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Natural disaster and bank stability: Evidence from the U.S. financial system

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Non-Technical Summary

Natural disasters like Hurricane Harvey, which swept through Texas in 2017, have the potential to devastate entire regions and to cause loss of life and property. They have become even more frequent and destructive over the last decades, as shown by empirical data. Policy makers worldwide worry that this may also have negative effects on financial stability and have thus started initiatives to analyze and mitigate consequences for the financial sector.

This study explores whether weather-related disasters such as hurricanes affect bank stability. Whether this is the case or not is not obvious. On the one hand, banks are affected because disaster-related damages immediately reduce banks' collateral values and the credit standings of their borrowers. Further, disaster-related damages may cause business disruptions and adversely affect economic growth in the banks' respective business regions. On the other hand, insurance payments, as well as public financial aid programs, support corporations and individuals in affected regions, and thereby mitigate the shock. Reconstruction activities may even boost economic growth.

The existing empirical evidence is mixed. A related cross-country study suggests that large-scale weather-related disasters have, on average, no significant negative effect on the stability of the banking sector in developed countries, but rather only in emerging countries. However, case-study evidence on the impact of Hurricane Katrina in the United States in 2005 shows that several measures of bank performance and stability were negatively affected by the disaster. The main contribution of our study is to present new and comprehensive evidence on the effects of weather-related disasters on bank stability for the U.S. financial system based on a large sample of more than 12,000 reported damages and 6,000 banks over the period from 1994 to 2012.

Our analysis provides new evidence that weather-related disaster damages in the banks' business regions indeed weaken bank stability and performance. This is reflected in significantly lower bank z-scores, higher probabilities of default, higher non-performing assets ratios, higher foreclosure ratios, lower return on assets and lower equity ratios in the two years following a natural disaster. For a relatively small number of (non-weather-related) geological disasters in the United States, such as earthquakes and tsunamis, we show that these disasters have even relatively stronger adverse effects on bank stability. Overall, the evidence reveals that natural disasters jeopardize borrowers' financial solvency and decrease bank stability, despite potential insurance payments and public aid programs. On a more positive note, we find that banks generally manage to recover from the adverse shock from weather-related disasters (but not from geological disasters) after some years, which is reflected in the bank stability and performance measures of affected banks that are not significantly worse than those of unaffected banks two or three years after a disaster.

Natural Disasters and Bank Stability: Evidence from the U.S. Financial System*

Felix Noth† and Ulrich Schüwer‡

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Abstract

We show that property damages from weather-related natural disasters significantly weaken the stability of banks with business activities in affected regions, as reflected in lower z-scores, higher probabilities of default, higher non-performing assets ratios, higher foreclosure ratios, lower returns on assets, and lower bank equity ratios. The effects are economically relevant and suggest that insurance payments and public aid programs do not sufficiently protect bank borrowers against financial difficulties. We also find that the adverse effects on bank stability dissolve after some years if no further disasters occur during that time.

Keywords: natural disasters, bank stability, non-performing assets, bank performance

JEL Classification: G21, Q54

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1 Introduction

Natural disasters like Hurricane Harvey, which swept through Texas in 2017, have the potential to devastate entire regions and to cause loss of life and property. They have become even more frequent and destructive over the last decades, as shown by empirical data (Leaning and Guha-Sapir, 2013; Melillo et al., 2014; United Nations, 2015). Policy makers worldwide worry that this may also have negative effects on financial stability and have thus started initiatives to analyze and mitigate consequences for the financial sector (Bank of England, 2015).

This study explores whether weather-related disasters such as hurricanes affect bank stability.[1] Whether this is the case or not is not obvious. On the one hand, banks are affected because disaster-related damages immediately reduce banks' collateral values and the credit standings of their borrowers. Further, disaster-related damages may cause business disruptions and adversely affect economic growth in the banks' respective business regions. On the other hand, insurance payments, as well as public financial aid programs, support corporations and individuals in affected regions, and thereby mitigate the shock. Reconstruction activities may even boost economic growth.

The existing empirical evidence is mixed. A study by Klomp (2014), with data for 169 countries during the period from 1997 to 2010, suggests that large-scale weather-related disasters have, on average, no significant negative effect on the stability of the banking sector in developed countries, but rather only in emerging countries. However,

[1] We use the term *weather-related* for all meteorological (hurricane/ storm, fog, extreme temperature), hydrological (flood, landslide, wave action) and climatological disasters (drought, wildfire). We consider geological disasters (earthquakes, tsunamis and volcanic eruptions) separately in an extension to our baseline analysis.

case-study evidence on the impact of Hurricane Katrina in the United States in 2005 shows that several measures of bank performance and stability were negatively affected by the disaster (Chavaz, 2016; Schüwer et al., 2018).[2] The main contribution of our study is to present new and comprehensive evidence on the effects of weather-related disasters on bank stability for the U.S. financial system based on a large sample of more than 12,000 reported damages and 6,000 banks over the period from 1994 to 2012.

Our analysis provides new evidence that weather-related disaster damages in the banks' business regions indeed weaken bank stability and performance. This is reflected in significantly lower bank z-scores, higher probabilities of default, higher non-performing assets ratios, higher foreclosure ratios, lower return on assets and lower equity ratios in the two years following a natural disaster. For a relatively small number of (non-weather-related) geological disasters in the United States, such as earthquakes and tsunamis, we show that these disasters have even relatively stronger adverse effects on bank stability. Overall, the evidence reveals that natural disasters jeopardize borrowers' financial solvency and decrease bank stability, despite potential insurance payments and public aid programs. On a more positive note, we find that banks generally manage to recover from the adverse shock from weather-related disasters (but not from geological disasters) after some years, which is reflected in the bank stability and performance measures of affected banks that are not significantly worse than those of unaffected banks two or three years after a disaster.

[2]Other related papers use natural disasters as a shock on mortgage risk (Garmaise and Moskowitz, 2009) or local credit demand (Berg and Schrader, 2012; Cortes and Strahan, 2017), but do not explore effects of natural disasters on bank stability.

The identification strategy of our analysis uses the exogeneity of the *timing* and *intensity* of natural disasters. In particular, by including bank fixed effects in all regressions, we use yearly variations from the banks' average long-term natural disaster-related damages in their business region as the main explanatory variable. The bank fixed effects further control for differences among banks' business models and local economic structures. Year-region fixed effects are also included to control for economic developments over time. Furthermore, we use different measures for banks' disaster-related damages in order to address potential concerns about the endogeneity of disaster-related damages and bank stability, which depends on the banks' respective business regions and local economic conditions.

The analysis is based on a comprehensive dataset of the *Hazards and Vulnerability Research Institute* at the University of South Carolina, which includes over 12,000 reported damages in the United States, including damages from hurricanes and floods, and yearly financial data for more than 6,000 banks over the period from 1994 to 2012, resulting in over 66,000 bank-year observations. The dataset thereby allows us to explore a large variation in natural disaster-related damages across regions, banks and time.

