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Felix Noth - Ulrich Schüwer

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

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Non-Technical Summary

Empirical data show that natural disasters, which have the potential to devastate entire regions and to cause loss of life and property, have become even more frequent and destructive over the last decades. 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 natural disasters affect bank stability. Whether this is the case or not is not obvious. On the one hand, banks are affected because disaster damages immediately reduce banks' collateral values and the credit standing of their borrowers. Further, disaster damages may cause business disruptions and adversely affect economic growth in the banks' 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.

Our analysis is based on a comprehensive dataset of over 13,000 reported disaster damages in the United States and yearly financial data for over 6,000 banks over the period 1994 to 2012, resulting in over 66,000 bank-year observations. The dataset thereby allows us to explore a large variation in disaster damages across regions, banks and time.

Results from our analyses show that disaster damages in the banks' business regions indeed weaken bank stability and performance. This is reflected in significantly lower bank z-scores (a measure of bank stability), higher probabilities of default, higher non-performing assets ratios, higher foreclosure ratios, lower returns on assets and lower equity ratios in the two years following a natural disaster. This evidence reveals that natural disasters jeopardize borrowers' financial solvency and decrease bank stability, despite potential insurance payments and public aid programs. On the positive side, we find that banks manage to recover from the adverse shock after some years if no further disasters occur in the meantime.

SHORTER PAPER

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

Felix Noth[†] and Ulrich Schüwer[‡]

February 2017

Abstract

We document that 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 in the meantime.

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

JEL Classification: G21, Q54

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1 Introduction

Empirical data show that natural disasters, which have the potential to devastate entire regions and to cause loss of life and property, have become even more frequent and destructive over the last decades (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 (e.g., Bank of England, 2015).

This study explores whether natural disasters affect bank stability. Whether this is the case or not is not obvious. On the one hand, banks are affected because disaster damages immediately reduce banks' collateral values and the credit standing of their borrowers. Further, disaster damages may cause business disruptions and adversely affect economic growth in the banks' 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.

Results from our analyses show that 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. This evidence reveals that natural disasters jeopardize borrowers' financial solvency and decrease bank stability, despite potential insurance payments and public aid programs. On the positive side, we find that banks manage to recover from the adverse shock after some years if no further disasters occur in the meantime.

The identification strategy of the analysis uses the exogeneity of the *timing* and *inten-*

sity of natural disasters. Consequently, we identify short-term and medium-term causal effects of natural disasters on bank stability. The interpretation of our results needs to consider that banks are presumably aware of general disaster risks in different regions across the U.S., and they can select to do business in affected regions or not. However, banks cannot anticipate the years when natural disasters occur or how harmful they will be in a particular year. We control for potential differences among banks' business models by including bank fixed effects in all regressions, and we control for economic developments over time by including year-region fixed effects. We also show in robustness regressions that results remain qualitatively unchanged when we hold the bank's business region constant, thus excluding that banks' expansions or other changes in banks' business regions over the sample period drive our results.

The analysis is based on a comprehensive dataset of over 13,000 reported disaster damages in the United States and yearly financial data for over 6,000 banks over the period 1994 to 2012, resulting in over 66,000 bank-year observations. The dataset thereby allows us to explore a large variation in disaster damages across regions, banks and time.

Our analysis contributes to the growing literature on 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 of economic growth rates in affected regions, while Cavallo et al. (2013) find no significant effect of natural disasters on economic growth for a sample of 196 countries worldwide. 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 U.S. that banks are significantly and negatively affected by natural disasters. In particular, our evidence that banks' non-performing assets and foreclosures 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 determinants of banks' financial distress and bank failures (e.g., Wheelock and Wilson, 2000; Cole and White, 2010). Further, several studies analyze bank lending and bank behavior in the aftermath of natural disasters (e.g., Garmaise and Moskowitz, 2009; Berg and Schrader, 2012; Lambert et al., 2015; Chavaz, 2016; Koetter et al., 2016; Cortes and Strahan, 2017). 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 natural disaster.

The paper proceeds as follows: Section 2 describes the data used in this study. Section 3 presents our empirical model and estimation results. Section 4 concludes.

