The Impact of Natural Disasters on the Performance and Solvency of U.S. Banks

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ABSTRACT

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This paper explores the effect of natural disasters on the profitability and solvency of U.S. banks. Employing a sample of 187 large-scale natural disasters that occurred in the U.S. between 2000 and 2014 and a sample of 2,891 banks, we find that natural disasters have a pronounced effect on the net-income-to-assets and the net-income-to-equity ratio of banks, as well as impaired loans and the return on average assets. We also observe significant effects on the equity ratio and the tier-1 capital ratio (two solvency measures). Interestingly, the latter are positive for regional banks which appear to voluntarily increase their capital reserves in response to natural disasters that affect part of their operations, but significantly negative for banks that operate locally or nationally.

Key Words: Natural Disasters, Banks, Bank Solvency, Bank Profitability

JEL Classification: G21, G28, G32

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Introduction

Systemic environmental risks are arguably one of the biggest risks faced by humanity nowadays (World Economic Forum, 2010). As climate change and resource depletion are on the rise, environmental risks increase, leading to financial and economic instability (Andrew et al., 2015). The economic and social impacts of systemic environmental risks are significant, and the world needs large-scale economic transformations to deal with such impacts (Alexander, 2014). The United Nations reports that it will cost the global economy nearly $28.6 trillion annually, equal to 18 percent of global GDP, to maintain the current scale of unsustainable economic activity by 2050 (Mattison et al., 2011). In addition, limiting the global rise in temperatures to 1.5 degrees would require almost $1 trillion of additional investment globally in new green infrastructure in buildings, transport, industry and energy annually to 2030 (as cited in Alexander, 2014).

Natural disasters, a type of environmental risk, are becoming more frequent, more intense and costlier (Freeman et al., 2003; Bitar et al., 2019). The average number of disasters per year increases to 329 in the latest 20 years, which is double that in 1978-1997 (United Nations Office for Disaster Risk Reduction & Centre for Research on the Epidemiology of Disasters, 2015). In 2013, the World Bank estimated that economic losses caused by disasters between 1980 and 2012 amounted to US$3.8 trillion, of which 74% were related to extreme weather events (World Bank, 2013). In 2016, the World Bank further reported that the impact of extreme natural disasters is equivalent to losses of about $520 billion in annual consumption, and that they force 26 million people into poverty every year (World Bank, 2016b).

The United Nations Office for Disaster Risk Reduction and the Centre for Research on the Epidemiology of Disasters (2018) released a report on economic losses and poverty related to disasters. According to the report, disaster-hit countries experienced direct economic losses of

US$2,908 billion between 1998 and 2017. Climate-related disasters accounted for 77% of total losses, valued at US$2,245 billion, while the percentage in 1978-1997 was 68% (US$895 billion of US$1,313 billion). Interestingly, direct economic losses related to weather extremes rose by 151% between 1998 and 2017.

The largest economic losses have been suffered by the USA, equaling almost US$ 945 billion (United Nations Office for Disaster Risk Reduction & Centre for Research on the Epidemiology of Disasters, 2018). For instance, Hurricane Katrina, which caused catastrophic damages in Florida and Louisiana in August 2005, is considered the costliest tropical cyclone on U.S. record. Total property damages were estimated at $125 billion. Similarly, according to a report by the Congressional Research Service, the earthquake and tsunami that occurred in Tohoku, Japan, in 2011, led to a nuclear crisis and seriously affected Japan’s economy. It is estimated that the physical capital losses from the disaster amounted to $195 billion to $305 billion (Cooper et al., 2011).

When a natural disaster occurs, the impacted country has to suffer the cost of reconstructing the lost infrastructure, job loss and unemployment aid, medical assistance for the victims, between other expenses, yet governments aren’t the only ones who bear a cost. According to Collier et al. (2013), Alexander (2014), Klomp (2014), Batten et al. (2016), and Brahmana et al. (2016), natural disasters constitute a systemic risk for financial intermediaries, which increase non-performing bank loans, resulting in loan defaults, a decrease of credit supply and an increased chance of bank bankruptcy. Large-scale natural disasters may weaken a bank’s ability to stay solvent and decrease the distance-to-default of banks, resulting in bank failures (Klomp, 2014). Batten et al. (2016) show that climate-related natural disasters may lead to losses for both banks and insurers. However, the losses may be less serious when the financial system has spread related risks through insurance and reinsurance.

However, even though natural disasters may have serious impacts on banks, they have been largely ignored by regulators. For example, the Basel III Accord does not adequately address systemic environmental risks, such as natural disasters - in banking activities and financial reforms (Van Gelder, 2011; Alexander, 2014; Ahmed et al., 2015).

To date, to the best of our knowledge, no empirical work has examined the impact of natural disasters on the performance of U.S. banks. This paper aims to address this gap and underline the need to integrate environmental risk in regulatory reform. As natural disasters become more frequent due to climate change, there is an increased need to modify our current guidelines. Specifically, we examine how natural disasters such as hurricanes and earthquakes affect the profitability of local, regional, and national banks. We use panel data including 187 highly destructive natural disasters that occurred in the U.S. from 1999 to 2014. We construct a measure that captures the damages of natural disasters based on information from the Emergency Events Database (EM-DAT), a Belgian-based disaster database administered by the Centre for Research on the Epidemiology of Disasters (CRED).[1] Our major findings are that natural disasters affect bank profitability and that they have the most impact on local banks, less impact on regional banks, and the least impact on national banks.