Our analysis contributes to the growing literature on the economic consequences of natural disasters. For example, Strobl (2011) investigates the effect of damages from hurricanes in the U.S. Gulf Coast region and finds a considerable decrease in economic growth rates in affected regions, while Cavallo et al. (2013) finds no significant effect of natural disasters on economic growth for a sample of 196 countries worldwide. Fomby et al. (2013) use data from 84 countries over the period from 1960 to 2007 and find that the effects of natural disasters on economic growth are insignificant for developed countries, but significant and dependent on the disaster type for developing countries. Klomp (2014) suggests that large-scale natural disasters negatively affect the stability of the banking sector in emerging countries, but not in developed countries. We add to this debate by providing new evidence for the United States that banks are significantly and negatively affected by weather-related natural disasters. In particular, our evidence that the non-performing assets and foreclosures of affected banks increase suggests that borrowers cannot meet their loan payments because they are not sufficiently protected against natural disasters. Our results thereby also add to the literature that examines the determinants of banks' financial distress and bank failures (Wheelock and Wilson, 2000; Cole and White, 2010). Further, several studies analyze bank lending and bank behavior in the aftermath of natural disasters (Garmaise and Moskowitz, 2009; Berg and Schrader, 2012; Koetter et al., 2016; Chavaz, 2016; Cortes and Strahan, 2017; Schüwer et al., 2018).[3] We add to this literature by showing that banks generally manage to overcome adverse effects on their stability and performance within some years after a weather-related natural disaster has occurred.

This paper proceeds as follows: Section 2 presents our identification strategy and empirical approach. Section 3 describes the data used in this study. Section 4 presents the estimation results. Section 5 concludes.

[3] Garmaise and Moskowitz (2009) use the 1994 Northridge earthquake in California, Berg and Schrader (2012) use volcanic eruptions in Ecuador between 2002 and 2007, Chavaz (2016) and Schüwer et al. (2018) use the 2005 Hurricane Katrina in the United States, Koetter et al. (2016) use the Elbe flooding in Germany, and Cortes and Strahan (2017) use all types of natural disasters in the United States between 2001 and 2010. For an analysis of catastrophic risk and the insurance market, see for example Froot (2001), Cummins et al. (2002) and Niehaus (2002). Studies by Jarzabkowski et al. (2015) and Biener et al. (2017) analyze the structure of the global reinsurance market.

2 Identification Strategy and Empirical Model

The identification of the causal effect of natural disasters on the stability of banks is challenging, because realized disaster-related damages are affected by local economic structure and disaster management, and are thus endogenous within local economic conditions. For example, lower wealth in a county may be associated with less protective measures against disasters. This endogeneity problem may also affect a bank's stability, which depends on local economic conditions. Furthermore, banks may choose their business regions and, hence, counties with more or less disaster risks for their business activities (within the geographic restrictions for banking and branching that depended on state legislation until all geographic restrictions were removed by the Dodd-Frank Act of 2010). However, banks cannot anticipate the years when natural disasters occur, i.e. the timing, or how harmful they will be, i.e. the intensity, in a particular year.

The identification strategy of our analysis addresses the endogeneity problem in several ways: (1) for our baseline regressions, we exploit the exogeneity of the *timing* and *intensity* of natural disasters, using a fixed effects OLS model with the yearly changes in a bank's average weather-related disaster damages (relative to total income) in its business region as the main explanatory variable. We do this by including bank fixed effects in all regressions, which further allows us to control for unobservable time-invariant variables, such as generic disaster risks, disaster management structures and economic structures in the banks' business regions. These fixed effects also capture time-invariant differences among business models, performances and stability of banks. Further, we control for economic developments over time by including year-region fixed effects. (2) We additionally calculate a disaster measure based on the original business regions of the banks in 1991 (the first year of our bank sample) in order to exclude the possibility that changes in banks' business regions drive our results. (3) Finally, we use a measure that reflects the share of counties affected by a disaster in a bank's business region in a certain year, and thus do not consider the amount of disaster-related damages, which may depend on local economic structures. Some further robustness regressions are presented in the results section.

Baseline model. In order to investigate whether disaster-related damages affect bank stability, we estimate the following fixed effects OLS regression model:

$$Y_{i,t} = \nu_i + \tau_t \times \gamma_f + \beta_0 \; dis_{i,t} + \beta_1 \; dis_{i,t-1} + \beta_2 \; dis_{i,t-2} + \beta_3 \; dis_{i,t-3} + \epsilon_{i,t}, \qquad (1)$$

where Y_{it} stands for alternative measures of bank stability and performance of bank i in year t. Bank fixed effects, ν_i, account for time-invariant differences among banks. Further, based on the location of a bank's headquarters, we account for different regional developments across the United States by including year-region fixed effects, $\tau_t \times \gamma_f$, for the twelve Federal Reserve Districts (Boston, New York, Philadelphia, Cleveland, Richmond, Atlanta, Chicago, St. Louis, Minneapolis, Kansas City, Dallas, and San Francisco). The main explanatory variable is a bank's exposure to weather-related disaster damages in its business region, dis_{it}, which is included with three lags to consider potential natural disasters that occurred in previous years. Since bank fixed effects are included, the coefficients of dis reflect the yearly changes in a bank's average weather-related disaster damages (relative to total income). Standard errors are clustered by state.[4]

3 Data

Our main data sources are the *Federal Deposit Insurance Corporation* (FDIC) for all bank financial data,[5] the *Home Mortgage Disclosure Act* (HMDA) database for banks' regional distribution of mortgage loans,[6] and the *Spatial Hazard Events and Losses Database for the United States* (SHELDUS) for all data on natural disasters.[7]

The sample includes yearly data on 6,136 U.S. banks from 1994 to 2012, which results in a total of 66,766 observations. The sample period starts in 1994 because we need two preceding years in order to calculate the bank z-score, a measure of bank stability, and the FDIC data is available from Q4 1992. The sample period ends in 2012 because raw data on disaster-related damages from SHELDUS was freely available only until then. We require that a bank has its headquarters in any federal state in the contiguous United States, that it existed at the beginning of our sample period (1994), that it reports loan data under the HMDA,[8] and has non-missing information for all variables we use in the analysis. As our main specifications include three lags of disaster-related damages, we also implicitly require that all banks exist in the dataset for a minimum of four consecutive

[4]Clustering by state accounts for potential within-state correlations across banks and over time. It is a more conservative approach compared to clustering by bank.

[5]See FDIC bank data & statistics (https://www.fdic.gov/bank/statistical/).

[6]See Home Mortgage Disclosure Act (https://www.ffiec.gov/hmda/).

[7]The SHELDUS database is provided by the *Hazards and Vulnerability Research Institute* at the University of South Carolina (http://hvri.geog.sc.edu/SHELDUS/). Recent empirical studies that use this database include Barrot and Sauvagnat (2016); Bernile et al. (2017); Cortes and Strahan (2017).

[8]The reporting of mortgage loan data is generally required for banks with assets above a certain threshold (e.g., $30 million for the year 2000) and a headquarters or branch office in a metropolitan statistical area (MSA). See https://www.ffiec.gov/hmda/ for details.

years. Bank financial data are winsorized at the 1st and 99th percentiles.

A short description of all variables, as well as summary statistics, are provided in Table 1 and Table 2, respectively. The following paragraphs provide further information about our main variables.

- Table 1 and Table 2 -

Bank stability and performance. We use several alternative measures of bank stability and bank performance that are commonly used in the literature (Laeven and Levine, 2009; Noth and Tonzer, 2017). First, we use banks' z-scores, which are defined as the natural logarithm of the sum of a bank's return on assets and its equity-to-asset ratios, standardized by the standard deviation of the bank's return on assets. A lower z-score indicates a lower distance to default, and hence, lower bank stability. Second, we use predicted probabilities of default (PD), which we calculate using a probability model.[9] Third, we use non-performing assets ratios (NPA) as a measure of the overall quality of the bank's loan book. Next, the foreclosure ratio (FOR) provides a measure of the volume of foreclosed property on a bank's balance sheet relative to the bank's total assets. Finally, we use return on assets (ROA) and equity-to-asset ratios (EQ), which are further indicators of bank performance and stability, and also used to calculate a bank's z-score. The development of these variables over time is shown in Figure 3 in the next section, where regression results are presented and interpreted.