2 Data

Our main data sources are the *Federal Deposit Insurance Corporation* (FDIC) for all bank financial data,[1] the *Home Mortgage Disclosure Act* (HMDA) database for banks' regional distribution of mortgage loans,[2] and the *Spatial Hazard Events and Losses Database for the United States* (SHELDUS) for all data on natural disasters.[3]

The sample includes yearly data on 6,136 U.S. banks from 1994 to 2012, which results in a total of 66,764 observations. The sample period starts in 1994 because we need two

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

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

[3]The SHELDUS database is provided by the *Hazards and Vulnerability Research Institute* at the University of South Carolina (http://hvri.geog.sc.edu/SHELDUS/).

preceding years 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 damages from SHELDUS was freely available only until then. We require that a bank has its headquarter anywhere in the contiguous U.S., existed at the beginning of our sample period (1994), reports loan data under the HMDA,[4] and has non-missing information for all variables we use in the analysis. We also require that all banks exist in the dataset for a minimum of six consecutive years, because our main specifications include five lags of disaster damages. 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 (see, e.g., 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

[4]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 home or branch office in a metropolitan statistical area. See https://www.ffiec.gov/hmda/ for details.

model.[5] 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 equity-to-asset ratios (EQ) and return on assets (ROA), which are further indicators of bank stability and performance, and also used to calculate a banks' 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.

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

First, we use more than 13,000 individual records on property damages, measured in US$, from the SHELDUS database for the period 1989 to 2012.[6] These US$ numbers are not directly informative for our purpose. For example, a US$ 100 million loss from disaster 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 a measure of local economic activity, i.e., a county's yearly total personal income, measured in US$.[7] For example, the standardized disaster damage we obtain for Orleans County in 2005, when Hurricane Katrina hit the region, is 0.95. Thus, according to our measure, total property

[5]Our probability model explains U.S. bank failures based on the FDIC's *failed bank list*. See the Appendix C for details.

[6]We consider reported damages of US$ 1 million or more from the database (inflation adjusted to 2012 dollars). The data starts in 1989, five years before our main sample period (1994 to 2012), because we use five lags of disaster damages in our main regressions. In robustness regressions with additional three lags, we use disaster damages since 1986.

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

losses nearly equalled 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 damages. We calculate $dis_{i,t}$ as the weighted average standardized disaster damages over all counties at year t, using the share of bank i's activities in each county j at year t as weights:

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

Ideally, we could measure banks' activities across counties based on the bank's total asset exposures, because the most direct effect of natural disasters on banks is presumably through 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 bank activities.

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

- Figure 1 and Figure 2 -

3 Empirical model and results

Model. To investigate whether natural disasters affect bank stability we estimate the following OLS regression model:

$$Y_{i,t} = \nu_i + \tau_t \times \gamma_f + \beta_0 \; dis_{i,t} + \beta_1 \; dis_{i,t-1} + \cdots + \beta_5 \; dis_{i,t-5} + \epsilon_{i,t}, \tag{1}$$

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 a bank's headquarters location, 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, San Francisco). The main explanatory variable is a bank's exposure to disaster damages in its business region, dis_{it}, which is included with five lags to consider potential natural disasters that occurred in previous years. Standard errors are clustered by state.[8]

Results. We start the discussion of regression results with short-term effects of 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 damages ($dis_{i,t-2}$ to $dis_{i,t-5}$).

Results for the effect of disaster 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 natural disaster in their business region become

[8] Clustering by state accounts for potential within-state correlations over banks and time, and is more conservative relative to clustering by bank.

less stable in the short term. This effect is also economically significant. If we consider a value of $dis_{i,t}$ equal to 0.14, which represents the average of the top 1 percent values of $dis_{i,t}$ over the period 1994 to 2012, this causes a decrease in a bank's standardized distance to default, $(ROA - EQ)/SD(ROA)$, of about 8.8 percent one year later (0.14 $\times$ 0.6285).[9] 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 0.088 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 damages also cause significantly higher predicted probabilities of default in the short term. In particular, an increase of $dis_{i,t}$ by 0.14 causes an increase of PD by about 0.3 percentage points in the following year (0.14 $\times$ 0.0217), which is economically highly relevant compared to 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 damages on non-performing assets ratios is significantly positive. An increase of $dis_{i,t}$ by 0.14 causes an increase of non-performing assets ratios by about 0.14 percentage points in the same year (0.14 $\times$ 0.0097), which is again economically relevant compared to banks' average non-performing assets ratios of 1.22 percent (see 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 0.14 causes an increase of about 0.02 percentage points in the same year (0.14 $\times$ 0.0016), which is economically relevant com-

[9] Remember that the bank z-score is defined as $ln\left(\frac{ROA-EQ}{SD(ROA)}\right)$.

pared to banks' average foreclosure ratios of 0.28 percent (see Panel (d) of Figure 3).