The remainder of this paper is organized as follows: In section 2, we review the previous literature related to the impact of natural disasters on the real economy and financial institutions; in Sections 3 and 4, we describe the data and methodology used in this study; in Section 5, we present our empirical results on the impact of natural disasters on the performance of U.S. banks; we conclude in Section 6.

[1] https://www.emdat.be/

Literature Review

Benson and Clay (2004) argue that natural disasters can have observable negative impacts on the economy in the long-term. Through case studies, they point out that disasters have negative long-term consequences for economic growth, development, and poverty reduction. Similarly, Noy (2009) reports severe adverse short-run macro-economic consequences caused by natural disasters. Using a model of short-run GDP growth, he finds that property damages caused by disasters negatively affect GDP growth.

Collier et al. (2013) model a representative lender managing a stock of equity and apply it to a Peruvian microfinance intermediary that is vulnerable to El Niño-related flooding. They demonstrate that in developing and emerging economies, natural catastrophes are a type of systemic risk for financial intermediaries. Their results show that natural disasters can result in large loan losses and lead to a decrease of credit supply holding back recovery for the influenced economy. In addition, they observe a large decrease in the lender's capital ratio, equity and loan origination shortly following a natural disaster.

Von Peter et al. (2012) find that transferring risk to insurance markets may mitigate the impacts of natural disasters. Relatedly, Batten et al. (2016) show that climate-related natural disasters may lead to losses for both banks and insurers. If banks cannot raise funds in time, they could reduce lending, which impacts the soundness of financial institutions and the stability of the financial system. However, the consequences of natural disasters may be less serious when the related risks are priced in advance through contracts. Allowing the financial system to spread them through insurance and reinsurance.

Alexander (2014) gives some historical examples of banking instability caused by natural disasters, such as bank losses, bank closures, related financial market stresses, and financial crises.

Some previous research reports the specific impacts of natural disasters on financial institutions. Steindl and Weinrobe (1983) investigate the deposit behavior at financial institutions after large-scale natural hazards. They argue that banks may experience extraordinary deposit withdrawals by their customers in the immediate post-disaster period. However, they observe no evidence of a run. In most cases, there is a significant increase in deposits. The increase in deposits might be attributable to four different sources: (1) cash deposits from residents within the area who hope to safekeep them from possible loss, (2) transfers of deposits by state and local governments as financial support for post-disaster recovery, (3) payments from insurance claims, (4) a decrease in withdrawals.

Natural disasters may also influence the number and the amount of non-performing bank loans. Brahmana et al. (2016) examine the impact of the 2004 Indian Ocean earthquake and tsunami on Indonesian non-performing bank loans. In Nias, an agricultural society located in Indonesia that depends on the natural environment, people rely on bank loans to maintain their local businesses and use up their loans to purchase crops, live stocks, machineries and lands. When the tsunami hit Nias it affected the citizens' loan repayment capability, increasing the local non-performing bank loans.

Another crucial study by Klomp (2014) analyzes data from around the globe to investigate the effects of natural disasters on banks' distance-to-default. Large-scale natural disasters may influence a bank's ability to stay solvent, leading to bank failure, which means that natural disasters may decrease the distance-to-default of banks.

In summary, the prior literature shows that natural disasters have an adverse effect on financial institutions, financial stability, and the economy. Additionally, the negative effects on bank stability appear to fade if there are no additional disasters in the post-disaster period (Noth & Schüwer, 2017). To the best of our knowledge, little previous research studies the impact of natural disasters on the performance of U.S. banks. This study attempts to close this gap in the literature.

Data

We retrieve data from Bankscope (U.S. banks) and EM-DAT (natural disasters) in order to investigate the effect of natural disasters on the performance of U.S. banks. Our data covers the years 2000 to 2014. We don't include data from 2015 to present, because Bankscope's data coverage ends in 2014, after which it migrated to a new database, Orbis Bank Focus.

Our disaster sample consists of 187 natural disasters. We collect data on natural disasters that occurred in the U.S. between 1999 and 2014 from EM-DAT, a disaster database administered by CRED. We excluded disasters with total damages below US$100 million, man-made disasters, and disasters without an exact date of occurrence from our sample. Table 1, Panel A, presents an overview of how we constructed our disaster sample.

*** Insert Table 1 About Here ***

We assume that (1) a bank is affected by a given natural disaster only when the disaster occurred in the state where the bank does most of its business; and (2) a bank continuously does most of its business in a state when it had most of its deposits in that state in both 2000 and 2014.

Our bank sample is composed of 2,891 banks. Similar to our natural disaster dataset, we form our bank dataset in multiple steps. Specifically, we first collect data on banks from Bankscope, then delete banks that lack complete data, are duplicate, and banks for which data is not available on the FDIC website. We further exclude banks that had most of their deposits in different states in 2000 and 2014, respectively. Table 1, Panel B, presents a summary of how we constructed our bank sample. Data on real GDP growth is retrieved from the Bureau of Economic Analysis (BEA), an agency of the U.S. Department of Commerce.

We expect that the impact of natural disasters on banking operations will be particularly significant for smaller and locally concentrated banks and unlikely to be significant for large organizations. Large institutions benefit from holding well diversified asset portfolios, therefore their exposure to natural disasters is diminished. We can use Hurricane Katrina in 2005 as an example: although it caused significant damages of $125 billion, it only affected about 5% of the 2,777 counties where the Bank of America, one of the largest U.S. banks actively supplied mortgage credit in 2005 (Cortés and Strahan, 2017). In fact, most of the natural disasters in our sample are, on average, much smaller and more localized than Hurricane Katrina, further reducing their potential impact on large banks. Hence, we control for the effect of bank size on the relationship between natural disasters and the performance of U.S. banks by differentiating between local, regional, and national banks. Specifically, we define the three bank types as follows: A local bank is a bank that operates predominantly in one state, which means more than 50% of its deposits are in that state. A regional bank has an asset/deposit concentration within few states, that is, less than 50% of their assets are within a single state, but more than 70% of their deposits are in the top five states in which they have deposits. We regard the remainder as national banks. Based on this classification, our sample consists of 2,872 local banks, 14 regional banks and 5 national banks.

