Accepted Manuscript

Title: Systematic Risk Factors and Bank Failures

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PII: S0148-6195(17)30190-X
DOI: https://doi.org/10.1016/j.jeconbus.2018.05.001
Reference: JEB 5809

To appear in: *Journal of Economics and Business*

Received date: 9-8-2017
Revised date: 7-4-2018
Accepted date: 2-5-2018

Systematic Risk Factors and Bank Failures

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Office of the Comptroller of the Currency

March 2018

Highlights

- Local housing market conditions contributed to bank failures.
- Interbank funding market conditions strongly contributed to post 2008 bank failures.
- Banking crises seemed to be driven by episode-specific risk factors.
- Finding the right systematic risk factors for the next banking crisis can be hard.
- Correctly gauging the impact of systematic factors on bank failures is challenging.

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We wish to thank two anonymous referees, Filippo Occhino, Min Qi, James Thomson, Mark Wu, and seminar participants at the Financial Management Association 2016 annual meetings; the 2016 International Banking, Economics, and Finance Association annual conference; the Office of the Comptroller of the Currency; the Federal Reserve Bank of Chicago; and the University of Akron for valuable comments. We thank Matthew Reardon for his excellent research support. The views expressed in this paper are those of the authors and do not necessarily reflect those of the Office of the Comptroller of the Currency or the U.S. Department of the Treasury. The authors take responsibility for any errors.

Abstract

We investigate the impact on bank failures of two systematic risk factors—the stress in the interbank funding market and conditions in the local housing market—in the two banking crises during the period from 1985–2011. We find that local housing market conditions had a stronger relation with bank failures during the first episode than during the second episode. By contrast, the interbank funding market condition only weakly helped to predict bank failures before 2005, but it had a very strong impact on bank failures during the latest banking crisis. Therefore, banking crises seemed to be driven by episode-specific risk factors. Accordingly, even though it is common wisdom at present that overall banking risk is more than just the sum of risks at the individual bank level and that macro-prudential overlay is important in bank regulation, finding the right systematic risk factors for the next banking crisis or correctly gauging their impact on bank failures might be challenging.

Keywords: bank failures, systematic risk factors, TED spread, local housing market conditions, interbank funding market conditions.

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JEL classifications: G21, G28, R10.

I. Introduction

The number of bank failures shot up substantially in the latest financial crisis. Investigating the determinants of bank failures is important, since banks play a fundamental role in the economy as the financial intermediaries between borrowers and ultimate lenders. In fact, there is ample evidence in the literature that banking crises can spill over to the real economy.[1]

Since the outbreak of the latest banking crisis, interest in the broad causes of bank failures has increased, and there has been much discussion on macro-prudential overlay in bank regulation, for example, as reflected in the recommendations in the new Basel III Accord. Although it is common wisdom presently that overall banking risk is more than just the sum of risks at the individual bank level based on information from financial statements, the literature has yet to thoroughly examine the critical systematic risk factors that contribute to banking crises. Even though the prior literature

[1] See, for example, Hoggarth et al. (2002); Boyd et al. (2005); Hutchison and Noy (2005); Dell'Ariccia et al. (2008); Bernanke, Gertler, and Gilchrist (1999); Campello et al. (2010); Serwa (2010); and Kupiec and Ramirez (2013).

has investigated some macroeconomic factors in bank failure models, researchers have not found any of them to be significantly related to bank failure probabilities in a consistent way (see literature review in section II).

In this paper, we study two systematic risk factors that have not been explored in-depth in bank failure models. We examine whether these two systematic risk factors added value to bank failure models after accounting for bank-specific risks, and whether their impact held in each of the two banking crises during the period from 1985–2011.[2]

The first factor is the condition of the interbank funding market, which we gauge using the TED spread. The TED spread is the spread between the three-month London Interbank Offered Rate (LIBOR) and the three-month U.S. Treasury bills rate. It is the borrowing cost in the interbank market, and it can be viewed as a measure of the health of the banking system, reflecting both the liquidity risk in the funding market and the perceived distress risk in the banking sector.

The second factor we use is the local housing price indices (HPIs). The relation between local housing market conditions and bank failures has not been fully researched in the prior literature. Given banks' substantial exposure to residential and commercial real estate (CRE) loans, it will not be particularly surprising to find some association between local HPIs and bank failures after controlling for bank-level financial ratios.

We find that, over the entire period from 1985–2011, both factors were significantly related to the probabilities of bank failures after controlling for bank-level risk factors, and the marginal effect of both factors on bank failures appeared to be quite strong and comparable to some

[2] Although these two variables have been used in banks' stress testing models, the stress testing exercise typically involves more than a dozen macro variables, and based on our analysis and the consensus from the bank failure literature, the majority of the macro variables are not statistically significant in bank failure models after controlling for bank financial statement information. These stress testing macro variables typically affect banks' capital, asset quality, earnings, and liquidity risks, and thus the stress testing exercise still focuses on risks at the individual bank level. Our study is distinctive from the stress testing exercises in the sense that we explore whether these two systematic risk factors would add value to bank failure models after accounting for bank-specific risks.

commonly used financial variables.

However, the influence from the two systematic risk factors varied in the two banking crises. Local HPIs were more critical in predicting bank failures in the first episode than in the latest banking crisis. Further analysis suggests that the finding of stronger effect from local housing market conditions in the first banking crisis is likely due to the fact that interstate branching was prohibited before the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994, and banks operating in multiple states should be less sensitive to local housing market conditions. The TED spread only marginally helped to predict bank failures before 2005, but its impact on bank failures was very strong during the latest banking crisis. The weak impact from TED spread on bank failures in the first episode was possibly because the first banking crisis was largely a CRE crisis,[3] instead of a crisis driven by liquidity concerns.

Our findings suggest that the impact on bank failures from the two systematic risk factors changed from one banking crisis to another. Even though the housing market conditions played a role in both banking crises, real estate conditions might not be the source of the next banking crisis. This is because banks have been quite stringent in mortgage lending since the latest banking crisis, while nonbank financial institutions have become major players in the mortgage lending business.[4] On the other hand, consumer debt due to student loans and auto loans has been rising dramatically since 2009.[5] It is very possible that the next crisis may not stem from the real estate sector. By contrast, the latest banking crisis had a large component in liquidity shortage, which was reflected

[3] See, for example, some research papers on the FDIC website dedicated to the banking crisis of 1980s and early 1990s: https://www.fdic.gov/bank/historical/history/vol1.html.

[4] See, for example, Buchak et al. (2017).

[5] For example, see the consumer debt report from the Federal Reserve Bank of New York: https://www.newyorkfed.org/medialibrary/interactives/householdcredit/data/pdf/HHDC_2017Q2.pdf. Further, the aggregate outstanding household debt has exceeded aggregate corporate debt (see Federal Reserve Flow of Funds Table D.3).

in the TED spread,[6] and we also find that the Fed liquidity injection programs helped to stabilize the banking system during the height of the latest banking crisis. As regulators have made efforts to address liquidity concerns and established some clearing houses following the latest financial crisis,[7] liquidity shortage might not be the source of the next crisis. If the next crisis is primarily driven by problems in bank fundamentals (as was largely the case in the first episode), regulators may not be able to calm the chaos in the banking system with liquidity injection as effectively as in the latest banking crisis.

Therefore, banking crises might be driven by episode-specific risk factors. Finally, it is possible that house prices or the TED spread might simply capture one or more latent bank-specific variables, such as management quality, that were difficult to observe and thus not included in the base model, and such unobserved characteristics might be reflected in another systematic risk factor(s) in the future. Consequently, finding the critical systematic factors in the next banking crisis or correctly gauging their impact on bank failures seems to be a challenge for bank regulators.

The rest of the paper proceeds as follows. In section II, we review the relevant literature. We describe our data in section III, and empirical results are reported in section IV. Section V provides a brief conclusion.

[6] The general view in the literature is that the latest financial crisis was caused by an aggregate liquidity shortage that posed funding problems for banks (for instance, Krishnamurthy [2009], Diamond and Rajan [2011], Cornett et al. [2011], Cetorelli and Goldberg [2012], Acharya and Merrouche [2013], and Acharya and Mora [2014]).

[7] The goal of establishing CDS clearing houses was to increase transparency and reduce counterparty risk in the credit default swap (CDS) market. The first CDS clearing house was ICE Clear Credit, where CDS started trading in March 2009. There is some evidence in the academic literature that a central clearing house increases liquidity (for example, Loon and Zhong [JFE 2016]).

II. Literature Review

II.A. Bank Failure Models

The 1970s and early 1980s witnessed a wave of research investigating bank failures and early warning systems; well-known examples are Meyer and Pifer (1970), Altman (1977), and Martin (1977). These studies set the standard for bank failure prediction models using financial ratios, which have been followed in later studies.[8] Although some bank failure models have used other variables, such as those based on equity market information,[9] these results are not very useful, as most banks (especially small banks) are privately held and do not have publicly traded equities. In general, the prevailing bank failure models among academics, as well as the judgment rating system and the early warning systems used by the banking regulatory agencies, are mostly focused on financial ratios that cover the four aspects of banks' financial status: capital, asset quality, earnings, and liquidity.[10]

From the turn of the millennium, researchers have started to explore other types of bank-specific risks. For example, Jin, Kanagaretnam, and Lobo (2011) study the relation between audit quality and bank failures, and Cole and White (2012) examine how portfolio concentration risk drives bank failures. Another stream of literature analyzes how nontraditional banking activities affect bank performance and the probability of bank failures (for example, Allen and Jagtiani [2000], DeYoung and Roland [2001], Stiroh [2004, 2006], De Jonghe [2010], and DeYoung and Torna [2013]).

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[8] For example, Whalen (1991), Tam and Kiang (1992), Bell (1997), Cole and Gunther (1998), Wheelock and Wilson (2000), Lanine and Vennet (2006), Davis and Karim (2008), and Cleary and Hebb (2016). See Gupta and Misra (1999) and Bellovary et al. (2007) for detailed surveys of the literature.

[9] For example, Pettway and Sinkey (1980); Pettway (1980); and Curry, Elmer, and Fissel (2007).

[10] The purpose of early warning models is to discriminate among banks likely to fail at a particular point in time. So investigating the broad causes of bank failures during banking crises is outside the purpose of early warning models, although this latter question is important for bank regulation in general among regulators and academics.

Although some papers (for example, Pantalone and Platt [1987]; Thomson [1991]; and Nuxoll, O'Keefe, and Samolyk [2003]) include national or local economic conditions among the explanatory variables for bank failure models, these studies find that the relation between macroeconomic variables and the probability of bank failures is largely mixed and often not clear-cut, after controlling for the individual risks at the bank level.[11]

Since the outbreak of the latest banking crisis, interest in the broad causes of bank failures during banking crises has increased. We aim to move forward our understanding in this area by empirically exploring the impact on the probabilities of bank failures from two systematic risk factors that have not been investigated thoroughly.