Further, we find a significant short-term decrease of return on assets (Col. 5) and decrease of bank equity (Col. 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 damages, as represented by the coefficients of $dis_{i,t-2}$ to $dis_{i,t-5}$. We find that banks manage to recover after some 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 for banks affected by natural disasters and unaffected banks after two years.[10] 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 provide for 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.

Robustness. The first set of robustness regressions extends the OLS regression model in the paper (Eq. 1), but excludes the years of the global financial crisis (2008 and 2009) in order to exclude effects of the financial turmoil during these years. As shown in Table 4, results remain qualitatively unchanged.

- Table 4 -

[10] One potential concern about these results is that we 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 in unreported regressions, using a linear probability model, whether dropping out of the sample is positively related to natural disasters in a bank's business region over a six year period. Regression results show that this is not the case. Specifically, we find that natural disasters in a bank's business region make it more likely that the bank stays in the sample.

Second, we recalculate the disaster measure $dis_{i,t}$. In particular, we use the (time-invariant) share of banks' mortgage lending activities in each county in 1989 as a proxy of banks' local bank activities for all years, instead of actual (time-varying) values. This excludes that changes in banks' local business activities over the sample period may affect the disaster measure. As shown in Table 5, results again remain qualitatively unchanged.

- Table 5 -

4 Conclusion

Our analysis provides empirical evidence that 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., up to two years after the disaster. These effects are economically significant. The results also show that negative effects fade out after two years if no further disasters occur.

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 climate 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 within some years.

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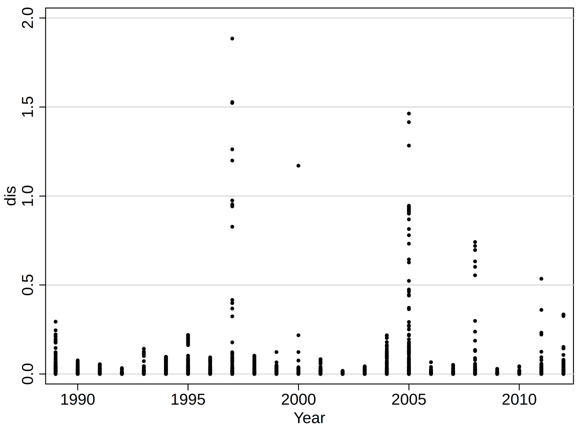
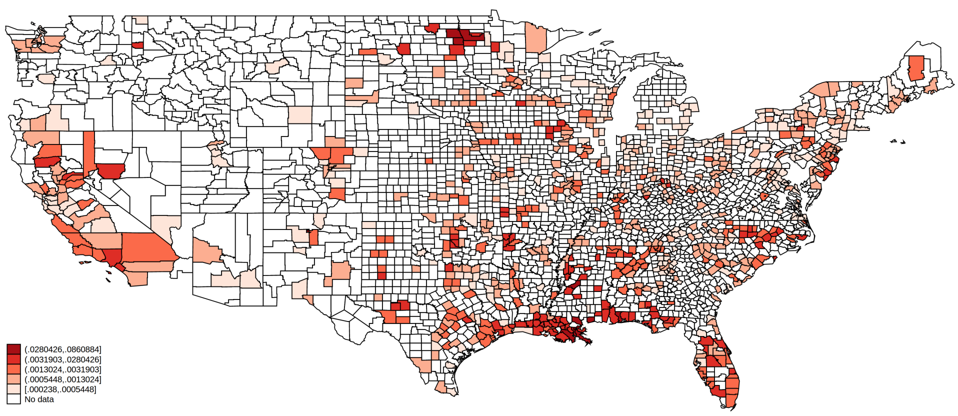
Appendix A: Figures