Methodology

In this section, we use the following base model to analyze the relationship between natural disasters and the performance of U.S. banks:

$$Performance_{ist} = \beta_0 + \beta_1 DamRatio_{st} + \beta_2 DamRatio_{st-1} + \beta_3 DamRatio_{st-2} + \sum_{j=4}^{n+3} \beta_j Control\, Variables_{ist}^{j} + \varepsilon_{ist} \quad (1)$$

Where $Performance_{ist}$ represents the performance of bank i in state *s* at time *t*. $DamRatio_{st}$ is our natural disaster variable that captures the damage of a given disaster (see details below) and $DamRatio_{st-1}$is the DamRatio in state *s* at time *t-1*, while the vector $\sum_{j=4}^{n+3} Control\, Variables_{ist}^{j}$ is a vector of control variables containing *n* elements. The final term ε_{ist} is the error term.

Following Bitar et al. (2019), we measure the damages of natural disasters using the following variable:

$$DamRatio_{st} = \frac{Dam_{st}}{GDP_{st-1}} \quad (2)$$

where Dam_{st} is the sum of the damages from natural disasters in state *s* during year *t*. GDP_{st-1} is state *s*'s gross domestic product (GDP) in year *t-1*. For disasters that affected more than one state, we assign the damages to the affected states evenly. For example, if a disaster caused damages of $1 billion, but affected 5 states, we assign a loss of $200 million to each of the five states.

Our measurements on bank performance can be divided in to three categories: loan write-offs, profitability, and capitalization. We expect that the impacts from natural disasters on banks do not materialize in the form of a one-off shock, bit that they affect banks gradually. From a time-sequence perspective, it is likely that natural disasters affect bank loan write-offs and profitability first, and that they negatively influence other balance sheet items with some delay. We thus postulate our hypotheses as follows:

H_1: Natural disasters positively affect a bank's loan write-offs.

A bank's loan write-offs increase as a direct consequence of natural disasters that occurred in the same year (*t*), the previous year (*t-1*), or the year before the previous year (*t-2*). That is, when considering loan write-offs as an outcome variable in Equation 1, we expect β_1>0, β_2>0, and β_3>0.

H_2: Natural disasters negatively affect bank profitability.

Specifically, we argue that a bank's net income to assets ratio (NIARatio), net income to equity ratio (NIERatio), return on average assets (ROAA), and return on average equity (ROAE) decrease as a direct consequence of natural disasters that occurred in the same year (*t*), the previous year (*t-1*), or the year before the previous year (*t-2*). That is, when employing each of these measures as possible outcome variables in Equation 1, we expect β_1<0, β_2<0, and β_3<0.

H_3: Natural disasters negatively affect a bank's capitalization.

In detail, we expect a bank's equity ratio (EquRatio) and tier 1 capital ratio (T1Ratio) to decrease as a direct consequence of natural disasters that occurred in the same year (*t*), the previous year (*t-1*), or the year before the previous year (*t-2*). That is, when employing both of these measures as possible outcome variables in Equation 1, we expect β_1<0, β_2<0, and β_3<0.

We measure bank loan write-offs using impaired loans. It is worth mentioning that we use impaired loans instead of non-performing loans (NPLs), because Bankscope doesn't report NPLs. However, impaired loans may be different from the official classification of NPLs. For instance, Klein (2013) argues that impaired loans is an accounting concept, while NPL is a regulatory concept.

Following the prior bank performance related literature (Pasiouras & Kosmidou, 2007; Kosmidou, 2008; Shen et al., 2009; Parashar, 2010; Soana, 2011; Pathan & Faff, 2013; Petria et al., 2015), our proxies for bank profitability include the net income to assets ratio (NIARatio), the net income to equity ratio (NIERatio), the return on average assets (ROAA), and the return on average equity (ROAE). ROAA expresses the ability of a bank to generate returns from its assets. ROAE reflects the ability to generate returns on its equity. The use of average assets and equity captures differences that occur in assets and equity during the fiscal year, measuring the bank performance more accurately than values at the end of the year. Finally, we measure bank capitalization using the equity ratio (EquRatio) – a widely used accounting ratio – and the tier 1 capital ratio (T1Ratio) – a regulatory measure.

We employ several control variables to mitigate the potential effects of other bank-specific and state-specific characteristics. Following the prior literature on bank capitalization (Barrios and Blanco, 2003; Altunbas and Carbo, 2007; Brewer et al., 2008; Peni and Vähämaa, 2012; Schaeck and Cihák, 2012; Kunt et al., 2013; Schepens, 2016), the bank-specific control variables used in our main regressions include: (1) bank size (SIZE), defined as the logarithm of a bank's total assets; (2) loan ratio (NLRatio), calculated as a bank's net loans over total assets; and (3) deposit level (DEPL), defined as the ratio of total customer deposits over total assets. We also include two state-specific control variable that characterize a state's economic well-being, because disasters may affect banks in states with weaker economies more than those in states with healthier economies. The state-level control variables used are: (1) the per capita real GDP of a given state (GDPPC) and (2) the economic growth (GDPG) in the state, measured as the annual growth in the state's real GDP.