II.B. Conditions in the Interbank Market and Financial Stability

Banks are commonly deemed to provide social value by supplying liquid claims (safe debt) to parties with imperfect access to the capital markets (for example, Diamond and Dybvig [1983], Gorton and Pennacchi [1990], Diamond and Rajan [2000], and DeAngelo and Stulz [2014]). However, this function creates a mismatch risk between real production and depositor demands, and merely temporary mismatch risk between real production and depositor demands because of production delays can create a funding shock, as explained in Diamond and Rajan (2005). When some banks face funding shocks, a well-functioning interbank market can help banks with funding shortages to borrow from those with surplus funds. However, there are frictions in the interbank market, such as asymmetric information, counterparty risk, moral hazard, liquidity hoarding, and overhang of illiquid securities (see Freixas and Jorge [2008]; Heider, Hoerova, and Holthausen [2009]; Acharya, Gromb, and Yorulmazer [2012], and Acharya and Merrouche [2013]). As a

[11] The macroeconomic variables investigated in the literature include state-level GDP growth; unemployment rate (both level and change); growth in personal income, population, and residential constructions; small business failure rate; growth in total loans issued by insured banks headquartered in the state; and growth in total assets held by insured banks headquartered in the state.

consequence, the interbank market may not always be able to efficiently channel funding to solvent but illiquid banks, and if it happens on a large scale, the malfunctioning interbank market can have a contagious effect on bank failures.

A major component of the interbank funding market that may quickly break down is the wholesale funding market. In recent decades, banks have increasingly borrowed short-term wholesale funds from nonfinancial corporations, households, and other financial institutions via brokered deposits, repurchase agreements, commercial paper, or money market mutual funds, for example (see the figure in Bao, David, and Han [2015]). Despite the benefits, short-term wholesale funds can be quickly withdrawn based on negative public signals and the subsequent anxiety among market participants about potential credit and/or liquidity risks in the financial sector (see, for example, Huang and Ratnovski [2011]). Scholars such as Acharya, Gale, and Yorulmazer (2011) argue that the short-term wholesale financiers were a major contributor to the latest financial crisis.

II.C. Local Housing Market Conditions and Bank Failures

Local housing market conditions are typically not among the economic variables examined in the literature on bank failure models. Further, although DeYoung and Torna (2013) include state home price growth among their list of explanatory variables, their sample period is from the third quarter of 2008 to the fourth quarter of 2010. Since it is widely acknowledged that the distressed housing market was one of the main factors behind the latest financial crisis, a finding that local housing market conditions were related to bank failure probability during this period is not surprising. It is more interesting to examine whether the relation between local housing market conditions and bank failures was unique during the latest period, or if such a relation held over other periods as well.[12]

There are reasons to expect a close connection between local housing market conditions and bank failures ex ante. First, residential mortgages constitute a major component of bank portfolios, and the performance of residential mortgages on the bank's balance sheet should be closely related to local housing market conditions. Second, CRE loans are another important component of bank portfolios, especially among small and medium-sized banks, and it is generally argued in the spatial equilibrium literature that prices of residential properties and CREs should be highly correlated (see, for example, Colby [1933], Rosen [1979], and Roback [1982]).

III. Data Description

III.A. Bank Failures

Our list of failed banks includes banks that were liquidated, taken into conservatorship, or needed assistance from the Federal Deposit Insurance Corporation (FDIC) to survive (i.e., to merge with another bank to remain open) from 1985 to 2011.[13] This list is obtained from the FDIC.[14]

It is often acknowledged that the official list of failed banks may not accurately measure economic insolvency because the FDIC's ability to liquidate troubled financial institutions is constrained by its staffing, and as a result, the FDIC may not liquidate all insolvent banks. The

[12] Although Aubuchon and Wheelock (2010) find bank failure rates are related to housing price changes between 1987 and 1992, their results are based on simple correlation analysis without controlling for bank financial ratios and other factors. We conduct a more thorough analysis and derive different insights, as will be discussed later.

[13] We do not use bank failure observations before 1984 because of the dramatic changes in call reports in 1984, which makes merging the pre-1984 and post-1984 data challenging. Further, there was no banking crisis before 1984, and the impact of systematic risk factors should mainly show up during banking crises. Therefore, missing the pre-1984 period should not have a major impact on the findings of this paper.

[14] The FDIC assistance transaction is unrelated to the Troubled Asset Relief Program (TARP). During the latest banking crisis, the well-known banks on our failure list are Citibank (assistance) and Bank of America (assistance), but other banks receiving TARP money, such as JPMC and PNC, are not among the list of failed banks.

earlier literature, for example, Thomson (1992) and Cole and Gunther (1998), has used a two-step approach modeling both bank insolvency and closure. However, using the insolvency measure is difficult in the later period because there is a general increase in banks' capital ratio over time, and this trend is not highly correlated with the cyclicality in the banking industry. The capital ratios of many failed banks in the latest banking crisis were by no means very low before they failed. For example, the mean capital ratio of the failed banks was 6 percent during the quarter before their closure in 2008. The 75th (90th) percentile capital ratio of the failed banks was above 7 percent (10 percent) one quarter before their closure during the period 2007–2009.

Why may banks with decent capital ratios fail? There are two possible reasons. First, capital ratios are backward looking, and they may not reflect the current bank condition. Second, capital ratios are based on book values. Barth, Bartholomew, and Bradley (1990) find that the book net worth might significantly understate the market net worth, and the capital ratio therefore may not reflect the actual stress the bank is facing. As a result, we find that capital ratios do not provide a good measure of a bank's credit risk in many cases in our sample.

Further, FDIC's staffing constraints may not be a serious concern in our paper because our bank failure definition goes beyond liquidation. FDIC resolves failures by paying insured depositors and acts as the receiver for failed banks, and the staffing limitation only affects liquidation activities. In emergencies, the FDIC can establish a bridge bank to house the failed bank assets until an orderly resolution is possible. If faced with a staffing constraint, FDIC can outsource liquidation activities, which was done during the 2007–2009 financial crisis via the use of loss-sharing agreements with failed-bank acquirers. Our definition of bank failures has covered both situations during emergencies. In addition, any potential staffing constraint at FDIC would only imply that the number of bank failures during the height of the banking crisis might be lower than it should be, which will pose an even bigger challenge for a bank failure model solely relying on bank-level financial variables, as can be seen from our evidence in section IV. It is further noted that staffing constraints might make quarterly bank failure observations overly noisy, which could make quarterly results unstable.

Our entire sample consists of 271,403 bank-year observations, with 1,773 failures. Table 1 reports the number of healthy and failed banks each year from 1985 to 2011.[15] There were two cycles of bank failures during the entire sample period. The first cycle happened during late 1980s and early 1990s, and the second cycle was related to the latest financial crisis. Bank failures occurred mainly among the small to medium-sized banks in the first banking crisis, but the latest banking crisis was widely spread, affecting not only the systemically important financial institutions, but also hundreds of smaller banks.

III.B. Summary Statistics

We obtained bank-level financial data during the period from 1984 to 2010 from the Consolidated Reports of Condition and Income (i.e., call report) from the Federal Reserve Bank of Chicago, and the data are adjusted for bank mergers.[16] Definitions of the explanatory variables are summarized in appendix A, and the summary statistics are reported in table 2. We include a rather comprehensive list of bank-level financial variables to cover the traditional four aspects of banking risks: capital, asset quality, earnings, and liquidity, and these variables are publicly

[15] For both one-year and one-quarter predictions, we use the failure observations from 1985Q1 to 2011Q4. We do not use the failures from 1984 even for the quarterly model, because it seems that a significant number of banks were still using the old call report forms, while some banks were using the new call report forms in 1984, as we find instability in summary statistics of financial reports during the first three quarters of 1984, and the summary statistics stabilize starting from 1984Q4. Therefore, we use bank failure observations starting from 1985 using bank financial ratios starting from 1984Q4.

[16] All bank failures are from January to December of each calendar year, and the explanatory variables are observed at the end of the prior calendar year.

available.[17] The financial variables reported here are all from the period before the failure occurs. To reduce the effect of outliers, bank-specific variables are winsorized at the 1 percent and 99 percent levels. We define the local housing market conditions at the state where the bank is headquartered, and the housing price index is sourced from the Federal Housing Finance Agency (FHFA).

The TED spread is downloaded from Haver Analytics. The TED spread represents the borrowing cost among banks that are considered to be of acceptable credit quality. It is a challenge to pin down whether the TED spread reflects the liquidity risk or distress risk in the banking sector, and the literature has provided arguments on both sides (see, for example, Taylor and Williams [2009]; Angelini, Nobili, and Picillo [2011]; and Schwarz [2015]). This debate is difficult to resolve, as credit risk and liquidity risk are much intertwined and influence each other.

To give an idea of the liquidity and credit risk components in the TED spread, we present the TED spread and the spread between the Treasury bill rate and the Overnight Indexed Swap rate (i.e., the OIS-T-bill spread) in panel A of figure 1, and the TED spread and two distress risk measures in the banking sector in panel B of figure 1.[18] The OIS-T-bill spread is commonly used as a pure measure of liquidity risk in the overnight interbank market (for example, Bai, Krishnamurthy, and Weymuller [2017]). The first measure of bank distress risk is based on the expected default frequency (EDF) from the Merton (1974) model. We first calculate the EDFs for each bank-month,[19] and then aggregate the EDFs across all banks for each month from January 1984 to December 2010. The second measure of overall credit risk in the banking sector is the

[17] We include the unused commitments and the loan-to-deposit ratio following Acharya and Mora (2015).
[18] We have also tried the bank failure probability measure developed by the Risk Management Institute (RMI) of the National University of Singapore (available via the website: http://rmicri.org/en/). The results are similar to those reported in the paper. We do not report such results due to space limitations.
[19] We follow the algorithm in Bharath and Shumway (2008). The raw data for constructing bank-level EDFs are sourced from Compustat and CRSP.

credit default swap (CDS) spread. In the graph we use the aggregate one-year CDS spreads of all financial firms from January 2001 to December 2010.[20] We argue that any distress risk in the banking sector should be reflected in either the equity market, where EDF derives its values, or the CDS market. It is obvious from figure 1 that the TED spread is much more correlated with the OIS-T-bill spread in panel A than with either bank distress risk measure in panel B. Therefore, figure 1 suggests that the TED spread is likely more driven by interbank liquidity risk than by credit risk.

However, the distinction between the two components in the TED spread is not critical to the main message in this paper. We merely argue that the information in the TED spread does not have much overlap with the information embedded in bank financial ratios, as the TED spread changes quickly with new market information and is reflective of the market's forward-looking views, while the bank financial ratios are rather stale and backward-looking.[21]

In addition, we include in our analysis a variable indicating whether a bank is a subsidiary of a multi-bank holding company, based on information from the Integrated Banking Information System (IBIS). This binary variable is equal to 1 if the bank is a member of a multi-bank holding company and equal to 0 otherwise. The reason for including this variable is because The Financial Institutions Reform, Recovery, and Enforcement Act of 1989 (FIRREA) required bank holding companies to inject capital into insolvent subsidiaries, so subsidiaries of multi-bank holding

[20] The series of aggregate CDS spreads is based on CDS data for all financial firms provided by Markit.com. More specifically, it is the monthly averaged one-year or five-year financial CDS spreads with Doc Clause=MR, Seniority Tier= SNRFOR (senior unsecured debt), and Currency=USD from January 2001 to December 2010. We have tried both one-year and five-year CDS spreads, and the results are similar. Due to space limitations, we only report results from one-year CDS spreads in the paper (to be more in line with the one-year forecasting horizon in the later bank failure regression analyses), and those using five-year CDS spreads are available upon request.