Figure 1: Yearly distribution of disaster damages



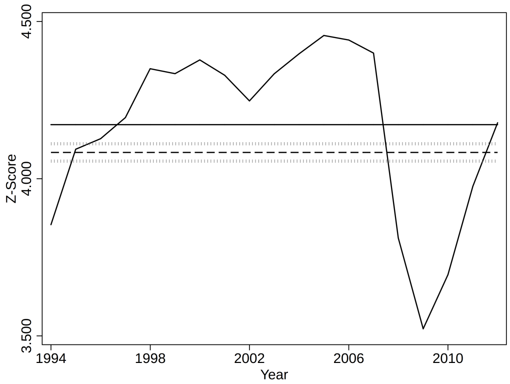
The figure shows average yearly disaster damages that banks face in their business regions, $dis_{i,t}$, for each year between 1989 and 2012. Source: Own calculations based on SHELDUS, Bureau of Economic Analysis and HMDA data.

Figure 2: Regional distribution of disaster damages

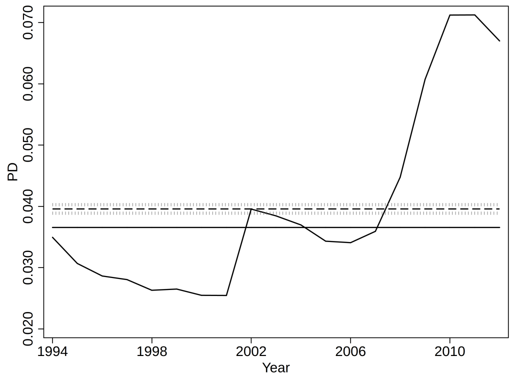


The figure illustrates the distribution of disaster damages across counties. The value of each county is the average value of $dis_{i,t}$ for all years from 1989 to 2012 and all banks with their headquarters in this county. Light colors and dark colors represent relatively low and high values, respectively. Source: Own calculations based on SHELDUS, Bureau of Economic Analysis and HMDA data.

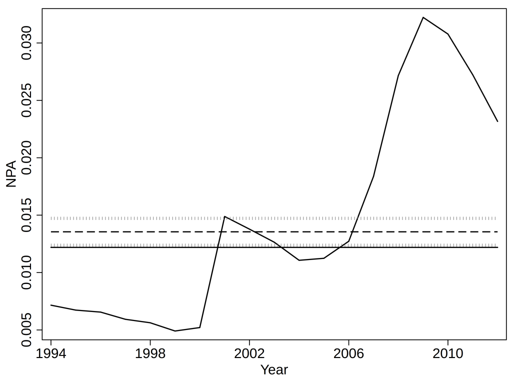
Figure 3: Bank stability and performance over time



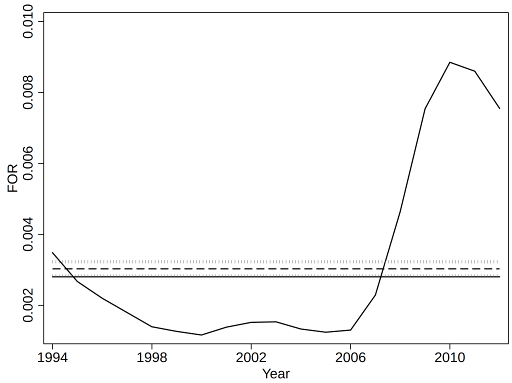
(a) z-score



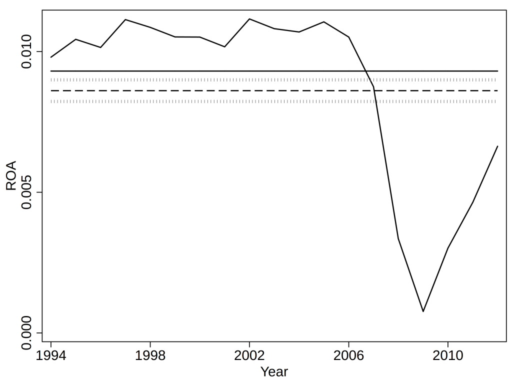
(b) probability of default (PD)



