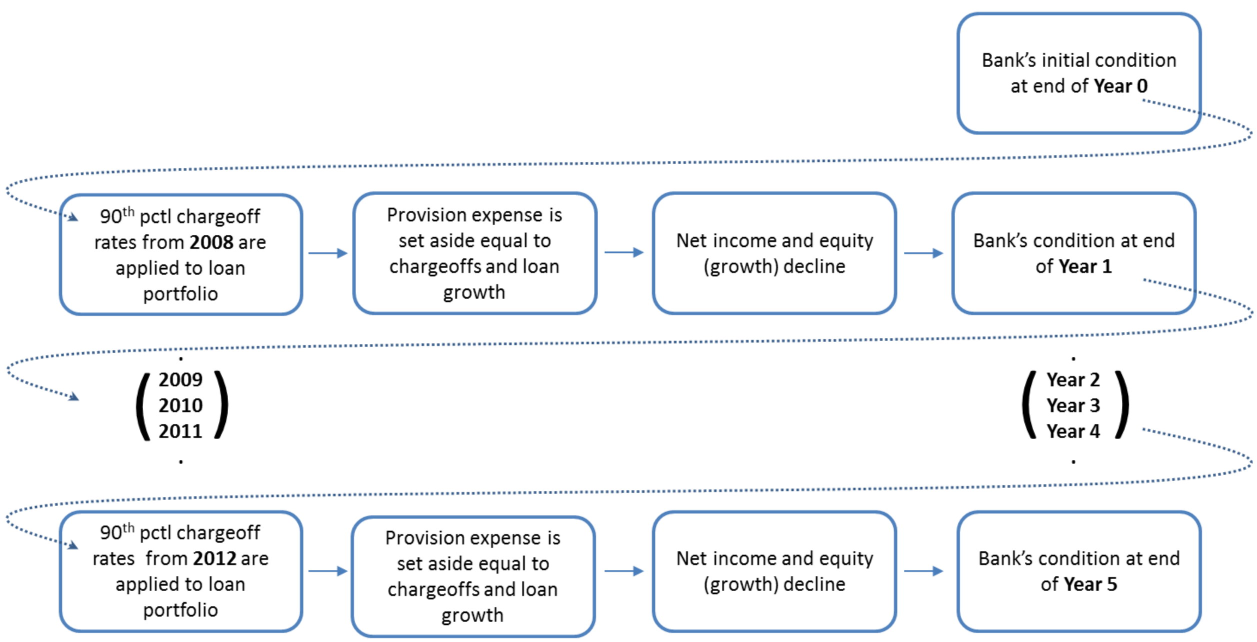
$$DIV_t = \max[0, d \cdot NI_t] \tag{6}$$

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

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

Finally, deposits are assumed to automatically adjust each period to balance the balance sheet, as in equation (1). Figure 3 provides a flow chart that succinctly summarizes the simulation logic.

Figure 3. Five-Year Simulation Flow Chart



IV. Stress Test Results

We focus on the aggregate stress test results. (The output for a representative bank is shown in Appendix C.) Table 2 displays the aggregate 5-year forecasts, which we label the "2014 stress tests." These are the stress tests run on the 105 Arkansas community banks using the chargeoff rates from Table 1. The initial condition of the banks (Year 0) is derived from their financial data at year-end 2014. Banks begin the simulation well capitalized with a mean equity to asset ratio of 11.9% and a median ratio of 11.0%. Despite the severe shocks that hit the banks, equity ratios remain high over the five-year horizon. The mean ratio in Year 5 (2019) is 10.9%. Just 3 of the 105 banks have equity to asset ratios that fall below 2% during the forecast horizon, implying that they would be closed by regulators without receiving additional capital injections. And just 9 banks have equity ratios that fall below 6.0%, the minimum Tier 1 leverage ratio under Basel III to be classified