[21] Due to space limitations, we do not report the correlations among explanatory variables. The correlations between TED spread and other variables are low, below 0.10. Therefore, the impact from TED is rather orthogonal to other commonly used financial variables to predict bank failures.

companies might be less likely to fail.[22]

Panel A of table 2 presents the descriptive statistics of the entire sample, as well as by healthy and failed bank-year observations. This panel suggests that failed banks were more risky, a result consistent with the findings of the extant bank failure literature (for example, Cole and White [2012]). However, some of the results from univariate analysis may be driven by the correlations among the bank-level variables. We will resort to regression analysis later in section IV to make formal inferences.

Panel B of table 2 provides summary statistics by banks of different size groups. It is clear that there is not much difference in terms of capital ratio or return on assets (ROA) across banks of different sizes. However, this panel suggests that larger banks and smaller banks adopt different business strategies. Smaller banks tend to target more risky borrowers (i.e., higher loan yields and more CRE loans). Larger banks, on the other hand, tend to have lower liquidities, as reflected in lower proportions of their assets invested in government securities, lower reliance on core deposits, and more holdings of brokered deposits and short-term liabilities. This phenomenon is most likely due to the funding advantages enjoyed by larger banks, but this funding strategy may make these banks more sensitive to the interbank funding risk. Larger banks also derive more of their income from noninterest earnings.

IV. Empirical Results

IV.A. The Model

Consider a cross-section of banks i ($i = 1, N$). For each bank i, we define an event history

[22] We would like to thank a referee for pointing this out.

$D_i(1), D_i(2), \ldots D_i(T)$, where $D_i(t)=1$ if bank i fails in period t and $D_i(t)=0$ otherwise. We stack these *N* separate event histories on top of each other, resulting in a column of zeros and ones, with one row for each bank-period observation. We use the discrete hazard model to predict bank failures throughout the paper, and the dependent variable consists of 0s and 1s, as defined above. Note that for failed banks, we only keep the first $D_i(t)=1$ in the analysis. Let $P_{i,t}$ be the probability of failure for bank *i* in period *t*, and the hazard model can be written as:

$$P_{i,t} = \frac{1}{\left[1+\exp\left(\begin{array}{l} -\gamma_0 - \gamma_1 \times TED\ Spread_{t-1} - \gamma_2 \times HPI\ changes_{t-1} \\ -\sum_i \beta_i \times Financial\ \text{var}iables_{t-1} - u_i \end{array}\right)\right]}$$

We do not add bank fixed effect in the model for two reasons. First is the well-known incidental parameters problem and additional assumptions required to incorporate fixed effects in logit models. Second, the majority of banks in our sample never fail, and adding bank fixed effect will eliminate these banks from estimation. For these reasons, we only add the bank random effect u_i in the model.

IV.B. Bank Failure Prediction

IV.B.1 Results over the entire sample 1985–2011

Table 3 presents regression results over the entire sample period for bank failures observed during 1985–2011. The first two columns report results from one-year-ahead predictions and the last two columns present results from one-quarter-ahead predictions. Columns 1 and 3 show the base model with bank-level financial variables only, and columns 2 and 4 show the results where TED spread and local HPI changes are included. We do not include in the base model some of the bank-level variables from table 2 because they do not show coefficient estimates that are statistically significant. Note that the main conclusions of the paper do not change if we use the full list of bank-level financial variables in table 2 or even additional variables beyond those in table 2, nor if we include a broad set of the macro variables.[23]

It is clear from the first column of table 3 that, compared with healthy banks, failed banks were less profitable and in weaker financial condition, as indicated by the lower capital ratios, lower ROAs, and more nonperforming assets (NPA). Failed banks earned lower net interest margins but they charged higher yield; the latter results suggest that failed banks were more aggressive in lending to riskier borrowers. Failed banks had more CRE loans and fewer mortgage-backed securities and were less likely to be part of a multi-bank holding company. The positive coefficient on the noninterest income ratio suggests that a higher proportion of the earnings of failed banks came from nontraditional businesses. Failed banks also had lower proportions of government securities, more brokered deposits, and higher short-term liabilities; these results suggest that failed banks were more subject to idiosyncratic liquidity risk, and such results are along the same lines as those among industrial firms (for example, He and Xiong [2012]).

The second column of table 3 adds the TED spread and changes in state-level HPI to the base model in the first column; we call this the full model. Note that the log-likelihood increases significantly from -4593 of the base model in column 1 to -4486 of the full model in column 2. Together with the changes in AIC and BIC from column 1 to column 2, the first two columns of table 3 point toward a substantial improvement in model fit when TED spread and changes in local HPI are incorporated into the base model for the one-year-ahead forecast. However, adding these two symmetric risk factors does not materially change the models' rank ordering abilities, as Area Under the Curve (AUC) remains the same at 0.98 in both the base and full models.

The coefficient estimate of the TED spread is significantly positive, indicating that banks were

[23] We will describe results from the analysis incorporating macroeconomic variables in section IV.C.

more likely to fail during periods when the TED spread was higher. In addition, changes in local HPI have a significantly negative coefficient estimate; therefore, bank failures were less likely to occur among banks in states or during periods with higher appreciation in house prices.

We next investigate the economic impact of both the TED spread and changes in local HPI from the marginal effects associated with the estimated coefficients in the second column of table 3. We evaluate the marginal effect at each point of the data and then take the average of the marginal effects over the entire sample. Due to space limitations, we discuss but do not report the marginal effects; these results are available upon request.

Among all variables, capital ratio had the largest economic impact: A drop of one standard deviation in capital ratio led to roughly a 0.88 percentage point increase in bank failure probabilities. This marginal impact was larger than that of all other variables. The economic impacts of the TED spread and changes in local HPI were quite comparable to that of other financial variables. A rise of one standard deviation in the TED spread was roughly associated with an increase of bank failure probability of 0.10 percentage points, and a fall of one standard deviation in state-level HPI was related to a rise of approximately 0.13 percentage points in the probabilities of bank failures. By comparison, a drop of one standard deviation in ROA could raise the probability of bank failure by 0.16 percentage points, and a drop of one standard deviation in net interest margin tended to increase bank failure probabilities by 0.10 percentage points. Further, a one standard deviation increase in noninterest income ratio was related to an increase of only about 0.04 percentage points in bank failure probabilities, and a one standard deviation rise in the proportion of CRE loans was likely to boost bank failure probabilities by 0.09 percentage points. Therefore, both statistically and economically, the interbank funding market and local housing market conditions had significant impact on bank failures at the annual forecast horizon.

The third column reports the base model over one-quarter-ahead prediction covering the entire period of 1985Q1–2011Q4, and the fourth column adds TED spread and local HPI changes to the model specification. A comparison of the first and third column of table 3 shows that most financial ratios retain their signs and statistical significance when the prediction horizon shortens from one year to one quarter. However, we do see opposite signs in the third column. For example, the coefficient of the core-deposit ratio is negative in the first column but positive in the third column. Since core deposits provide stable funding and retail depositors were typically the last to withdraw their funding (as is shown in Huang and Ratnovski [2011]), a higher core-deposit ratio should not lead to a higher bank failure probability intuitively. We also observe a change in the coefficient of loan-to-deposit ratio from the first column to the third column, and the negative coefficient in the third column is also counterintuitive. These findings are most likely driven by the noise in quarterly bank failure observations, as discussed in section III.A.

The fourth column shows that at the one-quarter-ahead prediction horizon, neither TED spread nor local HPI changes added significant value to bank failure models. Such results could be driven by the noise in bank failure observations, but it could also mean that, at the one-quarter forecast horizon, bank failures were predominantly affected by bank fundamentals over the entire period from 1985–2011, and the impact from the interbank funding market and local housing market was largely channeled through and reflected in the banks' worsening balance sheets. Note that the lack of significant coefficients in the one-quarter-ahead prediction for the two systematic risk factors in table 3 does not necessarily suggest these two factors are not important for bank regulation, as bank regulators and academics are typically equally interested, if not more interested, in forecasting bank failures for periods longer than one quarter.

Table 3 therefore suggests that the near-term causes of bank failures were basically bank fundamentals. However, TED spread and local housing market conditions were significantly related to bank failure probabilities in the longer forecast horizon, and they could thus warn of the looming banking crisis several quarters in the future.

To further understand the impact of local housing market conditions and funding market conditions at various stages of the business cycle, we plot in figure 2 the actual and fitted one-year-ahead bank failure rates from the base model (the first column in table 3) and the full model (the second column in table 3). It is clear that the two models largely track each other closely from 1985 to 2011, except for a few years. In the first episode, the advantage of the full model mainly showed up in its peak year of 1988, while in the latest banking crisis, the full model outperformed the base model during 2009–2011. Note that the base model underpredicted the height of both banking crises in 1988 and 2009, most likely because the worsening outlook had yet to be reflected in the backward-looking financial variables. If the FDIC had not been able to close all troubled banks in the banking crisis due to staffing constraints, the underprediction from a model based entirely on bank-level financial variables would have been even more drastic in these years. Further, figure 2 shows that the full model still underpredicted the extent of bank failures in 2009. This underprediction was possibly driven by the change in coefficient estimates over time; we will investigate this issue in the next section via subperiod analysis. The story for 2011 is different from that of 2009. In 2011, the base model actually overpredicted, while the full model yielded a fitted bank failure rate much closer to the actual realized bank failure rate. We dissect this phenomenon in table 4, which analyzes the contributions from the TED spread, the changes in local HPI, and financial variables for each year during the period 1985–2011.

To calculate the contribution from the TED spread, we first calculate

$$P_{i,t} = \frac{1}{\left[1 + \exp\left(\begin{array}{l} -\gamma_0 - \gamma_1 \times TED\ Spread_{t-1} - \gamma_2 \times HPI\ changes_{t-1} \\ -\sum_i \beta_i \times Financial\ \text{var}iables_{t-1} - u_i \end{array} \right)\right]}$$

and

$$\vec{P}_{i,t} = \frac{1}{\left[1 + \exp\left(-\gamma_0 - \gamma_2 \times HPI\ changes_{t-1} - \sum_i \beta_i \times Financial\ \text{var}iables_{t-1} - u_i \right)\right]}$$

The contribution from the TED spread will therefore be the difference between $P_{i,t}$ and $\vec{P}_{i,t}$. Contributions from changes in local HPI and bank-level financial variables are similarly defined. We report in table 4 the actual bank failure rates; the fitted bank failure rates from the full model; and the contributions from the TED spread, local HPI changes, and financial ratios, respectively.