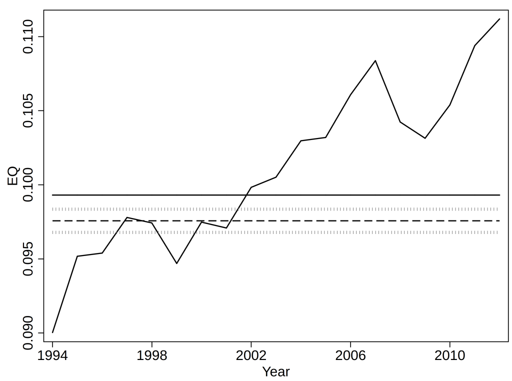
(c) non-performing assets ratio (NPA)



(d) foreclosure ratio (FOR)



(e) return on assets (ROA)



(f) equity (EQ)

The graphs illustrate the development of our measures of bank stability and performance over the sample period 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 disaster damages in a bank's business region $dis_{i,t}$ equal to 0.14, which represents the average of the top 1 percent values of $dis_{i,t}$ over the period 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 calculate the economic effect.

Appendix B: Tables

Table 1: Variable description

Variable name	Description
dis	**Yearly disaster damages:** The yearly property disaster damages 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, Bureau of Economic Analysis and HMDA data.
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	**Predicted probabilities 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).
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 (SD(ROA)). Source: Own calculations based on FDIC data.

Table 2: Summary statistics

	Mean	SD	Min	50th	Max
dis	0.0021	0.0278	0.0000	0.0001	1.8845
EQ	0.0993	0.0329	0.0522	0.0914	0.2549
FOR	0.0028	0.0061	0.0000	0.0004	0.0383
NPA	0.0122	0.0159	0.0000	0.0067	0.0950
PD	0.0365	0.0262	-0.0049	0.0299	0.1644
ROA	0.0093	0.0081	-0.0327	0.0100	0.0307
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 disaster damages on bank stability

Dependent variable:	Z-score	PD	NPA	FOR	ROA	EQ
dis	-0.4681***	0.0118***	0.0097*	0.0013	-0.0050***	-0.0124***
	(0.1201)	(0.0030)	(0.0051)	(0.0009)	(0.0017)	(0.0034)
L.dis	-0.6285***	0.0217***	-0.0005	0.0016**	-0.0008	-0.0093**
	(0.1637)	(0.0079)	(0.0027)	(0.0007)	(0.0010)	(0.0038)
L2.dis	-0.1931	0.0039	-0.0049	-0.0002	0.0005	-0.0046
	(0.1198)	(0.0036)	(0.0047)	(0.0013)	(0.0012)	(0.0042)
L3.dis	0.3543	-0.0044	-0.0103	-0.0025	0.0055	-0.0026
	(0.2181)	(0.0067)	(0.0065)	(0.0019)	(0.0035)	(0.0036)
L4.dis	0.3200	-0.0147	-0.0090	-0.0024	0.0059	0.0021
	(0.2547)	(0.0100)	(0.0063)	(0.0022)	(0.0036)	(0.0034)
L5.dis	0.4145	-0.0100	-0.0079	-0.0032	0.0036	0.0068
	(0.2581)	(0.0089)	(0.0057)	(0.0022)	(0.0029)	(0.0047)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year $\times$ region FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	66764	66764	66764	66764	66764	66764
Banks	6136	6136	6136	6136	6136	6136
Adj. within R2	0.0012	0.0021	0.0019	0.0007	0.0018	0.0005
Adj. R2	0.4007	0.5545	0.5415	0.4565	0.4750	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: Robustness regressions I – excluding the financial crisis of 2008/2009

Dependent variable:	Z-score	PD	NPA	FOR	ROA	EQ
dis	-0.5399***	0.0115***	0.0109**	0.0015**	-0.0057***	-0.0118***
	(0.0991)	(0.0032)	(0.0052)	(0.0007)	(0.0016)	(0.0034)
L.dis	-0.6434***	0.0229***	0.0004	0.0016**	-0.0011	-0.0084**
	(0.1866)	(0.0084)	(0.0019)	(0.0007)	(0.0007)	(0.0036)
L2.dis	-0.1261	0.0035	0.0002	0.0001	-0.0002	-0.0034
	(0.1790)	(0.0059)	(0.0052)	(0.0018)	(0.0015)	(0.0048)
L3.dis	0.0273	0.0039	-0.0024	-0.0002	0.0002	-0.0023
	(0.2143)	(0.0069)	(0.0051)	(0.0018)	(0.0022)	(0.0031)
L4.dis	-0.2445	-0.0023	-0.0025	0.0001	0.0004	-0.0012
	(0.2148)	(0.0091)	(0.0047)	(0.0023)	(0.0022)	(0.0028)
L5.dis	0.4367*	-0.0119	-0.0090*	-0.0036*	0.0043	0.0057
	(0.2474)	(0.0085)	(0.0052)	(0.0021)	(0.0029)	(0.0043)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × region FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	59361	59361	59361	59361	59361	59361
Banks	6136	6136	6136	6136	6136	6136
Adj. within R2	0.0011	0.0019	0.0016	0.0006	0.0013	0.0004
Adj. R2	0.4021	0.5619	0.5214	0.4617	0.4815	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.