In order to further investigate the effect of bank size on the relationship between natural disasters and bank performance, we add a series of interaction terms to our base model as follows:

$$
\begin{aligned}
&Performance_{ist} \\
&\quad = \beta_0 + \beta_1 DamRatio_{st} + \beta_2 DamRatio_{st-1} + \beta_3 DamRatio_{st-2} \\
&\quad + \beta_4 Local \times DamRatio_{st} + \beta_5 National \times DamRatio_{st} \\
&\quad + \beta_6 Local \times DamRatio_{st-1} + \beta_7 National \times DamRatio_{st-1} \\
&\quad + \beta_8 Local \times DamRatio_{st-2} + \beta_9 National \times DamRatio_{st-2}
\end{aligned}
$$

$$+\sum_{j=10}^{n+9}\beta_j Control\,Variables_{ist}^{j}+\varepsilon_{ist} \quad (3)$$

Table 2 provides definitions for all variables used in our analysis and Table 3 reports summary statistics for the variables. Impaired loans range from US$0 to $38.401 billion. The 95% percentile for this variable falls at the $17.403 million mark, suggesting the presence of a few large outliers. Other dependent and independent variables exhibit similar patterns. For instance, the maximum and 95% percentile of the damage ratio (DamRatio) is 850.404 and 15.166, while the median is 0.56 – likely driven by the fact that disasters are concentrated in a limited number of U.S. states.

*** Insert Table 2 About Here ***

*** Insert Table 3 About Here ***

Table 4 presents the correlation matrix between the different variables used in our study. According to the table, the correlations between all independent variable pairs are consistently below 0.3 in absolute terms. This suggests that multi-collinearity problems are unlikely to affect our analysis.

*** Insert Table 4 About Here ***

Empirical results

We report results for the impact of natural disasters on the loan write-offs, profitability and capitalization of all the 2,891 U.S. banks. Because the impact of natural disasters on banks of different sizes is not uniform, we also present results for local, regional, and national banks separately. Additionally, we provide the results for models that employ the interaction terms as outlined in Equation 3.

The relationship between natural disasters and bank loan write-offs

In Table 5, we present the empirical results examining the relationship between natural disasters and bank loan write-offs using a robust regression. Column (1) reports the impact of natural disasters on the non-performing loans of all the 2,891 U.S. banks. Columns (2) to (4) display the results for local, regional, and national banks in the United States.

*** Insert Table 5 About Here ***

The coefficients of DamRatio, L.DamRatio and L2.DamRatio (that is, the same-year, one-year lagged, and two-year lagged damage ratios) are negative in columns (1) to (3) and positive but insignificant in column (4), which is contrary to our first hypothesis under which we expected natural disasters to increase (rather than decrease) a bank's non-performing loans. The finding is difficult to explain and may be partly due to the fact that we impaired loans (instead of non-performing loans) in our regression. As Bankscope notes, "there is no conformity to defining impaired loans, both across country and intra-country" because all accounting standards "are vague in their definition of when a loan is impaired" and because "management discretion can change from one year to the next within a particular bank" (as cited in Bholat et al., 2016). Data for NPLs from Bankscope are not uniform across banks because NPLs are generally disclosed in the notes to the financial statements and their definition is inconsistent (Glen & Mondragón-Vélez, 2011). Another possible explanation may be that natural disasters cause previously impaired loans to be fully written off, which would reduce a bank's impaired loan balance, while increasing its actual loan write-offs.

The relationship between natural disasters and bank profitability

In Table 6 and Table 7, we report the test results of the impact of natural disasters on the profitability of banks in the United States. As in Table 5, columns (1) and (2) display the effects of natural disasters on all 2,891 U.S. banks in our sample, while columns (3) to (8) provide the results for our three subsamples (local, regional, and national banks).

*** Insert Table 6 About Here ***

In Table 6, the coefficients of DamRatio are negative in all columns, suggesting that natural disasters have a negative effect on the net-income-to-assets and the net-income-to-equity ratio of banks. The results in column (1) and (2) are significant and large, indicating that natural disasters decrease bank profitability pronouncedly. With respect to our subsamples, the coefficients of DamRatio are significant in columns (3) and (4) for the local bank subsample and in column (6) for the regional bank sample, but insignificant in the remainder demonstrating that natural disasters have the most impact on local banks, less impact on regional banks and are unlikely to affect national banks. This is consistent with our expectation that national banks are shielded against the impact of natural disasters as a result of their diversification across geographic regions and business lines (in contrast to local banks that frequently show little such diversification). Most of the coefficients of L.DamRatio and L2.DamRatio are positive and insignificant. One possible explanation is that the effects on bank profitability from natural disasters occur quickly and within a limited time frame. We obtain similar but less significant results in Table 7 where we examine two alternative proxies for bank profitability: a bank's return on average assets (ROAA) and its return on average equity (ROAE).

*** Insert Table 7 About Here ***

The relationship between natural disasters and bank capitalization

Table 8 reports the results examining the relationship between natural disasters and bank capitalization. The coefficients show significant effects on the equity ratio and the tier-1 capital ratio, but they are mostly limited to regional banks and insignificant for banks that operate locally or nationally. As expected, the results are negative (although insignificant) for our full sample as well as our local and national bank subsamples, providing weak support for the notion that natural disasters impair a bank's solvency. The fact that the coefficients for regional banks are significantly positive is surprising, but may be driven by these banks voluntarily increasing their capital reserves in response to a given disaster which would cause the observed adverse effect in their solvency ratios.