It is clear from this table that during the years when the rates of bank failures were low, the contributions from all three components were small. When bank failure rates shot up, bank fundamentals, as reflected in financial ratios, usually were the main contributors to the failures. The last row of the table indicates that, over the entire period, bank fundamentals had the largest impact on bank failures. However, at the height of both banking crises (for example, in 1988 and 2009), the roles played by TED and local HPI were economically important and comparable to that of bank-level variables. The negative contribution of TED in 2010 and 2011 indicates that the sharp drop in the TED spread after 2009 helped to mitigate the severity of the latest banking crisis, which explains why the base model overpredicted the bank failure rate in those two years, as depicted in figure 2.

The negative contribution of the TED spread after 2009 in table 4 also suggests that the Fed liquidity injection programs likely stabilized the turmoil at the apex of the latest banking crisis. Further, the findings from tables 3–4 and figure 2 indicate that the sum of the risks faced by individual institutions could deviate dramatically from the overall risk facing the entire banking system in crisis years, confirming the general consensus in banking regulation that macro-prudential overlay is critically important. However, how challenging is it to identify the critical systematic factors and to assess their economic impact for the next crisis? We next turn to subperiod analysis to develop more insights.

IV.B.2 Results over subsamples

We report results from the full model for the two subperiods, 1985–2005 and 2006–2011 respectively, in table 5, with the first two columns reporting one-year- and one-quarter-ahead failure predictions from 1985–2005, and the last two columns showing results for the subperiod 2006–2011.

It is clear from the first and third columns of table 5 that the coefficients of the changes in local HPI and the corresponding marginal effect (not reported here due to space limitations) were strong in both subperiods, suggesting that the impact of local housing market conditions on bank failures had been strong throughout both banking crises.[24] Further, the coefficient estimate of local HPI changes was slightly larger in the earlier period than in the latest banking crisis. What drove the change in the coefficient estimate of local HPI changes over the two periods in table 5? One possible explanation is the changes in banking operations over time. Before the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994, interstate branching was not allowed, and single-state banks should be more vulnerable to economic shocks in the states in which they were located. We next explore whether this change in banking regulation could explain the variations in the coefficient of the local HPI changes observed in table 5.

[24] This finding is different from that in Aubuchon and Wheelock (2010) that the bank failures during the first episode were less associated with distress in the housing market than in the latest banking crisis. Their results are derived from simple correlation analysis at the aggregate level.

We classify banks into single-state banks and multiple-state banks based on whether the bank had branches in multiple states using the Summary of Deposits, which is the FDIC's annual survey of branch office deposits for all FDIC-insured financial institutions. Figure 3 depicts the composition of banks operating in multiple states and single states over time. It is clear from this figure that more and more banks opened branches across states over time. We then run the full model within single-state banks for both subperiods,[25] and such results are reported in table 6. It is clear from this table that, for the one-year-ahead forecast, the coefficient estimate of local HPI changes is actually of a larger magnitude in the 2006–2011 subperiod than the 1985–2005 subperiod among the single-state banks. Therefore, the finding of smaller impact from local HPI changes in the latest banking crisis as indicated in the first and third columns of table 5 was indeed driven by multiple-state banks in the latter period.

For one-year-ahead prediction, the first column of table 5 shows that the coefficient estimate of the TED spread is 24.6 in the period 1985–2005, which is only marginally statistically significant. This coefficient rises to 104.0 in the subsequent period of 2006–2011. This result suggests that funding market conditions played a larger role in the latest banking crisis than in the earlier crisis. We argue that one driving factor behind this finding was the increasing reliance on wholesale funding over the past 30 years, as has been documented in Bao, David, and Han (2015). Another reason could be the growing usage of the over-the-counter financial derivative contracts. Both factors boosted the interconnectedness among banks in recent years, making banks more sensitive to the interbank market conditions.

By contrast, the coefficient estimates of some financial variables, for example, noninterest

[25] We are not able to run the model within multiple-state banks at the quarterly frequency because there are too few failure observations among multiple-state banks. The coefficient of the local HPI changes at the annual frequency is statistically nonsignificant among multistate banks.

income ratio, short-term liabilities ratio, and brokered deposits ratio, became statistically nonsignificant in the subperiod 2006–2011. Therefore, in the latest banking crisis, the funding market conditions and changes in local HPI seemed to have stronger impact on bank failures than some of the financial variables that have been suggested in the literature.

At the quarterly frequency, the second column of table 5 shows that the TED spread has a nonsignificant coefficient during the period 1985–2005, while the coefficient estimate of the local HPI change becomes significantly positive, which is counterintuitive. These results suggest that, for one-quarter-ahead forecasts during the first episode, either these systematic risk factors did not play an important role in bank failures, or the impact of these two factors was captured by the bank-specific financial variables included in the model. The fourth column of table 5, however, shows that both the TED spread and local HPI changes have significant and intuitive coefficient estimates during the period 2006–2011, even for one-quarter-ahead forecasts. So the impact from both systematic risk factors was strong and direct during the latest banking crisis. Such quarterly regression results hold in table 6 among the single-state banks as well.

Recall that in figure 2, even the full model still underpredicts the bank failure rates in 2009. Can the full model predict the latest banking crisis well if we estimate the failure probabilities for the two subperiods separately? We next plot in figure 4 the actual one-year bank failure rates and the predicted one-year failure rates from the base model and the full model for the two subperiods respectively. It is clear from both panels of figure 4 that if we estimate the full models in each subperiod, the full model is better able to capture both peaks of the two banking crises, and the major difference between figure 2 and figure 4 shows up in 2009.

Combining results from both banking crises, we can conclude that the interbank funding market played a bigger role in the latest banking crisis. The changing importance of the systematic risk factor raises a concern. If we could go back to 2006 and we knew that TED spread and local HPI changes were critical systematic risk factors in the next crisis based on past experience, but we did not know the changing economic impact from these factors, how much would we underestimate the severity of the latest banking crisis? To address this question, we next predict bank failure rates during 2006–2011 based on the full model developed using data from 1985–2005. We use the same coefficient estimates based on the first column of table 5, apply these coefficients to the realized values of the RHS variables during the period 2005–2010, and then predict the one-year ahead bank failure rates from 2006–2011. We plot such results in figure 5. It is clear from this figure that our prediction for each year from 2008 to 2011 would be substantially too low even if we could perfectly forecast the realizations in the RHS variables. For example, the bank failure rates in 2009 would be underpredicted by one percentage point, which translates into underprediction by 60 percent in relative terms. The degree of relative underprediction is even higher at 78.8 percent in 2008. The relative underprediction is 21.5 percent and 28.3 percent in 2010 and 2011, respectively; these numbers are lower relative to those in 2008–2009, but the magnitude is still alarming in these two years. Such underestimation of bank failures is entirely due to the changing economic impact of the same systematic risk factors.

Adding to the aforementioned challenge, it would be even more difficult to predict what the systematic risk factors would be in the next banking crisis. It is possible that real estate may not be the source of the next banking crisis, as banks' market share in mortgage lending has been declining in the past eight years (Buchak, Matvos, Piskorski, and Seru [2017]), while at the same time, U.S. household debt levels are hovering near record highs,[26] and such a rise in household debt in recent years is mainly due to nonmortgage debts. Banks have not yet experienced noticeable

[26] See, for example, news articles such as https://www.reuters.com/article/us-usa-fed-debt/americans-debt-level-notches-a-new-record-high-idUSKCN1AV1PY.

anomalies in the mortgage sector at present, but delinquency rates have been rising on other consumer debts, such as credit cards.[27] Therefore, the risks for the next banking crisis might stem from sources unknown in the past, and in this ever-changing financial environment, new systematic risk factors in the financial industry might be looming but unnoticed.

IV.C. Additional Investigations

As stated before, we have tried adding other macro variables to our hazard model. These include national-level macro variables, such as changes in real GDP, changes in industrial production, capacity utilization, level and changes in unemployment rate, and national HPI changes. Since the lion's share of the banks in our study consists of small banks, and their operations are oriented toward local businesses, we also tried including state-level macro variables such as state income growth, state population growth, level and changes of state unemployment rate, and state GDP growth. The relations between these macro variables and bank failures were not very stable across the two cycles of banking crises during our sample period. In particular, none of the macro variables we have investigated (other than local HPI changes and TED spread) showed coefficient estimates that were intuitive and statistically significant in the latest banking crisis. Such evidence is consistent with the prior findings in the literature on the relationship between macro variables and bank failures (for example, Nuxoll, O'Keefe, and Samolyk [2003]). More importantly, the coefficient estimates of the TED spread and local HPI do not change materially regardless of whether we include these macro variables or not among the RHS of the regressions, so the conclusions in this paper are not affected by the inclusion or exclusion of additional macro variables. We do not report such results because of space limitations and these

[27] See, for example, news articles such as https://www.reuters.com/article/us-usa-creditcards-delinquencies/rising-credit-card-delinquencies-to-add-to-u-s-banks-worries-idUSKCN1BQ2E0.

results are available upon request.

We have also examined results when only liquidated banks are defined as failed banks and repeated all the analyses. Results from such analyses do not change qualitatively from those presented in the paper; they are not reported because of space limitations and are available upon request.

Further, we have constructed adjusted TED spread by regressing TED spread on the two credit risk measures in figure 1. We call the residuals of such regressions the EDF- or CDS-adjusted TED spreads, and then replace the raw TED spread with the adjusted TED spreads in all the analyses conducted here. All results reported in the paper hold if we use the two adjusted TED spreads. Therefore, our results are not likely driven purely by the forward-looking distress risk as reflected in EDF or CDS, and liquidity risk in the interbank funding market played a key role in the stability of the banking system during recent banking crises.

Conclusion

We find that, over the entire period from 1985–2011, both conditions in the interbank funding market and changes in local HPI were significantly related to the probabilities of bank failures after controlling for bank-level risk factors, and the economic impact of both variables on bank failures was comparable to that of the commonly used bank-level financial variables. Local housing market conditions were strongly related with bank failures in both banking crises during our sample period. While the funding market conditions only weakly helped to predict bank failures during the first crisis, its impact was much stronger in the latest banking crisis. Without accounting for the changes in their economic impact, we would have significantly underestimated the severity of the latest banking crisis for each year from 2008 to 2011 even if we could perfectly predict the realizations in the explanatory variables. Further, we argue that the two systematic risk factors investigated in the paper might be episode specific, and new systematic risk factors might emerge in the next crisis. Therefore, even though it is common wisdom at present that overall banking risk is more than just the sum of risks at the individual bank level and the macro-prudential overlay is important in bank regulation, finding the right systematic risk factors for the next banking crisis or correctly gauging their impact on bank failures can be very challenging.

