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Abstract

Two of the most significant banking reforms to come out of the banking problems in the late 1980s and early 1990s were the increase in capital requirements from Basel 1 and the prompt corrective action (PCA) provisions of the Federal Deposit Insurance Corporation Improvement Act of 1991 (FDICIA). The PCA provisions require regulators to shut down banks before book capital becomes negative. We compare failures and FDIC losses on commercial banks in the pre-FDICIA commercial bank crisis of the mid-1980s to early 1990s with that in the recent financial crisis. Using a sample of community and mid-sized banks, we find that almost all the same bank characteristics predict failure and high losses in the two crises. Our results imply that for these classes of banks, the two crises were very similar. We find that the failure rate in the recent period was driven more by severe economic conditions than by the increased concentrations in real estate lending. The analysis suggests that the combination of PCA with higher capital levels helped reduce failure rates in the recent period. In contrast, the analysis suggests that the reforms did not help with FDIC losses. FDIC losses on failed commercial banks were approximately 14% of failed bank assets over the 1986-92 period, but increased to approximately 24% over the 2007-13 period. We find that the increased losses are not explained by variations in bank balance sheets or local economic conditions. Finally, we find that a discretionary accounting variable, interest accrued but not yet received, is predictive of both failure and higher FDIC losses.

Keywords: bank regulation, bank failures, Prompt Corrective Action, FDIC losses

JEL codes: G21, G28

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1. Introduction

From the mid-1980s to the early 1990s, the United States experienced a severe commercial banking crisis. There were 998 bank failures between 1986 and 1992 (see Figure 1). Of non-*de novo* banks in existence at the end of 1985, those holding 5.4% of bank assets and 6.0% of bank deposits failed and went through Federal Deposit Insurance Corporation (FDIC) receivership over this same period.[1]

Two of the more significant banking reforms that came out of this period were the increased regulatory capital requirements of Basel 1 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 1 by requiring bank supervisors to take certain actions against a bank if its regulatory capital drops below certain thresholds. The purpose of PCA was to force supervisors to intervene in the operations of a bank and even shut it down, if necessary, before a bank becomes too severely distressed. These provisions were motivated by the heavy use of forbearance by thrift and bank supervisors in the 1980s and the belief that this forbearance increased the losses to the FDIC, and ultimately taxpayers, from failed banks and thrifts.

Despite these reforms, the recent financial crisis severely impacted commercial banks. There were 403 failures over 2007 to 2013 (see Figure 1). Of non-*de novo* banks in existence as of the end of 2006, those holding 2.2% of bank assets and 3.1% of deposits went through FDIC receivership between 2007 and 2013.[3]

Of banks that failed, FDIC losses were large in both periods but significantly larger in the later period. Over 1986-92, the FDIC's losses on failed banks were nearly 14% of these banks' assets net of book equity.[4] Yet, despite the implementation of PCA, the FDIC's losses on failed banks over the period 2007-13 were significantly higher, approximately 24% of these banks' assets net of book equity.

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[1] These fractions were calculated by using as our denominator total commercial bank assets at the beginning of the period and then using as the numerator the assets or deposits of a failed commercial bank at the beginning of the period.
[2] Basel I and FDICIA were implemented in the early 1990s after the bank failures in our 1986-92 sample.
[3] Citibank received assistance in the form of loss protection in 2008, while similar protection was developed for Bank of America in early 2009 but never implemented. Neither of these large banks went through receivership, so they are not included in the numerator. For this reason, if we just consider the smaller banks in our sample, the numbers would be higher.
[4] 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. In the paper, we will typically refer to this as the adjusted loss ratio.

This paper compares commercial bank failures and FDIC losses on failed banks over these two crises. We use a sample of established community and mid-sized banks. We exclude large banks and *de novo* banks because they have different characteristics than other banks and, in the case of large banks, some of them received substantial government assistance that prevented their failure.

Our approach is to use bank characteristics in 1985 and 2006, right before each crisis fully developed, to estimate failure probabilities and FDIC losses over each period. By doing this, our estimation strategy can be seen as analyzing how banks, as defined by their characteristics, respond to a set of severe financial shocks. We estimate a regression model for both periods that identifies bank factors and state-level economic conditions that are related to bank failure and the size of FDIC losses. We use a Heckman selection model because, in addition to being interested in failure probability estimates in each period, we want to account for selection effects when modeling FDIC losses from failed banks. We then compare the two periods.

One of the biggest differences between the two periods is the increased concentration in commercial real estate lending and construction and land development lending (CLD) among community banks in the recent period. We analyze the degree to which these and other changes to bank characteristics account for differences in failure rates and FDIC losses by running several counterfactual experiments. In one, we take the characteristics of banks in 1985 Q4 and evaluate failure probabilities and FDIC losses conditional on failure using the estimated model for the 2007-13 period. In another, we do the converse.

We find that failure probabilities are most influenced by macroeconomic conditions. Banks with the characteristics of those in 1985 Q4 would have failed at a much higher rate if subject to the state-level economic shocks of 2007-13. Similarly, banks with the 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 effects on bank failures from the changes in bank balance sheets, but these effects are much smaller. We find that the higher capital levels of banks in 2006 Q4 offset the increased risks from concentrated real estate lending. The analysis suggests that the combination of PCA with higher capital levels helped reduce the failure rate. It also suggests that community and mid-size banks were not necessarily excessively risky going into this crisis.

In contrast, we find very little effect of changes in bank characteristics or state-level economic conditions on the size of FDIC losses. In our counterfactual exercise, losses would have been large in the 2007-13 period even if banks had not been so concentrated in CLD lending and looked like they did in 1985.

While our interpretation of the counterfactual exercise is that PCA is not directly related to the size of the losses, the analysis also shows that PCA was ineffective along this dimension. One purpose of PCA was to shut down a failing bank before its losses got too big, and on this dimension it failed. We argue that PCA was doomed to fail because of two interacting factors: 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 capital was still positive, as PCA requires. However, given that in this sample the market value of a failed bank's assets are typically anywhere between 75% and 85% of book value during a crisis, a failed bank simply does not have enough capital to absorb losses without calling on the deposit insurance fund.

A necessary condition for these losses to be so high, when book values are not negative, is that the book accounting values of a failed bank's assets dramatically exceed their economic value. Along these lines, we find that an accrual accounting variable, interest accrued but not yet received, significantly predicts bank failure and FDIC losses in both periods.[5]

One of our striking findings is that the two crises have very similar qualitative effects. Virtually the same variables predict failures in both periods, though the sizes of the estimates differ. We find that construction and land development (CLD) lending increases the failure probability in both periods, but it is insignificant for losses. Commercial and industrial (C&I) lending has the same effect. Bank size lowers losses in both periods, while it lowers the failure probability in the later period. Capital reduces the failure probability in both periods. Securities holdings also lower failure probabilities, while also lowering losses in the later period. Not surprisingly, core deposits lower failure probabilities and lower losses in the early period. Economic conditions have the expected effects. We find that state real estate conditions and increases in unemployment predict failure in both periods. Similarly, non-performing loans and non-CLD commercial real estate lending predict failure in both periods. Residential lending is only significant in the earlier period, lowering the failure probability.

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

[5] Bovenzi and Murton (1988), James (1991), and Osterberg and Thomson (1995) looked at this variable using samples that overlap with our 1986-92 period, but they only examined FDIC losses and not bank failures.

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. 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 Review

Our strategy is to use a Heckman selection procedure (Heckman, 1979) to jointly estimate the probability of bank failure and the losses to the FDIC conditional on failure. The empirical literature has typically looked at these separately.

Much of the literature that looks at FDIC losses on failed banks is based on data samples from the 1980s and early 1990s. Using a sample of failed banks from 1985 and 1986, Bovenzi and Murton (1988) regressed the 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.