[9] Our probability model explains U.S. bank failures based on the FDIC's *failed bank list.* Details and regression results are provided in the Appendix.

Natural disaster-related damages. Our main explanatory variable is $dis_{i,t}$, which denotes the average weather-related disaster damage in bank i's business region in year t. It is based on a measure of disaster-related damages on the county level and information about the banks' business activities in each county, as explained in the following.

First, we use more than 12,000 individual records on weather-related property damages, measured in US$, from the SHELDUS database for the period from 1991 to 2012.[10] These US$ numbers are not directly informative for our purpose. For example, a US$ 100 million loss from disaster-related damages may be highly relevant in a small county, but not relevant at all in New York County (Manhattan). Hence, we scale these numbers by using a measure of local economic activity, i.e. a county's yearly total personal income, measured in US$.[11] For example, the standardized disaster damage that we obtain for Orleans County in 2005, when Hurricane Katrina hit the region, is 0.95. Thus, according to our measure, total property losses nearly equaled the total personal income of the population of Orleans County in 2005.

Second, we need to identify to what extent individual banks operating in one or several counties are affected by disaster-related damages. We calculate $dis_{i,t}$ as the weighted average standardized disaster-related damages across all counties at year t, using the

[10]The SHELDUS database includes information about the disaster type (hurricane, flooding, earthquake, etc.), which allows us to differentiate between weather-related and geological natural disasters. We consider reported damages of US$ 1 million or more from the database (inflation adjusted to 2012 dollars). The data starts in 1991, three years before our main sample period (1994 to 2012), because we use three lags of disaster-related damages in our main regressions.

[11]Source: *Bureau of Economic Analysis* (see www.bea.gov.) Note that GDP is not available at the county level.

share of bank i's activities in each county j at year t as weights:

$$dis_{i,t} = \sum_{j=1}^{J} \frac{\text{county } j \text{ disaster damage}_{j,t}}{\text{county } j \text{ total personal income}_{j,t}} \times \frac{\text{local banking activities}_{i,j,t}}{\text{total banking activities}_{i,t}}.$$

Ideally, we could measure banks' activities across counties based on each bank's total asset exposures, because the most direct effect of natural disasters on banks is presumably through the damages of the borrowers' collateral values. This information is not available, however, the *Home Mortgage Disclosure Act* (HMDA) database provides data on the geographic spread of banks' mortgage loans, which we use as a proxy for local banking activities.

Figure 1 provides the yearly distribution of $dis_{i,t}$ for our sample. The highest values come from banks affected by the 1997 Red River flood in North Dakota and Minnesota or the 2005 Hurricane Katrina in the Gulf Coast region. Figure 2 illustrates the regional distribution of banks' average $dis_{i,t}$, based on the locations of the banks' headquarters. Our general conclusion from the figures is that there is considerable variation in disaster-related damages over time and across the United States.

- Figure 1 and Figure 2 -

As an alternative to disaster-related damages $dis_{i,t}$, we also use a disaster measure $dis\_geo_{i,t}$, which captures banks' yearly exposure to (non-weather-related) disaster damages from geological disasters, and is otherwise equivalent to $dis_{i,t}$. This measure is used for a set of regressions in an extension to our baseline analysis.

Further, we modify the way in which we calculate the measure of disaster-related damages $dis_{i,t}$ in two ways, in order to show the robustness of our results and to address potential endogeneity concerns. First, we recalculate disaster-related damages based on banks' local banking activities in 1991 (the first year of our sample), such that changes in the local bank activities across counties j of bank i over time t do not influence our results:

$$dis\_91_{i,t} = \sum_{j=1}^{J} \frac{\text{county } j \text{ disaster damage}_{j,t}}{\text{county } j \text{ total personal income}_{j,t}} \times \frac{\text{local banking activities}_{i,j,1991}}{\text{total banking activities}_{i,1991}}.$$

Second, we calculate a measure that abstracts from the amount of disaster-related damages, which may depend on local economic structures. In particular, we use a disaster dummy variable $affected_{j,t}$ instead of a (standardized) amount of disaster-related damages, where $affected_{j,t}$ has a value of one if county j was affected by a natural disaster (i.e. damages were reported for county j) in year t, and zero otherwise. We then calculate the share of counties affected by a disaster in bank i's business region in year t, based on the bank's local activities in 1991:

$$dis\_affected\_91_{i,t} = \sum_{j=1}^{J} affected_{j,t} \times \frac{\text{local banking activities}_{i,j,1991}}{\text{total banking activities}_{i,1991}}.$$

This measure contains less information about the impact of natural disasters on banks' business regions compared with $dis_{i,t}$ or $dis\_91_{i,t}$, but has the advantage that it is not affected by local economic conditions.

4 Results

4.1 Baseline Regressions

We start the discussion of regression results with the short-term effects of weather-related disaster damages on bank stability and performance, as shown by the coefficients of $dis_{i,t}$ and $dis_{i,t-1}$. Subsequently, we comment on the medium-term effects of disaster-related damages ($dis_{i,t-2}$ and $dis_{i,t-3}$).

Results for the effect of disaster-related damages on banks' z-scores are shown in Column (1) of Table 3. We find negative and significant effects of $dis_{i,t}$ and $dis_{i,t-1}$, which indicate that banks facing higher damages from a natural disaster in their business region become less stable in the short term. This effect is also economically significant. If we consider a value of $dis_{i,t}$ equal to 0.13, which represents the average of the top 1 percent values of $dis_{i,t}$ over the period from 1994 to 2012, this causes a decrease in a bank's standardized distance to default, $(ROA - EQ)/SD(ROA)$, of about 8.7 percent one year later (0.13×0.6654).[12] The effect is illustrated in Panel (a) of Figure 3, which shows the average development of z-scores over the sample period. The mean z-score (4.1716) is represented by a solid horizontal line, and the negative effect on the z-score of 0.087 is represented by the difference between the solid and the dashed lines (dotted lines around the dashed line represent the 90% confidence interval).

In Column (2), we find that disaster-related damages also cause significantly higher predicted probabilities of default in the short term. In particular, an increase of $dis_{i,t}$

[12] The bank z-score is defined as $ln\left(\frac{ROA-EQ}{SD(ROA)}\right)$.

by 0.13 causes an increase of PD by about 0.3 percentage points in the following year (0.13×0.0215), which is economically highly relevant compared to the banks' average probability of default of 3.65 percent during the sample period. The effect is illustrated in Panel (b) of Figure 3.

The short-term effect of disaster-related damages on non-performing assets ratios is significantly positive. An increase of $dis_{i,t}$ by 0.13 causes an increase in non-performing assets ratios by about 0.13 percentage points in the same year (0.13×0.0102), which is again economically relevant compared to the banks' average non-performing assets ratios of 1.22 percent (see also Panel (c) of Figure 3).

The adverse effects of natural disasters also materialize in the form of significantly higher foreclosure ratios. An increase of $dis_{i,t}$ by 0.13 causes an increase of about 0.02 percentage points after one year (0.13×0.0014), which is economically relevant compared to the banks' average foreclosure ratios of 0.28 percent (see also Panel (d) of Figure 3).

Furthermore, we find a significant short-term decrease in return on assets (Column (5)) and a decrease in bank equity (Column (6)), which are illustrated in Panels (e) and (f) of Figure 3, respectively.