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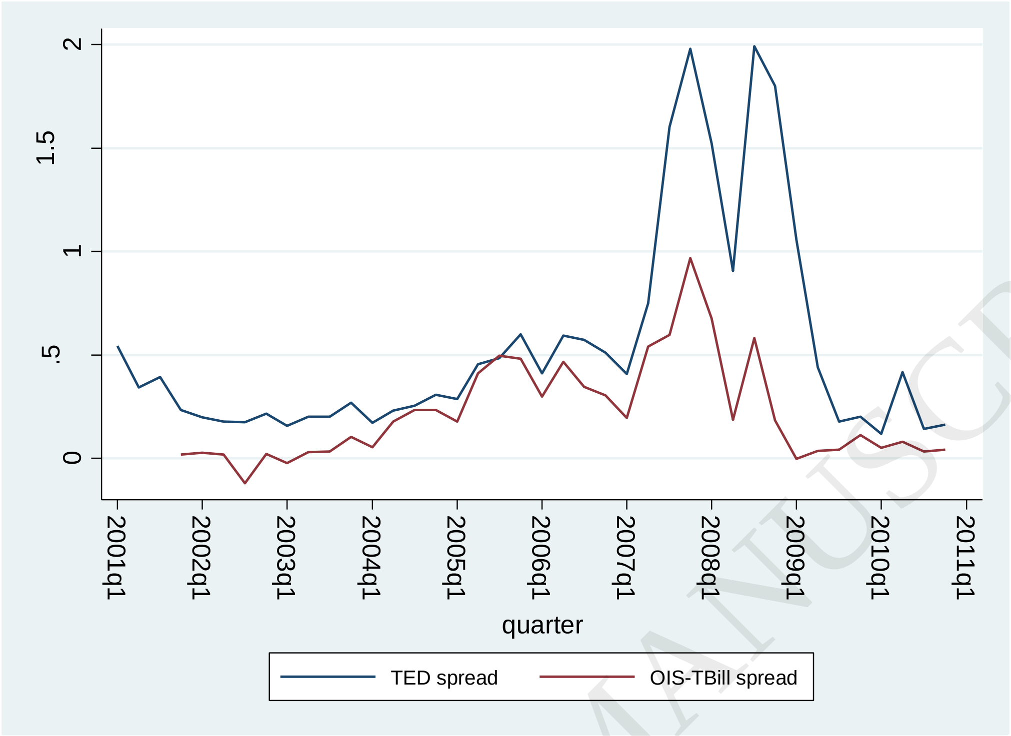
Figure 1: Quarterly Time Series of TED and Other Liquidity and Credit Measures

Panel A: Quarterly TED spreads vs. OIS-TBill (3m)



Panel B: Quarterly TED spreads vs. EDF and CDS

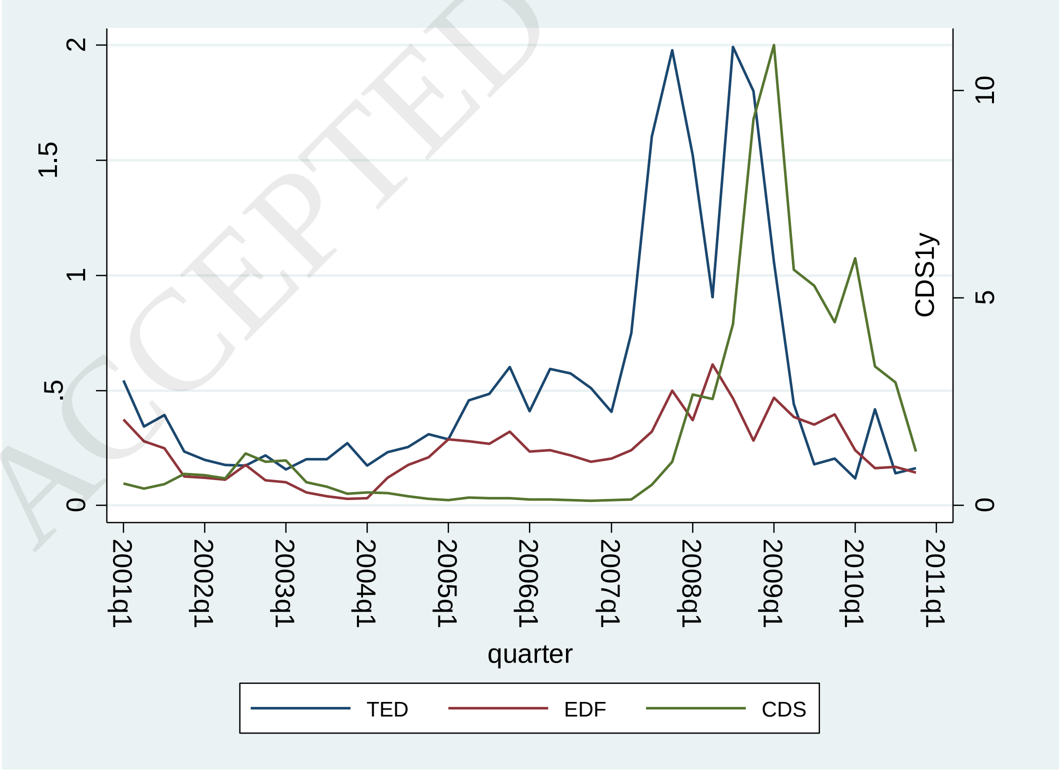


Figure 2: Observed vs. Fitted One-Year Bank Failure Rates (1985–2011)

This figure reports over the entire period of 1985–2011 the observed bank failure rates and fitted bank failure rates from the base model (the specification in the first column of table 3, using only bank-level financial variables) and the full model (the specification in the second column of table 3). The full model adds TED spreads and local HPI changes to the right-side variables of the base model.

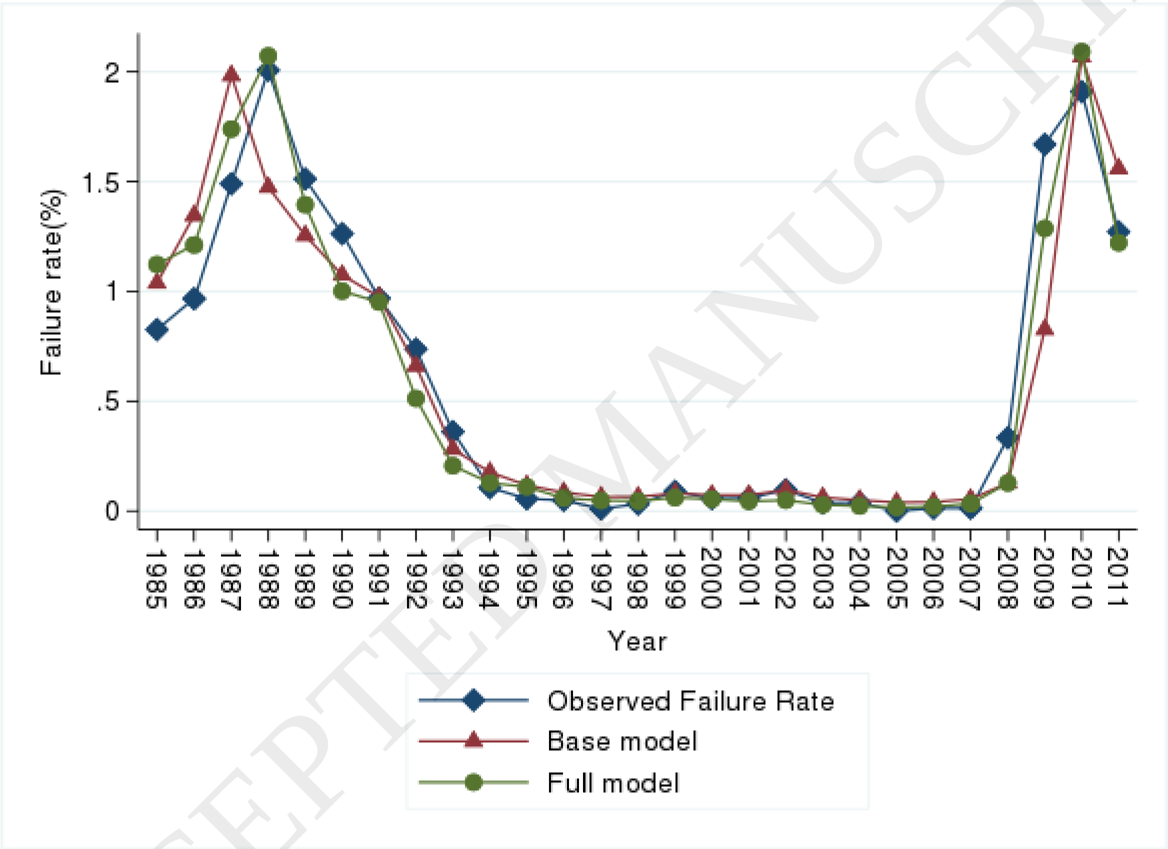


Figure 3: Proportion of Single State vs. Multiple State Banks

This figure reports the composition of banks operating in single state and multiple states over time.