More recently, Bennett and Unal (2014) examined FDIC losses over the 1986 to 2007 time period. The question they are interested in is the effect of the type of FDIC resolution on FDIC losses. On average, FDIC losses on private-sector reorganizations are less than those on failed banks that it liquidates. However, once they control for selection bias, they find that during periods of industry distress private-sector reorganizations of a failed bank are costlier than liquidation, while during normal time periods this result is reversed.

The second relevant literature is on the causes of the bank failure. 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 are unrelated to bank survival time. Whalen (1991) estimated a proportional hazards model of bank failure and, unlike the other papers, found that commercial real estate was insignificant, though this may be because all types of commercial real estate lending were lumped together in that analysis.

Less work has been done on the causes of bank failures in the recent crisis. Cole and White (2012) analyze Call Report data from 2004 to 2008 in order to determine the factors that led to bank failures in 2009. They find that commercial real estate lending, particularly in the area of construction and development, is a strong early predictor of bank failure. Noting that this result is consistent with research on earlier bank failures, the authors stress the importance of differentiating between commercial and residential real estate when evaluating a bank's portfolio and using these data in conjunction with CAMELS ratings to assess commercial bank risk. GAO (2013) also emphasizes 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. A paper that looks at geographic factors is Aubuchon and Wheelock (2010). They find that failure was also connected to regions with distress in real estate markets and declines in economic activity. Jin, Kanagaretnam, and Lobo (2011) examine the role of auditing quality in predicting bank failure. They find that a bank audited by reputable auditors has a lower probability of failure. This finding is in line with our interest in accounting lags in the recognition of true bank conditions.

Our paper builds on these two literatures – one looking at reasons for failure and the second looking at FDIC losses – by jointly estimating a model of failure and losses, conditional on failure. A model that considers both kinds of effects is needed to evaluate the effectiveness of PCA.

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, which will either be the Office of the Comptroller of the Currency for nationally chartered banks or its state regulator for state-chartered banks. 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.[6]

Once a bank is in the hands of the FDIC, the FDIC has several means of disposing of it, though 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 or liquidate it. In the former, this can be done 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.[7] 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 out to the bank's claimants, including the FDIC. For more details on how bank failures are resolved, see FDIC (1998) and Bennett and Unal (2008).

The most common type of transaction, particularly during the recent crisis, is a purchase and acquisition (P&A) transaction. In this kind of transaction, the acquiring bank assumes either all or some of the failed bank's liabilities and purchases all or some of the failed bank's assets. Any assets that are left after a P&A transaction are managed and then sold over time by the receivership. One feature of many P&A transactions, particularly in the first few years of the

[6] See Spong (2000) for a description of PCA.
[7] The FDIC can also provide open-bank assistance, which keeps the existing bank operating. Since 1992 this 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.

recent crisis, is the use by the FDIC of loss share agreements. These agreements leave a set of assets in the hands of the acquiring bank and the FDIC takes on or shares in losses on these assets that exceed some threshold.

The cost to the FDIC is essentially the negative of the market value of a bank (see Bennett and Unal (2008) for more details) and the market value of a failed bank is

Market value of assets – deposit liabilities + franchise value – receivership costs,

where the franchise value represents the value to an acquiring bank of intangibles like core deposits or a branch network.

The loss reported depends on what the FDIC can sell a bank for as well as how much is paid to depositors. In all of these transactions, the FDIC paid off insured depositors in whole.[8] What a bank is willing to pay for a failed bank or part of a failed bank depends on a lot 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.

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

Table 1 reports FDIC losses on commercial banks 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 24% while un-weighted losses are 30%. There is clearly a size effect as losses decline if observations are weighted by assets of the failed bank. Similarly, there is a *de novo* effect in that these 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.

[8] 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 non-interest bearing deposit transaction accounts.

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 where the distribution of losses looks more symmetric. In both periods, however, there are some banks with losses that exceed 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 -1.5%. It was this kind of observation, along with the high losses, that contributed to devising the PCA provisions. In contrast, the average capital of failed banks in the 2007-13 period was positive, about 1.5%, 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 an extra 3% of equity capital at time of failure did not provide much of an extra buffer to absorb losses.

4. Changes in Bank Activities

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 bank assets expressed as a percentage of assets for banks that failed. Non-farm, non-residential 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. A similar qualitative pattern is observed to that of failed banks, but the quantitative changes are much smaller. For example, CLD lending only increased from 2% to 7% of assets.

The literature has found that commercial real estate and CLD lending, in particular, increase the chance of bank failure, so it is possible that the increase in losses between the two periods was driven by this change in bank characteristics. In the following analysis, we will use our statistical models to evaluate this conjecture.

5. Data and Sample Construction

We examine commercial bank failures in the periods 1986-92 and 2007-13.[9] There were a total of 998 and 403 failures in those periods, respectively. In our main specifications, we model a subsample of 713 and 306 failures in each respective period because we exclude large banks and banks that were in *de novo* status in 1985 Q4 and 2006 Q4 or were started during the sample periods.

We set a threshold for large banks in the later period at $50 billion of assets. We chose this level because it is the threshold at which regulators will consider a bank systemically important. For the earlier period, we deflate this threshold by the growth in bank assets from 1985 Q4 to 2006 Q4 to get a threshold of $14.8 billion of assets.[10]

With general agreement among analysts that the crisis began in the second quarter of 2007, the 2006 Q4 date is a natural date to use before the start of the recent financial crisis. For the previous banking crisis, we use 1985 Q4 as our starting point because the FDIC does not report losses prior to 1986.[11] We use quarterly Reports of Condition and Income (Call Report) that banks file with their regulators.[12] These regulatory reports provide detailed information on the size, capital structure, and asset and liability composition of each commercial bank. We merge this sample with the FDIC's Historical Statistics on Banking (HSOB) dataset, which includes information on the dollar amount of estimated losses to the FDIC from bank failures.[13] In this paper, all loss estimates to the FDIC are as of December 31, 2013.[14] Note that, as is the case with most papers in the literature, we use loss estimates. The 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.[15] Driven by the importance of real estate lending for our empirical setup, we use

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[9] We do not consider failure of savings and loans, savings banks, or credit unions.
[10] Only one failed bank is excluded because of these thresholds. Republic Bank of Dallas had $15.8 billion of assets in 1985 Q4.
[11] There were numerous bank failures before 1986, but there were fewer in those years than in 1986. The year with the most number of failures is 1988.
[12] As reported to the Federal Reserve Board by the FFIEC 031 and 041 reporting forms.
[13] We filter the FDIC's historical loss data by "charter type" commercial banks. We examine failures within the United States proper only (i.e., excluding Puerto Rico and other territories).
[14] The FDIC updates losses on an annual schedule, in December of each year. The Failures and Assistance Transactions database is updated as needed, with the most recent update occurring in December 2014. The data for this paper was gathered in September 2014.
[15] 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.

Corelogic's Home Price Index (via Haver Analytics) to create a measure of real estate conditions during each period.[16]

Our dependent variable ("adjusted loss ratio") is the ratio of the cost to the FDIC of a given bank's failure divided by that bank's consolidated assets at the time of failure, net of its book equity.[17,18] Following the literature and applying knowledge from bank supervisory practices, we select a number of balance sheet and income statement variables to reflect the business model and financial condition of each institution in our sample.

Our baseline regressions are based on a Heckman selection model with bank-specific financial ratios measured at the beginning of the period, so failure probability and FDIC losses occurring any time within the period are explained by financial fundamentals measured in 1985 Q4 and 2006 Q4 for the early and later period, respectively. As described in the introduction, *de novo* banks have different fundamentals and resolution costs so we exclude them from the main analysis. We conduct our main regression analysis on two samples of established banks that were in existence at the beginning of each sample period. For the early period, we take established banks that filed a Call Report in 1985 Q4. For the second period, we take established banks that filed a Call Report in 2006 Q4. These criteria result in a regression sample of 12,658 at the end of 1985, of which 713 failed by 1992. The later period regression sample includes 6,590 banks at the end of 2006, of which 306 failed by the end of 2013. Exact definitions and sources of the variables are included in Table 3. Summary statistics of the samples used in these baseline regressions are reported in Table 4.