Table 2. Stress Test Results for 105 Arkansas Community Banks 2014-2019

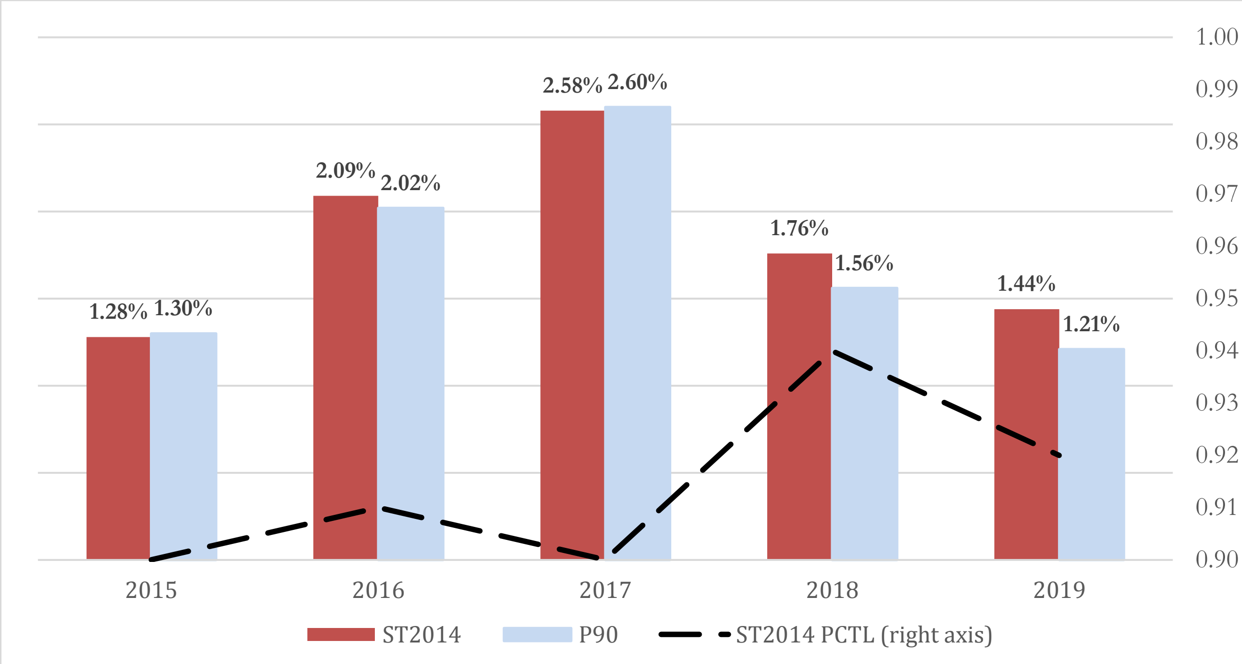
	Year 0	Year 1	Year 2	Year 3	Year 4	Year 5
Equity to Assets	2014	2015	2016	2017	2018	2019
Mean	11.92%	11.84%	11.57%	11.23%	11.05%	10.93%
Median	11.01%	11.03%	10.94%	10.82%	10.64%	10.56%
Min	4.54%	3.75%	1.92%	-0.90%	-3.70%	-6.24%
Max	31.70%	31.96%	32.18%	32.39%	32.58%	32.78%
Std	3.28%	3.39%	3.62%	4.00%	4.35%	4.71%
No. < 2%	0	0	1	2	2	3
No. < 6%	1	2	2	3	6	9
Chargeoffs to Loans	2014	2015	2016	2017	2018	2019
Mean	0.24%	1.25%	2.05%	2.32%	1.74%	1.42%
Median	0.14%	1.00%	1.21%	1.36%	1.37%	1.10%
Min	-0.98%	0.50%	0.58%	0.72%	0.78%	0.81%
Max	3.36%	3.53%	6.27%	8.52%	4.47%	4.12%
Std	0.46%	0.72%	1.64%	1.86%	0.95%	0.75%
ROA	2014	2015	2016	2017	2018	2019
Mean	1.09%	0.42%	0.09%	-0.02%	0.20%	0.32%
Median	0.99%	0.42%	0.26%	0.17%	0.26%	0.35%
Min	-1.43%	-2.41%	-2.91%	-2.82%	-2.79%	-2.56%
Max	4.53%	2.58%	2.40%	2.37%	2.36%	2.41%
Std	0.81%	0.70%	0.91%	0.96%	0.71%	0.71%
No. < 0%	5	22	34	36	29	23

as adequately capitalized. Not surprisingly, the stress test results show that bank profitability plummets. Table 2 lists mean ROA, which reaches its nadir in Year 3 (2017) at -2bp before recovering in Years 4 and 5.

Mean chargeoff rates from the 2014 stress tests are listed in Table 2 and they are also plotted in Figure 4 (ST2014) as the dark shaded series. The light shaded series in the figure (P90) displays the actual 90th percentile chargeoff rates for all Arkansas community banks between 2008 and 2012. The mean chargeoff rates from the 2014 stress tests track the 90th percentile benchmark very closely through the first three years of the simulation and they exceed the benchmark in the final two years. Figure 4 also plots as a dashed line (ST2014PCTL) the percentile of the mean chargeoff rates from the 2014 stress tests relative to the actual chargeoff rates between 2008 and 2012, where the right-hand axis represents the percentile ranking. The chargeoff percentile of 94% in 2018 is the biggest spread over the benchmark. These results suggest that selection of the 90th percentile chargeoff rate for each loan category produces forecasts of loan portfolio chargeoffs at reasonable confidence levels. For the 2014 stress test on Arkansas banks, the odds of a bank performing worse than the simulation in any given year between 2015 and 2019 range from 6% to 10%.

Arkansas banks at year-end 2014 are able to weather a severe downturn quite well. It is interesting to ask how community banks would have fared the same stress tests based on their financial conditions at year-end 2007. Because many banks did not report the subdivided NFR and CLD components separately until 2008, we estimate the component values of loans and chargeoffs at year-end 2007 by applying the percentages from the March 2008 call reports. Stress test results for the 143 community banks at year-end 2007 are in Table 3, and the performance is much worse. The number of failed banks rises from three to four, but more strikingly, the number of banks with equity ratios that fall below 6% rises from 9 to 25.

Figure 4. Mean Chargeoff Rates from Stress Tests Relative to 90th Percentile Benchmark



Two potential explanations exist for why banks perform much better in 2014 than in 2007. First, it could be that banks have adjusted their loan portfolios away from loan types such as CLD with high default rates. Figure 5 Panel A plots the broad-category loan shares for both years, and it shows little change. The CRE share, for example, declined in 2014 by just one percentage point to 42% of assets. The only meaningful changes are a decline of 3 percentage points in consumer loans and a 5 percentage point increase in residential mortgages. Panel B of Figure 5, however, shows more significant changes within the CRE portfolio. CLD loans declined by 13 percentage points between 2007 and 2014, NFR loans increased by 6 percentage points, and farm loans rose by 5 percentage points.