Table 5: Robustness regressions II – using banks' disaster damages *dis* based on banks' 1989 shares of business activities across countries

Dependent variable:	Z-score	PD	NPA	FOR	ROA	EQ
dis(89)	-0.4848***	0.0107***	0.0092*	0.0012	-0.0047***	-0.0123***
	(0.1098)	(0.0026)	(0.0049)	(0.0008)	(0.0016)	(0.0029)
L.dis(89)	-0.6383***	0.0209***	-0.0007	0.0014**	-0.0002	-0.0090***
	(0.1354)	(0.0073)	(0.0024)	(0.0007)	(0.0009)	(0.0033)
L2.dis(89)	-0.1920	0.0038	-0.0045	-0.0002	0.0006	-0.0052
	(0.1249)	(0.0031)	(0.0040)	(0.0012)	(0.0009)	(0.0041)
L3.dis(89)	0.3611**	-0.0040	-0.0097*	-0.0023	0.0057*	-0.0025
	(0.1700)	(0.0057)	(0.0055)	(0.0017)	(0.0030)	(0.0036)
L4.dis(89)	0.3257	-0.0139	-0.0087	-0.0022	0.0058*	0.0013
	(0.2189)	(0.0084)	(0.0055)	(0.0019)	(0.0031)	(0.0034)
L5.dis(89)	0.4071*	-0.0108	-0.0080	-0.0030	0.0035	0.0063
	(0.2372)	(0.0081)	(0.0053)	(0.0018)	(0.0026)	(0.0048)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × region FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	66764	66764	66764	66764	66764	66764
Banks	6136	6136	6136	6136	6136	6136
Adj. within R2	0.0014	0.0021	0.0019	0.0007	0.0019	0.0005
Adj. R2	0.4008	0.5545	0.5414	0.4564	0.4750	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.

Appendix C: Predictions of default probabilities

Data. The datasources are the *Federal Deposit Insurance Corporation* (FDIC) for all bank financial data[11] and the Bureau of Labor Statistics for county-level unemployment rates[12]. 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 U.S. and has non-missing information for all variables we use in the analysis.[13] See Table C-1 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 in principle insolvent, but may have been bailed out by the government.

Model. We predict banks' probabilities of default (PD) using the following linear probability model:[14]

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

The dependent variable $Fail_{i,t}$ is a binary variable. The variables ν_i and $\tau_t \times \gamma_f$ cover bank and year-region fixed effects to capture bank-invariant effects as well as developments over time in the twelve U.S. regulatory regions (Fed districts). Following the literature, we choose the first

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

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

[13] Note that different to the sample of the main analyses, we do not require that a bank existed in 1994 or reports HMDA data, in order to use as much information and bank failures as possible for this estimation.

[14] 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 (see, e.g., Greene et al., 2002; Fernandez-Val, 2009).

lag of all right-hand side variables to explain bank failures in a particular year (see Wheelock and Wilson, 2000; Cole and White, 2010).

Results. Results of the probability model are shown in Col. (1) of Table C-2. As expected, bank equity (EQ), return on assets (ROA) as well as measures of asset quality (IENC, FOR, NPA) significantly effect 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, Col. (2) and Col. (3) 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., Col. (2) of Table 3 and Panel (b) of Figure 3).

Table C-1: 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 birth date. 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). 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). Source: FDIC (https://www.fdic.gov/bank/individual/failed/).
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 percent 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: Bureau of Labor Statistics.

Table C-2: 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 C-1 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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