- Table 3 and Figure 3 -

Next, we consider medium-term effects of disaster-related damages, as represented by the coefficients of $dis_{i,t-2}$ and $dis_{i,t-3}$. We find that banks generally manage to recover after two years (some adverse effects already become insignificant after one year) if no other disasters occur in the meantime. In particular, bank stability and performance is not significantly different between banks affected and banks unaffected by natural disasters after two years. This evidence is consistent with alternative explanations. Banks in disaster areas may benefit from an economic recovery in affected areas, or they may make more conservative business decisions to protect against risks from future natural disasters. Which explanation is most relevant and what this means for the real economy are substantial questions that are, however, not the focus of this study.[13]

Damages from geological disasters In a further set of regression, we analyze the effect of damages from geological disasters – instead of weather-related damages – on bank stability, and thus replace the variables $dis_{i,t}$ to $dis_{i,t-3}$ with $dis\_geo_{i,t}$ to $dis\_geo_{i,t-3}$ in Equation (1). Previous studies have argued that geological disasters may have different effects on the economy and banks compared to weather-related disasters because of their different characteristics. For example, earthquakes are very rare events (even in the most exposed areas in California), while hurricanes occur relatively frequently in some areas along the Gulf Coast region. Further, weather-related disasters such as hurricanes are easier to forecast compared to geological disasters. A related study by Klomp (2014) finds that only geological disasters, and not weather-related disasters, have a negative effect on bank stability in developed countries.

Our dataset lists 12 earthquakes and two tsunamis between 1991 and 2012, including the 1994 Northridge earthquake in the Los Angeles metropolitan area (estimated damages reached a total of US$20 billion), the 2001 Nisqually earthquake in the state of Washington (US$2 billion), the 2003 San Simeon earthquake in the state of California (US$

[13] See, e.g., Chavaz (2016) and Schüwer et al. (2018) for studies that analyze bank behavior following a natural disaster based on Hurricane Katrina in 2005.

300 million), and the 2011 tsunami in Northern California and Oregon (US$ 43 million) that was caused by the 2011 Japan earthquake. A total of 651 out of 6,136 banks in our sample are affected by these geological disasters. The highest value of dis_geo in our dataset has a value of 0.1 and is related to the 1994 Northridge earthquake in Los Angeles County.[14]

Regression results are shown in Table 4. As before, we find that disaster damages have a significantly negative effect on bank stability, as reflected in significantly lower z-scores, higher probabilities of default, higher non-performing assets ratios, higher foreclosure ratios, lower returns on assets and lower bank equity ratios. These effects are also economically highly significant. For example, a value of dis_geo equal to 0.1, which is related to the 1994 Northridge earthquake, is associated with a 3.8 percentage point increase in the probability of default of affected banks (0.1×0.3838). Overall, the effects are very strong compared to the baseline regression results in Table 3. For example, consider regression results when PD is used as a dependent variable: the coefficient of $dis\_geo_{i,t}$ is 0.3838 (Column (2) of Table 4) compared to a coefficient of $dis_{i,t}$ equal to 0.0110 (Column (2) of Table 3). In addition, the adverse effects of geological disasters on banks' z-scores, probabilities of default and non-performing assets ratios become weaker but remain significant after three years. Hence, our results suggest that geological disasters have stronger and more long-lasting adverse effects on bank stability compared to weather-related disasters. However, we interpret these results with caution because of

[14] The value of 0.1 is calculated as the ratio of US$20 billion of damages from the 1994 Northridge earthquake and a total personal income in Los Angeles County in 1994 of US$ 208 billion, weighted by the share of a bank's business activities in Los Angeles County (which is 100 percent for some banks).

the relatively few geological disasters that are included in our sample.

4.2 Robustness

Disaster measure based on 1991 business activities. The first set of robustness regressions uses a measure for weather-related disaster damages that is similar to *dis*, but uses the (time-invariant) share of banks' mortgage lending activities in each county in 1991 as a proxy of banks' local banking activities for all years, instead of actual (time-varying) values.[15] This excludes the possibility that changes in banks' local business activities over the sample period may affect the disaster measure. As shown in Table 5, results remain qualitatively unchanged.

- Table 5 -

Disaster measure based on the share of affected counties. Next, we want to exclude the possibility that developments of local economic conditions that are not already captured by bank and year-region fixed effects drive our results. We therefore use a measure of disaster-related damages, *dis_affected_91*, which reflects the share of counties affected by a natural disaster in a bank's business region in a certain year. The amount of damages, which may be affected by economic conditions, is not included in this measure; only whether a disaster occurred in a certain county and year or not. Regression results are shown in Table 6. Compared to our baseline regression results (Table 3), the effects are weaker, but confirm the adverse effects of natural disasters on bank stability. For

[15] The year 1991 is the first year of our dataset with disaster-related damages, which is three years before the first year of the bank-level dataset.

example, if all counties in a bank's business region experience a natural disaster in a certain year (*dis_affected_91*=1, which represents the average of the top 1 percent of values of *dis_affected_91*), the probability of default (PD) of a bank increases significantly by 0.08 and 0.14 percentage points after one and two years, respectively. This is economically relevant compared to an average probability of default of banks in our sample of 3.65 percent, but lower than the 0.3 percentage points that we calculated for the baseline results (based on a value of $dis = 0.13$, which represents the average of the top 1 percent of values of dis). Note that the disaster measure *dis_affected_91* does not differentiate whether a natural disaster has a small or large impact on a county (different from dis or dis_91), which explains the relatively weaker effects.[16]

- Table 6 -

Excluding the global financial crisis. This set of robustness regressions reruns the OLS regression (Equation 1) without observations from the years of the global financial crisis (2008 and 2009) in order to exclude the effects of the financial turmoil during these years. As shown in Table 7, results remain qualitatively unchanged.

- Table 7 -

Further robustness. Three further robustness regressions are provided in the Appendix: (1) results remain qualitatively unchanged when standard errors are two-way clustered on bank and state levels. (2) Results are also largely similar, but generally

[16]Furthermore, we find in unreported regressions, where one further lag of *dis_affected_91* is included, that the negative effects on banks' probability of default dissolve after three years. This is in line with our results from the baseline regressions that bank stability recovers after some years.

weaker than in our baseline regression, when year×state fixed effects are included in the regressions instead of year×region fixed effects. This is not surprising because large natural disasters may affect many banks in one state at the same time. Hence, year×state fixed effects mask effects from large natural disasters, which explains the generally weaker regression results. (3) One potential concern about the results in the paper is that we may observe only surviving banks and not all banks affected by natural disasters, because some affected banks fail or are acquired, and hence drop out of the sample. We therefore test, using a linear probability model, whether dropping out of the sample is positively related to natural disasters in a bank's business region. Regression results show that this is not the case.

5 Conclusion and Further Research

Our analysis provides empirical evidence that weather-related natural disasters significantly weaken the stability of banks with business activities in affected regions. In particular, banks' z-scores decrease, probabilities of default increase, non-performing assets ratios and foreclosure ratios increase, and returns on assets and equity ratios decrease in the short term, i.e. within two years after the disaster. These effects are economically significant. The results also show that the negative effects of weather-related disasters (but not those of geological disasters) fade out after some years if no further disasters occur in the meantime.

The main message of the analysis is that natural disasters matter for bank stability.

Insurance payments and public aid programs obviously do not protect bank borrowers sufficiently against financial difficulties, which then result in higher non-performing assets ratios and lower bank stability in the short term. In view of a steady increase in weather-related natural disasters over the last decades, this evidence points to risks for bank borrowers and the financial sector that may become even more relevant in the future. The positive aspect of our evidence is that banks generally manage to digest the shock over a period of a few years.