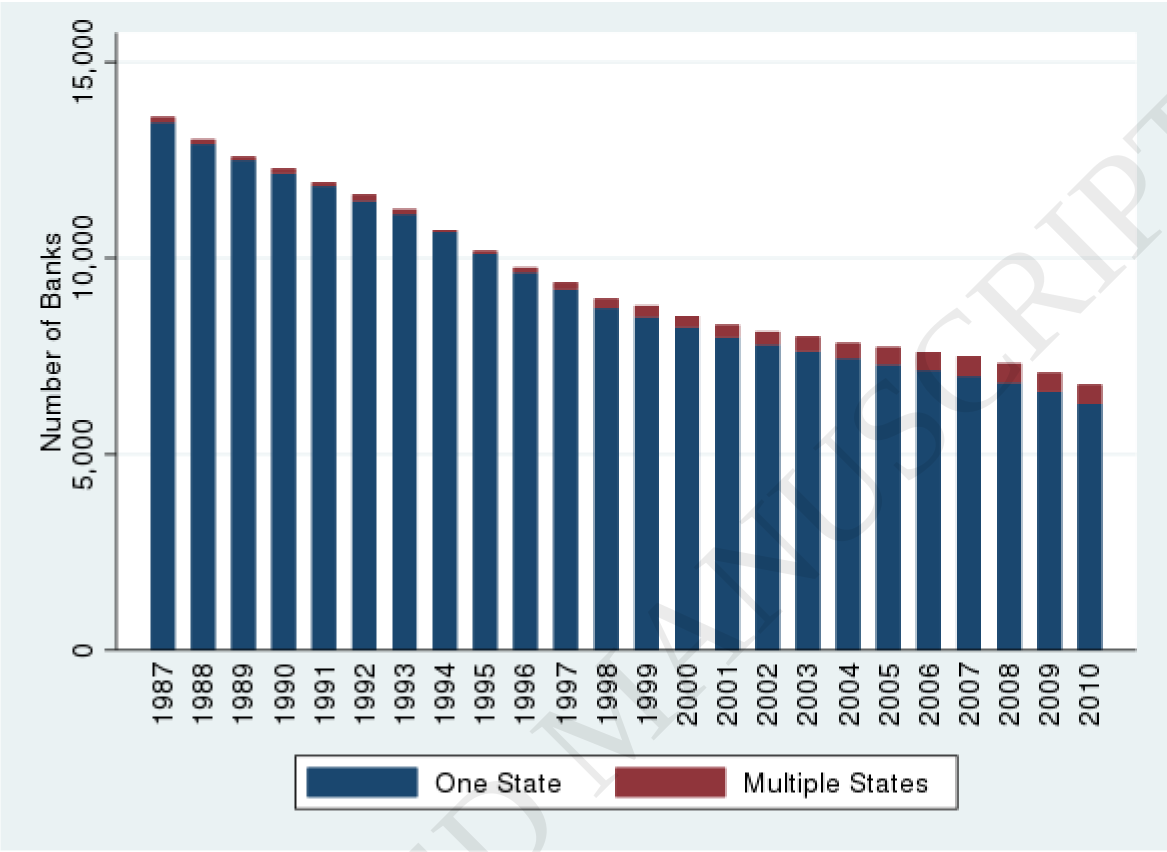


Figure 4(a): Observed vs. Fitted One-Year Bank Failure Rates for 1985–2005

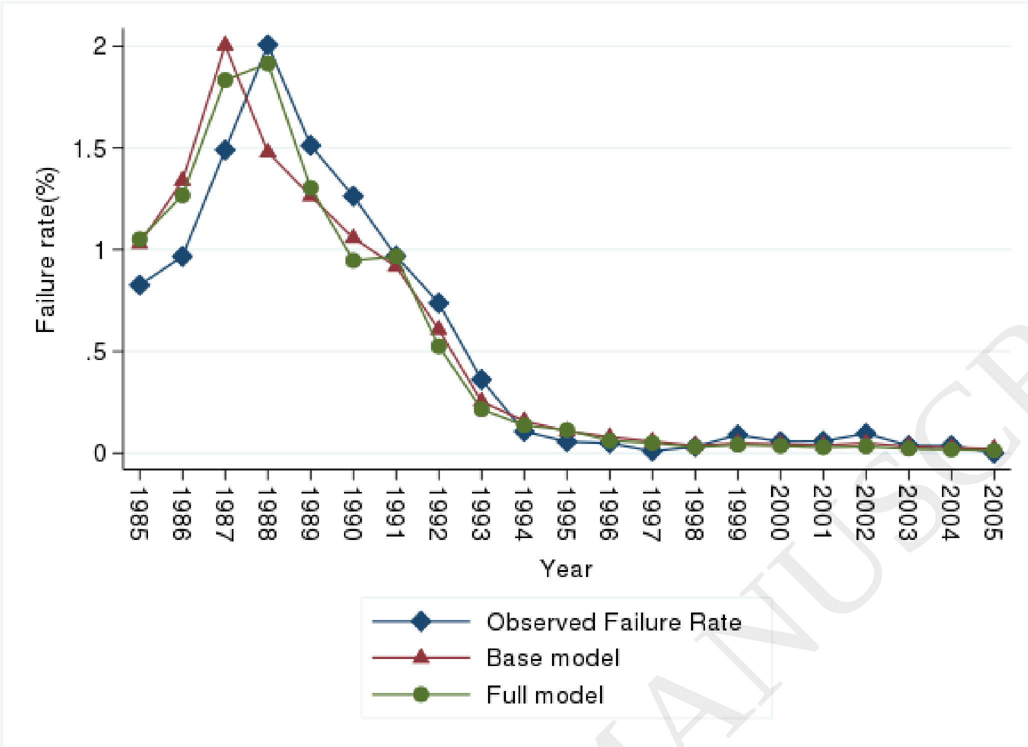


Figure 4(b): Observed vs. Fitted One-Year Bank Failure Rates for 2006–2011

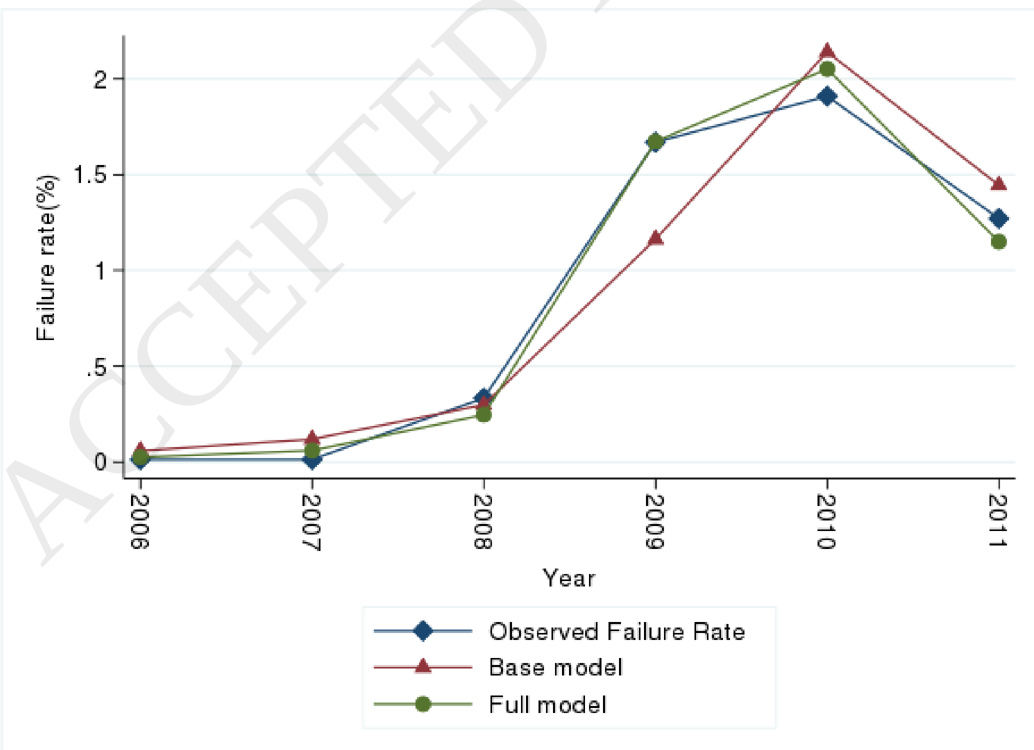


Figure 5: Observed vs. Forecasted One-Year Bank Failure Rates for 2006–2011 using 1985–2005 Estimates

The forecasted bank failure rate for 2006–2011 is calculated as follows: We use the same coefficient estimates based on the first column of table 5 (i.e., from the 1985–2005 period), apply these coefficients to the realized values of the explanatory variables during the period 2005–2010, and then predict the one-year bank failure rates from 2006–2011.

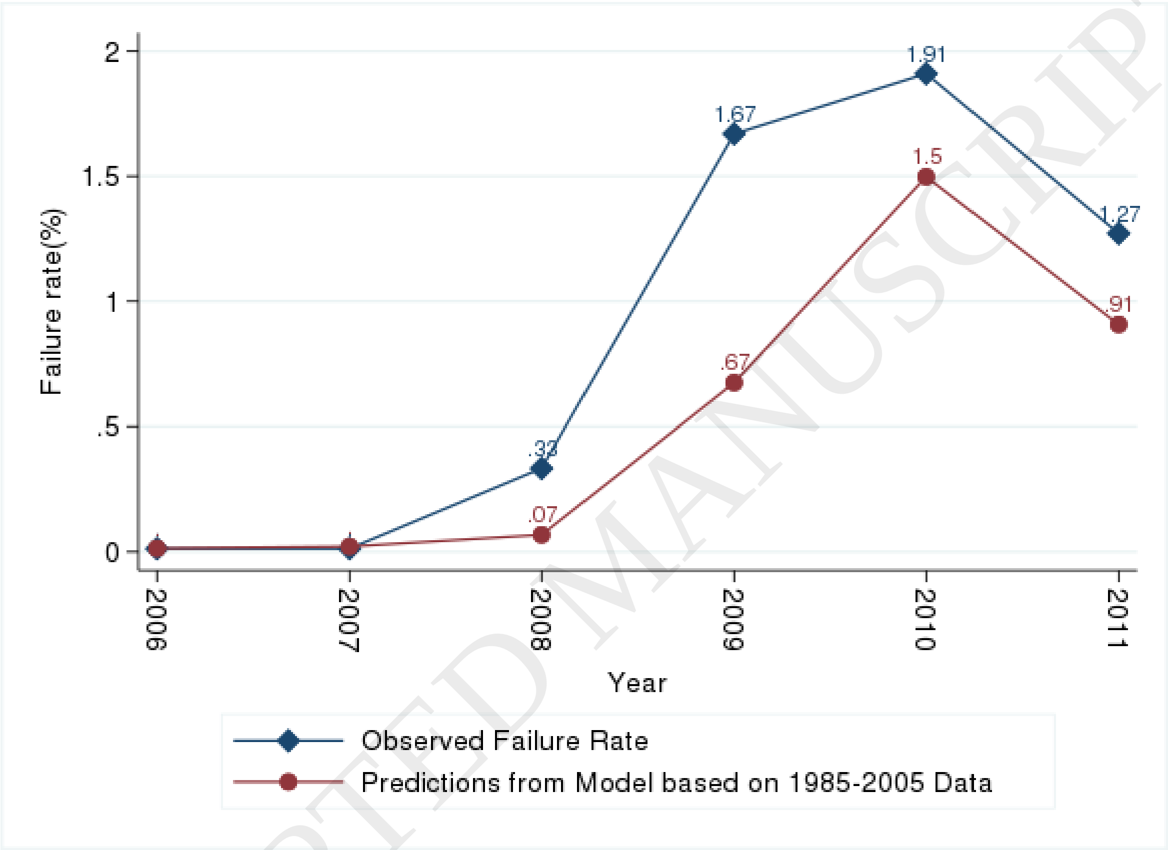


Table 1: Number of Failed Banks by Year and by Asset Sizes (1985–2011)

All banks are divided into three asset size groups: small, medium-sized, and large. Small banks are banks with total assets below $1 billion. Medium-sized banks are those with total assets between $1 billion and $50 billion. Large banks are those with total assets of $50 billion or more.

