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Failure rates of small commercial banks during the banking crisis of the late 1980s were about 7.6%, which is significantly higher than the 5.7% failure rate during the recent crisis. The higher rate is surprising because small banks had significantly increased their commercial real estate (CRE) lending by the second crisis, which is riskier than other types of lending, and economic shocks were more severe in the recent crisis. We compare failure rates in the two periods using a statistical model that allows us to decompose the effect of changes in bank characteristics and economic shocks on failure rates. We find that the severe economic shocks of the recent crisis had a larger impact on high bank failure rates than bank characteristics. Increases in risk from CRE lending were offset by higher capital levels and other changes in bank characteristics. The failure rate would have been much lower in the later crisis if banks were subject to the less severe economic shocks of the earlier crisis. To the extent that higher capital levels were due to Basel I and the prompt corrective action (PCA) provisions of the Federal Deposit Insurance Corporation Improvement Act of 1991, we find that these reforms were beneficial. We also compare Federal Deposit Insurance Corporation (FDIC) losses on failed banks between the two periods. Here, despite the PCA reforms, losses on failed banks were higher in the recent crisis than in the earlier one. These differences are not accounted for by changes in CRE concentrations or the relative size of economic shocks. On this dimension, the reforms of the early 1990s did not seem to help. Finally, we find that a discretionary accounting variable, interest accrued but not yet received, is predictive of both failure and higher FDIC losses in both crises.

JEL codes: G21, G28.
Keywords: bank regulation, bank failures, Prompt Corrective Action, FDIC losses.

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1. Introduction

This paper compares failures of small banks during the commercial bank crisis of the late 1980s and early 1990s with those during the recent financial crisis. Despite the recent crisis being much more severe than the earlier one, failure rates of commercial banks were higher in the earlier crisis. Of the 14,260 commercial banks in existence at the end of 1985, 1,085 or 7.6% failed over the 1986-1992 period. Of the 7,320 commercial banks in existence at the end of 2006, 416 or 5.7% failed over the 2007-2013 period.

The higher failure rate in the earlier crisis is surprising because of two significant differences between the two periods. The first difference is that in the later period lending by small banks became much more concentrated in commercial real estate (CRE) lending as well as construction and land development (CLD) lending. CRE lending, and CLD lending in particular, is widely considered to be riskier than other types of bank lending. The second difference is that the economic shocks in the later period were much more severe than in the earlier period. National unemployment during the Great Recession reached 10%, while it reached only 7.8% during the recession of 1990-1991. There were severe economic shocks in the earlier crisis, but these were primarily regional.

In contrast, Federal Deposit Insurance Corporation (FDIC) losses on failed commercial banks were higher in the recent crisis. Average FDIC losses on failed banks in our sample were 21.0% in the earlier crisis and 26.3% in the later crisis when measured relative to assets net of book equity.[1]

This increase in FDIC losses is striking because of differences in financial regulations between the two crises. After the commercial banking crisis of the late 1980s and early 1990s, along with the savings and loan crisis, which started even earlier, several financial regulatory reforms were implemented. Two of the more significant such reforms were the increased regulatory capital requirements of Basel I and the prompt corrective action (PCA) provisions in the Federal Deposit Insurance Corporation Improvement Act of 1991 (FDICIA).[2] The latter provisions built on the increased capital requirements of Basel I by requiring bank supervisors to take certain actions against a bank if its regulatory capital dropped below certain thresholds. The

[1] We adjust assets by subtracting book equity at time of failure. This adjustment takes into account the loss absorption capacity provided from book equity, if there is any, at time of failure.
[2] Basel I and FDICIA were implemented in the early 1990s at the very end of the earlier crisis.

purpose of PCA was to force supervisors to intervene in the operations of a bank and even shut it down, if necessary, before the bank became too severely distressed. These provisions were motivated by the heavy use of forbearance by thrift and bank supervisors in the 1980s and by the belief that this forbearance increased the losses to the FDIC, and ultimately taxpayers, from failed banks and thrifts. Therefore, one of the main purposes of PCA was to reduce forbearance and reduce losses to the FDIC from failed banks.

We compare the performance of small banks during the two crises for several reasons. First, it allows us to disentangle the degree to which their failures were due to changes in their business model over time, e.g., increased real estate lending, versus the relative severity of the economic shocks in the two crises. Second, small banks are not too big to fail, so their experience in the two crises is a way to compare the effectiveness of higher capital and PCA without the confounding effect of bailouts.

Our approach is to use a cross-sectional regression model in which bank characteristics in 1985 and 2006, right before each crisis fully developed, are regressed on failure over subsequent seven-year periods as well as on FDIC losses. The first advantage of this approach is that it captures how prepared banks are for a banking crisis. Most bank failures occur during crises, so this is the period that regulations need to be designed for. The second advantage is that it recognizes that a crisis need not cause a bank to fail right away, but instead may lead to failure in the future. The third advantage is that it provides a natural way to compare and analyze differences in mean failure rates and FDIC losses between the two periods. The final advantage is that this cross-sectional approach allows us to evaluate selection effects on FDIC losses with a Heckman selection model, which we do in the robustness analysis.

Consistent with the literature on bank failure, we find that CRE and CLD lending increases failure probabilities as does commercial and industrial (C&I) lending. We find that size, core deposits, securities holdings, and capital levels all reduce failure probability. Interestingly, despite the major role that residential mortgages played in the recent crisis, we find that, for our sample of banks, residential lending actually reduces failure probability, which is consistent with banking experience prior to 2007. State-level economic shocks also matter. We find that increases in unemployment rates and declines in house prices both increase failure probability.

To account for differences in failure rates and FDIC loss levels between the crises, we perform a decomposition exercise to see if failure rates are driven more by economic shocks or changes in bank characteristics, like CRE lending. We also analyze these results to assess the effects of the regulatory changes between the crises.

We find that increases in failure probabilities are most influenced by macroeconomic conditions. In our decomposition, banks with the balance sheet characteristics of those in 1985:Q4 would have failed at a higher rate if subject to the state-level economic shocks of 2007-13. Similarly, banks with the balance sheet characteristics of those in 2006:Q4 would have failed at a much lower rate if subject to the state-level economic shocks of 1986-92. There are increases in bank failures from the increased commercial real estate lending, but that effect is partially offset by other changes in bank characteristics such as the substantially higher capital levels in 2006:Q4 relative to those in 1985:Q4. The analysis suggests that the combination of PCA and higher capital levels helped reduce the failure rate. It also suggests that small banks were much healthier going into the recent crisis than they were in the earlier one and not as risky as they were in the 1980s.

In our analysis of the size of FDIC losses we find several variables that statistically significantly predict FDIC losses. For example, losses are smaller for banks with more core deposits and for those that are larger (in terms of assets). Nevertheless, we do not find consistent effects of changes in bank characteristics or state-level economic conditions on the size of FDIC losses. In our decomposition analysis, losses would have been large in the 2007-13 period even if banks had not been so concentrated in CRE lending and looked like they did in 1985.

This analysis suggests that PCA was ineffective at reducing FDIC losses in the event that a bank fails. We argue that PCA failed along this dimension for two related reasons: 1) When a bank fails, the market value of its assets is significantly less than its book value; 2) PCA triggers were set at levels such that capital levels of a bank on the path to failure were only a few hundred basis points higher than pre-PCA. We show that, on average, banks in the recent period were put into receivership while their book value of capital was still positive, as PCA requires. However, given that in this sample the market value of a failed bank's assets is typically anywhere between 75% and 85% of the assets' book value during a crisis, a failed bank simply does not have enough capital to absorb losses without calling on the deposit insurance fund.

Since book values of failed banks were positive, for FDIC losses to be so high, book accounting values of a failed bank's assets must have dramatically exceeded their economic value. Along these lines, we find that a discretionary accrual accounting variable, "interest accrued but not yet received," which can hide delinquent loans, significantly predicts bank failure and FDIC losses in both periods. The literature on FDIC losses has looked at this variable (Bovenzi and Murton, 1988; James, 1991; and Osterberg and Thomson, 1995), but the bank failure literature has not.

One aspect of our analysis should be kept in mind when assessing PCA and the higher capital requirements. The model is not a structural model, so the estimates also pick up other regulatory factors and governmental actions. In particular, there were large government interventions in the recent crisis, such as the Troubled Asset Relief Program, the Small Business Lending Fund, and the expansion of deposit insurance, which could have had effects on bank failure probabilities and FDIC losses though there were also interventions, such as forbearance, in the earlier period.[3] Nevertheless, the analysis allows us to conclude that even with the help of these additional interventions, PCA did not succeed in lowering FDIC losses and that the same bank characteristics predict failure in both periods.

2**. Literature**

In this paper, we analyze both the probability of bank failure and the losses to the FDIC once a failure has occurred. The empirical literature has typically looked at these separately.

The larger of the two literatures is on the causes of bank failures. Most of the research on the banking troubles of the 1980s and early 1990s found that commercial real estate concentrations played a significant role in failure. Fenn and Cole (2008) found this to be the case for bank failures from 1986 to 1992, and they found that construction loans played a larger role in bank failures than permanent loans. Cole and Gunther (1995) looked at the likelihood and timing of bank failure for banks that failed over the 1986 to 1992 period. They found that commercial real estate concentrations increased the likelihood of bank failure but were unrelated to bank survival time. Wheelock and Wilson (2000) used a competing risks model to jointly analyze failure and acquisition. They also found that commercial real estate lending increased

[3] In our robustness regressions, we include a period indicator, equal to one if the bank-quarter observation is in the early period. This is a broad proxy for the changes that occurred between the two periods, changes which included the regulatory reforms and and interventions discussed above.

failure probability as did some measures of managerial inefficiency. In contrast, Whalen (1991) estimated a proportional hazards model of bank failure and, unlike the other papers, found that commercial real estate lending was insignificant, though this may be because all types of commercial real estate lending were lumped together in that analysis.

There is a small but growing literature on the causes of bank failures in the recent crisis. Cole and White (2012) analyzed Call Report data from 2004 to 2008 in order to determine the factors that led to bank failures in 2009. They found that commercial real estate lending, particularly in the area of construction and development, is a strong early predictor of bank failure in this period. Noting that this result is consistent with research on earlier bank failures, the authors stressed the importance of differentiating between commercial and residential real estate when evaluating a bank's portfolio. They also found that many of the same variables that differentiated healthy and at-risk banks in the 1985-1992 time period did so in the recent crisis as well. GAO (2013) also emphasized the role of commercial real estate loans, construction and land development (CLD) loans in particular, as a cause of bank failures in the recent crisis. For a discussion of methodologies used for modeling bank failure, see Cole and Wu (2014), who analyzed both probit and hazard models.

A paper that looked at economic shocks is Aubuchon and Wheelock (2010). They found that failure was also connected to regions with distress in real estate markets and declines in economic activity. Jin, Kanagaretnam, and Lobo (2011) examined the role of auditing quality in predicting bank failure. They found that a bank audited by reputable auditors has a lower probability of failure. This finding is in line with our finding that the interest receivable variable predicts bank failure.

Most of the literature that looked at FDIC losses on failed banks is based on data from the 1980s and early 1990s. Using a sample of failed banks from 1985 and 1986, Bovenzi and Murton (1988) regressed losses on measures of asset quality as well as a few other variables right before bank failure. James (1991) built on this analysis by using a larger sample and including additional variables like the book value of equity and core deposits. Osterberg and Thomson (1995) did a similar analysis to James (1991) but used Call Report data and a sample from 1984 through 1992. They also regressed losses on bank data at various lags prior to failure. Schaek (2008) analyzed a sample from 1984 to 2003 and, using quantile regression methods, found that brokered deposits increase FDIC losses in high-cost bank failures.

More recently, Bennett and Unal (2014) examined FDIC losses over the 1986 to 2007 time period. The question they were interested in was the effect the type of resolution had on FDIC losses. On average, FDIC losses on private-sector reorganizations are less than those on the failed banks that it liquidates. However, once Bennett and Unal controlled for selection bias, they found that during periods of industry distress, private-sector reorganizations of a failed bank were costlier than liquidation, while during normal time periods this result was reversed. Given that their two samples spanned 1986-1991 and 1992-2007, they were not able to directly address the effect of the enactment of the FDICIA on losses to the FDIC. The selection bias controlled for was the difference between failed banks that have a higher franchise value and those that did not, as opposed to the difference between failed and surviving banks. Albeit in a different framework, we are able to confirm the importance of franchise value for more recent failures.

Our paper does not directly look at the incidence of forbearance, but a recent paper by Cole and White (2017) studied FDIC losses following the financial crisis and argued that FDIC losses were high because of delayed recognition of nonperforming loans. Using counterfactual tests, they specifically estimated the cost of delay in the closing of failed banks and asserted that forbearance was still occurring even after the passage of FDICIA and PCA. The possibility of delayed recognition is one reason that we look at book accounting values at the beginning of each crisis.

Our paper builds on these two literatures—one looking at reasons for failure and the other looking at FDIC losses—by simultaneously analyzing failure and FDIC losses. The advantage of this approach is that it allows us to compare how common factors, such as economic shocks and bank characteristics, affect these two important dimensions of bank resolution. Furthermore, by comparing the two bank crises, we can identify common factors and compare regulatory regimes, which is not possible in analysis of single crisis periods. Our approach allows us to not only gain a comprehensive understanding of the drivers of bank failures and losses to the FDIC in the more recent period, but also to assess the effectiveness of regulatory reforms and importance of changes in the banking industry over time.

3. The Mechanics of Bank Failure, Prompt Corrective Action, and FDIC Losses in the Two Periods

Banks are not subject to the bankruptcy code. Instead, when a bank becomes severely distressed, it can be put into receivership by its chartering agency. Once a bank is put into receivership, the FDIC handles its disposition. Before FDICIA, the FDIC could resolve a bank in any way it chose as long as it was less costly than a deposit payoff, which is basically a liquidation of the bank in which insured depositors are made whole by sales of the bank's assets, with any shortfall being covered by the FDIC. Since 1991, the FDIC has been required to resolve the bank in a way that is the least costly to the deposit insurance fund.