Table 3. Stress Test Results for 143 Arkansas Community Banks 2007-2012

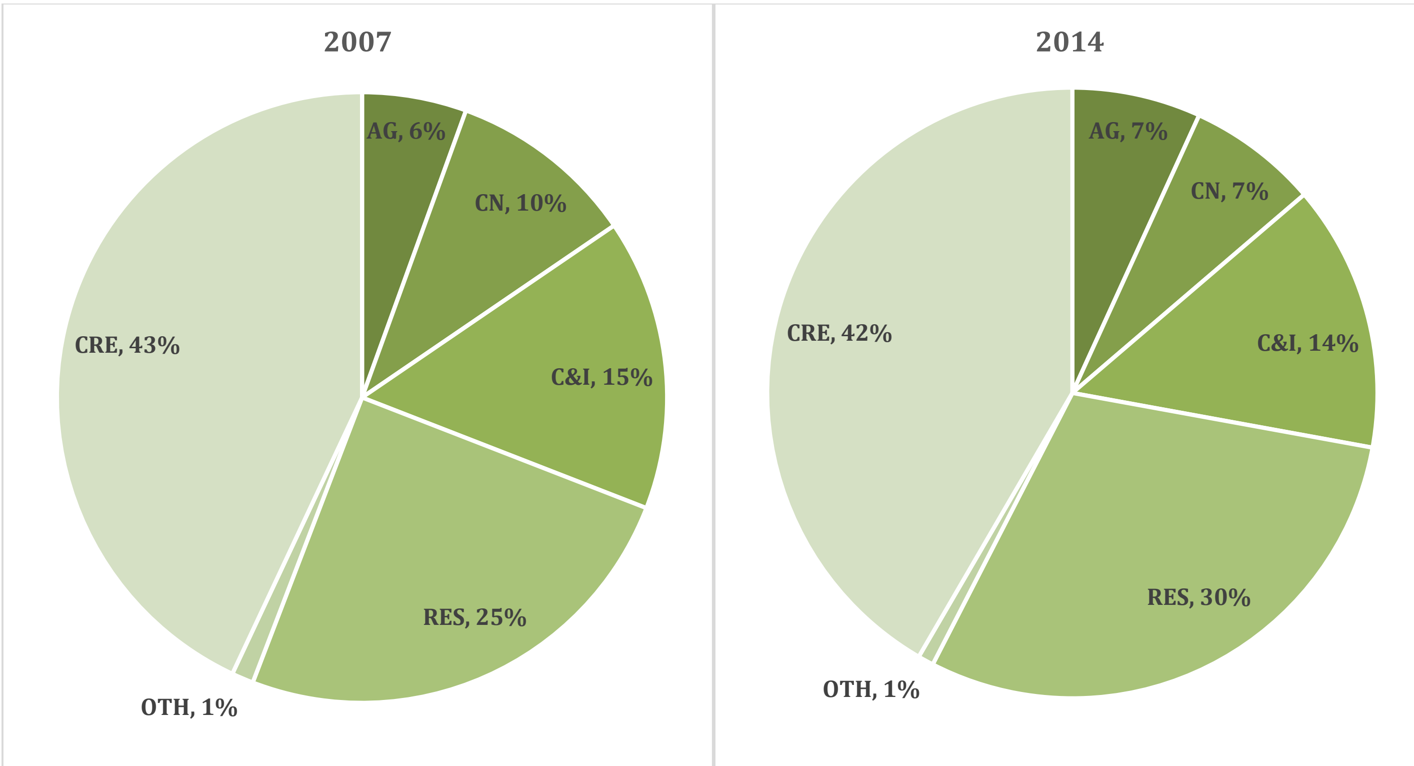
Equity to Assets	Year 0 (2007)	Year 1 (2008)	Year 2 (2009)	Year 3 (2010)	Year 4 (2011)	Year 5 (2012)
Mean	11.62%	11.53%	11.14%	10.74%	10.52%	10.37%
Median	10.75%	10.60%	10.21%	10.05%	9.99%	10.02%
Min	3.79%	3.05%	0.57%	-1.04%	-2.73%	-5.56%
Max	27.79%	28.02%	29.04%	30.02%	30.98%	31.91%
Std	3.96%	3.98%	4.23%	4.57%	4.85%	5.18%
No. < 2%	0	0	1	2	2	4
No. < 6%	1	1	3	13	20	25

Chargeoffs to Loans	2007	2008	2009	2010	2011	2012
Mean	0.25%	1.49%	2.42%	2.48%	2.00%	1.65%
Median	0.18%	1.15%	1.38%	1.49%	1.59%	1.24%
Min	-20.41%	0.57%	0.66%	0.82%	0.88%	0.69%
Max	5.80%	4.54%	7.69%	8.00%	5.22%	6.97%
Std	1.89%	0.89%	1.91%	1.81%	1.02%	1.10%