The bank *Size* variable is represented as the natural logarithm of a bank's assets, measured in thousands. The *Capital Ratio* variable reflects shareholder's equity and is normalized by assets. The *Securities Ratio* is created by adding the book value of all held-to-maturity securities for the early period (normalized by assets). Because the fair value of all available-for-sale securities is reported since 1992 only, the later period reflects this addition. The *Earnings Ratio* is created by dividing net income by total assets.

We use a number of real estate lending measures in this study. The *Construction and Land Development Loan Ratio* is total construction and land development loans divided by total

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[16] We match the HPI data to each respective bank by the state in which the bank is headquartered.

[17] 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. It is not clear why this discrepancy occurs, but we opted to drop the banks in which it occurred for consistency.

[18] 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 it failed.

loans. The *1-4 Family Real Estate Loan Ratio* is represented by real estate loans secured by 1-4 family residential properties divided by total loans. With CLD and 1-4 family residential lending measured separately, the O*ther Real Estate Ratio* 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.[19]

The *Commercial and Industrial Loan Ratio* is measured as the sum of commercial and industrial loans to both U.S. and non-U.S. addressees divided by total loans. The *Agricultural Loans Ratio* is represented by loans to finance agricultural production divided by total loans. The *Consumer Loan Ratio* is constructed differently in both periods due to differences in Call Reports. In the early period, it is represented by the sum of credit cards and related plans and other loans. In the later period, the ratio 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. We also construct ratios that measure a bank's asset quality. The *Non-Performing Loans Ratio* is calculated by adding loans that are *90+ Days Past Due* to *Non-Accrual Loans* and dividing by total assets.

Turning to liabilities, the *Core Deposit Ratio* is measured differently in both periods. In the early period, the variable was constructed by dividing the sum of total transaction accounts, money market deposit accounts, and total time deposits less than $100,000 divided by total deposits. The later period is the same variable specification with the exception of the addition of other non-transaction savings deposits (excluding money market deposit accounts). The *FHLB Advance Ratio* is only reported for the later period and measures the sum of FHLB advances with a remaining maturity or next re-pricing date of one year or less, one to three years, and over five years divided by total liabilities and minority interest.

We use two variables that capture loan accounting discretion on the part of bank management: interest receivables and loan loss reserves. The first variable is a balance sheet measure of interest income that is accrued but not yet 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.[20] For our

[19] The main components of other real estate are *multi-family real estate* loans, which are secured by multi-family residential properties divided by total loans, and *non-family/non-residential loans*, which cover properties like hotels, churches, hospitals, golf courses, and recreational facilities. (This excludes loans for property and land development purposes, which mature in 60 months or less.)

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

purposes, we take these assets and divide them by total assets to obtain what we call the *Interest Receivable Ratio*. The second accounting variable is the *Loan Loss Reserve Ratio*, which is defined as the allowance for loans and leases divided by total loans and leases, 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.

We use two variables that measure local economic performance. The first is *Peak to Trough*, which is a constructed measure of deteriorating real estate conditions in the state in which each bank is headquartered. It is calculated by subtracting the state minimum from the state maximum Corelogic Home Price Index value, as reported by Haver Analytics, and dividing by the minimum. This calculation is only made for states where the maximum point came before the minimum. It is coded with a value of zero for states that experienced no decline in house prices. This variable measures whether there was a drop in house prices in any sub-period of each period and, if so, what the largest such percentage drop was. This measure is particularly useful in the earlier period because house prices declined in 12 states, located primarily in the East Coast and oil-producing regions, but they did not decline at the same time. For the later period, 2006 house prices were the peak or close to the peak for most states and then dropped significantly for all states except North Dakota.

The second variable that we use to measure local economic performance is *Unemployment Increase*, which measures deterioration in labor markets in the state in which each bank is headquartered. In particular, we take the difference between the maximal and minimal unemployment rate over the period at the state level, conditional on the maximal unemployment occurring after the beginning of the period. If a state's unemployment level only decreased over the period then it is coded as a zero.

6. Regression Results and Analysis

We estimate the same model across the two periods. This increases the chance of omitted variables in the analysis. Nevertheless, we adopted this strategy in order to compare the periods closely and to allow for the counterfactual exercises.

Given the potential correlation between failure and losses given failure, we use a Heckman selection model as our empirical strategy. The main regression results shown in Table 5 are from a two-step estimator. The selection problem arises because losses to the FDIC are observed only for banks that fail. 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. 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 measure the financial condition of each bank at the beginning of the period studied (1985 Q4 and 2006 Q4, respectively). There are two advantages to this approach. First, a bank's characteristics can change leading up to failure as it sells assets and changes its funding profile. Second, the Heckman approach lends itself naturally to estimation of a cross-section selection model. The disadvantage to this approach is that condition is often measured several years before failure and time to failure varies across banks. Ideally, our estimation would occur in a cross-sectional time-series setting. However, there are very few observations of failure-quarters relative to quarterly observations for all banks in each period for this to be viable.[21] We pool failures in each period and model the two samples separately. We use a limited set of explanatory variables in order to maintain consistency across the two periods, to be able to compare the effects, and to better serve the counterfactual exercises in the next section. In some cases, notably the use of FHLB Advances, we are limited because of differences in reporting between the two periods.[22]

For our selection equation, we use all the variables previously described. 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 use a more parsimonious model of determinants of losses to the FDIC. We focus on size, security holdings, CLD lending, C&I lending, core deposits, and the interest receivable variable. A potential limitation of the loss-ratio regression is that we are not measuring determinants of the demand for failed bank assets and deposits, nor are we controlling for 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. 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. We also include two types of lending that have

[21] We were not able to achieve convergence in Stata when using panel Heckman estimation.
[22] When we include FHLB Advances in our robustness work, we find that in the later period this source of wholesale funding is not statistically significant for predicting failure. When a bank is put in receivership, the FDIC pays the FHLB in whole, so we also added them to the loss equation. Again, the variable was not significant. For this reason, these results are not reported.

been shown elsewhere in the literature to be associated with asset quality problems, commercial and industrial lending, and commercial real estate lending (including its components).

We exclude a variety of variables from the loss equation. However, the excluded variable that we consider for our exclusion restriction is the *Capital Ratio*. While it is certainly correlated with failure probability because regulators shut a bank down when this ratio gets low, it 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.

We use two variables that capture the severity of economic conditions. The first is our *Peak to Trough* variable, which measures declines in house prices. The second is *Unemployment Increase*, which measures increases in the unemployment rate. Both are measured at the state level and associated with a bank by the state where the bank is headquartered. We find that the coefficient on each is positively correlated with bank failure.

We include three real estate lending variables. Based on historical experience, 1-4 family residential lending was treated by banks and their supervisors as a safe type of lending entering the financial crisis. Consistent with this view, in the earlier period, its coefficient on the selection regression equation is negative and significant. In the later period, it is positive but not statistically significant. *CLD Loan Ratio* enters both the selection and outcome stages and has differing effects across the two stages. In both periods, higher CLD concentration is positively associated with failure and is statistically significant. It is not, however, statistically significant in the loss equations and the sign is even negative in the earlier period. The *Other Real Estate* concentration ratio is also positively associated with failure and is statistically significant.

The *C&I Loan Ratio* looks like the *CLD Loan Ratio* in that it is statistically significant and positively associated with failure. While positive, it is insignificant, however, for the loss equations. 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 both periods. The coefficient in the loss regression is only statistically significant in the later period (although note that the fair value of available-for-sale securities is only used in the definition of this variable in the later period).