In the past, chartering agencies had some flexibility as to when they put a bank into receivership, and this flexibility was used at times in the 1980s to practice forbearance, that is, to keep insolvent banks operating (White, 1991). In response, FDICIA required regulators to follow PCA, under which a bank faces restrictions on activities when its capital drops below certain levels. A bank that is well-capitalized does not face any restrictions. A bank is considered well-capitalized if its risk-based capital ratio is 10% or more, its Tier 1 risk-based capital ratio is 6% or more, and if its leverage ratio is 5% or more. As these capital ratios drop below various triggers, a bank can become undercapitalized, significantly undercapitalized, and critically undercapitalized, the latter being when its ratio of tangible equity to total assets is 2% or less. At various levels of undercapitalization there are restrictions on a bank's activities, such as restrictions on paying dividends, limits on growth and funding, and limits on bonuses paid to senior executives. When a bank is critically undercapitalized, the bank must be put into receivership or conservatorship within 90 days.[4]

Once a bank is in the hands of the FDIC, the FDIC has several means of disposing of it, though, as previously mentioned, since 1991 the FDIC has been required to do so in a way that is the least costly to the deposit insurance fund. When the FDIC disposes of a bank, it can either keep it in the private sector, liquidate it, or provide assistance to keep it open. In the first case, which is the predominant way of resolving a failing bank, the FDIC keeps it in the private sector by selling the whole bank or doing a purchase and acquisition agreement in which part or most of the bank is sold, usually at a negative price. If a bank is liquidated, then insured depositors are paid off and the receivership manages the assets in a way that maximizes recoveries that are paid

[4] See Spong (2000) for a description of PCA.

out to the bank's claimants, including the FDIC. Finally, the FDIC can provide assistance in a variety of ways such as injecting capital, guaranteeing loans, sharing in losses, or even transferring cash (known as open bank assistance). The FDIC's authority to provide open bank assistance has changed over time. From 1951 through the early 1980s, its authority was relatively limited, during the 1980s its ability was expanded, and then in 1991 it was severely restricted under FDICIA to events involving systemic risk only.[5] For more details on how bank failures are resolved, see FDIC (1998) and Bennett and Unal (2008).

The loss to the FDIC depends on what the FDIC can sell a bank for, as well as how much is paid to depositors. In all of the transactions in our sample, insured depositors were fully protected, meaning they suffered no losses.[6] What an acquiring bank is willing to pay for a failed bank or part of a failed bank depends on a number of factors, including the quality of the assets, the value of the bank's charter, its core deposits, and the loss-sharing agreement, if one exists. The FDIC takes these numbers and adds, according to some rule, its costs from closing the bank. This gives the reported loss numbers. These loss numbers are updated as the FDIC disposes of assets, loss-share agreements expire, and liabilities are resolved.

On average, the banks that failed during the recent crisis had non-negative book equity capital when they were put into receivership, as PCA required. Nevertheless, the losses to the FDIC were very high, which means that the market value of each bank's assets had to be significantly less than the asset's book value.

Table 1 reports FDIC losses on commercial bank failures expressed as a percentage of assets net of book equity. Losses are high regardless of the time period, but they are significantly higher in the 2007-13 period, despite occurring under the PCA regime. In the 2007-13 period, weighted losses are 21.2% while unweighted losses are 26.3%. There is clearly a size effect as losses decline if observations are weighted by assets of the failed bank. Also, *de novo* banks are much more expensive to resolve, but they are a relatively small share of the number of failed banks and an even smaller share of failed bank assets, so they do not materially impact the totals.

[5] For the periods we study, the FDIC provided open bank assistance 112 times from 1986 to 1992. Since 1992 this type of assistance has only been used for the "ring fencing," that is, loss protection, provided to Citibank in 2008 and offered, but never implemented, for Bank of America in early 2009.

[6] In the recent crisis, virtually all depositors were insured. Before September 2008, deposits were insured up to $100,000 dollars. In September 2008, during the financial crisis, the FDIC extended deposit insurance to up to $250,000 and for a period its Temporary Liquidity Guarantee Program provided full coverage to all noninterest-bearing deposit transaction accounts. Furthermore, the Dodd-Frank Act made the $250,000 deposit insurance amount retroactive to failures that occurred in 2008 before the emergency expansion in September 2008.

There are also differences in the distribution of losses between the two periods. Figure 2 shows these distributions. In the 1986-92 period, there is a substantial fraction of banks for which the losses are under 10% of assets. This is not true in the later period, in which the distribution of losses looks more symmetric. In both periods, however, there are some banks with losses exceeding 50% of assets.

PCA relies on book capital triggers to determine when to shut down a bank. Figure 3 reports the average capital ratio for failed banks in the 16 quarters prior to failure. In the 1986-92 period, the average capital level of a bank in the quarter before failure is about -2.0%. It was this kind of observation, along with the high losses, that motivated the PCA provisions. In contrast, the average capital of failed banks in the 2007-13 period was positive, about 1.4%, in the quarter before failure. The PCA critically undercapitalized level is 2%, so supervisors faithfully carried out this PCA provision. However, as our analysis will show, given the size of bank losses that were experienced, having this extra 3.4% of equity capital—the difference between -2.0% and 1.4%—at the time of failure did not provide much of an extra buffer to absorb losses.

4. Changes in Bank Activities and Size of Economic Shocks

One striking difference between the two periods is the increase in CRE and CLD lending by banks in our sample of community and mid-sized banks. Tables 2a and 2b show just how dramatic these changes were. For each period, Table 2a reports categories of bank assets expressed as a percentage of total assets for banks that failed. Nonfarm, nonresidential real estate (CRE) increased from 6% to 21% of bank balance sheets, while CLD lending increased from 4% to 22%. Conversely, consumer loans dropped from 13% to 2%, and commercial and industrial loans declined from 19% to 11%.

Table 2b reports asset concentrations for all banks in our sample, those that failed and those that did not. In both periods, the community banking sector as a whole is less concentrated in CRE lending than failed banks were. However, between the periods the growth in CRE lending was more dramatic in failed community banks than in all community banks, particularly for CLD lending. For example, CLD lending only increased from 2% to 7% of assets for all community banks, which is much less than the increase from 4% to 22% for failed community banks.

A second difference between the two periods is the distribution of economic shocks. While nationally, the Great Recession was much more severe than the 1990-1991 recession, some regions in the United States experienced very severe downturns in the 1986-1992 period. For example, Texas and other oil-producing states were severely hurt by the oil price collapse in the mid-1980s, and New England suffered a severe commercial real estate crisis around 1990.

Figure 4a shows a histogram of the size of unemployment shocks experienced by states during the 1986-1992 period. The unemployment shock is calculated by finding the subperiod within each period in which the difference between the starting unemployment rate and the highest subsequent unemployment rate is the greatest. If the difference is never positive, we set the value of this variable to zero. Figure 4b shows the corresponding histogram for the 2007-2013 period. In the early period, the increase in the unemployment rate was concentrated on the lower end of the distribution with pockets of larger increases throughout the country. In contrast, during the later period, the majority of states experienced an increase in the unemployment rate of at least 3%.

Figure 5a shows the histogram by state of the largest percentage drops in house price indices by states over the 1986-1992 period. The largest drop is calculated by taking the subperiod within each period with the largest percentage drop in the index between the starting quarter and subsequent quarters and then taking the greatest such drop. If prices increased over every subperiod, then we set the value of this variable to zero. Figure 5b shows the corresponding histogram for the 2007-2013 period. The story here is similar to the increase in unemployment in both periods.

Finally, an important economic shock specific to the 1980s was a drop in oil prices. Oil prices dramatically increased in 1979 and stayed at historically high levels until dropping dramatically and staying low in the late 1980s. Several states at the time were dependent on oil activity. For example, in 1986, Alaska, Louisiana, North Dakota, New Mexico, Oklahoma, Texas, and Wyoming received over 15% of their state-level gross state product from oil and gas extraction.

The literature has found that commercial real estate, CLD lending in particular, along with economic shocks increase the chance of bank failure. In the following analysis, we use our statistical models to disentangle the importance of these two effects.

5. Data and Sample Construction

We examine commercial bank failures in the periods 1986-92 and 2007-13.[7] There were a total of 1,085 and 416 failures in those periods, respectively. With general agreement among analysts that the recent financial crisis began in the second quarter of 2007, the 2006:Q4 date is a natural date to use as our starting point for the later crisis. For the earlier banking crisis, there is a less definitive starting period, so we use 1985:Q4 as the starting point of the earlier period because the FDIC does not report losses prior to 1986.[8]

Our sample consists of commercial banks that filed quarterly Reports of Condition and Income (Call Report) in 1985:Q4 and all commercial banks that filed a Call Report in 2006:Q4. We exclude banks that were in *de novo* status, which we define as in existence less than or equal to 20 quarters, in 1985:Q4 or 2006:Q4 or that were opened during the sample periods. We exclude *de novo* banks because it is well-documented that they are riskier than established banks and have different characteristics.[9]

We also exclude large banks because they have very different business models than community banks and because some were too big to fail. Our threshold for large banks in the later period is $10 billion of assets. We chose this level because it is the upper end of size thresholds commonly used to identify a community bank. To ensure comparability with the earlier period, we deflate this threshold by the growth in bank assets from 1985:Q4 to 2006:Q4 to get a threshold of $2.97 billion of assets for the earlier period.[10] We also drop banks that have a loan ratio under 5% as these are considered “nontraditional banks” in the literature. Finally, we also drop banks that are headquartered in U.S. territories. These criteria result in a sample that consists of 12,556 banks at the end of 1985, of which 774 failed by 1992, and 6,532 banks at the end of 2006, of which 300 failed by the end of 2013.

We identify failed banks and FDIC losses on failed banks by using the FDIC’s Historical Statistics on Banking (HSOB) data set. All loss estimates to the FDIC are as of December 31, 2015.[11] Note that, as is the case with most papers in the literature, we use loss estimates. The

[7] We do not consider savings and loans, savings banks, or credit unions.
[8] There were numerous bank failures before 1986, but there were fewer in those years than in 1986. The year with the largest number of failures is 1988.
[9] For an analysis of failures of *de novo* banks, see DeYoung (2013) and Lee and Yom (2016).
[10] We deflate by the growth of bank assets rather than a price index because price indices measure changes in the cost of goods rather than changes in asset valuations. These size thresholds exclude seven failed banks in the early period and two failed banks in the later period.
[11] The FDIC updates losses on an annual schedule, in December of each year.

FDIC provides an estimate of losses that they update as contractual agreements like loss-share agreements on purchases and acquisitions or asset dispositions are completed, so there is a possibility that the loss data will change.[12]

In the 1986-1992 period, the FDIC provided assistance to some banks that kept them open. We treat these banks as failures in our data set. Some of these banks also later failed. In those cases, we treat the bank as a single failure, and we use the FDIC losses from the assistance event rather than the subsequent failure.

Our dependent variable in the failure probit regressions is a dummy variable with a value of one if a bank fails, as defined above. Our dependent variable in the FDIC loss OLS regressions, the *Loss Ratio*, is the ratio of the cost to the FDIC of a given bank's failure divided by that bank's assets at the time of failure, net of its book equity.[13,14] Following the literature and applying knowledge from bank supervisory practices, our independent variables consist of bank balance sheet characteristics, bank performance measures, and state-level economic shocks.

For our main analysis we study how bank-specific financial ratios measured in 1985:Q4 and 2006:Q4, along with the size of local economic shocks, are statistically related to failure and FDIC losses that occur within each subsequent seven-year period. We run a separate pair of regressions for each time period. Exact definitions and sources of the variables are included in Appendix A. Summary statistics of the samples used in these baseline regressions are reported in Table 3.

We use several types of independent variables. These are:

Bank Size and Liabilities Variables

The variable *Size* is the natural logarithm of a bank's assets, measured in thousands of dollars. Our variable *Capital* is shareholders' equity as a percentage of assets.[15] Our other liability variable is a measure of core deposits (*Core Deposits*). Core deposits are considered stable and typically do not run, qualities which reduce the chance of liquidity problems. For this reason, core deposits are more valuable to banks than other deposits and often considered a

[12] Bennett and Unal (2014) report that as of April 10, 2014, the receiverships for only 21 of the 510 banks that failed since 2007 have been terminated.
[13] In the rare cases where the last reported Call Report quarter and the FDIC listed failure date do not correspond, we drop these observations from the dataset. There were 30 such banks in the early period and 3 in the later. It is not clear why this discrepancy occurs, but we opted to drop the banks for which it occurred for consistency.
[14] Strictly speaking, the bank's asset value is measured at the end of the quarter prior to failure, since no Call Report is filed in the quarter in which a bank fails.
[15] Capital is long-known to be important for predicting bank failure. For a recent analysis see Berger and Bowman (2013) and the citations within.

source of franchise value. Because of changes to the Call Report over time, the variable *Core Deposits* is measured differently in the two periods. In the early period, the variable is constructed by summing transaction accounts, money market deposit accounts, and time deposits less than $100,000 divided by total assets. In the later period, the variable is constructed in the same way with the addition of other nontransaction savings deposits.[16]

Bank Lending Variables

All our lending variables are expressed as a percentage of bank assets. We use several real estate lending measures. *Construction and Land Development Loans* (*CLD Loans*) are loans made to acquire land and undertake construction. *1-4 Family Real Estate Loans* are mainly residential mortgages. *Other Real Estate Loans* captures remaining commercial real estate loans and is calculated by subtracting the ratios for construction and land development loans and loans for 1-4 residential properties from the overall real estate loan ratio.[17]

Commercial and Industrial Loans (C&I Loans) and *Agricultural Loans* are also included. *Consumer Loans* are constructed differently in both periods due to changes in the Call Report. In the early period, it is represented by the sum of credit cards and related plans and other loans. In the later period, the variable is measured by the sum of loans to individuals for household, family, and other personal expenditures, as well as credit cards, other revolving credit plans, and other loans.