*** Insert Table 8 About Here ***

Results for the models with interaction terms

Table 9 presents the results for equation (3), i.e., our model that includes interaction terms between the lagged (and non-lagged) damage ratios and the different types of banks (with regional banks serving as the excluded reference category). The coefficients for the interaction terms support our earlier findings: relative to regional banks which exhibited significant negative effects on their profitability (e.g., the net-income-to equity ratio and return on average equity) in our earlier regressions, local banks exhibit a significantly smaller decline (culminating in significant positive coefficients on the respective interaction terms for local banks). Similarly, the interaction terms for local banks in the solvency regressions (model 6: equity ratio, and model 7: tier-1 capital ratio) are negative for local banks, suggesting that, relative to regional banks, local banks experience a decline in solvency following natural disasters. The effect persists over the full two-year lagged period, and is also pronounced for national banks (relative to regional banks as the benchmark category).

*** Insert Table 9 About Here ***

Conclusions

In this paper, we examine whether natural disasters affect the performance and solvency of U.S. banks using panel data of 187 highly destructive natural disasters that occurred in the United States from 1999 to 2014. Our major finding is that natural disasters negatively affect bank profitability, raising potential concerns for regulators who strive to ensure that environmental risks do not threaten financial stability. The impact appears to be most pronounced for local banks, less severe for regional banks, and unlikely to affect national banks, which is consistent with the notion that the latter two are more diversified and thus better able to withstand the impacts of natural disasters. We fail to find a positive relationship between natural disasters and non-performing bank loans (NPLs) which would partially explain the decrease in profitability. This may be partly due to the limited data availability of NPLs in Bankscope and may be caused by these loans being fully written off in response to a natural disaster. Finally, we observe significant effects on the equity ratio and the tier-1 capital ratio. Interestingly, they are positive for regional banks which appear to voluntarily increase their capital reserves in response to natural disasters, but significantly negative for banks that operate locally or nationally.

The results of this study complement existing research into the relationship between natural disasters and bank performance. We believe that our findings will contribute to the understanding of the impacts of natural disasters on U.S. banks as little empirical work has examined the impacts of natural disasters on the performance and/or solvency of these banks.

We acknowledge that our study has some limitations that should be explored and addressed in future research. Firstly, more recent data would result in a more advanced assessment of the impacts of natural disasters. Secondly, some reasonable assumptions were made due to data limitations in the databases we used for this study. For example, we assigned damages evenly to each state as state-level data is not provided in EM-DAT. A more thorough categorization of disaster-related data in future research would likely provide more accurate results. Lastly, limitations occur in the scope of our discussion. The bank performance measurements and disaster indicators could be further explored to investigate the detailed relationships between natural disasters, bank performance, and bank solvency as well as the channels through which natural disasters affect the latter. Additionally, the effects of using derivatives such as weather derivatives and catastrophe swaps are not involved in our study. The risk arising from natural disasters can be hedged to some extent by using these derivatives, which is worth further research.

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Table 1: Sample Formation Overview

Panel A: Construction of our Natural Disaster Sample

In this panel, we provide an overview of the methodology we employed when constructing our disaster sample. We started by collecting information on all natural disasters that occurred in the United States of America between 2000 and 2014 from the EM-DAT database, which provided us with 458 disasters. In next step, we deleted 266 disasters whose total damages were below US$100 million. Finally, we deleted 3 man-made disasters and 2 disasters for which the exact date of occurrence was unknown. Our final disaster sample is comprised of 187 natural disasters.

	Disasters
Natural Disasters from EM-DAT	458
Less	
Disasters with Total Damages Below US$100 Million	266
Man-made Disasters	3
Disaster without an Exact Date of Occurrence	2
TOTAL	187

Panel B: Construction of our Bank Sample

In this panel, we provide an overview of the methodology we employed when constructing our bank sample. We started by identifying and collecting information on all U.S.-head-quartered banks from Bankscope, which provided us with 5,816 banks. We then deleted 805 banks without complete data. Third, we deleted 155 duplicate banks. Fourth, we deleted 1,900 banks for which data was not available in the FDIC database. Finally, we deleted 65 banks that had most deposits in different states in 2000 and 2014, respectively. That is, banks for which the geographical focus changed during our sample period. Our final bank sample was composed of 2,891 banks.

	Banks
Banks from Bankscope	5,816
Less	
Banks without Complete Data	805
Duplicate Banks	155
Banks with No Data on the FDIC Website	1,900
Banks with Most Deposits in Different States in 2000 and 2014	65
TOTAL	2,891

Table 2: Definitions and Descriptions of Variables

Symbol	Name	Description	Sources
NPL	Non-performing loans	Impaired loans	Bankscope
NIERatio	Net income to equity ratio	Net income/equity	Bankscope
NIARatio	Net income to assets ratio	Net income/total assets	Bankscope
ROAA	Return on avg assets	Return/average total assets	Bankscope
ROAE	Return on avg equity	Return/average equity	Bankscope
EquRatio	Equity ratio	Equity/total assets	Bankscope
T1Ratio	Tier 1 capital ratio	Tier 1 capital/risk weighted assets	Bankscope
DamRatio	Damage ratio	Total damage from natural disasters in a given state and year divided by the previous year's GDP of the state	EM-DAT Disaster Database
SIZE	ln (total assets)	The natural logarithm of a bank's total assets	Bankscope
NLRatio	Net loan ratio	Net loans/total assets	Bankscope
DEPL	Total customer deposit ratio	Total customer deposits/total assets	Bankscope
GDPPC	Per capita real GDP	Per capita real GDP of a given state	BEA
GDPG	Real GDP growth rate	Annual growth in the real GDP of a given state	BEA

Table 3: Summary Statistics

In this table, we report the summary statistics for all dependent and independent variables used in this study.