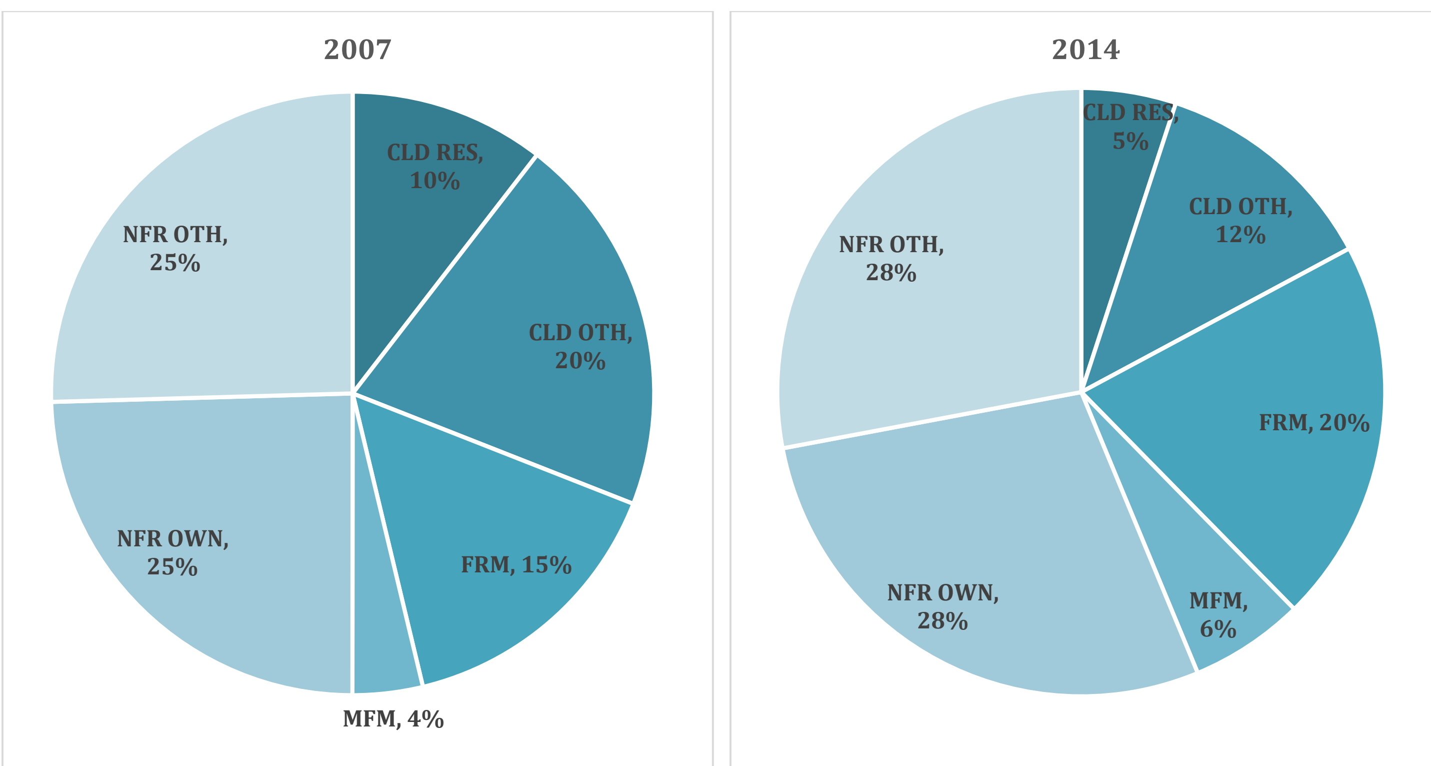
ROA	2007	2008	2009	2010	2011	2012
Mean	1.01%	0.37%	-0.04%	-0.06%	0.13%	0.27%
Median	1.06%	0.46%	0.32%	0.25%	0.24%	0.41%
Min	-3.73%	-2.54%	-3.68%	-3.47%	-2.96%	-2.83%
Max	7.27%	2.71%	2.62%	2.60%	2.63%	2.70%
Std	1.07%	0.72%	1.08%	1.02%	0.76%	0.80%
No. < 0%	13	34	56	56	50	37

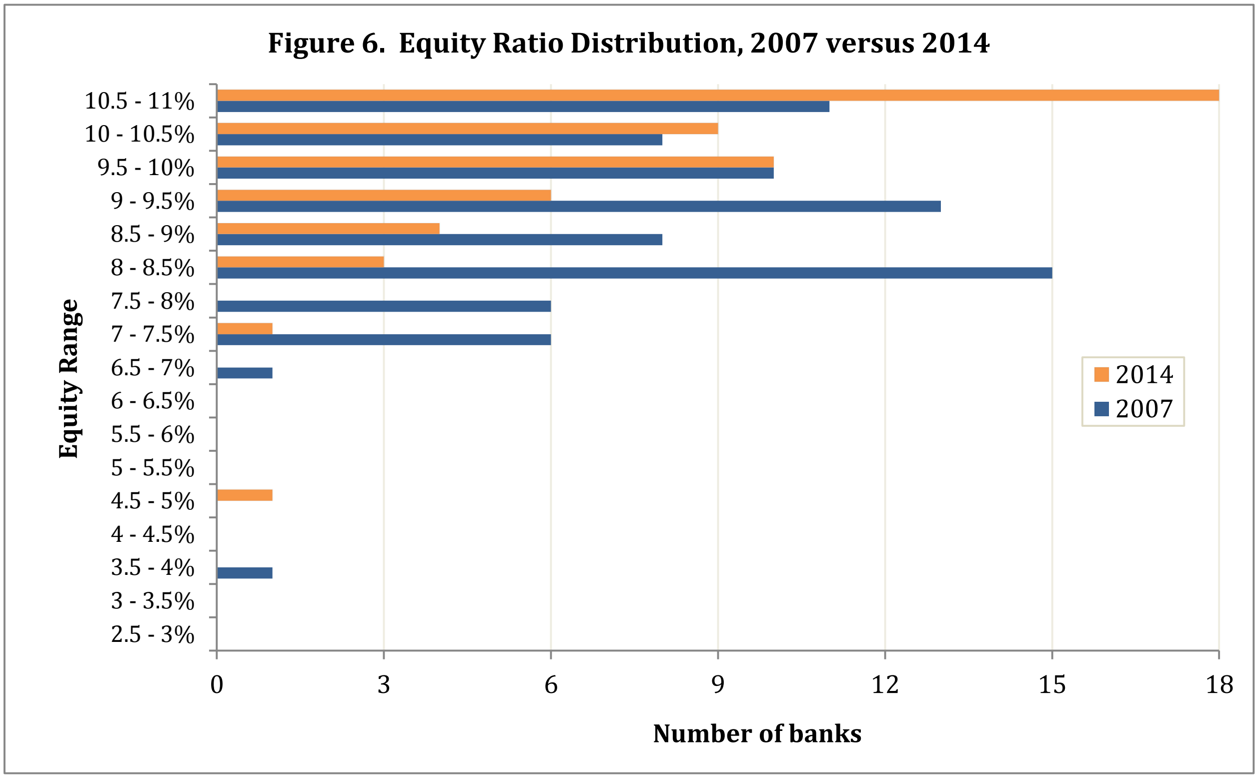
A second potential explanation for the improved stress-test performance in 2014 is that community banks held higher levels of capital. Surprisingly, the 2014 mean equity ratio of 11.9% is just 30bp higher than the 2007 ratio. The distribution, however, reveals that there were far more banks in 2007 with relatively low equity ratios. Figure 6 plots the number of banks by equity range for the years 2007 and 2014. In 2007 there were 29 banks with equity ratios below 8.5% compared with just 5 banks in 2014. It is likely that many of the banks that began the stress test with relatively low capital would dip below the 6% threshold.