In one specification of the model, we replace the various lending ratios with a Herfindahl-Hirschman index of concentration in lending. This variable is called *Loan Concentration*.

Finally, we also include a variable of indirect lending. In the early period, the *Securities* variable is the book value of all held-to-maturity and available-for-sale securities expressed as a percentage of assets. Since 1992, however, the Call Report has reported available-for-sale securities at fair value, so for the later period our *Securities* variable is the sum of the book value of all held-to-maturity securities and the fair value of available-for-sale securities.

[16] Nontransaction savings deposits include accounts subject to telephone or preauthorized transfer and savings deposits subject to no more than three transfers per month, passbook savings accounts, statement savings accounts, etc.

[17] In robustness analysis, instead of using *Other Real Estate Loans*, we use the components that make up this variable. These components are *Multifamily Real Estate*, which comprises loans secured by multifamily residential properties, divided by total assets, and *Nonfarm/Nonresidential Lending*, which are loans for properties such as hotels, churches, hospitals, golf courses, and recreational facilities. This variable excludes loans for property and land development purposes that mature in 60 months or less.

Bank Performance Variables

For bank performance, we use an asset quality measure and an income measure. The variable *Nonperforming Loans* is calculated by adding loans that are *90+ Days Past Due* to *Nonaccrual Loans* and dividing by total assets. The variable *Earnings* is created by dividing net income by total assets.

Bank Accounting Variables

We include two variables that capture loan accounting discretion on the part of bank management. The variable *Interest Receivable* is an asset on the balance sheet that measures interest income that has accrued but not yet been collected. In the early period, the Call Report reports income earned but not yet collected on loans. In the later period, the Call Report reports interest income accrued or earned but not yet collected on earning assets.[18] The variable *Loan Loss Reserve* is an asset on the balance sheet of reserves held for expected losses on loans.[19] Both variables are expressed as a percentage of bank assets.

Economic Shock Variables

We use three variables to measure statewide economic shocks that a bank experiences. Two of the variables are common to the two periods while the third is specific to the early period. The common variables are calculated from changes in economic conditions over 1986-1992 for the earlier period and over 2007-2013 for the later period. For each bank, both variables are measured at the state level and then applied to each bank by the state in which the bank is headquartered at the beginning of each period. Because we are interested in the size of shocks over time, we express our measures in terms of changes of the variable over each period.

The first variable is *Peak to Trough*, which measures the deterioration of real estate conditions. We define it as the largest percentage drop in the FHFA state-level house price index over any subperiod within the seven-year period.[20] This variable measures the size of a negative shock in real estate collateral values. This measure is particularly useful in the earlier period because house prices declined in some states, primarily those located on the East Coast and in oil-producing regions, but they did not decline at the same time. For the later period, the timing

[18] Accrued interest receivable related to securitized credit cards is not included in the later period definition of this variable.

[19] This variable is defined as the allowance for loans and leases divided by total assets, net of unearned income in the early period and the sum of the allowance for loans and leases and allocated transfer risk reserves in the later period.

[20] In the early period, there are a few states in which house prices never dropped. In these cases, the value of the shock is set to zero.

of the shocks is much more straightforward since for most states house prices were at their peak or close to the peak in 2006 and then they dropped significantly for all states except North Dakota.[21]

The second variable that we use to measure local economic performance is *Unemployment Increase*, which measures deterioration in labor markets in each state. We calculate this variable by taking the largest increase between an unemployment rate and a subsequent unemployment rate over any subperiod within the seven-year period.[22]

Our final economic shock variable is *Oil Shock*, a dummy variable that is applied to oil-producing states in the 1980s. Oil prices during the 1980s dramatically grew starting in 1979, peaked in 1980, steadily declined in the early 1980s, and then dramatically dropped in 1985. It is well-documented that this drop caused banking problems in the "oil patch" states during this period.[23] Because we are considering economic conditions at the end of 1985, the shock to these states occurs near the beginning of the early period, so unemployment changes will not pick up the fact that these states had already started experiencing this shock. For this reason, we include a dummy variable that identifies states highly susceptible to a drop in oil prices. For the early period, we identify oil dependent states as those with at least 15% of their gross state product coming from oil and gas extraction. These states are Alaska, Louisiana, North Dakota, New Mexico, Oklahoma, Texas, and Wyoming. In the later period, we do not include an oil dummy for an oil price drop because even though there was an enormous drop in oil prices in the second half of 2008, oil prices quickly recovered and stayed at higher levels during this period. In general, the high oil prices over this period are widely viewed as a positive economic shock for oil-producing states, such as North Dakota, West Virginia, and Texas, which benefited from the fracking developments of this period.

6. Regression Results

For our main model, we use a data set comprising bank observations from 1985:Q4 and 2006:Q4. Our approach is to use a cross-sectional regression model in which bank characteristics in 1985 and 2006, right before each crisis fully developed, along with subsequent economic shocks, are regressed on failure over subsequent seven-year periods as well as on

[21] See Figure 5.
[22] See Figure 4.
[23] Federal Deposit Insurance Corporation (1997).

FDIC losses. We run our regressions in each period separately, but with a common set of variables other than the oil price shock dummy variable. In doing this, we are explaining two different banking and economic environments with essentially the same model. Our own analysis, as well as prior literature, suggests that similar core variables explain the causes of failure and FDIC losses in both periods.

6.1 Failure Regression Results

We use a probit model to estimate the probability of bank failure. We include the bank characteristics and the state-level economic shock variables listed earlier. The results for the early period are reported in the first column of Table 4 and for the later period in the second column of Table 4.

We find that *Size* is associated with a decrease in the probability of failure, though it is only statistically significant in the early period. Even excluding large banks as we have done, this indicates that a larger bank has a lower probability of failure. For our liability variables, we find that *Capital* is negatively and significantly associated with failure as is *Core Deposits.*

For our lending variables, the two CRE variables, *CLD Lending* and *Other Real Estate Loans*, are positively associated with failure and are statistically significant in both periods, which is consistent with the well-documented riskiness of these types of lending in the literature. Also positive and statistically significant in both periods is *C&I Loans*. *Consumer Loans* is negative and statistically significant only in the later period. *Agricultural Loans* is statistically insignificant in both periods.

1-4 Family Real Estate Loans is negative and statistically significant in the early period. This result is consistent with the long-held view by banks and supervisors that residential real estate is a safe type of lending. Interestingly, this variable is insignificant in the later period despite the proximate cause of the recent financial crisis being a drop in residential house prices. Anecdotally, community banks were viewed as having stayed away from subprime and other risky mortgages, and our finding is consistent with that view, though community banks were likely indirectly exposed through their *CLD Lending*. Our indirect lending measure, *Securities,* is negatively and significantly related to bank failure probability in the early period. It is statistically insignificant in the later period.

Our performance variables have the expected effect. *Nonperforming Loans* is positive and associated with failure while *Earnings* is negatively associated with failure. Both are statistically significant.

The two accounting variables are statistically significant. *Loan Loss Reserves* has a negative effect on failure in the early period, though it is statistically insignificant in the later period. Loan loss reserves could work like capital in that they also provide a buffer to absorb losses. However, the variable is also a measure of expected losses, which would suggest a positive effect on failure. In our results, the buffer effect seems to dominate.[24]

The *Interest Receivable* variable is highly predictive of bank failure in our model and is highly significant in both periods.[25] The size of this accrual accounting variable reflects two possible factors. The first is the timing of loan payments. For example, some loans may not require repayment on a monthly basis, e.g., an agricultural loan that is made at planting time, but is not due until harvest time. Under accrual accounting rules, the bank would recognize earnings throughout the life of this loan even though the borrower does not make regular cash payments. The payments recognized on an accrual basis would go to the interest receivable account, which is an asset, until the cash payment is made, at which point the interest receivable account would be reduced and the cash asset would be increased. A benign explanation for high levels of this variable is that a bank with a high level of the *Interest Receivable* variable could have lots of loans with irregular payment schedules.

The second factor in the size of this variable is accounting discretion.[26] A bank has some discretion in when a delinquent loan is classified as no longer accruing income, so a loan could be treated as still accruing income even though it would likely default and should be put on nonaccrual status. In this case, the size of *Interest Receivable* reflects future problem loans as well as loans that are already problems, but not being recognized as such. The positive

[24] One caveat to our analysis is that the manner in which loan loss reserves enter the capital calculation changed between the two periods. Under FDICIA, loan loss reserves moved from tier 1 to tier 2 capital, so it is possible that banks had a stronger incentive to build reserves in the earlier period, which would be consistent with our finding here.

[25] Some of the literature on FDIC losses has identified the importance of this variable (Bovenzi and Merton, 1988; James, 1991), but to our knowledge its connection to bank failure has not been previously identified.

[26] It is important to note that the interest receivable account at a bank will not grow based on the performance of consumer loans. This arises from the fact that these loans are generally charged-off before they get to nonaccrual status. Therefore, for this loan category, banks are not able to employ judgment in deciding when to write off the interest receivable account. In general, the flexibility in accounting rules related to the interest receivable account lies mostly in the construction and land development, commercial real estate, and commercial and industrial loan categories.

correlation of this variable with failure suggests that it is being used to hide troubled loans and illustrates one way in which book accounting values can significantly lag economic value.

Finally, as expected, we find that the house price shock, *Peak to Trough*, and the unemployment shock, *Unemployment Increase,* are both positively related to failure and statistically significant. Furthermore, the *Oil Shock* variable used in the early period is also positive and statistically significant.

6.2 Marginal Analysis of Probit Regression

We evaluate marginal effects of the independent variables by considering a one standard deviation increase in each variable when the probit regressions are evaluated at the sample means.[27] Table 5 reports these effects. In the early period, the only variable that changes the failure rate by over 1.00% is *Interest Receivable.* Other variables have significant, but not as large effects. Variables that change the failure rate by at least 0.50% are *Capital*, *Securities, Nonperforming Loans, Core Deposit*s, *Peak to Trough*, and *Oil Shock*. In the later period, the only variable that changes the failure rate by over 1.00% is *CLD*, which increases it by a substantial 2.38%. A few variables change the failure rate between 0.50% and 1.00%. These are *Unemployment Increase, Peak to Trough, Interest Receivable, Nonperforming Loans,* and *Core Deposits.*

6.3 FDIC Loss Regression Results and Marginal Effects

For FDIC losses, we run an OLS regression on each period separately. We discuss possible selection effects later in Section 8. The results of the OLS regression are reported in Table 4 Columns (3) and (4). In this approach, we are not directly measuring determinants of the demand for failed bank assets and deposits, nor are we controlling for the type of resolution (as is the focus of Bennett and Unal, 2014). However, by including securities, core deposits, and size, we are picking up proxies for the franchise value of a bank, which has value to acquirers. Securities are liquid and thus easier to sell, core deposits are valuable to acquirers because of their stability, and larger banks usually have larger branch networks.

[27] For the economic shock variables, the mean and standard deviation values used were those of the sample of banks and not those of the states. Table 3 reports the latter and not the former.

Consistent with franchise value helping with FDIC recoveries, both higher *Core Deposits* and *Size* are statistically significantly associated with lower losses. *Securities* is also associated with lower losses in the later period and significant at the 5% level. A one standard deviation increase in this variable reduces the FDIC loss rate by 390 basis points (bp).

Core Deposits has a moderate quantitative effect on losses. A one standard deviation increase in *Core Deposits* reduces FDIC losses by 240 bp in the earlier period and 130 bp in the later period. *Size* has a larger effect. A one standard deviation increase in *Size* lowers FDIC losses by 270 bp in the earlier period and a sizeable 440 bp in the later period.

For the loan ratios, we find in the earlier period that four of the variables have a positive effect on FDIC losses and are significant. These are *CLD Loans*, *Other Real Estate Loans*, *C&I Loans*, and *Agricultural Loans,* though only *C&I Loans* is significant at the 1% level. In the later period, the only lending ratio that is significant is *Agricultural Loans,* which reduces FDIC losses. Interestingly, *1-4 Family Real Estate Loans* is insignificant in both periods, which, as we discussed in the probit regression, is likely true in the later period because community banks stayed away from holding risky mortgages on their balance sheets. Columns (3) and (4) of Table 6 report FDIC losses when the lending variables are replaced with *Loan Concentration.* Here, it is positive and statistically significant in both periods.

In general, one standard deviation increases in the lending variables have relatively small effects on FDIC losses. In the later period, the exception is *Agricultural Loans,* which reduces FDIC losses by 710 bp. In the early period, *C&I Lending* is the only lending variable with a significant marginal effect. A one standard deviation increase in this variable increases FDIC losses by 180 bp. The quantitative effects of the other significant lending variables in both periods are much smaller.

The performance variable *Earnings* is not statistically significant. In contrast, the performance variable *Nonperforming Loans* is positive and significant in both periods. Nevertheless, a one standard deviation increase in this variable has only a small effect on FDIC losses.

Higher *Nonperforming Loans* indicate poorer asset quality, but the level of this variable is also tied to the timing of the recognition of loan losses. It is possible that we are picking up some of this discretionary accounting in the *Interest Receivable* variable, which we find to be highly predictive of higher losses in both periods. Unlike *Nonperforming Loans,* however, the *Interest*

Receivable variable has a large quantitative effect on FDIC losses. In the early period, a one standard deviation increase in this ratio increases losses by 230 bp, while in the later period, it increases it by a sizable 510 bp. In contrast to *Interest Receivable*, the other accounting variable, *Loan Loss Reserves*, is insignificant in both periods.