Higher core deposits reduce failure probabilities in both periods and reduce losses in both periods, though the coefficient on the loss equation is only significant in the later period. A higher *Capital Ratio* is, unsurprisingly, related to a lower probability of failure. However, the *Loan Loss Reserve* variable, while negatively associated with failure, is not statistically significant. For *Size*, we find it is negatively associated with failure but only statistically significant in the earlier period. 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 productivity are as expected. The *Earnings Ratio* is negatively associated with failure and statistically significant. Similarly, a higher *Non-Performing Loan* ratio is positively associated with failure and is statistically significant in both periods.

A variable that is highly predictive of failure and losses is the *Interest Receivable Ratio*. Reported as "Interest earned but not collected" in Call Reports of the earlier period, this variable refers to interest payments due for loans (in all loan categories) that are accruing interest.[23] The size of this variable reflects two factors. The first factor is payment structure. For example, one loan could be due on 7/15 and another on 7/31. Different due dates would then result in different reported accrued interest for these two loans even if the only way in which they differed was the payment date. Furthermore, some commercial loans have an extended payment period (quarterly or twice a year). All else equal, a bigger share of these loans would result in a bigger interest earned but not collected variable.

The second factor is accounting discretion. A bank has some leeway in its accounting treatment of loans, so an asset that is not being repaid could be treated as accruing income when its probability of default has gone up. In this case, the size of the *Interest Receivable Ratio* reflects loans that, in the future, would probably end up in non-accrual status. When a loan moves to non-accrual status, the interest should be backed out of the "interest earned but not collected" asset so this variable will mechanically drop in value in that quarter's Call Report filing. It is possible then that this variable would be correlated with future non-accrual loans.

In separate analyses, we examined the correlation between the lagged values of the *Interest Receivable Ratio* and loans that are *Non-Accrual* and loans that are *90 Days Past Due*, the two components of our *Non-Performing Loan Ratio*. In the 1986-92 period, we found that there was a positive correlation of 0.21 between *Non-Accrual* and *Interest Receivable Ratio* lagged at eight quarters. This correlation stays positive but declines with the number of lags and

[23] 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.

is 0.12 for the contemporaneous correlation. The correlation between *90 Days Past Due* and *Interest Receivable Ratio* is 0.20 at eight quarters and increases to 0.28 for contemporaneous correlation. Interestingly, correlations are different in the later period. The correlation is around -0.10 with *Non-Accrual* for all the lags, while it is about 0.15 with *90 Days Past Due* for all the lags. It seems that there are different dynamics with this variable in the two periods even though it is highly significant in the regression model for both periods.

Although the economic significance of the coefficients cannot be interpreted directly from Table 5, statistical significance and the direction of the effects can be compared across the two periods. To summarize, the results reported in Table 5 are directionally in line with expectations and qualitatively similar across the two periods for several regressors. It is striking that, although we are measuring the structure of the balance sheet and the performance of the bank long before failure for a large portion of the failed banks, we still find strong statistical significance. Management's decisions on the structure of the balance sheet made long before the crisis have significant influence on outcomes during the crises.

In Table 6, 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 the second period coefficients are not significant for standard loss determinants as compared to OLS, suggesting that in regular OLS analysis (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.

To interpret the economic significance of the coefficients, we calculate marginal effects. The selection equation is a probit equation, which is nonlinear, so marginal effects cannot be directly computed from the coefficients. Instead, we follow the literature and evaluate marginal effects at the mean values of the independent variables. However, for failure rates, rather than reporting the marginal effect from an infinitesimal change in a variable, we calculate the effect of increasing each independent variable, holding the other variables at their means, by one standard deviation.

Table 7 reports these effects. First, note that in the first row the failure probabilities evaluated at the mean, in both periods, are slightly more than 1%, which is much less than what is observed in the data. The reason for this is that failure probabilities are much higher for banks with large deviations from the mean for certain variables.

The calculated marginal effects can be substantial at the mean values. In the earlier period, the largest effect is increasing the *Interest Receivable* variable by one standard deviation. The house price index also has a substantial effect. Both increase the failure probability by over 100 basis points. Also important is capital, which reduces the failure probability by 82 basis points. In the later period, the largest effects are from the real estate variables. The *CLD Loan* variable has a particularly big effect, raising failure rates by 412 basis points, while *Other Real Estate* raises it by 176 basis points.

For the loss equation, the reported marginal effects are conditional on the loss observation taking a positive value, with values of the remaining explanatory variables held constant at their means. If a variable enters both estimation stages, that variable's combined effect is reported; the direct effect to the loss variables and the indirect effect through selection. This is because a change in an independent variable not only affects the size of the loss ratio but also the probability that an observation is in the sample. Here, we provide a different unit of measurement than for the failure probability. In particular, we calculate the effect of the marginal change by multiplying the marginal change to losses from the independent variable by its standard deviation and then dividing it by the mean value of losses for the period. The advantage of this calculation is that it allows for comparison across the two periods.

Table 8 reports these marginal effects. These effects are all relatively small. For example, in the earlier period, a one standard deviation increase of the *Interest Receivable Ratio* is associated with an increase of the loss ratio by only 0.65%. The corresponding effect for the later period is a similarly small 0.53%. In the later period, CLD lending gets up to a still small 1.82% increase in the loss ratio. In future work, we will check whether measuring the marginal effects at distributions other than the mean identify nonlinear effects.

7. Counterfactual Exercises

The regression results show that CLD and other real estate lending played an important role in both banking crises. In this section, we assess whether the large change in bank characteristics, such as the increase in real estate lending, between the two periods can account for failure probabilities and the large difference in FDIC losses. We do this by running a counterfactual exercise where we take the independent variables in each period and calculate the losses conditional on failure using the estimated coefficients in the other period.[24] This exercise tells us if changes in bank characteristics and differences in the severity of macroeconomic shocks can account for differences in failure probabilities and FDIC losses.

Table 9 reports the counterfactual exercises for bank failure rates. For this exercise, we simply used the probit selection equation results. The first observation is that macroeconomic effects (the unemployment and house price variables) are important. The actual failure rate for our sample over 1986-92 was 5.7%. Under the counterfactual where bank characteristics stay the same but macroeconomic conditions are those from the later period, the failure rate would increase to 11.6%. Similarly, the actual failure rate in the 2007-13 period was 4.7%. If bank characteristics in this later period stay the same, but macroeconomic conditions are those from the earlier period, the failure probability would drop to 1.4%.

The surprising finding is that changes in bank characteristics from 1985 to 2006, which includes the increased concentration in real estate lending, do not increase failure rates but instead actually decrease them. This can be seen in the last row of both columns in Table 9. First, in the 1986-92 period, when macroeconomic conditions are left unchanged but bank characteristics are changed to those of 2006 Q4, the failure rate drops to 3.3%. Similarly, in the later period, when only macroeconomic conditions are changed to those of 1985 Q4, the failure rate drops to a very low 1.4%. Despite the increased concentrations in CLD and other real estate lending, which do increase failure probabilities, banks in the 2006 Q4 period had other characteristics that greatly reduced failure probabilities. The most important such characteristic is capital. Capital is negative and statistically significant for predicting failure probabilities. Average capital in the later period was around 11%, compared with a smaller 8.5% in the earlier period. The higher average capital more than offsets the increased risk from the real estate

[24] For all counterfactuals where bank characteristics in one period are applied to estimated coefficients in the other period, we adjust bank size by the ratio of the average size between the two periods. We make this adjustment because bank size is a nominal variable and average size of banks, as well as total assets in the banking sector, grew between the two periods. Roughly, the size adjustment for a 1985 Q4 bank operating in the 2007-13 environment is on the order of three, that is, a $1 billion bank in 1985 Q4 is treated as a $3 billion bank in 2006 Q4 and vice versa.

concentrations. Meanwhile, there are other variables, such as lower C&I concentrations, higher core deposit ratios, and lower non-performing loan ratios that reduce failure probabilities for 2006 banks relative to 1985 banks.