Figure 5. Panel A. Mean Arkansas Community Bank Loan Portfolios, 2007 and 2014



Panel B. Mean Arkansas Community Bank Commercial Real Estate Portfolios, 2007 and 2014





To more clearly distinguish between these competing explanations, we ran stress tests on hypothetical bank balance sheets. First, we identified the 102 community banks that existed in the data both in 2007 and 2014, and we ran a baseline stress test on those banks at year-end 2014. Table 4 shows that 2 banks violated the 2% equity threshold, and 8 banks violated the 6% equity threshold. Then we adjusted the loan share of each bank in 2014 to equal its loan share in 2007, and reran the stress tests. The results show two additional banks dipping below the 6% equity threshold. Returning the loan portfolios back to their 2014 shares, we set each bank's equity-to-asset ratio in 2014 equal to the ratio in 2007, and ran the stress tests a third time. Relative to the base case, one additional bank drops below the 2% threshold while 6 additional banks drop below the 6% threshold. The results from Table 4 show that while loan portfolio adjustments and increases in equity both play a role in insulating banks against a severe downturn, the improvement in equity ratios between 2007 and 2014 is the primary reason that banks weathered the stress tests much better in 2014.

Table 4. Number of community banks with equity less than threshold value

Simulation	Equity < 2%	Equity < 6%
Banks in 2014 that existed in 2007 (N=102)	2	8
Banks in 2014 with 2007 loan portfolio	2	10
Banks in 2014 with 2007 equity ratios	3	14

V. In-Sample Model Performance

The value added from a stress test is the ability to detect banks that are the most vulnerable to a sudden adverse shock. Out-of-sample testing of our model is not yet possible because its parameters are based on recent experience. However, we can compare predicted stress test outcomes with actual bank experience for the sample of banks that survived the five-year period between 2008 and 2012. We do not expect the stress test outcomes to replicate real-world experience because we apply the 90th percentile loss rates to *all* banks regardless of the actual chargeoffs incurred. It should be the case, however, that banks that entered the crisis period in more vulnerable positions tended to perform the worst in the stress tests.

The most direct in-sample test is to compare the stress test results with the set of banks that either failed or issued equity because of financial distress between 2008 and 2012. Two banks failed in Arkansas during that period. ANB Financial failed in May 2008 because of a high concentration of risky commercial real estate loans, many of which subsequently defaulted. The stress test accurately identified that failure, forecasting that its equity ratio would dip below 2% in Year 3. First Southern Bank failed in December 2010 from fraud. The bank purchased approximately $23 million in fraudulent special improvement district bonds in 2008 and 2009. (FDIC, 2012) In its last call report filing dated September 30, 2010, the bank reported an equity ratio of 10.0%; the failure was sudden and unrelated to loan performance. The stress test model is not designed to detect fraud, and indeed the model did not project First Southern Bank to cross any equity thresholds during the five-year horizon.

In addition to analyzing the failures, we conservatively identified 13 banks that issued equity due to financial distress between 2008 and 2012, meaning that an infusion of capital was necessary to offset losses from high loan defaults. To identify these banks as systematically as possible, we examined the 48 Arkansas community banks that issued equity between 2008 and 2012, either directly or through their holding companies. For each year and bank, we computed the ratio of the amount of the equity issue to total outstanding equity, and then summed the ratios over the five-year period. A cumulative ratio of 20%, for example, shows that on average a bank raised new capital equal to 20% of its existing capital. We also summed each bank's return on assets during the five years. We ranked the banks from worst to best on each measure and then summed the ranks. Banks with the lowest (worst) summed rankings were more likely to issue equity to offset poor earnings results between 2008 and 2012. After compiling the rankings, we carefully scrutinized the equity issuance patterns at each bank to confirm that equity issuance was correlated with poor earnings. We removed three banks from the list because it was clear that the large equity issues were used to fund rapid asset expansion rather than to offset losses.

We wish to compare the 13 distressed equity issuers with the banks from the 2007 stress test that crossed the 2% and 6% equity thresholds. Of the 4 banks projected to have equity ratios below 2%, one was the failed bank ANB Financial, and another was acquired in 2009 and dropped out of the sample. The remaining two banks are among the 13 that issued equity under distress. The stress test predicted 18 additional banks that survived through 2012 to cross the 6% equity threshold. Of those, 9 were among the 13 banks that issued equity due to financial distress. In sum, the stress test correctly identified the one bank that failed from credit risk between 2008 and 2012, and 11 of the 20 banks that became distressed enough to issue equity to boost their capital positions.

Another approach to measuring the in-sample performance of the stress-test is to compare the model's results with traditional early warning signals of bank distress. Stress tests differ from early warning signals in that stress tests dynamically subject banks to hypothetical adverse shocks and then examine which banks fail the test; in contrast, early warning signals are static indicators designed to detect banks with relatively 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 the stress tests. We examine the Tier 1 Leverage ratio and a failure probability model.

A simple and potentially powerful early warning signal is the Tier 1 Leverage ratio—Tier 1 capital to total assets. Banks with higher capital cushions can, all else equal, absorb more losses before failure. Although our model does not separately specify Tier 1 capital (though it could easily be integrated), equity to assets and Tier 1 leverage are highly correlated. How likely is the stress test to flag banks with the lowest equity to asset ratios in Year 0? In fact, using year-end 2007 call report data as Year 0, Table 5 shows that the spearman rank correlation coefficient between the actual Year 0 equity ratios and the projected Year 5 ratios is 0.76. (The correlations from the 2014 equity ratios and Year 5 stress tests outcomes are also listed for completeness.) A closer look, however, reveals significant discrepancies in the ranking of individual banks. The Arkansas bank projected to have the lowest equity ratio at year-end 2012 has the 58th lowest equity ratio in 2007 out of the 143 Arkansas Community Banks. On the other hand, ANB Financial has the 2nd lowest projected equity ratio at Year 5 and the lowest equity ratio in 2007. The most extreme case is that a bank ranked 114th with an initial equity ratio of 13.7% in 2007 is projected to have the 9th lowest equity ratio of 3.8% in 2012. Although the equity ratios are highly correlated, the individual rankings of the most distressed banks as measured by the actual equity ratios at Year 0 and the projected equity ratios at Year 5 are quite different.