	All banks			Large banks			Mid-sized banks			Small banks		
Year	Obs	Failed	Percent	Obs	Failed	Percent	Obs	Failed	Percent	Obs	Failed	Percent
1985	14,285	118	0.83%	6	0	0.00%	273	1	0.37%	14,006	117	0.84%
1986	14,273	138	0.97%	7	0	0.00%	307	1	0.33%	13,959	137	0.98%
1987	14,093	210	1.49%	7	0	0.00%	337	1	0.30%	13,749	209	1.52%
1988	13,601	273	2.01%	7	0	0.00%	355	6	1.69%	13,239	267	2.02%
1989	13,026	197	1.51%	7	0	0.00%	376	4	1.06%	12,643	193	1.53%
1990	12,587	159	1.26%	7	0	0.00%	380	1	0.26%	12,200	158	1.30%
1991	12,284	119	0.97%	8	0	0.00%	381	11	2.89%	11,895	108	0.91%
1992	11,930	88	0.74%	8	0	0.00%	368	6	1.63%	11,554	82	0.71%
1993	11,621	42	0.36%	7	0	0.00%	392	1	0.26%	11,222	41	0.37%
1994	11,242	12	0.11%	7	0	0.00%	399	0	0.00%	10,836	12	0.11%
1995	10,703	6	0.06%	7	0	0.00%	394	0	0.00%	10,302	6	0.06%
1996	10,178	5	0.05%	7	0	0.00%	418	0	0.00%	9,753	5	0.05%
1997	9,756	1	0.01%	10	0	0.00%	385	0	0.00%	9,361	1	0.01%
1998	9,379	3	0.03%	18	0	0.00%	359	0	0.00%	9,002	3	0.03%
1999	8,961	8	0.09%	16	0	0.00%	380	1	0.26%	8,565	7	0.08%
2000	8,782	5	0.06%	15	0	0.00%	384	0	0.00%	8,383	5	0.06%
2001	8,518	5	0.06%	17	0	0.00%	379	1	0.26%	8,122	4	0.05%
2002	8,293	8	0.10%	18	0	0.00%	382	0	0.00%	7,893	8	0.10%
2003	8,116	3	0.04%	19	0	0.00%	396	0	0.00%	7,701	3	0.04%
2004	7,995	3	0.04%	21	0	0.00%	414	0	0.00%	7,560	3	0.04%
2005	7,829	0	0.00%	22	0	0.00%	419	0	0.00%	7,388	0	0.00%
2006	7,723	1	0.01%	24	0	0.00%	447	0	0.00%	7,252	1	0.01%
2007	7,596	1	0.01%	24	0	0.00%	467	0	0.00%	7,105	1	0.01%
2008	7,491	25	0.33%	27	2	7.41%	487	6	1.23%	6,977	17	0.24%
2009	7,308	122	1.67%	26	3	11.54%	485	23	4.74%	6,797	96	1.41%
2010	7,068	135	1.91%	24	0	0.00%	489	15	3.07%	6,555	120	1.83%
2011	6,765	86	1.27%	25	0	0.00%	493	5	1.01%	6,247	81	1.30%
All	271,403	1773	0.65%	391	5	1.28%	10,746	83	0.77%	260,266	1685	0.65%

Table 2: Summary Statistics of Explanatory Variables, Annual Data, 1984–2010

The variables are defined in appendix A. All numbers are expressed in real values, except for size, which is the natural logarithm of total assets (expressed in thousands of U.S. dollars).

Panel A: Summary statistics of all banks and by failure status

Variable	All banks			Healthy banks		Failed banks		
	Mean	Median	Std	Mean	Median	Mean	Median	t-values*
Size	11.239	11.080	1.325	11.240	11.081	11.019	10.738	7.01
Capital ratio	0.097	0.089	0.035	0.097	0.089	0.046	0.036	61.72
Return on assets	0.008	0.010	0.011	0.008	0.010	-0.029	-0.038	152.67
Net interest margin	0.040	0.040	0.009	0.040	0.040	0.032	0.031	37.22
Loan yields	0.098	0.097	0.025	0.098	0.097	0.112	0.117	-23.96
Noninterest income ratio	0.009	0.006	0.027	0.009	0.006	0.011	0.008	-2.52
Government securities ratio	0.190	0.163	0.145	0.191	0.164	0.071	0.041	34.57
Brokered deposits ratio	0.009	0.000	0.032	0.008	0.000	0.033	0.000	-32.255
Short-term liability ratio	0.350	0.305	0.200	0.350	0.306	0.283	0.195	14.14
Core-deposits ratio	0.652	0.674	0.123	0.652	0.673	0.679	0.703	-9.25
Loan-to-deposit ratio	0.670	0.671	0.196	0.670	0.671	0.676	0.685	-1.33
Unused commitments ratio	0.070	0.049	0.075	0.070	0.049	0.044	0.025	14.14
Nonperforming assets ratio	0.014	0.007	0.019	0.013	0.007	0.085	0.102	-164.91
Commercial real estate loans ratio	0.217	0.171	0.178	0.217	0.171	0.284	0.232	-15.93
Mortgage-backed assets ratio	0.582	0.582	0.242	0.583	0.582	0.516	0.475	11.53
Loan growth	0.102	0.071	0.205	0.104	0.071	-0.079	-0.123	37.37
Loan mix	0.394	0.363	0.215	0.393	0.361	0.532	0.551	-27.06
OREO ratio	0.004	0.001	0.008	0.004	0.001	0.027	0.026	-124.92
Consumer loans charge-off	0.000	0.000	0.001	0.000	0.000	0.000	0.000	-1.60
Commercial loans charge-off	0.000	0.000	0.001	0.000	0.000	0.001	0.000	-32.07

*T tests of the differences between healthy and failed banks.

Table 2 (continued)

Panel B: Summary statistics by bank size

Variable	Large banks		Mid-sized banks		Small banks	
	Mean	Median	Mean	Median	Mean	Median
Size	18.570	18.284	14.845	14.602	11.079	11.021
Capital ratio	0.091	0.081	0.086	0.079	0.097	0.089
Return on assets	0.009	0.011	0.009	0.011	0.008	0.010
Net interest margin	0.030	0.030	0.036	0.036	0.040	0.040
Loan yields	0.076	0.073	0.085	0.083	0.099	0.098
Noninterest income ratio	0.026	0.021	0.017	0.011	0.009	0.006
Government securities ratio	0.036	0.020	0.109	0.086	0.193	0.167
Brokered deposits ratio	0.028	0.010	0.026	0.000	0.008	0.000
Short-term liability ratio	0.494	0.547	0.517	0.554	0.343	0.295
Core-deposits ratio	0.389	0.371	0.521	0.544	0.658	0.677
Loan-to-deposit ratio	0.863	0.889	0.842	0.843	0.662	0.664
Unused commitments ratio	0.339	0.391	0.182	0.165	0.065	0.046
Nonperforming assets ratio	0.015	0.009	0.014	0.008	0.014	0.007
Commercial real estate loans ratio	0.131	0.104	0.295	0.260	0.214	0.168
Mortgage-backed assets ratio	0.430	0.449	0.642	0.681	0.580	0.579
Loan growth	0.072	0.042	0.101	0.075	0.102	0.071
Loan mix	0.412	0.437	0.495	0.494	0.390	0.356
OREO ratio	0.002	0.000	0.003	0.001	0.004	0.001
Consumer loans charge-off	0.002	0.001	0.001	0.001	0.000	0.000
Commercial loans charge-off	0.002	0.001	0.001	0.001	0.000	0.000

Table 3: TED Spread, Local House Prices, and Bank Failures

This table reports the effects of conditions in the interbank funding market, as measured by the TED spread and local house prices on bank failures at the one-year and one-quarter forecast horizon. We use the discrete hazard model to predict bank failures, and the dependent variable is equal to 1 if bank i fails in year/quarter t and 0 otherwise. Let $P_{i,t}$ be the probability of failure for bank *i* in year/quarter *t*, and the hazard model in this table has the following specification:

$$P_{i,t} = \frac{1}{\left[1 + \exp\begin{pmatrix} -\gamma_0 - \gamma_1 \times TED\ Spread_{t-1} - \gamma_2 \times HPI\ changes_{t-1} \\ -\sum_i \beta_i \times Financial\ \mathrm{var}iables_{t-1} - u_i \end{pmatrix}\right]}$$

where u_i is the random effect. We call this specification the full model in the table. The sample period is 1985–2011 (in terms of the dependent variable).

As a comparison, this table also reports the effect of financial variables only on bank failures at the one-year and one-quarter forecast horizon with the following model specification:

$$P_{i,t} = \frac{1}{\left[1 + \exp\left(-\gamma_0 - \sum_i \beta_i \times Financial\ \mathrm{var}iables_{t-1} - u_i\right)\right]}$$

We call this specification the base model in the table. Variables are defined in appendix A. *, **, and *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively. Standard errors are reported in the brackets.

Table 3 (continued): Prediction estimation results 1985–2011

	Annual	Annual	Quarterly	Quarterly
TED Spread		67.85***		11.83*
		[9.57]		[6.95]
HPI Changes		-6.68***		0.65
		[0.67]		[1.55]
Size	-0.08***	-0.05	-0.05	-0.04
	[0.03]	[0.03]	[0.03]	[0.03]
Capital Ratio	-59.15***	-59.67***	-78.02***	-77.88***
	[2.23]	[2.23]	[2.88]	[2.88]
Return on Assets	-38.39***	-35.56***	-40.08***	-39.98***
	[2.19]	[2.20]	[2.32]	[2.33]
Net Interest Margin	-34.30***	-28.38***	-33.34***	-33.04***
	[3.88]	[4.03]	[3.37]	[3.38]
Loan Yields	12.91***	11.70***	8.52***	8.14***
	[2.08]	[2.23]	[1.92]	[1.94]
Non-Interest Income Ratio	3.46***	3.56***	3.09*	2.94*
	[0.94]	[0.94]	[1.67]	[1.73]
Government Securities Ratio	-3.58***	-4.31***	-3.03***	-3.11***
	[0.37]	[0.38]	[0.32]	[0.32]
Brokered Deposits Ratio	5.76***	5.11***	3.90***	3.87***
	[0.64]	[0.65]	[0.52]	[0.52]
Short-Term Liabilities Ratio	0.53**	0.51**	0.86***	0.86***
	[0.25]	[0.25]	[0.22]	[0.22]
Core-Deposits Ratio	-0.67***	-0.41	0.77***	0.79***
	[0.25]	[0.26]	[0.23]	[0.24]
Loan-to-Deposit Ratio	0.44*	0.08	-0.71***	-0.73***
	[0.25]	[0.26]	[0.24]	[0.24]
Unused Commitments Ratio	-1.29**	-0.68	-1.10*	-1.09*
	[0.58]	[0.59]	[0.59]	[0.59]
Non-Performing Assets Ratio	21.12***	20.16***	16.70***	16.77***
	[1.05]	[1.09]	[1.08]	[1.08]
Commercial Real Estate Loans Ratio	1.76***	1.30***	0.52**	0.52**
	[0.28]	[0.28]	[0.25]	[0.25]
Mortgage-Backed Assets Ratio	-1.47***	-1.18***	-0.68***	-0.65***
	[0.21]	[0.22]	[0.19]	[0.19]
Part of Multiple Bank Holding Company	-0.22***	-0.34***	-0.25***	-0.26***
	[0.08]	[0.08]	[0.07]	[0.07]
Observations	271398	271398	1051087	1047873
Log Likelihood	-4593.19	-4486.43	-5934.44	-5931.57
AUC	0.98	0.98	0.98	0.98
AIC	9222.38	9012.85	11904.88	11903.13
BIC	9411.58	9223.08	12118.46	12140.38

Table 4: Contributions to Bank Failures by TED Spreads, Local HPI Changes, and Bank-Level Financial Ratio Variables in One-Year-Ahead Forecast, 1985–2011

To calculate the contribution from TED spread, we first calculate

$$P_{i,t} = \frac{1}{\left[1+\exp\begin{pmatrix}-\gamma_0-\gamma_1\times TED\ Spread_{t-1}-\gamma_2\times HPI\ changes_{t-1}\\ -\sum_i \beta_i \times Financial\ \text{var}iables_{t-1}-u_i\end{pmatrix}\right]}$$

$$\vec{P}_{i,t} = \frac{1}{\left[1+\exp\left(-\gamma_0-\gamma_2\times HPI\ changes_{t-1}-\sum_i \beta_i \times Financial\ \text{var}iables_{t-1}-u_i\right)\right]}$$

The contribution of TED spreads is the difference between $P_{i,t}$ and $\vec{P}_{i,t}$. Contributions from other variables are similarly defined.