Capital is particularly valuable in the earlier period. We ran a simple counterfactual where we uniformly increased each bank's capital level to get a sense of its role in reducing failure probabilities. If capital is raised 250 basis points in the earlier period, to get capital close to the later period's averages, the failure probabilities would drop to 3.6%. While still valuable in the later period, a similar increase would only drop failure probabilities to 4.1%. The difference is due to the significantly larger negative coefficient that was estimated on capital in the earlier period.

In contrast to failure probabilities, we find little effect from the counterfactuals on loss ratios. Table 10 shows these results. In the earlier period, actual loss ratios are 20.3% and changing macro conditions raises it to only 24.1%. Similarly, actual losses in the later period are 28.6% and changing the macroeconomic conditions actually raises it slightly to 30.4%. Here, changing bank characteristics in the later period to those of 1985 Q4 actually raises losses to 37.1%. One important factor seems to be the constant terms, which is higher in the later period.

The lack of difference in predicted losses from changes in bank characteristics is evidence that the change in bank commercial real estate concentrations does not explain what is driving the big change in FDIC losses. Our analysis suggests that if a bank fails, then losses will be high regardless of the time period, albeit higher in the later period. So by this metric PCA was ineffective. However, our analysis also found that changes to bank characteristics, particularly the higher capital levels, reduced failure probabilities, so the degree to which these changes are attributable to PCA suggests that PCA was effective on this dimension.

8. Conclusion

This paper compared bank failure rates and FDIC losses on failed banks between two banking crises, 1986-92 and 2007-13. We estimated a two-stage Heckman selection model for each period to assess the causes of bank failures and the causes of FDIC losses. We found that for community and mid-sized banks, the two crises were very similar. Virtually identical variables predicted bank failure as well as FDIC losses, though the size of estimates differed. Capital, security holdings, CLD lending, non-performing loans, core deposits, house price drops, and unemployment increases all significantly predicted bank failure in both periods.

Interestingly, an accounting variable that is a relatively small asset on the balance sheet, the *Interest Receivable Ratio*, predicted both bank failures and higher FDIC losses.

Our analysis finds that the primary difference between the two crises was the size of the economic shocks, and that these were the biggest factors in determining failure probabilities. The often noted increased concentration of real estate lending also contributed to increased bank risk in the recent crisis, but this was offset by the less noted higher capital levels of banks.

In contrast, in our counterfactual experiments, neither changes in bank balance sheets nor state-level economic shocks explain the large increase in FDIC losses between the earlier and later period. We also found that, while on average PCA led to banks being shut down before they had negative book capital, capital levels before failure were only about 300 basis points higher on average in the later period, so this extra amount of capital was not enough to absorb an appreciable amount of losses on banks that were put into receivership. It is possible that demand for bank assets is a factor influencing the value of a failed bank's assets. Additional data collection and empirical work would be required to address the demand side for failed bank assets.

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Figure 1 - Commercial bank failures, 1986-2013
Numbers of failed commercial banks in each year from 1986 to 2013.

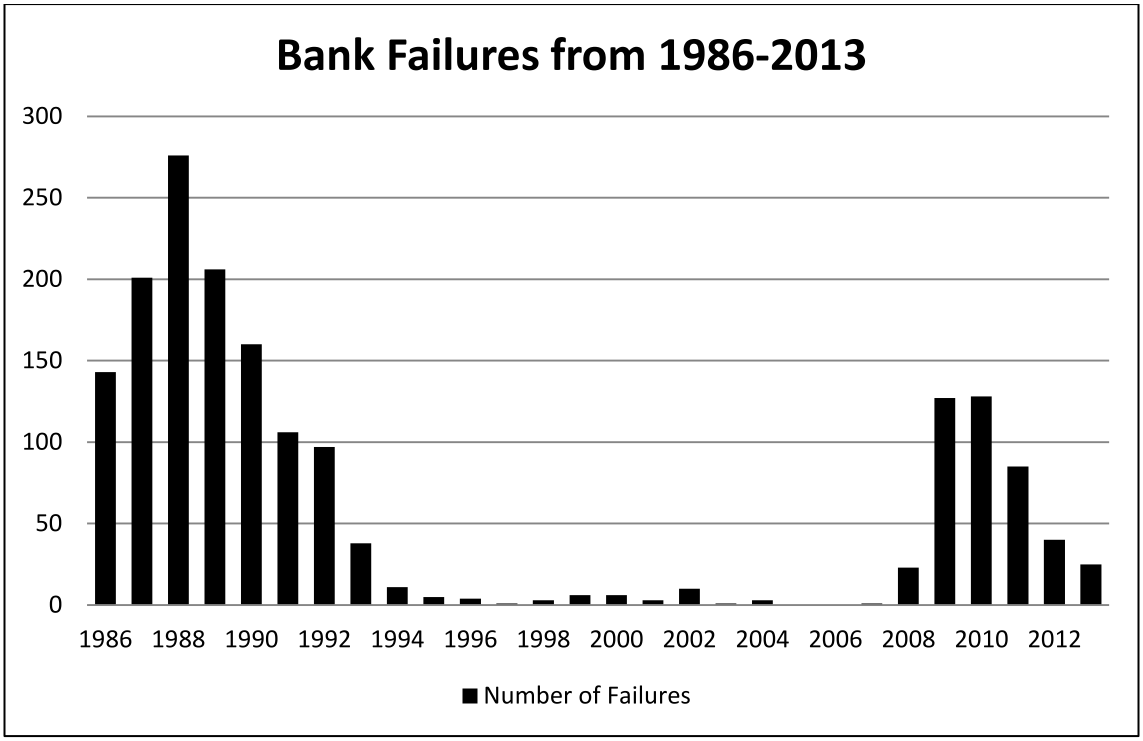

Figure 2 –Distribution of losses on failed banks, 1986-92 and 2007-13
The graphs below show the distributions of losses in each period for all failed banks except *de novo* banks.