Table 5. Spearman Rank Correlations of Early Warning Signals and Stress Test Outcomes

Variable rank	Year 5 projected equity rank (2012)	Variable rank	Year 5 projected equity rank (2019)
Equity ratio, 2007	0.76	Equity ratio, 2014	0.73
DFP, 2007	0.65	DFP, 2014	0.58
CRE/TA, 2007	0.20	CRE/TA, 2014	-0.04

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 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.[6]

We rank banks by their DFP from highest to lowest (so that riskier banks have lower ranks) and compare those rankings with the Year 5 equity ratio stress test projections. The rank correlation coefficient from the 2007 data shown in Table 5 is 0.65 (and 0.58 for the 2014 simulation). Of the eight Arkansas community banks with the lowest projected equity ratios in Year 5, four of them are also in the top 8 riskiest banks as ranked by failure probability. But once again, large discrepancies exist in the ordering of the banks. The bank with the lowest projected equity ratio in Year 5 has the 11th highest DFP in 2007. And one bank ranked 3rd by the DFP is projected to have the 40th lowest equity ratio. Though the DFP signals are more similar to the stress test signals for the riskiest banks than the initial equity ratio signals, the ordering is different enough to suggest that the stress tests are capturing an independent dynamic.

[6] The variables in the early SEER model and the 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.

Finally, we compare equity rankings in Year 5 to CRE rankings—banks ranked by their proportion of CRE loans to total loans. Because the recession hit CRE loans particularly hard, we might expect to see a correlation between rankings of banks with CRE loan concentrations and banks with the worst performance in the stress tests. The spearman rank correlation coefficient, however, is 0.20, much lower than the other correlations. Indeed, the bank projected to have the 3rd lowest equity ratio in Year 5 has the 139th highest CRE loan concentration.

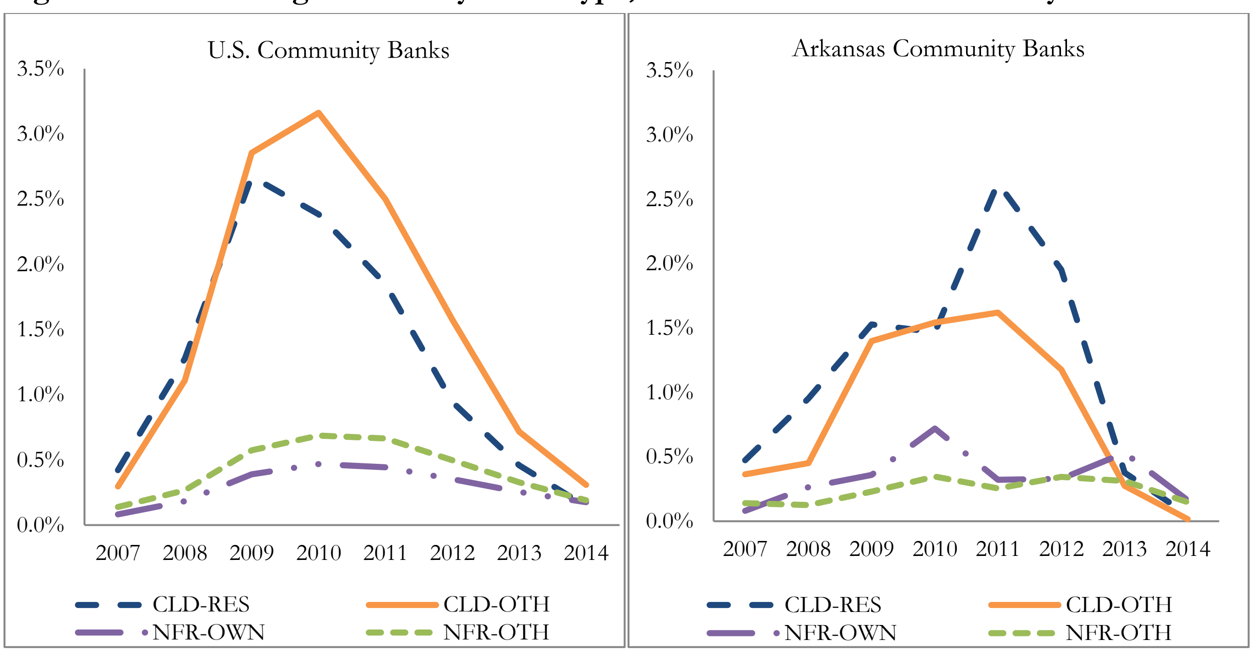
In sum, the stress test model proposed here, built on historical loss rates, is highly correlated in sample with banks that displayed more risk during the 2008-2012 period. Stress test projections identify more than half of the banks that issued equity to restore their capital that was eroded from high chargeoffs, and the projections are correlated with banks that had relatively low equity ratios and high failure probabilities in 2007. Yet, the stress test does not replicate the results of other early warning signals. The risk rankings are different enough to suggest that the stress tests are capturing dynamic aspects of bank risk.

VI. Benefits from Loan Portfolio Reallocations

In addition to identifying banks with potentially elevated risk, we can use the community bank stress test to assess the performance outcomes from hypothetical loan portfolio adjustments. We are particularly interested in exploring the effects from 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. These loan types were split beginning with the 2007 call reports because there was a presumption that the default risks from residential construction and owner-occupied commercial real estate were lower than loans from their respective "other" counterparts.