Finally, we find that *Unemployment Increase* is positively associated with losses, but the *Peak to Trough* variable is positive and significant only in the early period. The marginal effects of *Unemployment Increase* are 230 bp in the early period and 240 bp in the later. For *Peak to Trough*, it is smaller at 140 bp in the early period. Finally, the *Oil Shock* variable is insignificant.

7. Decomposition Exercises

As we discussed earlier, two of the most significant differences for small banks between the two banking crises were the increase in the concentration of commercial real estate lending and the increase in the severity of the economic shocks. To disentangle these effects, we decompose the differences in failure rates between the two periods into changes from estimated coefficients, changes in bank characteristics, and changes in the severity of economic shocks.

Table 7, Panel A shows predicted probabilities of various combinations of estimated coefficients, bank characteristics, and macro conditions.[28] The first row shows the sample failure rates for each period. The second row shows the predicted failure rates for the early and late regressions, which are very close to the sample failure rates.

The third row of the first column shows failure rates when bank and economic characteristics from 2006 are run through the 1985 model, that is, the coefficient estimates from the early period are used on 2006 data. In this case, despite the increases in CRE lending and severity of economic shocks, the predicted failure rate increases only from 6.14% to 7.59%.

More illuminating are the effects when just bank characteristics or just the economic shocks are changed. The fourth row of the first column shows the predicted failure rates when banks in 1985 operate under the early-period model but are subject to later-period economic shocks. The failure rates in this calculation are 7.65%, which is about the same as the 7.59% that comes from changing bank characteristics and economic shocks. In contrast, when bank

[28] For all decomposition exercises where bank characteristics in one period are applied to estimated coefficients in the other period, we adjust bank size by the growth in total bank assets between the two periods. As explained earlier, we make this adjustment because bank size is a nominal variable and the average size of banks, as well as total assets in the banking sector, grew between the two periods.

characteristics are changed to those in 2006, but economic shocks stay the same as in the 1986-92 period, the failure rate drops to a much lower 3.64%. This surprising drop occurs despite the much higher CRE concentrations of banks in 2006.

An analysis of changes in failure probabilities (not shown) when evaluated at the variable means gives insight into these results. Not surprisingly, the larger unemployment shocks and house price shocks in the later period increase failure rates. A change in *Unemployment Increase* from its early-period mean value to its later-period mean value increases failure rates by 50 bp. The corresponding change for *Peak to Trough* increases the failure rate by 154 bp. However, not all of the changes in bank characteristics between the two periods increase bank risk. While increases in the means of both *CLD Lending* and *Other Real Estate Loans* (and decreases in *Securities* and *Core Deposits*) substantially increase the probability of bank failure, changes in other bank characteristics offset these increases. The biggest offset is from the increased mean of *Capital*, which is 220 basis points higher in 2006 than in 1985, but it is also offset to a lesser extent by lower levels of *Nonperforming Loans* and *Interest Receivable* ratios and higher levels of *1-4 Family Real Estate Loans*.

An alternative decomposition in which the coefficients from the later-period model are fixed tells a similar though less pronounced story. The third row of the second column shows the predicted failure rates when the coefficients on the later-period model are used on 1985 data. Here, there is a substantial drop to 1.59%, which is much less than the actual failure rate of 4.65%.

The fourth row of the second column shows the failure rate when just bank characteristics are changed. Here, the failure rate drops to 2.65%. The drop is even larger when just the economic shocks are changed to the lower early-period levels. In this case, the failure rate is a very low 1.95%.

The larger drop in the failure probability from changes in economic shocks than from changes in bank characteristics is consistent with the findings above. An analysis of changes in each set of bank characteristics when evaluated at sample means for the later period estimates gives some insight into why. Lower levels of *CLD Loans* and *Other Real Estate Loans* in the early period lower failure rates, but this reduction is offset by the higher level of *Nonperforming Loans* and *Interest Receivable* as well as the lower levels of *Capital* in the earlier period.

Meanwhile, the smaller size of the mean *Unemployment Increase* and *Peak to Trough* shocks in the earlier period lowers the failure rate.

Of course, the difference in failure rates between the two periods is not only due to changes in the independent variables, but also due to changes in the size of the estimated coefficients. However, the analysis above suggests that the increase in the severity of economic shocks was a force for increased failure rates, but that changes in bank characteristics on the whole did not necessarily raise the failure rate. In particular, while community banks did become riskier through increased commercial real estate lending from the early to the later period, this change was offset to a large degree by increased capital and other changes in bank balance sheets.

The importance of capital in the decompositions is consistent with a long literature in banking that finds that capital makes banks safer.[29] To further explore the role of capital, we ran a counterfactual exercise in which we raised capital for all banks by 500 basis points and then calculated failure rates using the estimated models. In the early period, the failure rate drops enormously from 6.16% to 2.21%, which is not surprising given the very large value of the coefficient on capital in the early period. In the later period, there is also a drop, though it is smaller. The drop in that model is from 4.65% to 3.42%. While these are reduced-form estimates, they are consistent with the frequent finding that capital reduces failure probabilities.

We also performed a similar decomposition exercise for FDIC losses. For this decomposition, we took into account that changes in bank characteristics and economic shocks would affect the pool of failed banks from which FDIC losses would be observed. We did this for both decompositions by calculating each bank's probability of failure and then using these failure rates to weight each bank's contributions to FDIC losses.

Table 7 Panel B shows the results for the FDIC loss counterfactuals. The fourth row of column one shows the *Loss Ratio* in the early model, with bank characteristics in 1985, and the economic shocks of 2006. FDIC losses increase from 19.27% to 26.19%. In contrast, just changing bank characteristics in the early period to those of banks in 2006 has little effect on the loss ratio. The fifth row of column one shows this decomposition ratio to be 19.87%.

In contrast, effects are different when considering the decomposition using the model of the later period. In this case, as shown in the fifth row of column two, changing just the

[29] See the discussion in Berger and Bowman (2013).

economic shocks only slightly lowers the loss ratio from 24.99% to 23.29%. Changing just bank characteristics, as shown in the fourth row of column two, greatly increases the loss ratio from 24.99% to 35.67%.[30]

The different implications from the two FDIC loss decompositions suggest that, unlike with bank failure, we cannot attribute differences in FDIC loss ratios more to changes in bank balance sheets or changes in economic shocks. Another difficulty in interpreting causal factors from the two FDIC loss regressions is the large difference in the size of the constant terms. In the later period, the coefficient on the constant term is 0.70, which is much higher than the 0.42 found in the earlier period. Narrowly, this difference reflects the higher FDIC losses in the later period, but it could be picking up a variety of factors including a common economic shock to all states or other changes to market or regulatory conditions that uniformly affected failed banks.

Finally, the higher FDIC loss ratios observed in this crisis compared with those in the earlier crisis is sometimes pointed to as evidence that PCA was a failure (GAO, 2011). Our decomposition analysis suggests that loss ratios alone are not sufficient for assessing the effectiveness of PCA. In particular, our analysis found that higher levels of bank capital significantly reduced bank failure rates. Because PCA was a factor in raising bank capital levels, then to this extent PCA reduced *total* FDIC losses, which is more important than losses conditional on failure. Because our dependent variable is a loss ratio rather than a loss, we cannot use our models to calculate a reduced-form estimate of the total loss. Nevertheless, based on our analysis of failure rates, this effect seems sizeable.

8. Additional Analysis

Our main findings are robust to extensive additional specifications. In this section, we discuss the inclusion of additional variables as well as different methodological approaches to the model. The overall results of the main model are robust to the various specifications discussed below.

For our first robustness exercise, we considered the inclusion of variables proposed by other studies in the literature. In addition to *Core Deposits* and *Securities, Cash* is another measure of liquidity and would be expected to be negatively related to both failures and losses.

[30] We also performed the decomposition solely on the sample of failed banks. Failure rates were uniformly higher, but the same pattern was observed as in the reported numbers.

Cash is defined as the sum of interest-bearing balances, noninterest-bearing balances, and securities with a remaining maturity of one year or less, normalized by total assets. This variable does not explain the probability of failure, but it does enter the loss regression with a negative sign, as expected.

We focus on *Nonperforming Loans*, but the literature considers several other measures of loan performance. One measure of delinquency is *30-89 Days Past Due*, which we find can perform as a substitute for *Nonperforming Loans*. When this variable is added to the failure and loss models, it is positively and significantly associated with both failures and losses. We also assess *Other Real Estate Owned* (*OREO*),[31] a variable which comprises properties that have been repossessed by the bank due to foreclosure and is, therefore, often related to nonperforming assets in the literature. Given that real estate is a relatively illiquid asset category, high levels of *OREO* can have a negative effect on a bank's liquidity position. When added to the failure and loss model, the *Other Real Estate Owned* ratio is a positive and significant predictor of failures in both periods, but is positive and significant for losses only in the earlier period. Because this is a lagging variable, levels of *Other Real Estate Owned* are likely low in cases where the variable is measured a number of years before failure.

A more recent addition to the literature, Chernykh and Cole (2015), uses the *Nonperforming Assets Coverage Ratio* (*NPACR*), which is created by adding capital (represented by shareholders' equity) and loan loss reserves, subtracting nonperforming assets, and then normalizing the sum by total assets.[32] *NPACR* is negative and significant in both of our failure and loss models. The addition does not materially change our main results, though *Loan Loss Reserves* is no longer significant in the earlier failure model.

FHLB Advance measures the sum of Federal Home Loan Bank advances with a remaining maturity or next repricing date of one year or less, one to three years, and over five years. When a bank is put into receivership, the FDIC pays the FHLB in whole, so we also added *FHLB Advance* to the loss equation. This variable is only available for the later period and it is statistically insignificant in explaining failures or FDIC losses.

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[31] Not to be confused with the *Other Real Estate Loans* variable. When we break the *Other Real Estate Loans* variable (from our main specification) into its component parts—*Nonfarm and Nonresidential Real Estate*, *Farmland*, and *Multifamily* lending—we find that the separate categories are not significant in the loss model. In the failure model, *Multifamily* is positively and significantly related to failure, while *Farmland* is negatively and significantly associated.

[32] Chernykh and Cole (2015).

In addition to assessing the effect of individual loan categories and the effect of CLD in particular, we hypothesize that lending concentration risk, regardless of the type of lending, is associated with an increased probability of failure. For this specification, we replace our direct lending ratios with *Loan Concentration,* a Herfindahal-Hirshman index of concentration by lending type, for each bank's loan portfolio. Results can be found in Table 6. We find that *Loan Concentration* is positively and significantly related to failure and FDIC losses, supporting the bank supervisory tenet that any excessive concentration in lending, not just in CLD lending, could be risky.

We also perform methodological robustness checks. One such check involves pooling the data sets of the two periods and including a period indicator. Recall that we estimated our main model on two samples (one for each period) so we could separately look at the differential effects of the financial and macroeconomic variables in the early and later periods. In pooling the two periods, we are imposing the restriction of same-magnitude effects across the two periods and treating banks that exist in both periods as independent entities, which we find to be an inferior approach to studying the two crises separately. The results are reported in Table 8. Consistent with our main findings, here we find that the *Period Indicator* variable is positive and statistically associated with failure, indicating that banks in the early period had a higher probability of failing. We also find that the *Period Indicator* variable is negative but statistically insignificantly related to losses. Note that to adjust for the differences in the size of the banking industry across the two periods as well as to avoid picking up the effect of this size difference in the coefficient of the *Period Indicator,* we apply an adjustment to the *Size* variable in the early period.[33]

In our main model, we measure bank financial ratios at the beginning of the period which, for some banks, is up to six years prior to failure. We also considered a model which assesses financial variables closer to the time of failure. In unreported tables, measuring the financial ratios in the four or eight quarters prior to bank failure, we find that more variables become significant as a bank gets closer to failure but that the estimates are directionally similar to our main model. A related but separate matter to the question of measuring financial conditions at time of failure is the question of measuring demand for failed bank assets. It is

[33] The size adjustment is accomplished by multiplying total assets in the early period by about 3.4 to adjust for the difference in the amount of total assets in the banking industry between the two periods.

possible that demand for bank assets is a factor influencing the value of a failed bank. Additional data collection and empirical work would be required to address the demand side for failed bank assets beyond the controls we have included in the main model.

Losses to the FDIC are observed only for banks that fail, posing a selection problem. Banks that fail may differ in important unmeasured ways from healthy banks and in ways in which error terms in failure probabilities are correlated with error terms in losses. To address this, we explored a Heckman selection approach. We find that our main results hold.

When variations of the main models shown earlier are combined into selection and outcome stages of the Heckman model, we find very limited evidence of selection bias. Attempting to build in an exclusion restriction, we ran a more parsimonious outcome stage, which focused primarily on factors that affect portfolios and franchise value at the time of failure.[34] The regression results shown in Table 9 are from a two-step estimator. The selection stage has a binary dependent variable taking the form of failure=1 and 0 otherwise within the period. In the outcome stage, we model the size of the losses for failed banks. We run the Heckman model on three distinct samples: the early period, the later period, and a pooled data set consisting of the observations from both periods with a dummy variable (*Period Indicator*) equal to one if the bank-quarter observation is in the early period.

For our selection equation, we include all the variables used in our main model from Table 4. These can be broken into several types. There are variables that describe the economic conditions in the bank's state, the business model of the bank in terms of lending and funding, performance ratios, and variables that capture the role of accounting measures.

We exclude a variety of variables from the loss equation. One such variable is *Capital Ratio* and while it is certainly correlated with failure probability because regulators shut a bank down when this ratio gets low, *Capital Ratio* should not necessarily be correlated with losses. Once a bank's capital is exhausted, it is insolvent, and if a bank gets to that point, how much capital it had a few years before should be irrelevant for losses. Indeed, in most specifications we examined, this variable was insignificant if added to the loss equation.