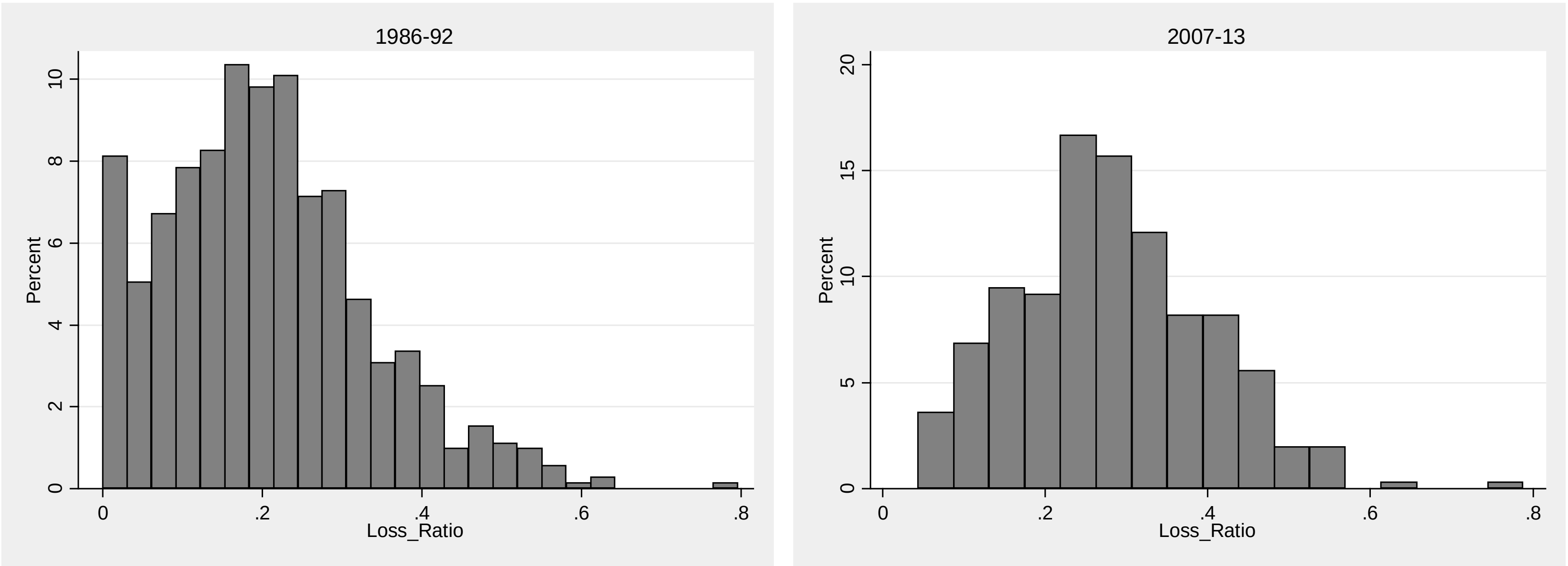

Figure 3 – Average capital ratio for all failed banks in the 16 quarters prior to failure
This figure shows the average capital ratio for all failed banks from one to 16 quarters prior to failure. The capital ratio is defined as total equity capital divided by total assets. The solid lines represent banks in the later period and the dashed lines represent banks in the early period. Both *de novos* and non-*de novos* are included in this graph as well as banks formed during the sample periods that failed before the end of it.

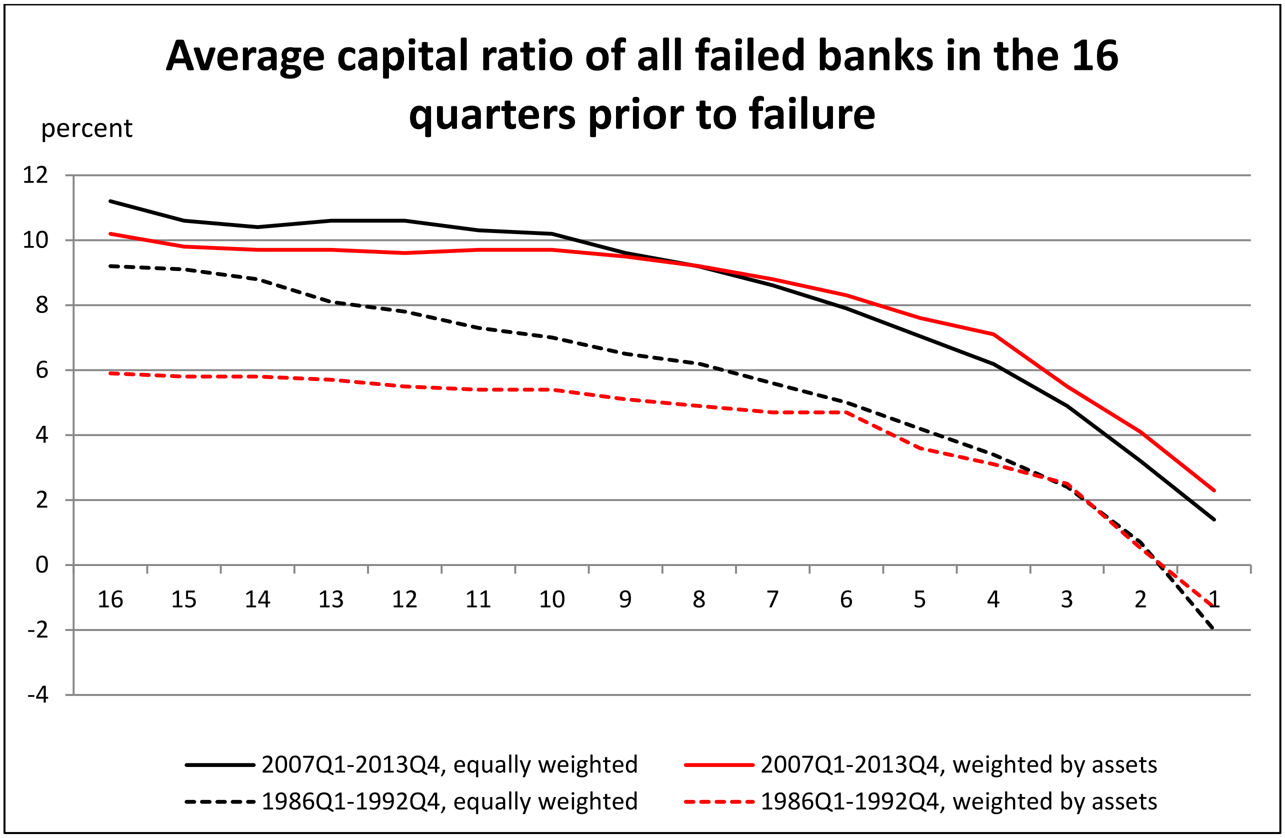

Table 1 – Average adjusted loss ratios, equally weighted and weighted by assets
This table shows the ratio of FDIC losses to assets net of book equity for commercial banks that failed between 2007-13 and 1986-92, respectively. The sample is divided into three categories: all banks, established banks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

	2007-13		
	All Banks (403)	Established Only (306)	*De novos* Only (97)
Equally Weighted	29.7	28.6	33.8
Weighted by Assets	23.8	23.1	35.2

	1986-92		
	All Banks (998)	Established Only (714)	*De novos* Only (284)
Equally Weighted	21.9	20.3	26.0
Weighted by Assets	13.8	13.2	24.7

Table 2a – Asset concentration of failed community and mid-sized banks (% of assets)
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 non *de novo* banks with less than $50 billion in assets, while in 1986 it is one with less than $14.8 billion in assets.[25]

	1985Q4	**2006Q4**
Securities	17	13
Agricultural loans	7	1
Consumer loans	13	2
C&I Loans	19	11
Constr. Land Develop. Loans	4	22
1-4 Family Real Estate	9	13
Multi-Family Real Estate	1	3
Non-Farm Non-Residential Real Estate	6	21

Table 2b - Asset concentration of all community and mid-sized banks (% of assets)
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 non *de novo* banks with less than $50 billion in assets, while in 1986 it is one with less than $14.8 billion in assets.

	1985Q4	**2006Q4**
Securities	29	22
Agricultural loans	7	5
Consumer loans	12	5
C&I Loans	12	10
Constr. Land Develop. Loans	2	7
1-4 Family Real Estate	11	16
Multi-Family Real Estate	0*	1
Non-Farm Non-Residential Real Estate	5	15

* There is some multi-family real estate lending in 1985 Q4, but it rounds to zero.

[25] The asset limit excludes one failed bank in the early period

Table 3 – Variable definitions

Description, creation, and sources for all variables used in the analysis. Most variables are from Call Reports. All ratio variables are normalized by either total assets or total loans with the exception of the FHLB ratio which is divided by domestic liabilities and minority interest. *De novo* banks are defined as those who were in existence for 20 quarters or less.