Figure 7 plots mean chargeoff rates by these four loan categories for all U.S. community banks (left chart) and Arkansas community banks (right chart). Chargeoff rates at U.S. banks for residential construction loans were lower than other construction loans after 2009, though the chargeoff rates were similar before then. In contrast, Arkansas banks exhibited higher mean chargeoff rates for CLD-RES loans than for CLD-OTH loans. A similar pattern emerges for NFR loans. At the national level, chargeoff rates for owner-occupied NFR loans were lower than for other NFR loans, but the reverse is true for Arkansas banks. Overall, defaults on NFR loans were much lower than defaults on CLD loans. These patterns suggest that stress test results for Arkansas banks will show significant benefits from shifting lending from CLD loans to NFR loans rather than shifting within the CLD and NFR loan types.

Figure 7. Mean Chargeoff Rate by Loan Type, U.S. and Arkansas Community Banks



We construct five hypothetical balance sheets of the 143 Arkansas community banks at year-end 2007, each time beginning with the base 2007 data so that the changes are not cumulative.. We 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 Year 0 for the stress tests.

Table 6. Stress test outcomes from hypothetical loan portfolio shifts

Portfolio shift:	Eq < 2%	Eq < 6%
Base 2007 loan portfolio	4	25
CLD-OTH to CLD-RES	4	19
CLD-RES to CLD-OTH	5	27
NFR-OTH to NFR-OWN	5	24
NFR-OWN to NFR-OTH	4	24
CLD TO NFR	2	10

Stress test results in Table 6 show that just two of the portfolio reallocations result in meaningful differences in the number of banks that cross an equity threshold relative to the base case. Shifting loans from CLD to NFR leads to a reduction from 4 to 2 in the number of banks with less than 2% equity, and the number of banks that cross the 6% equity threshold falls from 25 to 10. Of course, this hypothetical loan reallocation is an extreme example where banks make no construction loans. The other meaningful portfolio reallocation is the shift from CLD-OTH into CLD-RES where the number of banks crossing the 6% equity threshold drops from 25 to 19. This outcome seems puzzling at first glance because as Figure 7 shows, mean chargeoffs were generally higher for CLD-RES loans. A closer look reveals that 5 of the 6 banks that avoided the 6% equity threshold were from the Little Rock MSA where chargeoffs on CLD-OTH loans were much higher. This example illustrates the importance of clustering the banks in sensible ways to capture effects from the different banking markets across the U.S.

VII. Conclusion

We propose a simple community bank stress testing model that can be used systematically by U.S. banks and supervisors and poses no additional regulatory burden on banks. The model is dynamic, designed to capture sudden and sharp deterioration in banking conditions. As such, it complements traditional early warning models such as regulatory capital ratios and failure probability models. They key assumption is that the chargeoff rate on a given loan type will equal the 90th percentile chargeoff rate derived from all community banks in a given geography (MSA) each year between 2008 and 2012. In addition to its simplicity, an advantage of the model is that it imposes a severe but reasonable shock that yields a confidence level above 90 percent. The main limitation is that the model is rigidly backward looking. It will represent future bank distress patterns only to the extent that the future resembles the past. The backward-looking chargeoff rates, however, can be modified by the user if desired.

We apply the stress test to the 105 Arkansas community banks, taking their initial condition from call report data at year-end 2014. Just three of the banks have equity ratios that fall below the critical 2% threshold during the next five years. Stress test run on year-end 2007 bank data are much than the 2014 results primarily because bank equity ratios have improved. Changes in bank portfolios towards historically lower risk loan types also have reduced default risk but more modestly. Indeed, during the Great Recession, if banks had focused on lending more heavily within the newly segregated owner-occupied and residential construction sectors prior to 2008, they would have seen little improvement in stress test outcomes because the 90th percentile default rates within each of the nonfarm, nonresidential and construction and land development categories were similar. The stress tests confirm the importance of strong capital because of its ability to cover unexpected losses arising from a variety of sources.

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Appendix A. 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]

Appendix B. Simulation Inputs

Commercial Real Estate Portfolio Stress Test

HISTORICAL LOSS RATES

Call Report Date of Simulation			
Year:	2014		
Quarter:	4		
Bank name	**Cert**	**MSA**	**Asset Growth Rate**
Sample Community Bank	###	NONE	3%

Enter dollar amounts as year-to-date

Commercial Real Estate	**Loan Amount ($000s)**	**Annual Interest rate (%)**	**Current net losses ($000s)**
MULTIFAM	1,193	5.66%	0
NFR-Other	790	5.66%	0
NFR-Owner Occupied	3,925	5.66%	-419
FARM	3,359	5.66%	0
CLD-Other	1,552	5.66%	0
CLD-Residential	358	5.66%	0

Other Loans & Securities	**Asset Amount ($000s)**	**Annual Interest rate (%)**	**Current net losses ($000s)**
1 to 4 Family Mortgages	21,719	4.83%	-2
Consumer	4,760	8.20%	16
Commercial & Industrial	2,405	7.97%	0
Agricultural	1,059	7.97%	0
Other Loans	89	5.66%	0
Securities	89,736	2.84%	
Federal Funds Sold	3,650	0.33%	
Interest Bearing Balances	1,870	1.24%	

Other Items	**($000s)**
Interest expense	672
Noninterest expense	3,287
Noninterest income	410
Provision expense	-342
Securities & Extra. gains	193
Taxes	0
Dividend Payout	876
Loan Loss Reserves (ALLL)	460
Average assets	140,403
Non-earning assets	4,398
Total Liabilities	118,674