CLD Loan Ratio enters both the selection and outcome stages and has effects of different magnitudes across the samples. In both periods, higher CLD concentration is positively

[34] For the purpose of this exercise, we used the *Capital Ratio* and several other balance sheet variables as our exclusion restriction.

associated with failure and is statistically significant. It is not, however, statistically significant in the loss equations. In the pooled model, however, it is positive and significant in both the loss and failure stages. The *Other Real Estate Loans* ratio is also positively associated with failure across all specifications but is only significant in the early period.

The *C&I Loan Ratio* looks like the *CLD Loan Ratio* in that it is statistically significant and positively associated with failure across all specifications. It is positive and significant in the loss stage of the early and pooled models, but negative and insignificant in the later period. In contrast, securities are often considered safe assets and, consistent with this perspective, we find that the larger the share of assets held in the form of securities, the lower the probability of failure in all cases; however *Securities* is significant only in the early and pooled specifications.

Higher *Core Deposits* reduce failure probabilities in both periods and reduce losses across all samples, though the coefficient on the loss equation is significant only in the early and pooled samples. A higher *Capital Ratio* is, unsurprisingly, related to a lower probability of failure. The *Loan Loss Reserve* variable, is negatively associated with failure and is significant in the early and pooled models. The *Interest Receivable* variable is positive and significant for failure and losses in all three regressions. For *Size*, we find it is negatively associated with failure but statistically significant only in the early and pooled samples. More interesting, however, is that it is negatively associated with losses and statistically significant. It is possible that the larger bank networks provide some franchise value to acquirers.

Results for measures of bank profitability are as expected, with the *Earnings Ratio* negatively associated with failure and statistically significant. Similarly, a higher *Nonperforming Loan* ratio is positively associated with failure and is statistically significant in both periods. The macroeconomic variables behave as expected and are uniformly positive and significant across all specifications. The *Period Indicator*, which indicates the earlier period, is statistically significant in both regressions and indicates lower losses and higher probability of failure in the earlier banking crisis.

Although the economic significance of the coefficients cannot be interpreted directly from Table 9, statistical significance and the direction of the effects can be compared across the two periods. To summarize, the results reported in Table 9 are directionally in line with expectations and qualitatively similar across the two periods for several regressors.

In Table 10, we report the size of the selection effects by comparing the Heckman loss equation with an OLS-estimated loss equation. Note that the Heckman correction serves to shift the conditional expectations of those banks likelier to fail due to unobservable factors in the right direction. The reported negative lambda (which is the coefficient on the inverse Mills ratio) implies that the unobservables of the selection stage and the unobservables of the outcome stage are negatively related. This is consistent with smaller coefficients in the Heckman outcome stage compared to regular OLS. Note that some second-period coefficients are not significant for standard loss determinants as compared to OLS, suggesting that in regular OLS analysis (one that does not correct for the conditional nature of observing FDIC losses) several regressors are picking up the indirect effect on losses through the probability of observing those losses given failure.

Admittedly, we do not have a good instrument with which to identify the selection effect. We cannot conclude that selection is unimportant. Rather, we point to Tables 9 and 10 as suggestive that our main conclusions are directionally robust.

9. Conclusion

This paper compared bank failures and FDIC losses on failed banks in the banking crisis of 1986-92 with those in the banking crisis of 2007-13. We studied small banks because their concentration in real estate lending has led to questions about the validity of their business model and because they can be used to study the effectiveness of PCA and other financial reforms without worrying about the confounding effects of too-big-to-fail bailouts. We found that despite the passage of twenty years and large changes in small bank balance sheets, essentially the same variables predict bank failure in both crises. Commercial real estate lending and severe economic shocks increased risk while capital and variables related to franchise value, like core deposits, reduced risk. We also found that an accrual accounting variable, interest accrued but not yet received, was highly predictive of failure. Furthermore, despite the recent financial crisis being highly related to the poor performance of residential mortgages, residential mortgage lending does not predict failure or losses for small banks. It is also striking that, although we measured the structure of the balance sheet and the performance of the bank long before failure for many of the failed banks, we still found strong statistical significance. Management decisions made before a crisis on the structure of the balance sheet have significant influence on outcomes during and immediately after the crises.

In a decomposition exercise to see if failure rates were accounted for more by economic shocks or by changes in bank characteristics, we found that failure probabilities were most influenced by macroeconomic conditions. Between the two crises, increased CRE lending did increase bank risk, but this was offset by other changes in bank characteristics, particularly higher capital. An implication of our analysis for assessing the viability of community banks is that increased CRE concentrations may be appropriate if a bank has enough capital. Furthermore, to the extent that PCA and the Basel I capital requirements increased bank capital between the two periods, these reforms were a success.

In contrast, in our analysis of FDIC losses on failed banks, we did not find difference in losses between the two periods to be driven by bank characteristics, the size of economic shocks, or the regulatory regime. As planned, PCA led banks to be shut down before they reached negative book capital. However, given the size of losses, a few hundred extra basis points of capital in the later period would not have materially reduced losses on failed banks. A fundamental problem with PCA is that book accounting numbers lag economic values, and our finding that an accrued interest variable significantly predicted failure and FDIC losses is evidence of this. Nevertheless, we do not consider the high FDIC losses conditional on failure as necessarily implying that PCA failed. The higher capital levels that are partly due to PCA significantly reduced bank risk, and while they seem not to have helped with losses conditional on failure, by reducing failure rates they lowered total losses experienced by the FDIC.

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Figure 1 - Commercial bank failures, 1986-2013
Number of failed commercial banks and assistance transactions in each year from 1986 to 2013 (Source: FDIC Historical Statistics on Banking). There were no bank failures or assistance transactions in 2005 or 2006.

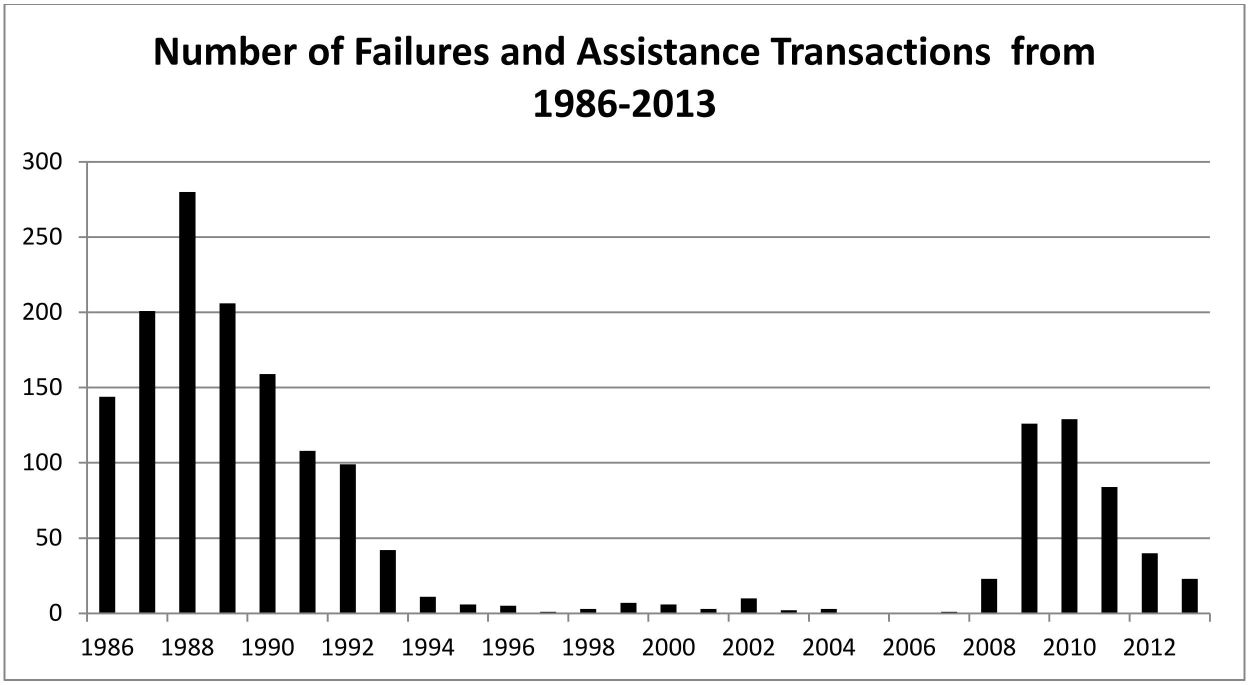


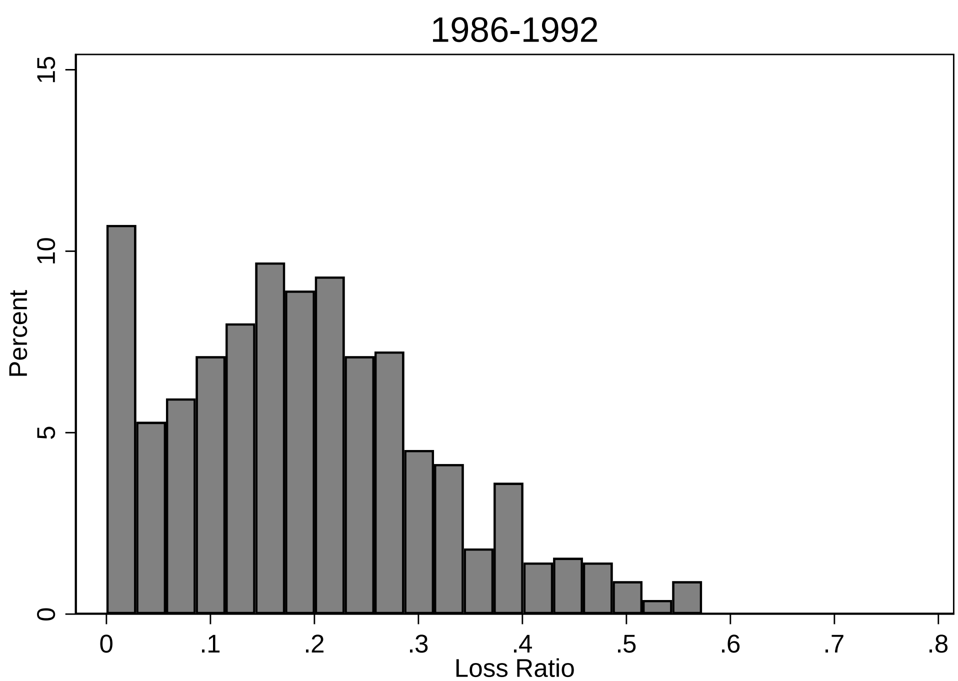
Table 1 – Average loss ratios, equally weighted and weighted by assets
This table shows the ratio of FDIC losses to assets net of book equity for commercial banks in our sample that failed between 2007-13 and 1986-92, respectively. The sample is divided into three categories: all banks, established banks (in existence for more than 20 quarters), and *de novo* banks (in existence for 20 quarters or less). Losses are as of December 31, 2015.

	1986-92		
	All Banks (1,079)	Established Banks (774)	*De novo* Banks (305)
Equally Weighted	21.0	19.3	25.3
Weighted by Assets	17.4	16.9	22.0

	2007-13		
	All Banks (401)	Established Banks (304)	*De novo* Banks (97)
Equally Weighted	26.3	25.0	30.3
Weighted by Assets	21.2	20.0	31.7

Figure 2 –Distribution of losses on failed banks, 1986-92 and 2007-13

The graphs below show the distributions of FDIC losses as a share of assets, net of book equity in each period for all failed banks in our sample.



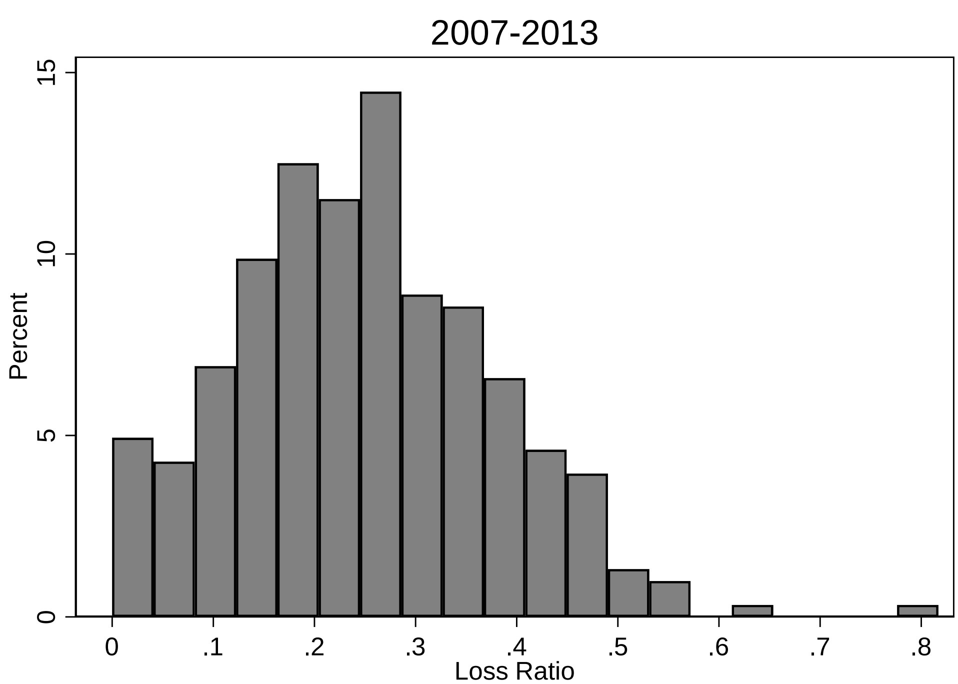


Figure 3 – Average capital ratio for all failed banks in the 16 quarters prior to failure
This figure shows the average capital ratio for all failed banks from one to 16 quarters prior to failure. The capital ratio is defined as total equity capital divided by total assets. The solid lines represent banks in the later period, and the dashed lines represent banks in the early period. Mature and *de novo* banks are included in this graph.