Variable Name	Description	Variable Creation	Source
FDIC Losses	estimated losses to the FDIC		FDIC Historical Statistics on Banking (HSOB)[26]
Loss Ratio	estimated losses to the FDIC divided by total assets of bank at time of failure	FDIC Losses / Total Net Assets at Failure	FDIC HSOB
Total Net Assets at Failure	Assets of a failed bank minus book equity at latest filed Call Report before failure	Assets at failure reported by FDIC – rcfd3210	FDIC HSOB and Call Report
Adjusted Loss Ratio	estimated losses to the FDIC divided by net assets of bank at time of failure	FDIC Losses / Total Net Assets at Failure	FDIC HSOB
C&I Loan Ratio	commercial and industrial loans divided by total loans and leases net of unearned income	rcfd1766 / rcfd2122	Call Report
CLD Loan Ratio	(domestic) construction and land development loans divided by total (domestic) loans and leases net of unearned income	rcon1415 / rcfd2122	Call Report
Agricultural Loan Ratio	agricultural loans divided by total loans and leases net of unearned income	rcfd1590 / rcfd2122	Call Report
Consumer Loan Ratio	credit card and other consumer loans divided by total loans and leases net of unearned income	(rcfd2008 + rcfd2011) / rcfd2122 in early period and (rcfdb538 + rcfdb539 + rcfd2011)/rcfd2122 in later period	Call Report
Real Estate Loan Ratio	loans secured by real estate divided by total loans and leases net of unearned income	rcfd1410/rcfd2122	Call Report
1-4 Family Real Estate Loan Ratio	(domestic) RE loans backed by 1-4 family residential properties divided by total (domestic) loans and leases net of unearned income	rcon1430 / rcfd2122	Call Report
Other Real Estate Loan Ratio	1-4 family loan ratio and CLD loan ratio subtracted from total real estate loans	RE Loan Ratio-CLD Loan Ratio-1-4 Family RE Ratio	Call Report
Multi-Family Real Estate Loan Ratio	(domestic) RE loans backed by multi-family residential properties divided by total (domestic) loans and leases net of unearned income	rcon1460 / rcfd2122	Call Report
Non-Farm/ Non-Residential Loans Ratio	(domestic) RE loans backed by nonfarm nonresidential properties divided by total (domestic) loans and leases net of unearned income	rcon1480/rcfd2122	Call Report

[26] FDIC Historical Statistics on Banking can be found at https://www2.fdic.gov/hsob/SelectRpt.asp?EntryTyp=30

FHLB Advance Ratio	FHLB advances divided by liabilities and minority interest (only in later period)	(rcfdf055 + rcfdf056 + rcfdf057 + rcfdf058) / rcfd2948 or (rcfd2651 + rcfdb565 + rcfdb566)/rcfd2948 prior to 2006Q3	Call Report
Loan Loss Reserves Ratio	allowance for loan and lease losses plus allocated transfer risk reserves divided by total loans and leases net of unearned income	rcfd3123 / rcfd2122 in early period and (rcfd3123 + rcfd3128)/rcfd2122 in later period	Call Report
Past Due Loans	loans 90 or more days past due, divided by assets	rcfd1407/rcfd2170	Call Report
Non-Accrual Loans	Non-accruing loans, divided by assets	rcfd1403/rcfd2170	Call Report
Nonperforming Loans Ratio	loans 90 or more days past due plus non-accruing loans, divided by assets	(rcfd1407 + rcfd1403) / rcfd2170	Call Report
Interest Receivable Ratio	accrued interest receivable divided by total assets	rcfd2164 / rcfd2170 in early period and rcfdb556/rcfd2170 in later period	Call Report
Size	the natural logarithm of a bank's assets	ln(rcfd2170)	Call Report
Capital Ratio	bank equity divided by assets	rcfd3210 / rcfd2170	Call Report
Securities Ratio	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)/rcfd 2170 in later period	Call Report
Core Deposits Ratio	core deposits (gathered in a bank's demographic area) divided by total liabilities	(rcon2215 + rcon6810 + rcon6648)/rcfd2948 in early period and (rcon2215 + rcon6810 + rcon0352 + rcon6648)/rcfd2948 in later period	Call Report
Earnings	net income divided by assets	riad4340 / rcfd2170	Call Report
Peak to Trough	Difference in peak to trough HPI values when the maximum occurred prior to the minimum	(HPI_Max - HPI_Min)/HPI_Min if maximum occurred before minimum in the given time period	Corelogic HPI Data via Haver
Unemployment Increase	Increase in the unemployment rate during the period when the maximum occurs after the beginning of the period	Unem_Max – Unem_Min conditional on maximum occurring after beginning of period	Haver
De novo	1 if less than or equal to 20 quarters since birth, 0 otherwise		Call Report

Table 4– Summary statistics for 1985 Q4 and 2006 Q4
Summary statistics of variables for our sample.

Panel A – Early Period

1986-92								
	N	**Mean**	**SD**	**Min**	**P25**	**Median**	**P75**	**Max**
Adjusted Loss Ratio	713	0.203	0.124	0	0.112	0.193	0.277	0.573
Size	12662	10.690	1.195	6.923	9.891	10.577	11.295	16.506
Capital	12662	0.085	0.030	-0.070	0.067	0.079	0.095	0.837
Securities	12662	0.290	0.145	0	0.181	0.276	0.384	0.862
CLD Loan	12658	0.027	0.050	0	0	0.007	0.030	0.606
C&I Loans	12658	0.223	0.134	0	0.124	0.199	0.298	0.958
Core Deposits	12662	0.784	0.105	0	0.733	0.801	0.855	1
Peak to Trough	12662	0.054	0.095	0	0	0	0.070	0.451
Earnings	12662	0.007	0.014	-0.201	0.005	0.010	0.013	0.182
Non-Performing Loans	12662	0.017	0.020	0	0.004	0.010	0.021	0.305
Agricultural Loans	12658	0.139	0.193	0	0.001	0.042	0.212	0.999
1-4 Residential Properties	12658	0.209	0.137	0	0.103	0.187	0.292	0.983
Consumer Loans	12658	0.237	0.139	0	0.137	0.212	0.311	1.058
Other Real Estate	12658	0.135	0.090	0	0.067	0.122	0.188	0.738
LLR	12658	0.015	0.010	0	0.009	0.012	0.016	0.274
Interest Receivable	12662	0.009	0.006	0	0.005	0.008	0.012	0.056
Unemployment Increase	12662	1.185	1.459	0	0	0.167	2.333	6

Table 4 (cont.)

Panel B – Later Period

2007-13								
	N	**Mean**	**SD**	**Min**	**P25**	**Median**	**P75**	**Max**
Adjusted Loss Ratio	306	0.285	0.120	0.045	0.201	0.281	0.361	0.851
Size	6618	11.850	1.290	7.102	10.987	11.729	12.580	17.723
Capital	6618	0.110	0.058	-0.001	0.084	0.097	0.118	1
Securities	6618	0.220	0.146	0	0.115	0.194	0.302	0.998
CLD Loan	6590	0.103	0.118	0	0.017	0.061	0.150	0.905
C&I Loans	6590	0.151	0.098	0	0.083	0.132	0.196	0.920
Core Deposits	6617	0.748	0.135	0	0.683	0.766	0.838	0.999
Peak to Trough	6618	0.201	0.119	0	0.121	0.182	0.284	0.587
Earnings	6618	0.012	0.015	-0.356	0.008	0.011	0.015	0.595
Non-Performing Loans	6618	0.006	0.008	0	0.001	0.003	0.008	0.118
Agricultural Loans	6590	0.082	0.131	0	0.0001	0.017	0.111	0.810
1-4 Residential Properties	6590	0.251	0.157	0	0.134	0.228	0.342	1
Consumer Loans	6590	0.087	0.098	0	0.030	0.061	0.111	1
Other Real Estate	6590	0.309	0.139	0	0.217	0.303	0.387	1
LLR	6590	0.014	0.012	0	0.010	0.012	0.015	0.571
Interest Receivable	6590	0.008	0.004	0	0.005	0.007	0.010	0.056
Unemployment Increase	6618	4.826	1.584	1.267	3.933	4.7	5.967	9.633
FHLB Ratio	6617	0.041	0.058	0	0	0.016	0.064	0.976