The empirical evidence presented in this section raises the question about the economic channels that drive the effects of natural disasters on bank stability. For example, are the higher non-performing assets and foreclosure ratios of banks primarily direct consequences of property losses, repair expenses, rental losses and (temporary) illiquidity of borrowers, or indirect consequences of adverse economic conditions and lower economic growth? Why does bank stability recover after a few years? Is it because the economic situation of the banks' borrowers improves or because banks make more conservative credit decisions? Based on the bank-level evidence presented in this paper, we can only speculate about these things. To explore relevant economic channels, further research using household-level, county-level and credit-level data is needed.

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Appendix A: Figures

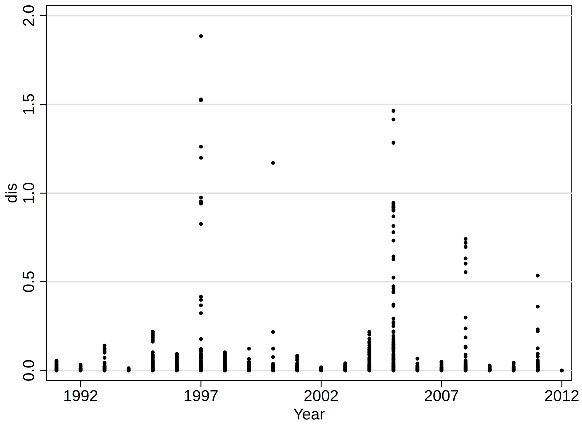


Figure 1: Yearly distribution of weather-related disaster damages

This figure shows disaster-related damages that banks face in their business regions, $dis_{i,t}$, for each year between 1991 and 2012. The most striking values are related to the Red River flood in North Dakota and Minnesota (1997), the Cerro Grande Fire in New Mexico (2000), Hurricane Katrina and Hurricane Ike in the Gulf Coast region (2005 and 2008, respectively), and Hurricane Irene along the East Coast of the United States (2011). Source: Own calculations based on SHELDUS, U.S. Bureau of Economic Analysis and HMDA data.

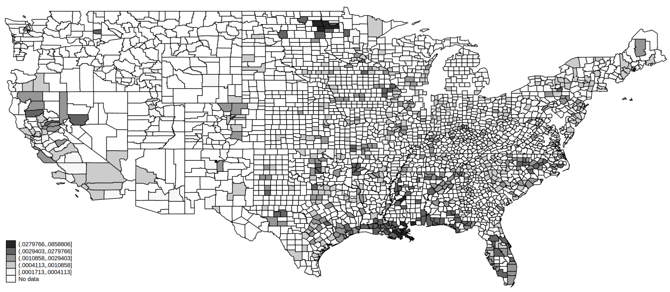
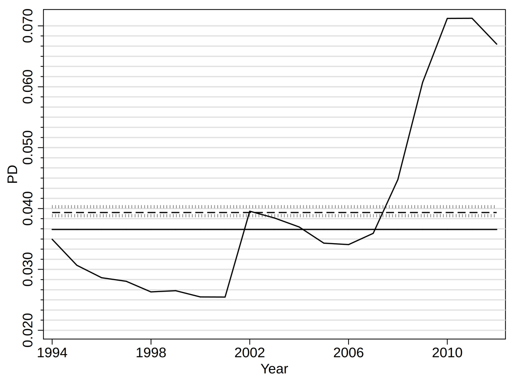


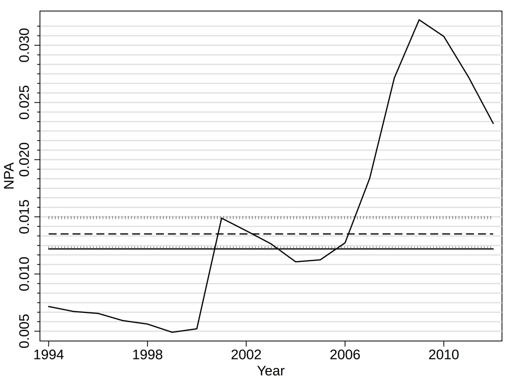
Figure 2: Regional distribution of weather-related disaster damages

This figure shows the distribution of weather-related disaster damages across counties. The value of each county is the average value of $dis_{i,t}$ for all years from 1991 to 2012 and all banks that have their headquarters in this county. Light colors and dark colors represent relatively low and high values, respectively. Source: Own calculations based on SHELDUS, U.S. Bureau of Economic Analysis and HMDA data.

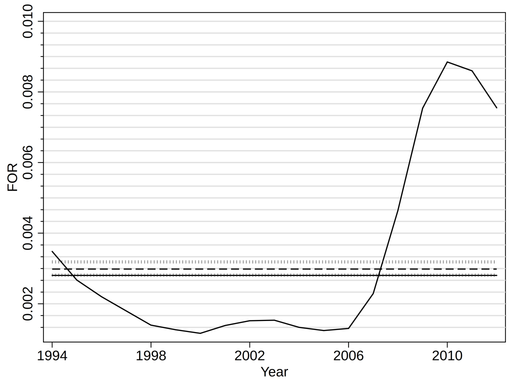
(a) z-score



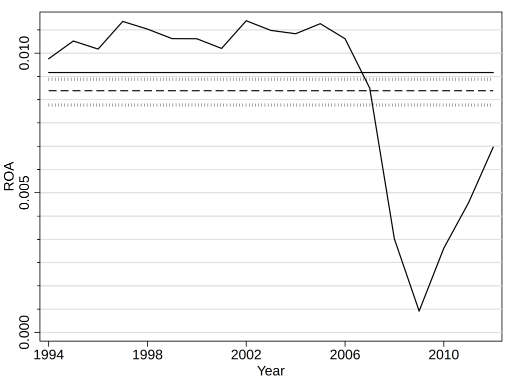
(b) probability of default (PD)



(c) non-performing assets ratio (NPA)



(d) foreclosure ratio (FOR)



(e) return on assets (ROA)

(f) equity (EQ)

Figure 3: Bank stability and performance over time

These graphs show the development of bank stability and performance measures over the sample period from 1994 to 2012. The horizontal solid lines in each graph represent the mean value of each variable. The difference between the solid and the dashed lines represents the economic effect from weather-related disaster damages in a bank's business region $dis_{i,t}$ equal to 0.13, which represents the average of the top 1 percent of values of $dis_{i,t}$ over the period from 1994 to 2012 (dotted lines around the dashed line represent the 90% confidence interval). In particular, the largest significant coefficient from $dis_{i,t}$ and $dis_{i,t-1}$ is chosen to illustrate the economic effect.