Variable	No. of Observations	Mean	Std. Dev.	Median	5% Percentile	95% Percentile	Min	Max
NPL	43,327	18,298.560	507,247	429.000	0.000	17,403	0.000	38,401,178
NIERatio	43,327	0.090	0.199	0.089	-0.006	0.204	-3.318	33.085
NIARatio	4,3327	0.010	0.025	0.010	-0.001	0.021	-0.329	4.439
ROAA	43,327	1.013	1.488	0.985	-0.056	2.127	-27.253	71.781
ROAE	43,327	9.322	9.144	9.167	-0.581	21.254	-153.278	213.215
EquRatio	43,327	11.176	5.153	10.171	7.191	17.636	-0.622	98.148
T1Ratio	43,327	18.172	17.443	15.000	9.600	34.200	-0.080	569.230
DamRatio	43,327	3.972	27.755	0.560	0.000	15.166	0.000	850.404
SIZE	43,327	11.811	1.300	11.685	9.992	13.957	7.676	21.177
NLRatio	43,327	59.609	15.919	61.521	30.447	82.189	0.000	98.770
DEPL	43,327	0.833	0.082	0.851	0.703	0.912	0.000	1.006
GDPPC	43,327	48,726.420	7101	48,382.00	37,374	59,915	30,564	79,894
GDPG	43,327	1.819	2.427	1.900	-2.400	5.400	-8.800	22.400

Table 4: Correlation Matrix

In this table, we report the Pearson correlations among all dependent and independent variables used in our analysis.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) **NPL**													
(2) **NIERatio**	-0.005												
(3) **NIARatio**	-0.004	0.421***											
(4) **ROAA**	-0.006	0.343***	0.716***										
(5) **ROAE**	-0.009*	0.425***	0.454***	0.661***									
(6) **EquRatio**	0.000	-0.017***	0.225***	0.377***	-0.037***								
(7) **T1Ratio**	-0.014***	-0.009*	0.219***	0.350***	-0.043***	0.820***							
(8) **DamRatio**	-0.003	0.004	0.003	0.007	0.010**	0.006	0.006						
(9) **SIZE**	0.194***	0.023***	-0.015***	-0.006	0.077***	-0.171***	-0.207***	-0.006					
(10) **NLRatio**	0.002	0.022***	-0.044***	-0.056***	0.094***	-0.285***	-0.421***	-0.028***	0.216***				
(11) **DEPL**	-0.035***	-0.016***	-0.169***	-0.283***	-0.040***	-0.560***	-0.442***	-0.005	-0.200***	0.040***			
(12) **GDPPC**	0.018***	-0.029***	-0.034***	-0.056***	-0.069***	0.004	0.020***	-0.054***	0.095***	-0.020***	0.019***		
(13) **GDPG**	-0.009*	0.068***	0.041***	0.071***	0.141***	-0.010**	0.005	0.024***	-0.059***	-0.059***	0.035***	0.126***	

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5: Robust Regressions to Determine the Effect of Natural Disasters on NPLs

This table presents the results for the impacts of natural disasters on non-performing loans (NPLs) using impaired loans as a proxy. In column (1), we study the effect of natural disasters on the NPLs of all 2,891 banks. In columns (2) to (4), we investigate the effect of natural disasters on the NPLs of banks in each of our subsamples.

	(1)	(2)	(3)	(4)
	All Banks	Local Banks	Regional Banks	National Banks
DamRatio	-29.725*	-1.243	-1.2e+03***	1.1e+05
	(0.063)	(0.508)	(0.000)	(0.183)
L.DamRatio	-55.652***	-3.458	-1.8e+03***	3.7e+04
	(0.004)	(0.230)	(0.000)	(0.537)
L2.DamRatio	-57.684***	-7.070***	-1.8e+03***	1.1e+05
	(0.005)	(0.010)	(0.000)	(0.203)
L.SIZE	8.5e+04***	1.1e+04***	3.7e+05***	2.9e+06***
	(0.000)	(0.000)	(0.000)	(0.000)
L.NLRatio	-1.4e+03***	-20.224**	2,071.149	-2.8e+05*
	(0.000)	(0.011)	(0.709)	(0.059)
L.DEPL	2.3e+04	-1.4e+04***	3.9e+06***	3.2e+07**
	(0.336)	(0.000)	(0.002)	(0.019)
L.GDPPC	-0.117	-0.001	-38.999***	-292.001
	(0.505)	(0.969)	(0.000)	(0.371)
L.GDPG	-627.351	-496.475***	-1.4e+05***	-1.2e+06***
	(0.570)	(0.000)	(0.001)	(0.004)
N	40,022	39,756	196	70
Adj.R^2	0.041	0.119	0.471	0.482

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6: Robust Regressions to Determine the Effect of Natural Disasters on a Bank's Net Income to Assets and Net Income to Equity

This table presents the results for the impact of natural disasters on banks' net income to assets ratio and net income to equity ratio. In columns (1) and (2), we study the effect of natural disasters on all 2,891 banks in our sample. In columns (3) to (8), we investigate the effect of natural disasters on our bank subsamples.