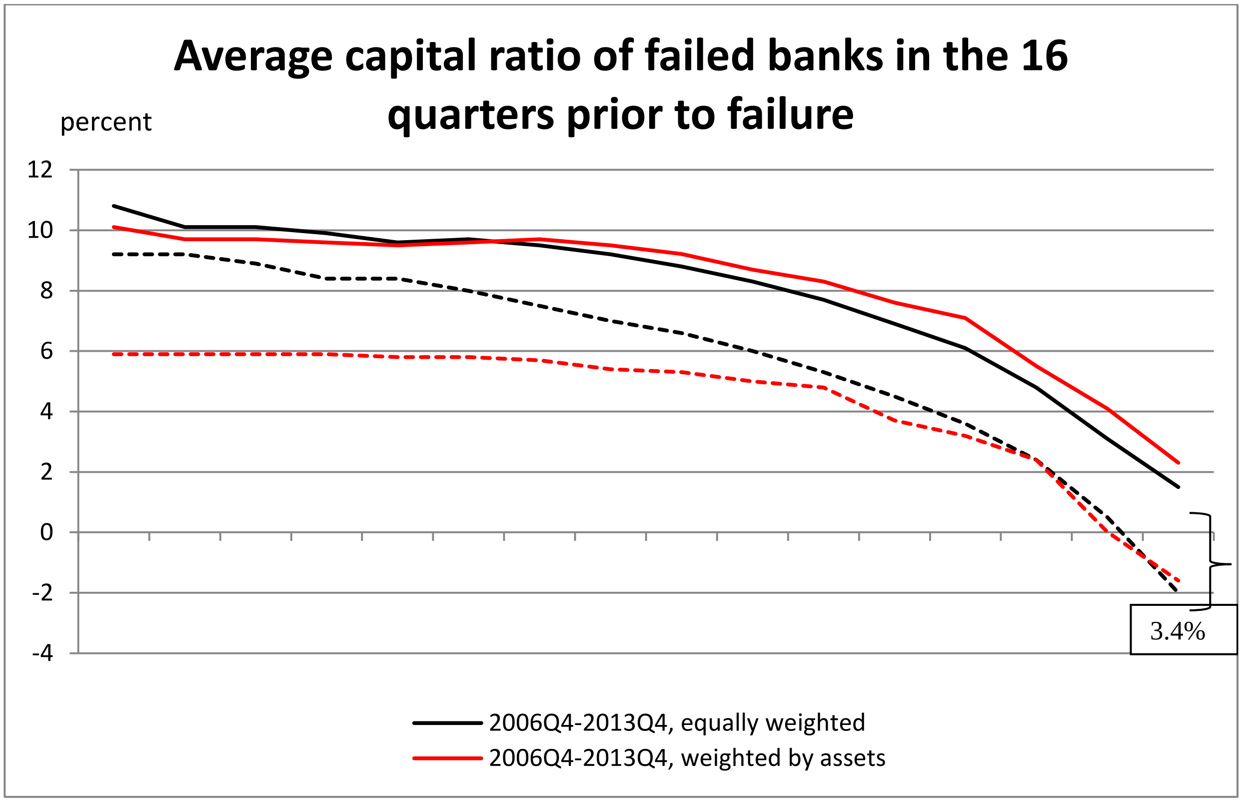


Table 2a – Asset concentration of failed banks (% of assets)
This table shows securities and various loan categories reported as a percentage of total bank assets for failed banks in our sample. In 2006, our sample includes all mature banks with less than $10 billion in assets, while in 1986 it includes mature banks with less than $2.9 billion in assets.[35]

	1985 Q4	2006 Q4
Securities	16	13
Agricultural Loans	7	1
Consumer Loans	13	2
Comm. & Ind. Loans	19	11
Constr. Land Develop. Loans	4	22
1-4 Family Real Estate Loans	9	13
Multifamily Real Estate Loans	1	3
Nonfarm Nonresidential Real Estate Loans	6	21

Table 2b - Asset concentration of all banks (% of assets)
This table shows securities and various loan categories reported as a percentage of total bank assets for all banks in our sample. In 2006, our sample includes all mature banks with less than $10 billion in assets, while in 1986 it includes mature banks with less than $2.9 billion in assets.

	1985:Q4	2006:Q4
Securities	29	22
Agricultural Loans	7	5
Consumer Loans	12	5
Comm. & Ind. Loans	12	10
Constr. Land Develop. Loans	2	7
1-4 Family Real Estate Loans	11	16
Multifamily Real Estate Loans	0*	1
Nonfarm Nonresidential Real Estate Loans	5	15

[35] The asset limit excludes seven failed banks in the early period and two failed banks in the later period.

* There is some multifamily real estate lending in 1985:Q4, but it rounds to zero.

Figure 4a – Change in unemployment variable, 1986-1992

The graphs below show the distribution of the change in the unemployment rate by state for the 1986-1992 and 2007-2013 periods. The variable, *Unemployment Increase*, is calculated by taking the largest drop in the unemployment rate over any subperiod in the seven-year period.

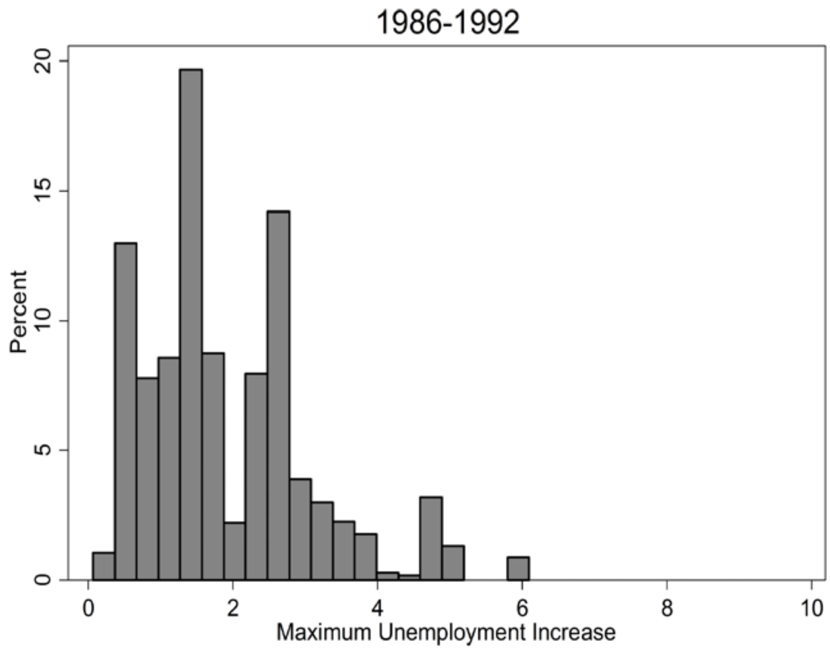


Figure 4b - Distribution of change in unemployment variable, 2007-2013

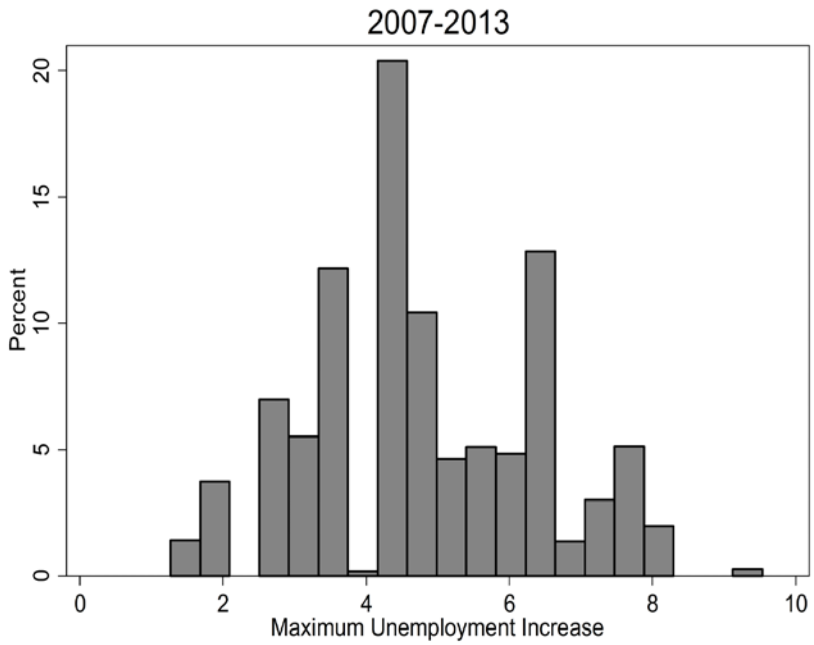

2007-2013
Percent
0
5
10
15
20
0
2
4
6
8
10
Maximum Unemployment Increase

Figure 5a – Peak to trough house price index variable, 1986-1992

The graphs below show the distribution of the peak to trough variable by state in both period samples. The variable of interest, *Max HPI*, is calculated as the largest percentage drop of state-level HPI values for all possible subperiods over each seven-year period. If house prices increased over the entire period, then the variable is coded as a zero.

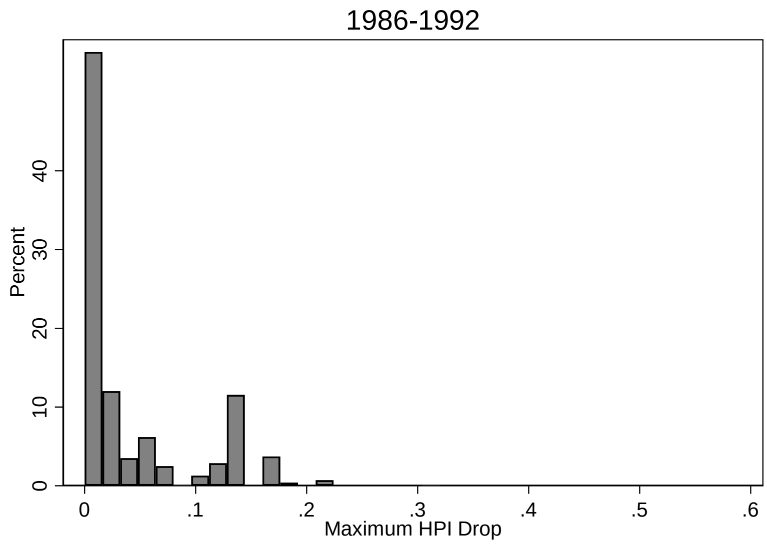


Figure 5b – Peak to trough house price index variable, 2007-2013

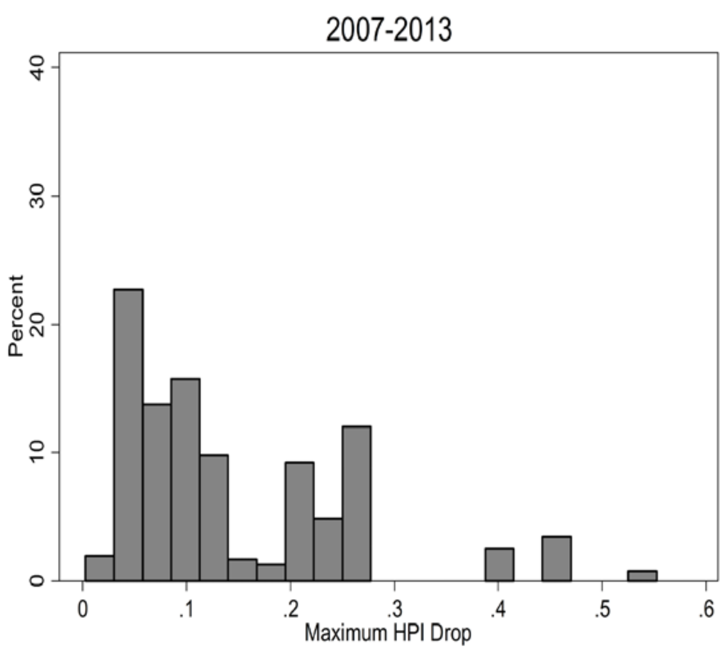


Table 3– Summary statistics for 1985:Q4 and 2006:Q4

This table presents summary statistics for the two datasets in our sample: Early Period (Panel A) and Later Period (Panel B). All financial variables are normalized by total assets with the exception of Size, which is defined by the natural log of total assets. All variables are defined in Appendix A.

Panel A – Early Period

Variable	N	Mean	SD	Min	p25	Median	p75	Max
Loss Ratio	774	0.193	0.126	0	0.101	0.183	0.272	0.573
Size	12,556	10.654	1.119	6.923	9.884	10.567	11.272	14.899
Capital	12,556	0.085	0.028	-0.070	0.068	0.080	0.096	0.443
Earnings	12,556	0.007	0.014	-0.201	0.005	0.010	0.013	0.182
Core Deposits	12,556	0.719	0.092	0	0.673	0.734	0.782	0.935
Securities	12,556	0.291	0.144	0	0.183	0.278	0.385	0.862
1-4 Family Real Estate Loans	12,556	0.108	0.077	0	0.050	0.094	0.152	0.727
Constr. Land Devel. Loans	12,556	0.015	0.032	0	0	0.003	0.016	0.394
Other Real Estate Loans	12,556	0.070	0.052	0	0.031	0.060	0.098	0.537
Comm. & Ind. Loans	12,556	0.120	0.086	0	0.056	0.100	0.163	0.800
Consumer Loans	12,556	0.122	0.079	0	0.066	0.106	0.161	1.012
Agricultural Loans	12,556	0.067	0.095	0	0.001	0.022	0.098	0.604
Loan Concentration	12,556	0.108	0.063	0.001	0.063	0.098	0.141	1.024
Loan Loss Reserves	12,556	0.007	0.006	0	0.004	0.006	0.009	0.106
Nonperforming Loans	12,556	0.017	0.020	0	0.004	0.010	0.021	0.305
Interest Receivable	12,556	0.010	0.006	0	0.005	0.008	0.012	0.056
Unemployment Increase	51	2.516	1.486	0.067	1.300	2.467	3.433	6.100
Peak to Trough	51	0.049	0.065	0	0.007	0.024	0.070	0.320
Oil State Indicator	51	0.138	0.344	0	0	0	0	1

Table 3 (cont.)