Appendix B: Tables

Table 1: Variable description

Variable name	Description
dis	**Weather-related disaster damages:** The yearly property damages from weather-related disasters over total personal income in a bank's business region for each bank and year, using the banks' regional distribution of mortgage loans of each year as weights. Source: Own calculations based on SHELDUS, U.S. Bureau of Economic Analysis and HMDA data. See Section 3 for details.
dis_91	**Weather-related disaster damages based on 1991 business activities:** Same as *dis*, but using the banks' regional distribution of mortgage loans in 1991 (the first year of our sample) as weights. Source: Own calculations based on SHELDUS, U.S. Bureau of Economic Analysis and HMDA data. See Section 3 for details.
dis_affected_91	**Weather-related disaster damages based on the share of affected counties:** The share of counties affected by a weather-related natural disaster in a bank's business region for each bank and year, using the banks' regional distribution of mortgage loans in 1991 as weights. Source: Own calculations based on SHELDUS, U.S. Bureau of Economic Analysis and HMDA data. See Section 3 for details.
dis_geo	**Geological-related disaster damages:** The yearly property damages from (non-weather-related) geological incidences over total personal income in a bank's business region for each bank and year, using the banks' regional distribution of mortgage loans of each year as weights. Source: Own calculations based on SHELDUS, U.S. Bureau of Economic Analysis and HMDA data. See Section 3 for details.
EQ	**Equity ratio:** The ratio of a bank's total equity to total assets. Source: FDIC ($eqv/100$).
FOR	**Foreclosure ratio:** The ratio of a bank's other real estate owned, which is not directly related to its business and consists largely of foreclosed property, to total assets. Source: FDIC ($ore/asset$).
NPA	**Non-performing assets ratio:** The ratio of a bank's loans past due 30-90+ days but still accruing interest and nonaccrual loans to total assets. Source: FDIC ($(p3asset + p9asset + naasset)/asset$).
PD	**Probability of default:** The predicted value from a linear probability model explaining the occurrence of a bank failure in a particular year. Bank failures come from the FDIC's *failed bank list* (transaction types PA, PI, PO, PI). To account for public bailouts, we include "technical" bank failures if the sum of a bank's equity and reserves is lower than half of its non-performing assets (see Cole and White, 2010). See the Online Appendix for details.
ROA	**Return on assets:** A bank's net income as a percent of average total assets. Source: FDIC ($roa/100$).
Z-score	**Z-score:** The natural logarithm of the sum of a bank's equity ratio (EQ) and its return on assets (ROA), standardized by the standard deviation of return on assets using a rolling 8-quarter window. Source: Own calculations based on FDIC data.

Table 2: Summary statistics

Variable		Mean	SD	Min	50th	Max
dis	weather-related disaster damages	0.0018	0.0275	0.0000	0.0000	1.8845
dis_91	weather-related disaster damages	0.0017	0.0287	0.0000	0.0000	1.9601
dis_affected_91	weather-related disaster damages	0.2445	0.3662	0.0000	0.0000	1.0000
dis_geo	geological-related disaster damages	0.0001	0.0030	0.0000	0.0000	0.0964
EQ	equity	0.0993	0.0329	0.0522	0.0914	0.2549
FOR	foreclosure ratio	0.0028	0.0061	0.0000	0.0004	0.0383
NPA	non-performing assets ratio	0.0122	0.0159	0.0000	0.0067	0.0950
PD	probability of default	0.0365	0.0262	-0.0049	0.0299	0.1644
ROA	return over assets	0.0093	0.0081	-0.0327	0.0100	0.0307
Z-Score	z-score	4.1716	0.9600	1.0654	4.2561	6.0490

Notes: See Table 1 for a description of all variables.

Table 3: Effects of weather-related disaster damages on bank stability

Dep. variable:	Z-score	PD	NPA	FOR	ROA	EQ
dis	-0.4908***	0.0110***	0.0102*	0.0009	-0.0050**	-0.0124***
	(0.1487)	(0.0032)	(0.0058)	(0.0008)	(0.0020)	(0.0031)
L.dis	-0.6654***	0.0215**	-0.0002	0.0014**	-0.0012	-0.0097***
	(0.1972)	(0.0090)	(0.0025)	(0.0005)	(0.0009)	(0.0035)
L2.dis	-0.2208	0.0043	-0.0043	-0.0001	-0.0002	-0.0050
	(0.1339)	(0.0031)	(0.0040)	(0.0011)	(0.0009)	(0.0039)
L3.dis	0.2987	-0.0034	-0.0091	-0.0021	0.0046	-0.0035
	(0.1812)	(0.0053)	(0.0056)	(0.0016)	(0.0031)	(0.0032)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year×region FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	66,766	66,766	66,766	66,766	66,766	66,766
Banks	6,136	6,136	6,136	6,136	6,136	6,136
Adj. within R2	0.0009	0.0012	0.0012	0.0002	0.0009	0.0004
Adj. R2	0.4005	0.5541	0.5411	0.4562	0.4745	0.6750

Notes: See Table 1 for a description of all variables. Standard errors are clustered at the state level. ***, ** and * indicate significant coefficients at the 1%, 5%, and 10% levels, respectively.

Table 4: Effects of geological-related disaster damages on bank stability

Dep. variable:	Z-score	PD	NPA	FOR	ROA	EQ
dis_geo	-5.4433***	0.3838***	0.1407***	0.1018***	-0.0832***	-0.1147***
	(0.6210)	(0.1160)	(0.0459)	(0.0351)	(0.0185)	(0.0156)
L._dis_geo	-3.5688***	0.3357***	0.1288***	0.0885***	-0.0400***	-0.0598***
	(0.6426)	(0.0987)	(0.0376)	(0.0306)	(0.0136)	(0.0178)
L2._dis_geo	-4.1894***	0.2663***	0.1074***	0.0566**	-0.0227**	-0.0520**
	(0.5070)	(0.0772)	(0.0219)	(0.0281)	(0.0091)	(0.0210)
L3._dis_geo	-0.9321**	0.1963***	0.0347***	0.0186	0.0084	0.0046
	(0.4479)	(0.0555)	(0.0106)	(0.0185)	(0.0065)	(0.0159)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year×region FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	66,766	66,766	66,766	66,766	66,766	66,766
Banks	6,136	6,136	6,136	6,136	6,136	6,136
Adj. within R2	0.0004	0.0040	0.0015	0.0041	0.0012	0.0002
Adj. R2	0.4002	0.5554	0.5413	0.4583	0.4746	0.6749

Notes: See Table 1 for a description of all variables. Standard errors are clustered at the state level. ***, ** and * indicate significant coefficients at the 1%, 5%, and 10% levels, respectively.

Table 5: Robustness regressions - using banks' weather-related disaster damages based on 1991 business activities across counties (dis_91)

Dep. variable:	Z-score	PD	NPA	FOR	ROA	EQ
dis_91	-0.4986***	0.0099***	0.0096*	0.0008	-0.0048**	-0.0120***
	(0.1352)	(0.0028)	(0.0055)	(0.0007)	(0.0019)	(0.0025)
L.dis_91	-0.6744***	0.0208**	-0.0003	0.0012***	-0.0006	-0.0093***
	(0.1647)	(0.0082)	(0.0023)	(0.0004)	(0.0008)	(0.0030)
L2.dis_91	-0.2200	0.0042	-0.0040	-0.0001	0.0000	-0.0055
	(0.1418)	(0.0027)	(0.0035)	(0.0009)	(0.0007)	(0.0037)
L3.dis_91	0.3076**	-0.0030	-0.0085*	-0.0019	0.0049*	-0.0032
	(0.1395)	(0.0046)	(0.0048)	(0.0014)	(0.0026)	(0.0032)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year×region FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	66,766	66,766	66,766	66,766	66,766	66,766
Banks	6,136	6,136	6,136	6,136	6,136	6,136
Adj. within R2	0.0010	0.0012	0.0012	0.0002	0.0010	0.0004
Adj. R2	0.4006	0.5541	0.5411	0.4562	0.4745	0.6750

Notes: See Table 1 for a description of all variables. Standard errors are clustered at the state level. ***, ** and * indicate significant coefficients at the 1%, 5%, and 10% levels, respectively.