	(1) All Banks NIARatio	(2) All Banks NIERatio	(3) Local Banks NIARatio	(4) Local Banks NIERatio	(5) Regional Banks NIARatio	(6) Regional Banks NIERatio	(7) National Banks NIARatio	(8) National Banks NIERatio
DamRatio	-2.977**	-20.975**	-2.893**	-18.539*	-5.925	-90.030***	-13.709	-94.930
	(0.011)	(0.038)	(0.016)	(0.069)	(0.145)	(0.008)	(0.897)	(0.931)
L.DamRatio	0.120	9.130	0.188	11.623	0.210	-48.718**	-3.755	-78.830
	(0.924)	(0.336)	(0.884)	(0.219)	(0.948)	(0.033)	(0.971)	(0.941)
L2.DamRatio	0.232	18.261*	0.283	20.650**	1.630	-37.185*	32.152	368.281
	(0.861)	(0.072)	(0.835)	(0.043)	(0.608)	(0.091)	(0.661)	(0.612)
L.SIZE	-529.117***	4,491.687***	-507.647***	4,857.304***	-287.705	-3.7e+03	337.256	5,571.325
	(0.000)	(0.000)	(0.000)	(0.000)	(0.244)	(0.106)	(0.407)	(0.207)
L.NLRatio	-35.593***	174.483	-34.239***	182.732*	-508.571***	-4.1e+03***	85.633	1,090.717
	(0.000)	(0.110)	(0.000)	(0.095)	(0.000)	(0.000)	(0.258)	(0.160)
L.DEPL	-4.6e+04***	1.5e+04	-4.6e+04***	1.4e+04	2865.784	1.0e+05	-1.4e+04*	-1.7e+05**
	(0.000)	(0.324)	(0.000)	(0.368)	(0.856)	(0.368)	(0.073)	(0.026)
L.GDPPC	-0.136***	-1.315***	-0.136***	-1.310***	-0.436***	-4.182***	0.066	0.270
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.002)	(0.768)	(0.906)
L.GDPG	505.104***	6,496.518***	501.676***	6,481.177***	1,526.937***	1.4e+04***	831.724***	8,449.980***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
N	40,022	40,022	39,756	39,756	196	196	70	70
Adj.R^2	0.085	0.008	0.086	0.008	0.285	0.312	0.209	0.262

***** p<0.01, ** p<0.05, * p<0.1**

Table 7: Robust Regressions to Determine the Effect of Natural Disasters on ROAA and ROAE

This table presents the results for the impacts of natural disasters on a bank's return on average assets (ROAA) and return on average equity (ROAE). In columns (1) and (2), we study the effect of natural disasters on all 2,891 banks. In column (3) to (8), we investigate the effect of natural disasters on our bank subsamples.

	(1) All Banks ROAA	(2) All Banks ROAE	(3) Local Banks ROAA	(4) Local Banks ROAE	(5) Regional Banks ROAA	(6) Regional Banks ROAE	(7) National Banks ROAA	(8) National Banks ROAE
DamRatio	-283.672**	-1.418	-280.198**	-1.225	-365.985	-5.707	-1.5e+03	-14.134
	(0.020)	(0.106)	(0.025)	(0.168)	(0.384)	(0.101)	(0.892)	(0.900)
L.DamRatio	-5.198	1.321	-4.119	1.556*	268.963	-3.303	-778.643	-8.093
	(0.967)	(0.129)	(0.974)	(0.072)	(0.413)	(0.165)	(0.942)	(0.940)
L2.DamRatio	17.596	1.774*	24.394	2.040**	106.743	-4.371**	2,537.378	32.115
	(0.899)	(0.081)	(0.864)	(0.045)	(0.738)	(0.049)	(0.737)	(0.664)
L.SIZE	-5.5e+04***	501.730***	-5.3e+04***	542.087***	-3.1e+04	-380.064*	4.0e+04	590.996
	(0.000)	(0.000)	(0.000)	(0.000)	(0.211)	(0.099)	(0.352)	(0.188)
L.NLRatio	-3.5e+03***	35.852***	-3.4e+03***	36.703***	-5.0e+04***	-418.910***	1.1e+04	129.186
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.190)	(0.116)
L.DEPL	-4.8e+06***	530.310	-4.8e+06***	393.866	2.4e+05	8,954.318	-1.4e+06*	-1.7e+04**
	(0.000)	(0.610)	(0.000)	(0.706)	(0.879)	(0.471)	(0.083)	(0.029)
L.GDPPC	-13.922***	-0.139***	-13.916***	-0.138***	-41.561***	-0.421***	5.794	0.033
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.001)	(0.806)	(0.888)
L.GDPG	5.2e+04***	621.255***	5.1e+04***	619.314***	1.6e+05***	1,429.562***	8.9e+04***	910.561***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
N	40,022	40,022	39,756	39,756	196	196	70	70
Adj.R^2	0.087	0.042	0.088	0.042	0.278	0.310	0.226	0.291

*** p<0.01, ** p<0.05, * p<0.1

Table 8: Robust Regressions to Determine the Effect of Natural Disasters on Equity Ratio and Tier 1 Capital Ratio

This table presents the results for the impact of natural disasters on banks' equity ratio and Tier 1 capital ratio. In columns (1) and (2), we study the effect of natural disasters on all 2,891 banks. In columns (3) to (8), we investigate the effect of natural disasters on our bank subsamples.