Panel B – Later Period

Variable	N	Mean	SD	Min	p25	Median	p75	Max
Loss Ratio	304	0.249	0.128	0	0.155	0.245	0.335	0.817
Size	6532	11.814	1.203	8.388	10.983	11.719	12.547	16.101
Capital	6532	0.107	0.040	-0.001	0.084	0.097	0.118	0.886
Earnings	6532	0.011	0.009	-0.356	0.008	0.011	0.015	0.215
Core Deposits	6532	0.671	0.113	0	0.614	0.685	0.747	0.916
Fed. Home Loan Bank Advances	6532	0.037	0.051	0	0	0.015	0.057	0.884
Securities	6532	0.219	0.143	0	0.115	0.194	0.302	0.943
1-4 Family Real Estate Loans	6532	0.162	0.107	0	0.082	0.146	0.220	0.737
Constr. Land Develop. Loans	6532	0.073	0.092	0	0.010	0.039	0.103	0.739
Other Real Estate Loans	6532	0.207	0.111	0	0.129	0.198	0.270	0.860
Comm. & Ind. Loans	6532	0.098	0.068	0	0.051	0.084	0.127	0.767
Consumer Loans	6532	0.052	0.057	0	0.020	0.038	0.066	1.003
Agricultural Loans	6532	0.051	0.084	0	0	0.011	0.066	0.590
Loan Concentration	6532	0.271	0.168	0.001	0.147	0.239	0.366	1.283
Loan Loss Reserves	6532	0.009	0.004	0	0.006	0.008	0.010	0.071
Nonperforming Loans	6532	0.006	0.008	0	0.001	0.003	0.008	0.118
Interest Receivable	6532	0.008	0.004	0	0.005	0.007	0.010	0.056
Unemployment Increase	51	4.999	1.704	1.267	4.167	4.867	6.367	9.533
Peak to Trough	51	0.157	0.119	0.003	0.070	0.129	0.219	0.553

Table 4 – Early and later period failure and loss models

The table shows results from the failure and loss models. Columns (1) and (2) show regressions for the early- and later-period failure models. Panel A shows results from the failure model, and Panel B shows results from the loss model. Columns (3) and (4) show regressions for the early- and later-period loss model. Variable definitions are provided in Appendix A. All financial variables are normalized by total assets with the exception of *Size*, which is defined by the natural log of total assets. Standard errors appear in brackets. Levels of significance are indicated by *, **, and *** for 10%, 5%, and 1%, respectively.

Panel A	**(1)**	**(2)**	**Panel B**	**(3)**	**(4)**
	Early Period Failure	**Later Period Failure**		**Early Period Loss**	**Later Period Loss**
Size	-0.15***	-0.03	**Size**	-0.02***	-0.04***
	[0.03]	[0.03]		[0.005]	[0.01]
Capital	-15.17***	-3.98***	**Capital**	-0.13	-0.37
	[1.39]	[1.21]		[0.22]	[0.26]
Earnings	-5.08***	-11.21***	**Earnings**	-0.09	0.99
	[1.74]	[2.83]		[0.25]	[0.94]
Core Deposits	-2.00***	-1.75***	**Core Deposits**	-0.26***	-0.12**
	[0.25]	[0.29]		[0.04]	[0.05]
Securities	-1.80***	-0.37	**Securities**	-0.00	-0.27**
	[0.28]	[0.55]		[0.06]	[0.12]
1-4 Family Real Estate Loans	-1.23***	0.01	**1-4 Family Real Estate Loans**	0.09	-0.06
	[0.41]	[0.56]		[0.07]	[0.12]
Constr. Land Develop. Loans	2.94***	4.52***	**Constr. Land Develop. Loans**	0.16*	0.14
	[0.57]	[0.56]		[0.09]	[0.12]
Other Real Estate Loans	1.07**	0.96*	**Other Real Estate Loans**	0.18**	-0.10
	[0.44]	[0.54]		[0.07]	[0.12]
Comm. & Ind. Loans	1.42***	1.22*	**Comm. & Ind. Loans**	0.20***	-0.07
	[0.33]	[0.64]		[0.06]	[0.13]
Consumer Loans	0.38	-2.10*	**Consumer Loans**	-0.04	0.17
	[0.34]	[1.25]		[0.06]	[0.30]
Agricultural Loans	0.30	-1.14	**Agricultural Loans**	0.13*	-0.85***
	[0.42]	[1.15]		[0.07]	[0.30]
Loan Loss Reserve	-8.11*	-15.32	**Loan Loss Reserve**	0.44	-1.06
	[4.46]	[10.16]		[0.56]	[2.27]
Nonperforming Loans	8.24***	16.55***	**Nonperforming Loans**	0.44***	1.80***
	[1.10]	[3.35]		[0.15]	[0.63]
Interest Receivable	40.01***	38.74**	**Interest Receivable**	3.75***	12.71***
	[4.72]	[15.32]		[0.76]	[3.32]
Peak to Trough	3.51***	1.56***	**Peak to Trough**	0.25*	-0.11
	[0.71]	[0.39]		[0.14]	[0.08]
Unemployment Increase	0.04*	0.08**	**Unemployment Increase**	0.02***	0.015**
	[0.03]	[0.03]		[0.01]	[0.007]
Oil State Dummy	0.51***		**Oil State Dummy**	0.01	
	[0.10]			[0.02]	
Constant	1.64***	-1.31*	**Constant**	0.42***	0.70***
	[0.45]	[0.68]		[0.08]	[0.14]
Number of Observations	12,556	6,532	**Number of Observations**	774	304
Pseudo R2	0.39	0.31	**Adjusted R2**	0.21	0.26

Table 5 – Marginal analysis of failure rates

This table shows the effect on the failure rate from a one standard deviation increase in each independent variable when the failure rate is calculated using the mean values of the independent variables. Note that mean and standard deviation for the *Unemployment Increase*, *Peak to Trough*, and *Oil State* variables are all taken with respect to the sample of banks and not the sample of states, as is reported in Table 3. These values are as follows: For the early period, the mean and standard deviation of *Unemployment Increase* were 1.92 and 1.13, respectively. For *Peak to Trough* they were 0.042 and 0.057, respectively. For *Oil State* they were 0.199 and 0.399, respectively. For the later period, the mean and standard deviation of *Unemployment Increase* were 4.82 and 1.601, respectively. For *Peak to Trough* they were 0.133 and 0.108, respectively.

	Early Period	**Later Period**
Failure rate at means	1.31%	1.43%
Variable	Change in Failure Probability	
Size	-0.48	-0.14
Capital	-0.91	-0.49
Earnings	-0.22	-0.33
Core Deposits	-0.51	-0.58
Securities	-0.66	-0.18
1-4 Family Real Estate Loans	-0.29	0.01
Comm. Land Develop. Loans	0.35	2.38
Other Real Estate Loans	0.20	0.44
Comm. & Ind. Loans	0.47	0.33
Consumer Loans	0.10	-0.38
Agricultural Loans	0.10	-0.31
Loan Loss Reserve	-0.16	-0.21
Nonperforming Loans	0.67	0.56
Interest Receivable	1.06	0.67
Peak to Trough	0.85	0.74
Unemployment Increase	0.18	0.51
Oil State Dummy	0.85	

Table 6 – Early and later period HHI (Loan Concentration) models

Panel A shows results from the failure model, and Panel B shows results from the loss model. The loan concentration *Herfindahl-Hirschman Index* variable is included in the regression, replacing the six individual loan category variables. Variable definitions are provided in Appendix A. All financial variables are normalized by total assets with the exception of *Size*, which is defined by the natural log of total assets. Standard errors appear in brackets. Levels of significance are indicated by *, **, and *** for 10%, 5%, and 1%, respectively.

Panel A	(1)	(2)	Panel B	(3)	(4)
	Early Period Failure HHI	Later Period Failure HHI		Early Period Loss HHI	Later Period Loss HHI
Size	-0.09***	0.04	**Size**	-0.02***	-0.04***
	[0.02]	[0.03]		[0.004]	[0.01]
Capital	-14.91***	-3.64***	**Capital**	-0.14	-0.47*
	[1.36]	[1.11]		[0.22]	[0.25]
Earnings	-5.13***	-9.77***	**Earnings**	-0.09	1.27
	[1.72]	[2.76]		[0.25]	[0.95]
Core Deposits	-2.23***	-1.67***	**Core Deposits**	-0.25***	-0.12**
	[0.24]	[0.26]		[0.04]	[0.05]
Securities	-2.21***	0.13	**Securities**	0.03	-0.09
	[0.26]	[0.39]		[0.05]	[0.09]
Loan Concentration	0.92**	2.50***	**Loan Concentration**	0.32***	0.16***
	[0.40]	[0.24]		[0.08]	[0.04]
1-4 Family Real Estate Loans			**1-4 Family Real Estate Loans**		
Constr. Land Develop. Loan s			**Constr. Land Develop. Loan s**		
Other Real Estate Loans			**Other Real Estate Loans**		
Comm. & Ind. Loans			**Comm. & Ind. Loans**		
Consumer Loan			**Consumer Loans**		
Agricultural Loans			**Agricultural Loans**		
Loan Loss Reserve	-6.27	-12.29	**Loan Loss Reserve**	0.46	-1.06
	[4.40]	[8.73]		[0.55]	[2.17]
Nonperforming Loans	8.52***	15.22***	**Nonperforming Loans**	0.47***	1.74***
	[1.09]	[3.22]		[0.14]	[0.63]
Interest Receivable	41.45***	24.54***	**Interest Receivable**	4.14***	5.42***
	[3.83]	[9.31]		[0.63]	[1.76]
Peak to Trough	3.85***	1.99***	**Peak to Trough**	0.21	-0.10
	[0.70]	[0.36]		[0.14]	[0.08]
Unemployment Increase	0.03	0.05*	**Unemployment Increase**	0.02***	0.014*
	[0.03]	[0.03]		[0.005]	[0.007]
Oil State Dummy	0.54***		**Oil State Dummy**	0.01	
	[0.10]			[0.02]	
Constant	2.16***	-2.32***	**Constant**	0.38***	0.67***
	[0.45]	[0.54]		[0.08]	[0.11]
Number of Observations	12,556	6,532	**Number of Observations**	774	304
Pseudo R2	0.38	0.26	**Adjusted R2**	0.21	0.22

Table 7 – Decomposition results

This table shows the results from the decomposition exercise where the changes in estimated coefficients and independent variables between the two periods are used for both the failure and loss models to account for differences in failure rates and FDIC losses between the two periods. Panel A shows results for the failure rate, and Panel B shows results for the loss ratio. Rows (1) and (2) show predicted versus actual values for the early and later period datasets. Row (3) of both panels shows the value of the dependent variable when bank characteristics and economic shocks of one period are used in the other period model. Row (4) of both panels shows the value of the dependent variable when the bank characteristics of the earlier period and the macroeconomic characteristics of the later period are used in each period model. Row (5) of both panels shows the value of the dependent variable when the bank characteristics of the later period and the macroeconomic characteristics of the earlier period are used in each period model. For Panel B, loss ratios in Rows (2) – (5) are calculated by first calculating failure rates using the appropriate period model and then using the predicted failure rates to calculate the weighted sum of expected FDIC loss ratios.

Panel A – Failure rate

Probability of Failure	
1986-92	**2007-13**
6.16 (actual)	4.65 (actual)
6.14 (β_{85},x_{85})	4.63 (β_{06},x_{06})
7.59 (β_{85},x_{06})	1.59 (β_{06},x_{85})
7.65 (β_{85},$x_{85,}$ $macro_{06}$)	2.65 (β_{06},$x_{85,}$ $macro_{06}$)
3.64 (β_{85},$x_{06,}$ $macro_{85}$)	1.95 (β_{06},$x_{06,}$ $macro_{85}$)

Panel B – Loss ratio

All Banks

Loss Ratio	
1986-92	**2007-13**
19.27 (actual)	24.99 (actual)
19.36 (β_{85},x_{85})	25.03 (β_{06},x_{06})
31.41 (β_{85},x_{06})	35.07 (β_{06},x_{85})
26.19 (β_{85},$x_{85,}$ $macro_{06}$)	35.67 (β_{06},$x_{85,}$ $macro_{06}$)
19.87 (β_{85},$x_{06,}$ $macro_{85}$)	23.29 (β_{06},$x_{06,}$ $macro_{85}$)

Table 8 – Pooled failure and loss model

The table shows results from the failure and loss models. Panel A shows results from the failure model, and Panel B shows results from the loss model. Column (1) shows the regression results for the pooled failure model, and Column (2) shows the results for the pooled loss model. Variable definitions are provided in Appendix A. All financial variables are normalized by total assets with the exception of *Size* which is defined by the natural log of total assets. *Period Indicator* is equal to one for an observation in the early period and zero for the later period. Standard errors appear in brackets. Levels of significance are indicated by *, **, and *** for 10%, 5%, and 1%, respectively.