Table 5 – Heckman selection model for 1986-92 and 2007-13 periods

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. All variables are as defined in Table 4. 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) 1986-92		(2) 2007-13	
	Loss Equation	Selection Equation	Loss Equation	Selection Equation
Loss Ratio				
Size	-0.02***	-0.20***	-0.04***	-0.03
	[0.004]	[0.03]	[0.01]	[0.04]
Securities Ratio	-0.04	-1.61***	-0.14**	-1.22***
	[0.06]	[0.25]	[0.07]	[0.33]
CLD Loan Ratio	-0.01	2.55***	0.10	5.59***
	[0.06]	[0.48]	[0.06]	[1.27]
C&I Loan Ratio	0.04	1.22***	0.02	2.91**
	[0.03]	[0.38]	[0.06]	[1.32]
Core Deposit Ratio	-0.17***	-2.14***	-0.07	-1.62***
	[0.04]	[0.23]	[0.05]	[0.26]
Interest Receivable	2.02***	50.14***	5.30***	40.91***
	[0.71]	[4.48]	[1.57]	[14.55]
Capital Ratio		-12.95***		-2.86**
		[1.36]		[1.18]
Peak to Trough		2.88***		0.90**
		[0.22]		[0.46]
Earnings Ratio		-3.33*		-12.58***
		[1.74]		[3.13]
Non-Performing Loans		7.64***		15.94***
		[1.09]		[3.38]
Agricultural Loans		0.08		1.24
		[0.41]		[1.47]
1-4 Residential Properties		-0.80**		1.86
		[0.42]		[1.29]
Other Real Estate		0.85**		2.76**
		[0.42]		[1.27]
Consumer Loan		0.30		0.76
		[0.37]		[1.47]
Loan Loss Reserve		-1.60		-10.29
		[2.57]		[7.19]
Unemployment Increase		0.07***		0.13***
		[0.02]		[0.04]
Constant	0.54***	2.00***	0.80***	-3.57**
	[0.06]	[0.56]	[0.09]	[1.39]
Lambda		-0.05***		-0.05**
		[0.01]		[0.02]
Censored Observations		11,945		6,284
Uncensored Observations		713		306
Wald Statistic		34.70		73.91
Pseudo R^2		0.137		0.204

Table 6 – 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. Levels of significance are indicated by *, **, and *** for 10%, 5%, and 1%, respectively.

	(1) 1986-92		(2) 2007-13	
	Loss Equation Heckman	Loss Equation OLS	Loss Equation Heckman	Loss Equation OLS
Loss Ratio				
Size	-0.02***	-0.02***	-0.04***	-0.04***
	[0.004]	[0.004]	[0.01]	[0.01]
Securities Ratio	-0.04	-0.15***	-0.14**	-0.19***
	[0.06]	[0.05]	[0.07]	[0.06]
CLD Loan Ratio	-0.01	0.06	0.10	0.20***
	[0.06]	[0.06]	[0.06]	[0.04]
C&I Loan Ratio	0.04	0.08**	0.02	0.03
	[0.03]	[0.03]	[0.06]	[0.07]
Core Deposit Ratio	-0.17***	-0.25***	-0.07	-0.13***
	[0.04]	[0.04]	[0.05]	[0.04]
Interest Receivable	2.02***	3.98***	5.30***	5.34***
	[0.71]	[0.60]	[1.57]	[1.57]
Constant	0.54***	0.55***	0.80***	0.74***
	[0.06]	[0.07]	[0.09]	[0.09]
Adjusted R-Squared		0.15		0.23

Table 7 – Marginal effects on bank failure rates
Marginal effects produced by the probit selection equation. The failure rate is evaluated by setting all independent variables at their means. The marginal effect for each variable is then calculated by increasing it by its standard deviation while keeping the other variables at their means. Italicized variables are in both the selection and loss equations. Non-italicized are only in the selection equation. Marginal effects for variables that are significant in the selection equation are in bold.

	1986-92	**2007-13**
Failure Rate Evaluated at Mean	1.25%	1.13%
	Marginal Effects	
Size	**-0.60%**	-0.11%
Securities	**-0.58%**	**-0.43%**
CLD Loan	**0.48%**	**4.12%**
C&I Loans	**0.64%**	**1.30%**
Core Deposits	**-0.57%**	**-0.51%**
Interest Receivable	**1.17%**	**0.64%**
Peak to Trough	**1.03%**	**0.39%**
Capital	**-0.82%**	**-0.41%**
Earnings	**-0.14%**	**-0.45%**
Non-Performing Loans	**0.59%**	**0.44%**
Agricultural Loans	0.05%	0.58%
1-4 Residential Properties	**-0.31%**	1.21%
Consumer Loans	0.14%	0.24%
Other Real Estate	**0.27%**	**1.76%**
LLR	-0.05%	-0.32%
Unemployment Increase	**0.37%**	**0.77%**

Table 8 – Marginal effects on FDIC losses

Effects calculated by multiplying the calculated marginal effect by the standard deviation of its corresponding independent variable. After this step, the resulting product is scaled by the mean value of losses in the period considered. This method allows for a side-by-side comparison of the effects of each variable.

	1986-92	**2007-13**
	Marginal Effects	**Marginal Effects**
Size	-0.59	-0.29
Securities	-0.48	-0.56
CLD Loans	0.13	1.82
C&I Loans	0.57	0.78
Core Deposits	-0.54	-0.63
Interest Receivable	0.65	0.53
Peak to Trough	0.53	0.29
Capital	-0.75	-0.44
Earnings	-0.09	-0.51
Non-Performing Loans	0.29	0.34
Agricultural Loans	0.03	0.44
1-4 Residential Properties	-0.21	0.78
Consumer Loans	0.08	0.20
Other Real Estate	0.15	1.03
LLR	-0.03	-0.33
Unemployment Increase	0.19	0.54

Table 9 – Counterfactual failure rate exercise results

This table displays actual, predicted, and counterfactual rates of failure for both periods using our sample. The first row shows the actual failure rate in our sample. The second row shows the failure rate predicted from the selection equation. The third row displays the failure rate when the variable coefficients from one period are applied to the bank characteristics in the other. The fourth row displays the predicted failure rate in both periods with the bank characteristics of 1985 Q4 and the macroeconomic values of the later period. The fifth row displays the failure rate in both periods with bank characteristics of 2006 Q4 and the macroeconomic values of the earlier period. In all the counterfactuals where bank characteristics from one period are used with coefficient estimates from the other period, bank size is adjusted by the ratio of average size in the two periods.

Probability of Failure			
1986-92		**2007-13**	
5.7	(actual)	4.7	(actual)
5.6	(β_{85}, x_{85})	4.7	(β_{06}, x_{06})
10.8	(β_{85}, x_{06})	1.3	(β_{06}, x_{85})
11.6	$(\beta_{85}, x_{bank,85}, x_{macro,06})$	2.6	$(\beta_{06}, x_{bank,85}, x_{macro,06})$
3.3	$(\beta_{85}, x_{bank,06}, x_{macro,85})$	1.4	$(\beta_{06}, x_{bank,06}, x_{macro,85})$

Table 10 - Counterfactual loss ratio exercise results

This table displays actual, predicted, and counterfactual loss ratios for both periods. The first row shows the average adjusted loss ratio for our sample. The second row represents the loss ratio that is predicted using the Heckman results of both dependent variables in both periods. The third row displays the predicted loss ratio when the variable coefficients from one period are applied to the bank characteristics in the other. The fourth row displays the predicted loss ratio in both periods with the bank characteristics of 1985 Q4 and the macroeconomic values of the later period. The fifth row displays the predicted loss ratio in both periods with bank characteristics of 2006 Q4 and the macroeconomic values of the earlier period. In all the counterfactuals where bank characteristics from one period are used with coefficient estimates from the other period, bank size is adjusted by the ratio of average size in the two periods.

Adjusted Loss Ratio			
1986-92		**2007-13**	
20.3	(actual)	28.6	(actual)
23.9	(β_{85}, x_{85})	31.3	(β_{06}, x_{06})
21.0	(β_{85}, x_{06})	36.6	(β_{06}, x_{85})
24.1	$(\beta_{85}, x_{bank,85}, x_{macro,06})$	37.1	$(\beta_{06}, x_{bank,85}, x_{macro,06})$
19.2	$(\beta_{85}, x_{bank,06}, x_{macro,85})$	30.4	$(\beta_{06}, x_{bank,06}, x_{macro,85})$