Table 6: Robustness regressions - using the share of affected counties (*dis_affected_91*)

Dep. variable:	Z-score	PD	NPA	FOR	ROA	EQ
dis_affected_91	-0.0060	0.0002	0.0004	0.0001	-0.0003**	-0.0002
	(0.0147)	(0.0004)	(0.0003)	(0.0001)	(0.0001)	(0.0004)
L.dis_affected_91	-0.0260	0.0008*	0.0007	0.0002	-0.0002	-0.0004
	(0.0178)	(0.0005)	(0.0004)	(0.0001)	(0.0002)	(0.0003)
L2.dis_affected_91	-0.0363*	0.0014**	0.0011**	0.0003*	-0.0003	-0.0004
	(0.0189)	(0.0006)	(0.0005)	(0.0002)	(0.0002)	(0.0004)
L3.dis_affected_91	-0.0048	0.0013**	0.0007	0.0002	-0.0002	-0.0001
	(0.0116)	(0.0006)	(0.0005)	(0.0002)	(0.0002)	(0.0003)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year×region FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	66,766	66,766	66,766	66,766	66,766	66,766
Banks	6,136	6,136	6,136	6,136	6,136	6,136
Adj. within R2	0.0002	0.0011	0.0015	0.0006	0.0006	0.0000
Adj. R2	0.4001	0.5540	0.5413	0.4564	0.4743	0.6749

Notes: See Table 1 for a description of all variables. Standard errors are clustered at the state level. ***, ** and * indicate significant coefficients at the 1%, 5%, and 10% levels, respectively.

Table 7: Robustness regressions - excluding the financial crisis of 2008/2009

Dep. variable:	Z-score	PD	NPA	FOR	ROA	EQ
dis	-0.5298***	0.0097***	0.0109*	0.0009	-0.0053***	-0.0115***
	(0.1133)	(0.0032)	(0.0056)	(0.0006)	(0.0018)	(0.0030)
L.dis	-0.6493***	0.0219**	0.0003	0.0013**	-0.0012*	-0.0085**
	(0.2089)	(0.0091)	(0.0017)	(0.0005)	(0.0006)	(0.0033)
L2.dis	-0.0823	0.0018	-0.0001	-0.0002	-0.0004	-0.0031
	(0.1530)	(0.0053)	(0.0051)	(0.0016)	(0.0013)	(0.0043)
L3.dis	0.0115	0.0035	-0.0013	0.0002	-0.0006	-0.0031
	(0.2010)	(0.0063)	(0.0048)	(0.0015)	(0.0018)	(0.0029)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year×region FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	59363	59363	59363	59363	59363	59363
Banks	6,136	6,136	6,136	6,136	6,136	6,136
Adj. within R2	0.0008	0.0013	0.0009	0.0000	0.0007	0.0003
Adj. R2	0.4019	0.5616	0.5211	0.4613	0.4812	0.6845

Notes: See Table 1 for a description of all variables. Standard errors are clustered at the state level. ***, ** and * indicate significant coefficients at the 1%, 5%, and 10% levels, respectively.

Online Appendix

This appendix is for online publication only and provides further robustness regressions and information for the paper "Natural disasters and bank stability: Evidence from the U.S. financial system".

A1. Further robustness regressions

Regression results in the paper are presented with standard errors clustered at the state level. Results remain unchanged when standard errors are two-way clustered at bank and state level, as shown in Table OA1. This is not surprising because banks are generally nested within states, with the exception of a few banks that change the location of their headquarters from one state to another during the sample period.

The regression model in the paper includes year×region fixed effects, where region is one of twelve U.S. Federal Reserve Districts. Table OA2 shows results with year×state fixed effects instead of year×region fixed effects. Results are largely similar, but generally weaker than in our baseline regression with year×region fixed effects in the paper. Note that large natural disasters may affect many banks in one state at the same time. Hence, year×state fixed effects mask effects from large natural disasters, which explains the generally weaker regression results.

Finally, one potential concern about the results in the paper is that we may observe only surviving banks and not all banks affected by natural disasters, because some affected banks fail or are acquired, and hence drop out of the sample. We therefore test, using a linear probability model, whether dropping out of the sample is positively related to natural disasters in a bank's business region. Regression results show that this is not the case (see Table OA3). The first specification with year×region fixed effect shows significantly negative coefficients of lagged disaster-related damages, which suggests that natural disasters in a bank's business region make it even more likely that the bank stays in the sample. The second specification with year×state fixed effects shows insignificant coefficients.

Table OA1: Baseline results with two-way clustering of standard errors

Dep. variable:	Z-score	PD	NPA	FOR	ROA	EQ
dis	-0.4908***	0.0110***	0.0102*	0.0009	-0.0050**	-0.0124***
	(0.1417)	(0.0031)	(0.0055)	(0.0008)	(0.0019)	(0.0029)
L.dis	-0.6654***	0.0215**	-0.0002	0.0014***	-0.0012	-0.0097***
	(0.1880)	(0.0085)	(0.0024)	(0.0005)	(0.0008)	(0.0033)
L2.dis	-0.2208*	0.0043	-0.0043	-0.0001	-0.0002	-0.0050
	(0.1275)	(0.0029)	(0.0038)	(0.0010)	(0.0008)	(0.0037)
L3.dis	0.2987*	-0.0034	-0.0091*	-0.0021	0.0046	-0.0035
	(0.1726)	(0.0051)	(0.0053)	(0.0016)	(0.0029)	(0.0030)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year×region FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	66,766	66,766	66,766	66,766	66,766	66,766
Banks	6,136	6,136	6,136	6,136	6,136	6,136
Adj. within R2	0.0009	0.0012	0.0012	0.0002	0.0009	0.0004
Adj. R2	0.4005	0.5541	0.5411	0.4562	0.4745	0.6750

Notes: See Table 1 for a description of all variables. Standard errors are two-way clustered at the bank and state level. ***, ** and * indicate significant coefficients at the 1%, 5%, and 10% levels, respectively.

Table OA2: Baseline results with year×state (instead of year×region) fixed effects

Dep. variable:	Z-score	PD	NPA	FOR	ROA	EQ
dis	-0.2973***	0.0011	0.0065	-0.0014	-0.0024**	-0.0085**
	(0.1056)	(0.0036)	(0.0047)	(0.0011)	(0.0012)	(0.0041)
L.dis	-0.4215***	0.0124*	-0.0014	-0.0006	-0.0004	-0.0053
	(0.1247)	(0.0067)	(0.0016)	(0.0008)	(0.0009)	(0.0057)
L2.dis	-0.3067	-0.0009	0.0000	-0.0009	-0.0011*	0.0000
	(0.1863)	(0.0023)	(0.0018)	(0.0008)	(0.0006)	(0.0065)
L3.dis	-0.1100	0.0009	0.0018	-0.0004	-0.0012	-0.0027
	(0.1997)	(0.0019)	(0.0013)	(0.0008)	(0.0010)	(0.0051)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year×state FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	66,766	66,766	66,766	66,766	66,766	66,766
Banks	6,136	6,136	6,136	6,136	6,136	6,136
Adj. within R2	0.0002	0.0002	0.0001	0.0000	0.0000	0.0001
Adj. R2	0.4104	0.5780	0.5595	0.4883	0.4963	0.6805

Notes: See Table 1 for a description of all variables. Standard errors are clustered at the state level. ***, ** and * indicate significant coefficients at the 1%, 5%, and 10% levels, respectively.

Table OA3: Linear probability model of bank exit

Dep. variable:	Bank exit (1/0)	
dis	0.0022	0.0233
	(0.0227)	(0.0257)
L.dis	-0.0363***	0.0027
	(0.0106)	(0.0119)
L2.dis	-0.0364**	-0.0207
	(0.0140)	(0.0240)
L3.dis	-0.0357***	0.0268
	(0.0122)	(0.0231)
Bank FE	Yes	Yes
Year×region FE	Yes	-
Year×state FE	-	Yes
Observations	66,766	66,766
Banks	6,136	6,136
Adj. within R2	-0.0000	-0.0000
Adj. R2	0.2276	0.2332

Notes: See Table 1 for a description of all variables. The dependent variable is one for the year the bank exits the sample, and zero otherwise. Standard errors are clustered at the state level. ***, ** and * indicate significant coefficients at the 1%, 5%, and 10% levels, respectively.