	Average failure rate		Marginal contributions		
Year	Actual	Fitted	TED spreads	Local HPI changes	Bank level financial ratios
1985	0.86%	1.15%	0.32%	0.07%	0.76%
1986	1.00%	1.24%	0.14%	0.10%	1.01%
1987	1.52%	1.78%	0.14%	0.13%	1.51%
1988	2.04%	2.12%	0.54%	0.64%	0.94%
1989	1.54%	1.43%	0.34%	0.21%	0.87%
1990	1.26%	1.00%	0.21%	0.03%	0.76%
1991	0.98%	0.96%	0.05%	0.21%	0.70%
1992	0.74%	0.52%	-0.02%	0.05%	0.48%
1993	0.36%	0.20%	-0.03%	0.03%	0.20%
1994	0.11%	0.13%	-0.03%	0.03%	0.13%
1995	0.06%	0.11%	-0.01%	0.03%	0.09%
1996	0.05%	0.06%	0.00%	0.00%	0.06%
1997	0.01%	0.05%	-0.01%	0.00%	0.05%
1998	0.03%	0.05%	0.00%	0.00%	0.05%
1999	0.09%	0.06%	0.00%	-0.01%	0.06%
2000	0.06%	0.05%	0.00%	0.00%	0.05%
2001	0.06%	0.04%	0.00%	-0.01%	0.05%
2002	0.10%	0.05%	-0.01%	-0.01%	0.07%
2003	0.04%	0.03%	-0.01%	0.00%	0.04%
2004	0.04%	0.02%	-0.01%	0.00%	0.04%
2005	0.00%	0.02%	-0.01%	0.00%	0.03%
2006	0.01%	0.02%	0.00%	-0.01%	0.03%
2007	0.01%	0.03%	0.00%	0.00%	0.04%
2008	0.34%	0.13%	0.02%	0.03%	0.09%
2009	1.70%	1.31%	0.39%	0.46%	0.45%
2010	1.92%	2.10%	-0.10%	0.69%	1.51%
2011	1.28%	1.23%	-0.26%	0.32%	1.18%
Total	0.66%	0.66%	0.08%	0.11%	0.47%

Table 5: Full Model Prediction Estimation Results for Two Subperiods

This table reports the effects of TED spread and house prices on bank failures for two subperiod samples. We use the same specification as in table 3. Variables are defined in appendix A. *, **, and *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively. Standard errors are reported in the brackets.

	Annual 1985-2005	Quarterly 1985-2005	Annual 2006-2011	Quarterly 2006-2011
TED Spread	24.62*	0.32	104.01***	39.26***
	[12.57]	[9.07]	[17.62]	[12.05]
HPI Changes	-7.05***	3.13*	-4.77***	-8.11**
	[0.77]	[1.77]	[1.67]	[3.35]
Size	-0.12***	-0.09***	0.24***	0.19***
	[0.04]	[0.03]	[0.07]	[0.06]
Capital Ratio	-64.18***	-79.17***	-65.37***	-83.81***
	[2.76]	[3.30]	[4.62]	[6.46]
Return on Assets	-32.75***	-38.06***	-38.84***	-43.42***
	[2.41]	[2.46]	[5.98]	[7.82]
Net Interest Margin	-28.60***	-32.53***	-56.40***	-44.20***
	[4.44]	[3.69]	[11.74]	[10.34]
Loan Yields	11.77***	8.58***	62.21***	24.03***
	[2.51]	[2.24]	[7.66]	[7.40]
Non-Interest Income Ratio	4.16***	5.24***	2.20	-5.07
	[0.89]	[1.12]	[4.70]	[4.23]
Government Securities Ratio	-3.58***	-2.65***	-4.76***	-3.70***
	[0.40]	[0.34]	[1.54]	[1.42]
Brokered Deposits Ratio	6.15***	4.75***	0.75	-0.58
	[0.97]	[0.67]	[1.00]	[0.94]
Short-Term Liabilities Ratio	-0.79**	-0.24	0.23	0.28
	[0.35]	[0.30]	[0.72]	[0.67]
Core-Deposits Ratio	-0.46	0.97***	0.00	0.09
	[0.30]	[0.27]	[0.59]	[0.52]
Loan-to-Deposit Ratio	0.28	-0.65**	0.33	-0.41
	[0.29]	[0.27]	[0.61]	[0.59]
Unused Commitments Ratio	-1.62**	-1.38**	2.52*	1.75
	[0.71]	[0.68]	[1.36]	[1.42]
Non-Performing Assets Ratio	19.76***	16.96***	25.21***	17.45***
	[1.19]	[1.17]	[2.95]	[3.28]
Commercial Real Estate Loans Ratio	1.25***	0.54*	1.10*	0.16
	[0.34]	[0.30]	[0.56]	[0.53]
Mortgage-Backed Assets Ratio	-1.34***	-0.61***	-1.70***	-2.01***
	[0.24]	[0.22]	[0.60]	[0.56]
Part of Multiple Bank Holding Company	-0.21**	-0.19**	-0.16	0.15
	[0.09]	[0.08]	[0.20]	[0.19]
Observations	227447	886584	43951	153576
Log Likelihood	-3656.27	-4987.68	-752.13	-883.70
AUC	0.98	0.99	0.98	0.98
AIC	7352.53	10015.36	1544.26	1807.39
BIC	7559.23	10249.26	1718.07	2006.23

Table 6: Prediction Estimates for Banks in a Single State

This table reports the effects of TED spread and house prices on bank failures for banks operated in single states. Variables are defined in appendix A. *, **, and *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively. Standard errors are reported in the brackets.

	Annual 1985-2005	Quarterly 1985-2005	Annual 2006-2011	Quarterly 2006-2011
TED Spread	-19.65	14.35	90.74***	35.94**
	[15.89]	[10.60]	[18.80]	[14.08]
HPI Changes	-4.66***	5.05**	-5.50***	-13.12***
	[0.92]	[2.29]	[1.77]	[4.03]
Size	0.03	0.13***	0.13	0.09
	[0.05]	[0.04]	[0.08]	[0.08]
Capital Ratio	-65.65***	-73.52***	-66.14***	-76.49***
	[3.91]	[4.54]	[4.87]	[7.10]
Return on Assets	-41.67***	-41.01***	-38.37***	-37.80***
	[3.03]	[3.10]	[6.40]	[9.00]
Net Interest Margin	-51.61***	-45.05***	-55.08***	-36.53***
	[6.51]	[5.08]	[12.47]	[11.77]
Loan Yields	24.52***	20.63***	65.71***	13.24
	[3.70]	[3.32]	[8.50]	[8.46]
Non-Interest Income Ratio	2.67	1.06	-0.19	-10.26*
	[1.65]	[2.69]	[5.50]	[5.24]
Government Securities Ratio	-7.25***	-5.75***	-3.61**	-5.97***
	[0.56]	[0.44]	[1.64]	[1.83]
Brokered Deposits Ratio	3.56***	3.21***	1.06	-1.11
	[1.16]	[0.81]	[1.05]	[1.11]
Short-Term Liabilities Ratio	-1.72***	-1.05***	0.62	0.85
	[0.44]	[0.40]	[0.77]	[0.82]
Core-Deposits Ratio	-0.27	0.92**	-0.14	0.00
	[0.42]	[0.38]	[0.62]	[0.60]
Loan-to-Deposit Ratio	-1.70***	-2.11***	0.63	-0.98
	[0.35]	[0.32]	[0.67]	[0.70]
Unused Commitments Ratio	-2.97***	-3.81***	3.46**	1.30
	[0.90]	[0.92]	[1.47]	[1.70]
Non-Performing Assets Ratio	14.63***	11.06***	25.59***	18.58***
	[1.70]	[1.52]	[3.11]	[3.83]
Commercial Real Estate Loans Ratio	0.78*	-0.15	0.94	-0.12
	[0.41]	[0.37]	[0.59]	[0.59]
Mortgage-Backed Assets Ratio	-1.50***	-0.78***	-1.05	-1.53**
	[0.31]	[0.28]	[0.64]	[0.64]
Part of Multiple Bank Holding Company	-0.13	-0.12	-0.12	0.09
	[0.11]	[0.10]	[0.22]	[0.23]
Observations	181338	746552	41071	143574
Log Likelihood	-2138.06	-3024.77	-677.27	-691.66
AUC	0.99	0.99	0.98	0.98
AIC	4316.11	6089.54	1394.55	1423.32
BIC	4518.27	6320.01	1567.01	1620.82

Appendix A: Variable Definitions

This table describes the definitions of variables included in regression analyses.

Variable	Description
Failure	For annual panel data, this dummy variable equals 1 if the bank fails between the end of year *t* and the end of year *t*+1. For quarterly panel data, this dummy variable equals 1 if the bank fails between the end of quarter *t* and the end of quarter *t*+1.
Size	Natural logarithm of total assets
Capital ratio	Equity capital to total assets ratio
Return on assets	Net income to total assets ratio
Net interest margin	Net interest income to total asset ratio
Loan yields	Yields on loan
Noninterest income ratio	Noninterest income to total assets ratio
Government securities ratio	Government securities to total assets ratio
Brokered deposits ratio	Brokered deposits to total assets ratio
Short-term liability ratio	Short-term liabilities to total assets ratio, where short-term liabilities include repo, saving deposits, time deposit with maturity within one year, other borrowed money with maturity within one year, and other liabilities.
Core-deposits ratio	Core deposits to total assets ratio
Loan-to-deposit ratio	Loan-to-deposit ratio
Unused commitments	Unused commitments to total assets ratio
Nonperforming assets ratio	Nonperforming assets to total assets ratio. Nonperforming assets is the sum of nonperforming loans (NPL) and other real estate owned (OREO)
Commercial real estate loans ratio	Commercial real estate loans to total assets ratio
Mortgage-backed assets ratio	Mortgage-backed assets (residential loans, MBS, and structured notes) to total assets ratio
Loan growth	Rate of loan growth from the previous year
Loan mix	Loan mix is a measure of concentration risk. It is the sum of commercial and industrial loans, and commercial real estate loans to total assets ratio.
OREO ratio	OREO ratio is the other real estate owned to total assets ratio
Consumer loans charge-off	Consumer loan charge-off ratio is consumer loan charge-offs to total assets ratio
Commercial loans charge-off	Commercial loan charge-off ratio is the commercial & industrial loan charge-offs to total assets ratio
Local HPI changes	Changes in state-level housing price index (HPI) from the previous year
TED spread	The spread of the three-month LIBOR over the three-month Treasury rate
Part of multiple bank holding company	A dummy variable equal to 1 if bank belongs to a bank holding company with multiple banks, and 0 otherwise