Appendix C. Stress Test Results for an Individual Bank

Sample Community Bank

Balance Sheet ($000s)	***0***	***1***	***2***	***3***	***4***	***5***
Interest Bearing Balances	1,870	1,926	1,984	2,043	2,105	2,168
Federal Funds Sold	3,650	3,760	3,872	3,988	4,108	4,231
Securities	89,736	92,428	95,201	98,057	100,999	104,029
Net Loans	40,749	41,614	42,407	43,191	43,967	44,821
Principal from Existing Loans	41,209	33,635	34,562	35,485	36,407	37,395
Amortized Principal Reinvested	0	7,223	7,075	6,921	6,762	6,611
New Loans	0	1,226	1,249	1,272	1,295	1,320
LLR	460	470	479	488	496	506
Total Earning Assets	136,005	139,728	143,464	147,280	151,179	155,248
Non-Earning Assets	4,398	4,518	4,639	4,763	4,889	5,020
Total Assets	140,403	144,246	148,103	152,042	156,068	160,269
Liabilities	118,674	122,135	125,636	129,223	132,897	136,717
Equity	21,729	22,111	22,467	22,820	23,170	23,551

Net Charge-offs (annualized in $000s)	***0***	***1***	***2***	***3***	***4***	***5***
Net charge-offs	-405	362	461	494	525	471

Income Statement (annualized in $000s)	***0***	***1***	***2***	***3***	***4***	***5***
Interest income	4,940	5,064	5,187	5,311	5,439	5,575
Interest expense	672	690	709	728	747	767
Net Interest Income	4,268	4,374	4,478	4,584	4,692	4,808
Noninterest expense	3,287	3,377	3,467	3,559	3,654	3,752
Noninterest income	410	421	432	444	456	468
Provision	-342	371	469	502	534	481
Securities & Extraordinary gains	193	0	0	0	0	0
Operating income	1,926	1,047	974	966	960	1,043
Taxes	0	345	321	319	317	344
Net income	1,926	701	652	647	643	699
Dividend Payout	876	319	297	294	293	318
Retained Earnings	1,050	382	356	353	351	381

Annualized Net Loan Losses (% of loans)	***0***	***1***	***2***	***3***	***4***	***5***
Net CRE Losses	-3.75%	0.42%	0.54%	1.11%	1.11%	0.96%
MULTIFAM Losses	0.00%	0.00%	0.00%	2.12%	0.93%	0.94%
NFR Losses	-8.89%	0.37%	0.53%	0.80%	1.11%	1.20%
NFR-Other Losses	0.00%	0.16%	0.48%	0.71%	0.73%	1.02%
NFR-OwnerOccupied Losses	-10.68%	0.22%	0.46%	0.98%	0.63%	0.48%
FARM Losses	0.00%	0.20%	0.17%	0.32%	0.21%	0.63%
CLD Losses	0.00%	1.40%	1.80%	2.68%	4.04%	2.32%
CLD-Other Losses	0.00%	1.49%	1.61%	2.21%	4.17%	2.95%
CLD-Residential Losses	0.00%	1.70%	1.80%	1.90%	2.68%	0.38%
Mortgage Loss	-0.01%	0.57%	0.83%	0.73%	0.99%	0.94%
Consumer Loss	0.34%	2.50%	2.58%	2.18%	1.53%	1.48%
CI Loss	0.00%	1.85%	2.74%	2.61%	2.63%	1.17%
Ag Loss	0.00%	0.42%	0.64%	0.88%	0.61%	0.69%

Other Loan Loss	0.00%	14.56%	5.47%	10.85%	7.30%	16.87%
Net charge-offs to total loans	-0.99%	0.87%	1.09%	1.14%	1.19%	1.05%

Profitability and Capital (%)	***0***	***1***	***2***	***3***	***4***	***5***
ROA (annualized)	1.37%	0.49%	0.44%	0.43%	0.41%	0.44%
ROE (annualized)	8.86%	3.17%	2.90%	2.84%	2.78%	2.97%
Equity to assets	15.48%	15.33%	15.17%	15.01%	14.85%	14.69%

Loans by Category ($000s)	***0***	***1***	***2***	***3***	***4***	***5***
CRE Loans	11,177	11,465	11,747	11,969	12,195	12,444
MULTIFAM	1,193	1,229	1,266	1,276	1,302	1,328
NFR	4,715	4,839	4,958	5,066	5,160	5,251
NFR-Other	790	812	833	852	871	888
NFR-Owner Occupied	3,925	4,034	4,136	4,218	4,317	4,426
FARM	3,359	3,453	3,550	3,645	3,746	3,834
CLD	1,910	1,940	1,962	1,967	1,944	1,956
CLD-Other	1,552	1,575	1,596	1,607	1,587	1,586
CLD-Residential	358	362	367	370	371	381
Mortgage	21,719	22,242	22,718	23,229	23,688	24,169
Consumer	4,760	4,780	4,797	4,833	4,902	4,974
CI	2,405	2,431	2,436	2,443	2,450	2,494
Ag	1,059	1,086	1,112	1,135	1,162	1,188
Other	89	78	76	70	67	57
Loan growth		2.12%	1.91%	1.85%	1.80%	1.94%

Income Statement (YTD in $000s)	***0***	***1***	***2***	***3***	***4***	***5***
Interest income	4,940	5,064	5,187	5,311	5,439	5,575
Interest expense	672	690	709	728	747	767
Net Interest Income	4,268	4,374	4,478	4,584	4,692	4,808
Noninterest expense	3,287	3,377	3,467	3,559	3,654	3,752
Noninterest income	410	421	432	444	456	468
Provision	-342	371	469	502	534	481
Securities & Extraordinary gains	193	0	0	0	0	0
Operating income	1,926	1,047	974	966	960	1,043
Taxes	0	345	321	319	317	344
Net income	1,926	701	652	647	643	699
Dividend Payout	876	319	297	294	293	318
Retained Earnings	1,050	382	356	353	351	381