A2. Predictions of default probabilities

Data The data sources that we use for the prediction of the banks' default probabilities are the *Federal Deposit Insurance Corporation* (FDIC) for all bank financial data[17] and the U.S. Bureau of Labor Statistics for county-level unemployment rates[18]. The sample includes yearly data on 15,536 U.S. banks from 1992 to 2012, which results in a total of 187,719 observations. We require that a bank has its headquarters anywhere in the contiguous United States and has non-missing information for all variables we use in the analysis.[19] See Table OA4 for a description of all variables.

The number of bank failures in this sample is 1,321. It includes final bank failures from the FDIC's *failed bank list* as well as "technical" bank failures. The latter considers banks with a reported sum of equity and reserves below half of non-performing assets. It is based on Cole and White (2010) and accounts for banks that were insolvent in principle, but may have been bailed out by the government.

[17]See FDIC bank data & statistics (https://www.fdic.gov/bank/statistical/) and failed bank list (https://www.fdic.gov/bank/individual/failed/).

[18]See Local Area Unemployment Statistics (https://www.bls.gov/lau/).

[19]Note that, in contrast to the sample of the main analyses, we do not require that a bank existed in 1994 or reports HMDA data. In doing so, we aim to use as much information and as many bank failures as possible for this estimation.

Model We predict banks' probabilities of default (PD) using the following linear probability model:[20]

$$
\begin{aligned}
Fail_{i,t} = \nu_i + \tau_t \times \gamma_f &+ \beta_1 AGE_{i,t-1} + \beta_2 CIR_{i,t-1} + \beta_3 COI_{i,t-1} + \beta_4 EQ_{i,t-1} \\
&+ \beta_5 FOR_{i,t-1} + \beta_6 IENC_{i,t-1} + \beta_7 LIQ_{i,t-1} + \beta_8 LOA_{i,t-1} + \beta_9 NPA_{i,t-1} \\
&+ \beta_{10} RE_{i,t-1} + \beta_{11} ROA_{i,t-1} + \beta_{12} SIZE_{i,t-1} + \beta_{13} UR_{i,t-1} + \epsilon_{i,t}.
\end{aligned}
$$

The dependent variable $Fail_{i,t}$ is a binary variable with a value of one if bank i fails in year t, and zero otherwise. The variables ν_i and $\tau_t \times \gamma_f$ cover bank and year-region fixed effects, respectively, to capture bank-invariant effects, as well as developments over time in the twelve U.S. regulatory regions (Federal Reserve Districts). In line with the literature, we choose the first lag of all right-hand-side variables.

Results Results of the probability model are shown in Table OA5. As expected, bank equity (EQ), return on assets (ROA), as well as measures of asset quality (IENC, FOR, NPA), significantly affect a bank's failure probability. Further, bank liquidity (LIQ), the ratio of a bank's gross loans to total assets (LOA) and bank size (SIZE) turn out to have significant effects. As a reference, Column (2) and Column (3) of Table OA5 show descriptive statistics for the respective variables.

Predicted probabilities of default (PD) are then used as a measure of bank stability for the regressions of the paper (see, e.g., Column (2) of Table 3).

[20] A linear probability model allows us to include bank and year-region fixed effects. With a nonlinear probability model, the introduction of many fixed effects leads to i) practical problems because the presence of many variables makes the estimation much more difficult, and ii) the incidental parameters problem (Greene et al., 2002; Fernandez-Val, 2009).

Table OA4: Predictions of default probabilities/ variable description

Variable name	Description
AGE	**Age:** Banks' age as the natural logarithm of the quarterly distance to each bank's date of establishment. Source: FDIC ($\ln(qtr - birthqtr)$).
CIR	**Cost-to-income ratio:** The ratio of banks' total cost to income. Source: FDIC ($nonix/(nim + nonii)$).
COI	**Commercial and industrial loan ratio:** The ratio of banks' commercial and industrial loans to total assets. Source: FDIC ($lnci/asset$).
EQ	**Equity ratio:** The ratio of total equity to total assets. Source: FDIC ($eqv/100$).
FAIL	**Bank failure:** Bank failures come from the FDIC's *failed bank list* (transaction types PA, PI, PO, PI). Source: FDIC (https://www.fdic.gov/bank/individual/failed/). To account for public bailouts, we include "technical" bank failures if a bank's sum of equity and reserves is lower than half of its non-performing assets (see, Cole and White, 2010).
FOR	**Foreclosure ratio:** The ratio of a bank's other real estate owned, which is not directly related to its business and consists largely of foreclosed property, to total assets. Source: FDIC ($ore/asset$).
IENC	**Income earned, not collected on loans:** The ratio of banks' income not collected on loans to total assets. Source: FDIC ($oaienc/asset$).
LIQ	**Liquidity:** The ratio of difference between federal funds purchased and sold to total assets. Source: FDIC ($(frepp - frepo)/asset$).
LOA	**Gross loan ratio:** The ratio of banks' gross loans to total assets. Source: FDIC ($lnlsgr/asset$).
NPA	**Non-performing assets ratio:** The sum of loans past due 30-90+ days but still accruing interest and nonaccrual loans, scaled by total assets. Source: FDIC ($(p9asset + p3asset + naasset)/asset$).
RE	**Real estate loan ratio:** The ratio of banks' real estate loans to total assets. Source: FDIC ($lnre/asset$).
ROA	**Return on assets:** Net income as a percentage of average total assets. Source: FDIC ($roa/100$).
SIZE	**Bank size:** The natural logarithm of banks' total assets. Source: FDIC ($\ln(asset)$).
UR	**Unemployment rate:** The yearly unemployment rate for each U.S. county. Source: U.S. Bureau of Labor Statistics.

Table OA5: Predictions of default probabilities

	Linear probability model Dependent variable: FAIL (0/1)	Descriptive Statistics Mean	 SD
L.AGE	0.0027	5.1996	1.1752
	(0.0023)		
L.CIR	0.0001	0.7790	4.3787
	(0.0002)		
L.COI	0.0033	0.1423	0.1178
	(0.0052)		
L.EQ	-0.1311***	0.1129	0.0766
	(0.0113)		
L.FOR	1.0031***	0.0030	0.0091
	(0.1216)		
L.IENC	-0.4684***	0.0062	0.0042
	(0.1399)		
L.LIQ	-0.0101**	0.0062	0.0042
	(0.0045)		
L.LOA	-0.0264***	0.6174	0.1686
	(0.0037)		
L.NPA	1.4264***	0.0137	0.0199
	(0.0754)		
L.RE	0.0028	0.6599	0.2215
	(0.0036)		
L.ROA	-0.4055**	0.0088	0.0305
	(0.1878)		
L.SIZE	0.0030***	11.6809	1.3834
	(0.0010)		
L.UR	-0.0144	0.0572	0.0271
	(0.0109)		
Bank FE	Yes		
Year×region FE	Yes		
Observations	187719		
Banks	15536		
Adj. within R2	0.1532		
Adj. R2	0.3418		

Notes: The first column shows results of the linear probability model. The second and third columns show descriptive statistics for the respective variables. See Table OA4 for a detailed description of all variables. Standard errors are clustered at the bank level. ***, ** and * indicate significant coefficients at the 1%, 5%, and 10% levels, respectively.

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