Panel A	**(1)**	**Panel B**	**(2)**
	Pooled Failure		**Pooled Loss**
Size	-0.09***	**Size**	-0.03***
	[0.02]		[0.004]
Capital	-9.11***	**Capital**	-0.26
	[0.94]		[0.17]
Earnings	-9.22***	**Earnings**	0.16
	[1.53]		[0.24]
Core Deposits	-1.83***	**Core Deposits**	-0.21***
	[0.18]		[0.03]
Securities	-1.48***	**Securities**	-0.04
	[0.24]		[0.05]
1-4 Family Real Estate Loans	-0.70**	**1-4 Family Real Estate Loans**	0.12**
	[0.30]		[0.06]
Constr. Land Develop. Loans	4.15***	**Constr. Land Develop. Loans**	0.28***
	[0.31]		[0.05]
Other Real Estate Loans	0.73**	**Other Real Estate Loans**	0.06
	[0.29]		[0.05]
Comm. & Ind. Loans	1.20***	**Comm. & Ind. Loans**	0.19***
	[0.29]		[0.05]
Consumer Loans	0.12	**Consumer Loans**	-0.05
	[0.32]		[0.06]
Agricultural Loans	-0.10	**Agricultural Loans**	0.07
	[0.38]		[0.07]
Loan Loss Reserve	-8.71**	**Loan Loss Reserve**	0.50
	[3.94]		[0.54]
Nonperforming Loans	9.42***	**Nonperforming Loans**	0.55***
	[1.03]		[0.14]
Interest Receivable	40.35***	**Interest Receivable**	3.77***
	[4.34]		[0.73]
Peak to Trough	2.19***	**Peak to Trough**	-0.10*
	[0.29]		[0.06]
Unemployment Increase	0.06***	**Unemployment Increase**	0.02***
	[0.02]		[0.004]
Oil State Dummy	0.65***	**Oil State Dummy**	0.05***
	[0.07]		[0.01]
Period Indicator	0.37***	**Period Indicator**	-0.02
	[0.09]		[0.02]
Constant	0.14	**Constant**	0.54***
	[0.38]		[0.07]
Number of Observations	19,088	**Number of Observations**	1,078
Pseudo R2	0.35	**Adjusted R2**	0.23

Table 9 – Heckman selection model

Heckman selection model for failure probability and loss ratio in both periods. The sample excludes *de novos* (defined as banks in existence for 20 quarters or less) and banks over our asset thresholds. Bank-specific financial ratios are measured in 1985:Q4 and 2006:Q4 respectively. Column (1) marks the Heckman selection regression results for the early period, Column (2) for the later period, and Column (3) for the pooled model. All variables are as defined in Appendix A. All financial variables are normalized by total assets with the exception of *Size* which is defined by the natural log of total assets. The variable, *Period Indicator*, is equal to one for an observation in the early period and zero for the later period. Standard errors appear in brackets. Levels of significance are indicated by *, **, and *** for 10%, 5%, and 1%, respectively. The loss equation represents the estimated loss upon failure, whereas the selection equation is a probit equation that predicts the probability that a bank will fail.

	(1)		(2)		(3)	
	1986-92		2007-13		Pooled	
	Selection Equation	**Loss Equation**	**Selection Equation**	**Loss Equation**	**Selection Equation**	**Loss Equation**
Loss						
Size	-0.15***	-0.01***	-0.03	-0.04***	-0.09***	-0.02***
	[0.03]	[0.004]	[0.03]	[0.01]	[0.02]	[0.004]
Capital	-15.17***		-3.98***		-9.11***	
	[1.39]		[1.21]		[0.94]	
Earnings	-5.08***		-11.21***		-9.22***	
	[1.74]		[2.83]		[1.53]	
Core Deposits	-2.00***	-0.20***	-1.75***	-0.08	-1.83***	-0.16***
	[0.25]	[0.04]	[0.29]	[0.06]	[0.18]	[0.03]
Securities	-1.80***	0.04	-0.37	-0.11	-1.48***	-0.03
	[0.28]	[0.06]	[0.55]	[0.07]	[0.24]	[0.04]
1-4 Family Real Estate Loans	-1.23***		0.01		-0.70**	
	[0.41]		[0.56]		[0.30]	
Constr. Land Develop. Loans	2.94***	0.08	4.52***	0.13	4.15***	0.12***
	[0.57]	[0.09]	[0.56]	[0.08]	[0.31]	[0.05]
Other Real Estate Loans	1.07**		0.96		0.73**	
	[0.44]		[0.54]		[0.29]	
Comm. & Ind. Loans	1.42***	0.14**	1.22*	-0.04	1.20***	0.13***
	[0.33]	[0.05]	[0.64]	[0.09]	[0.29]	[0.04]

Consumer Loans	0.38		-2.10*		0.12	
	[0.34]		[1.25]		[0.32]	
Agricultural Loans	0.30		-1.14		-0.10	
	[0.42]		[1.15]		[0.38]	
Loan Loss Reserve	-8.11*		-15.32		-8.71**	
	[4.46]		[10.16]		[3.94]	
Nonperforming Loans	8.24***		16.55***		9.42***	
	[1.10]		[3.35]		[1.03]	
Interest Receivable	40.01***	3.48***	38.74**	5.69***	40.35***	3.20***
	[4.72]	[0.65]	[15.32]	[1.69]	[4.34]	[0.59]
Peak to Trough	3.51***		1.56***		2.19***	
	[0.71]		[0.39]		[0.29]	
Unemployment Increase	0.04*		0.08**		0.06***	
	[0.03]		[0.03]		[0.02]	
Oil State Dummy	0.51***				0.65***	
	[0.10]				[0.07]	
Period Indicator					0.37***	-0.08***
					[0.09]	[0.01]
Constant	1.64***	0.45***	-1.31*	0.81***	0.14	0.63***
	[0.45]	[0.06]	[0.68]	[0.10]	[0.38]	[0.06]
Lambda	-0.04***		-0.04**		-0.04***	
	[0.01]		[0.02]		[0.01]	
Censored Observations	11,782		6,228		18,010	
Uncensored Observations	774		304		1,078	
Wald Statistic	66.29		70.68		188.49	

Table 10 – Heckman loss equation and OLS loss equation for both periods

The loss equation in the Heckman model is compared to an OLS regression that uses the variables in the Heckman loss equation. Column (1) shows the regression results for the early period, Column (2) for the later period, and Column (3) for the pooled model. Variable definitions are provided in Appendix A. All financial variables are normalized by total assets with the exception of *Size*, which is defined by the natural log of total assets. The variable, *Period Indicator*, is equal to one for an observation in the early period and zero for the later period. Standard errors appear in brackets. Levels of significance are indicated by *, **, and *** for 10%, 5%, and 1%, respectively.

	(1)		**(2)**		**(3)**	
	1986-92		**2007-2013**		**Pooled Model**	
	Loss Equation Heckman	**Loss Equation OLS**	**Loss Equation Heckman**	**Loss Equation OLS**	**Loss Equation Heckman**	**Loss Equation OLS**
Loss						
Size	-0.01***	-0.02***	-0.04***	-0.04***	-0.02***	-0.02***
	[0.004]	[0.004]	[0.01]	[0.01]	[0.004]	[0.004]
Securities	0.04	-0.05	-0.11	-0.14*	-0.03	-0.10**
	[0.06]	[0.05]	[0.07]	[0.07]	[0.04]	[0.04]
Core Deposits	-0.20***	-0.25***	-0.08	-0.13***	-0.16***	-0.21***
	[0.04]	[0.04]	[0.06]	[0.05]	[0.03]	[0.03]
Constr. Land Develop. Loans	0.08	0.16*	0.13	0.25***	0.12***	0.24***
	[0.09]	[0.09]	[0.08]	[0.05]	[0.05]	[0.04]
Comm. & Ind. Loans	0.14**	0.19***	-0.04	-0.03	0.13***	0.17***
	[0.05]	[0.05]	[0.09]	[0.09]	[0.04]	[0.04]
Interest Receivable	3.48***	4.76***	5.69***	5.56***	3.20***	4.41***
	[0.65]	[0.58]	[1.69]	[1.70]	[0.59]	[0.54]
Period Indicator					-0.08***	-0.05***
					[0.01]	[0.01]
Constant	0.45***	0.43***	0.81***	0.74***	0.63***	0.57***
	[0.06]	[0.06]	[0.10]	[0.10]	[0.06]	[0.05]
Adjusted R-Squared		0.16		0.21		0.19

Appendix A – Variable Definitions

Description, derivation, and sources for all variables used in the analysis. Financial variables are from the Call Reports and the macroeconomic variables were collected from Haver Analytics. All ratio variables are normalized by total assets for the purpose of keeping a consistent denominator throughout. The data used to create the *Loss Ratio* come from the FDIC's Historical Statistics on Banking.

Variable Name	**Description**	**Variable Derivation from Source**	**Source**
Agricultural Loans	Agricultural loans divided by total loans and leases net of unearned income	rcfd1590 / rcfd2170	Call Report
Capital	Bank equity divided by assets	rcfd3210 / rcfd2170	Call Report
Cash	Interest-bearing balances, noninterest-bearing balances and securities with remaining maturity of one year or less, divided by assets	(rcfd0081 + rcfd0071 + rcfda248)/rcfd2170	Call Report
Commercial and Industrial (C&I) Loans	Commercial and industrial loans divided by total assets	rcon1766 / rcfd2170	Call Report
Construction and Land Development (CLD) Loans	(Domestic) construction and land development loans divided by total assets	rcfd1415 / rcfd2170	Call Report
Consumer Loans	Credit card and other consumer loans divided by total loans and leases net of unearned income	(rcfd2008 + rcfd2011) / rcfd2170 in early period and (rcfdb538 + rcfdb539 + rcfd2011)/rcfd2170 in later period	Call Report
Core Deposits	Core deposits (gathered in a bank's demographic area) divided by total assets	(rcon2215 + rcon6810 + rcon6648)/rcfd2170 in early period and (rcon2215 + rcon6810 + rcon0352 + rcon6648)/rcfd2170 in later period	Call Report
Denovo	Equal to 1 if less than or equal to 20 quarters since birth of bank; 0 otherwise		Call Report
Earnings	Net income divided by assets	riad4340 / rcfd2170	Call Report
Farmland	Real estate loans secured	rcon1420	Call Report

	by farmland		
Federal Home Loan Bank (FHLB) Advance	FHLB advances divided by assets	(rcfdf055 + rcfdf056 + rcfdf057 + rcfdf058) / rcfd2170 or (rcfd2651 + rcfdb565 + rcfdb566)/rcfd2170 prior to 2006Q3	Call Report
Interest Receivable	Accrued interest receivable divided by total assets	rcfd2164 / rcfd2170 in early period and rcfdb556/rcfd2170 in later period	Call Report
Loan Concentration	Herfindahl-Hirschman index calculating concentration in a given loan type	(*CLD Loano*^2)+(*C&I Loan*^2)+(*Agricultural Loans*^2)+(*Consumer Loans*^2)+(*1-4 Family Real Estate Loans* ^2) + (*Other Real Estate Loans*^2)	Call Report
Loan Loss Reserves	Allowance for loan and lease losses plus allocated transfer risk reserves divided by assets	rcfd3123 / rcfd2170 in early period and (rcfd3123 + rcfd3128)/rcfd2170 in later period	Call Report
Loss Ratio	Estimated losses to the FDIC divided by net assets of bank at time of failure	FDIC Estimated Losses / FDIC Total Assets	FDIC Historical Statistics on Banking
Multifamily	(Domestic) real estate loans backed by multifamily residential properties divided by total assets	rcon1460 / rcfd2170	Call Report
Nonaccrual Loans	Nonaccruing loans, divided by total assets	rcfd1403/rcfd2170	Call Report
Nonfarm and Nonresidential Loans	(Domestic) real estate loans backed by nonfarm nonresidential properties divided by total assets	rcon1480 / rcfd2170	Call Report
Nonperforming Loans	Loans 90 or more days past due plus nonaccrual loans, divided by assets	(rcfd1407 + rcfd1403) / rcfd2170	Call Report
Nonperforming Asset Coverage ratio (NPACR)	Capital plus reserves minus nonperforming assets, divided by total assets	(rcfd3210 + rcfd3123 -(rcfd1403 + rcfd1406 + rcfd1407 + rcfd2150))/rcfd2170	Call Report
Oil State	Equal to one if the oil and gas extraction share of		Bureau of Economic

	Gross State Product is higher than 15% in the early period		Analysis
1-4 Family Real Estate Loans	(Domestic) real estate loans backed by 1-4 family residential properties divided by total assets	rcon1430 / rcfd2170	Call Report
Other Real Estate Owned Ratio (OREO)	Other real estate owned, divided by total assets	rcfd2150/rcfd2170	Call Report
Other Real Estate Loans	*1-4 Family Real Estate* Loans ratio and *CLD.Loans* ratio subtracted from *Total Real Estate Loans* ratio	rcfd1410/fcfd2170- rcfd1415 / rcfd2170 - rcon1430 / rcfd2170	Call Report
Past Due Loans	Loans 90 or more days past due, divided by assets	rcfd1407/rcfd2170	Call Report
Peak to Trough	The largest percentage drop in the house price index within each state over any subperiod within each period.	Note: if house prices did not drop over a time period then this variable is coded as zero.	FHFA HPI Data
Total Real Estate Loans	Loans secured by real estate	rcfd1410/rcfd2170	Call Report
Securities	The book value of all held-to-maturity securities plus the fair value of all available-for-sale securities, divided by assets	rcon0390 / rcfd2170 in early period and (rcfd1754 + rcfd1773)/rcfd2170 in later period	Call Report
Size	The natural logarithm of a bank's assets	ln(rcfd2170)	Call Report
Unemployment Increase	Largest increase in unemployment in each state for any subperiod over each period		U.S. Bureau of Labor Statistics
Unstable Funding Ratio	(Domestic) time deposits of $100,000 or more divided by total assets	rcon2604 / rcfd2170	Call Report