	(1) All Banks EquRatio	(2) All Banks T1Ratio	(3) Local Banks EquRatio	(4) Local Banks T1Ratio	(5) Regional Banks EquRatio	(6) Regional Banks T1Ratio	(7) National Banks EquRatio	(8) National Banks T1Ratio
DamRatio	-0.277	-2.056	-0.463	-2.418	5.133***	3.631*	-4.701	-8.426
	(0.687)	(0.306)	(0.490)	(0.231)	(0.000)	(0.079)	(0.647)	(0.651)
L.DamRatio	0.001	-1.575	-0.214	-1.881	6.984***	2.801	-7.390	-5.785
	(0.999)	(0.434)	(0.753)	(0.354)	(0.000)	(0.171)	(0.559)	(0.772)
L2.DamRatio	0.125	-1.682	-0.080	-1.913	6.699***	0.918	0.992	18.435
	(0.841)	(0.417)	(0.893)	(0.362)	(0.000)	(0.647)	(0.934)	(0.352)
L.SIZE	-964.319***	-3.1e+03***	-1.0e+03***	-3.2e+03***	123.464	-477.417***	-159.584	-342.035**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.167)	(0.000)	(0.194)	(0.010)
L.NLRatio	-68.781***	-383.259***	-68.122***	-382.559***	-63.155*	-255.776***	-41.943**	-107.268***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.062)	(0.000)	(0.029)	(0.000)
L.DEPL	-3.6e+04***	-9.9e+04***	-3.7e+04***	-9.9e+04***	-7.3e+03	-8.9e+03	2,532.245	1.5e+04***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.178)	(0.331)	(0.199)	(0.000)
L.GDPPC	0.027***	0.115***	0.027***	0.115***	0.086**	0.034	0.023	-0.109*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.022)	(0.586)	(0.691)	(0.078)
L.GDPG	-49.312***	-212.961***	-50.619***	-216.182***	-19.041	14.935	-29.733	-64.239
	(0.000)	(0.000)	(0.000)	(0.000)	(0.803)	(0.897)	(0.588)	(0.328)
N	40,022	40,022	39,756	39,756	196	196	70	70
Adj.R^2	0.419	0.390	0.422	0.391	0.153	0.330	0.089	0.717

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 9: Summary of Regression Results for Equation (3)

This table presents the results for Equation (3) in which we add interaction terms to our main regression model (Equation (1)). Columns (1) to (7) provide the regression results for each of our dependent variable for our full sample of 2,891 banks.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	NPL	NIARatio	NIERatio	ROAA	ROAE	EquRatio	T1Ratio
DamRatio	7.735	-3.588**	-95.920***	-119.490	-6.529***	8.497***	13.018***
	(0.974)	(0.050)	(0.000)	(0.529)	(0.000)	(0.000)	(0.000)
L.DamRatio	1.265	-0.413	-79.901***	206.862	-6.945***	10.924***	12.318***
	(0.996)	(0.872)	(0.000)	(0.414)	(0.000)	(0.000)	(0.000)
L2.DamRatio	384.038	-0.175	-74.999***	-85.685	-8.786***	10.778***	9.506***
	(0.148)	(0.960)	(0.000)	(0.803)	(0.000)	(0.000)	(0.000)
L.SIZE	8.5e+04***	-527.455***	4,529.165***	-5.5e+04***	505.441***	-967.436***	-3.1e+03***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.NLRatio	-1.5e+03***	-35.521***	174.879	-3.5e+03***	35.898***	-68.766***	-383.232***
	(0.000)	(0.000)	(0.109)	(0.000)	(0.000)	(0.000)	(0.000)
L.DEPL	2.6e+04	-4.6e+04***	1.5e+04	-4.8e+06***	522.863	-3.6e+04***	-9.9e+04***
	(0.285)	(0.000)	(0.326)	(0.000)	(0.615)	(0.000)	(0.000)
L.GDPPC	-0.056	-0.137***	-1.317***	-13.961***	-0.139***	0.027***	0.115***
	(0.761)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.GDPG	-647.821	505.227***	6,498.480***	5.2e+04***	621.459***	-49.434***	-213.118***
	(0.557)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Local_DamRatio	-41.804	0.651	76.834***	-165.312	5.250***	-8.969***	-15.415***
	(0.860)	(0.765)	(0.000)	(0.468)	(0.000)	(0.000)	(0.000)
National_DamRatio	1.3e+04	-81.246	-593.425	-7.9e+03	-69.347	-10.284	1.099
	(0.288)	(0.450)	(0.545)	(0.483)	(0.493)	(0.562)	(0.983)
Local_L.DamRatio	-61.382	0.573	91.142***	-213.948	8.465***	-11.154***	-14.185***
	(0.822)	(0.843)	(0.000)	(0.454)	(0.000)	(0.000)	(0.000)
National_L.DamRatio	326.646	-37.452	-185.139	-4.2e+03	-21.721	-25.417	-29.791
	(0.981)	(0.752)	(0.877)	(0.727)	(0.858)	(0.218)	(0.609)
Local_L2.DamRatio	-456.718*	0.442	95.354***	108.380	10.801***	-10.876***	-11.403***
	(0.079)	(0.907)	(0.000)	(0.771)	(0.000)	(0.000)	(0.000)
National_L2.DamRatio	1.7e+04	-76.786	92.891	-8.0e+03	0.676	-54.688***	-115.608**
	(0.254)	(0.173)	(0.883)	(0.165)	(0.992)	(0.010)	(0.039)
N	40,022	40,022	40,022	40,022	40,022	40,022	40,022
Adj.R^2	0.042	0.008	0.085	0.087	0.042	0.419	0.390

*** p<0.01, ** p<0.05, * p<0.1