After the Storm: Natural Disasters and Bank Solvency

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EXECUTIVE SUMMARY:

This study examines how natural disasters affect the solvency of banks. It explores (1) whether and how natural disasters affect bank solvency, (2) how accounting and regulatory measures of bank solvency reflect a bank's true affectedness, and (3) whether the effects vary across different types of banks. Analyzing a comprehensive dataset on natural catastrophes and detailed financial statements for 9,928 banks that operate in 149 countries, the main finding is that damages from disasters matter: they negatively affect capital ratios, and the severity of their impact depends on a bank's location, capitalization, and business model. Particularly, the results show that accounting measures of solvency are more sensitive to disasters than are regulatory measures. Evidence of a bank's sensitivity to natural disasters and the suitability of capital ratios to assess this sensitivity may both be helpful for financial institutions and regulatory authorities in designing appropriate risk mitigation strategies.

Keywords: Natural disasters, Banks, Solvency, Traditional capital, Regulatory capital

JEL Classification: G21, G28, G32

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1. Introduction

The recent rise in the frequency and severity of natural disasters such as floods, droughts, wildfires, and extreme winds (hurricanes, typhoons, tornadoes, etc.) is often attributed to climate change and climate change itself to our production and consumption behavior (Rummukainen, 2012; Mechler and Bouwer, 2015; WEF, 2018). Because natural disasters primarily affect the real economy, research on their economic effects has mainly focused on their impact on production and growth (Hallegatte, 2014; Arouri et al., 2015; Lesk et al., 2016). Only recently has research started to explore how such disasters affect financial institutions and the broader financial markets. The relevance of natural disasters for the risk and the risk management of individual institutions can be explained through their claims – e.g., via loans, bonds, and stocks – on the real economy. In addition, financial institutions, particularly banks and the banking network, may be exposed to operational risks if disasters hit the institutions' physical locations and computer systems. Finally, in case banks have to cut their lending following a disaster, it reduces their income opportunities and imposes capital constraints on their customers (Brei et al., 2019).

There is a growing concern among financial regulators and central banks that damages may affect the financial system as a whole (Batten et al., 2016). The *Network for Greening the Financial System* that comprises many of the world's most influential central banks and supervisory authorities has recently outlined the need to incorporate climate risks into financial policies and regulatory frameworks (NGFS, 2018). In addition, the European Union's *High-Level Expert Group on Sustainable Finance* has repeatedly argued that the financial system is a crucial component in any intended moves to shift the overall economy towards a more sustainable system, i.e., a system that balances the needs of our economy, society, and ecology (HLEG, 2018). Financial institutions, especially banks, are expected to provide the financial expertise, backing, and networking necessary for the transition towards sustainability (SFSG, 2018).

Whether and how a given financial institution is affected by a natural disaster is difficult to assess. Its claims against exposed counterparties (e.g., mortgage loans, business loans, etc.) may be affected with varying levels of intensity. In addition, even if a given loan has to be written off because, e.g., a firm is forced out of business or a residential property is damaged beyond repair and the homeowners have to default on their loans, the disaster may create new demand for loans

as restructuring and rebuilding activities commence (Cortés and Strahan, 2017; Barth et al., 2019).

Challenges may arise from both disasters themselves (physical risks) as well as from changes in the legal framework (transition risks). A further complexity arises from the interconnectivity of different actors in the financial markets that makes them reciprocally vulnerable to risks. For example, interbank lending in the money markets or the participation of banks in insurance companies can indirectly transfer risks among institutions (Battiston et al., 2017). In a similar fashion, the impact from disasters depends on the risk management strategies of both banks and their customers, i.e., the instruments applied to hedge the damages from disasters (Benson and Clay, 2004). The multiple factors affecting banks and the banking system may explain why evidence of the effects from natural disasters is mixed, and a more granular perspective is needed.

Against the backdrop of the rising frequency and severity of natural disasters in recent years and the complex effects external shocks have on bank stability, this study aims to explore whether and how damages from natural disasters translate into potential solvency problems for banks, whether the effect varies across different types of banks, and how different measures of solvency reflect this effect. Particularly, we address the following research questions:

- to what extent do natural disasters affect bank solvency,
- do natural disasters affect accounting based measures of solvency as much as they affect regulation based measures, and
- are different types of banks affected differently by natural disasters?

Our study focuses on bank solvency because a bank's ability to withstand risks and remain solvent even under adverse conditions is existential for both its own stability as well as the soundness of the financial system as a whole (Flannery and Giacomini, 2015). Recent research provides additional evidence that the capital ratio of banks has an impact on bank lending in the context of natural disasters. Rehbein and Ongena (2021) find that banks with low capital levels tend to lend less in the aftermath of a disaster. Moreover, banks that have lower solvency ratios and are affected by floods also reduce the lending to companies not directly affected by a disaster.

Banking regulations typically focus on ensuring that banks maintain sufficient capital. The ability of the banking system to manage risks is driven both by individual institutions' ability to absorb damages and by the diversification of risks within the system (Batten et al., 2016). Although

banking regulations have undergone considerable refinements in recent years, particularly after the 2007/2008 subprime mortgage crisis, they are only now starting to consider natural disasters as a potential risk factor (EBA, 2019). Our study aims to shed light on the possibility that natural disasters may pose the next big threat for our economy and for our financial system. That way, banks and bank regulators can better prepare themselves for the predicted increase in the severity and frequency of such events.

The remainder of our paper is structured as follows: Section 2 provides an overview of the research related to bank solvency and natural disasters, and further outlines the contribution of this study in the context of the existing literature. Section 3 develops the underlying hypotheses about banks' sensitivity to natural disasters in the context of existing theories and discusses the measurement of this sensitivity. Section 4 explains the database and section 5 the methodological approach of the study. Section 6 discusses our results and explores both the affectedness of specific types of banks from natural disasters as well as the suitability of the accounting capital ratio and the regulatory capital ratio to assess this effect. Robustness tests in Section 7 further support the results, and section 8 concludes.

2. Evidence from the literature

Thomson (1998) is one of the first authors to include environmental factors into the risk analysis of banks. He examines the composition of assets of six major banks headquartered in the United Kingdom and assigns risk weights depending on the inclusion of environmentally critical industries. His approach is conceptual with simplified assumptions about the risk characteristics of industries and bank portfolios. In line with this, Klomp (2014) investigates the association between natural disasters and bank stability. His approach focuses on a country's banking system as a whole and on the system's aggregated z-score. Using data for 169 countries, he concludes that natural disasters increase the likelihood of bank default. Battiston et al. (2017) model the climate risk of the financial system as a whole. Their model is based on the assumption that climate risk affects the equity holdings of financial institutions in carbon risk sensitive industries. They find that first-round effects manifest as losses in critical equity holdings, while second-round effects are driven by the connectivity of financial institutions that have been hurt in the first round.

Cortés and Strahan (2017) investigate the lending behavior of banks in the aftermath of a natural disaster. They ask how banks that operate in multiple local markets adjust their lending when

credit demand in a particular local market increases after a natural disaster. Based on data for the mortgage lending of small banks in different counties of the United States (US), they find that these banks tend to cut loans in non-core connected markets and increase the securitization of mortgages. In a similar analysis of US banks, Barth et al. (2019) conclude that natural disasters incentivize institutions to attract more deposits in order to meet the higher loan demand, and that therefore they raise both interest rates on deposits and loans. Koetter et al. (2019) obtain comparable results when analyzing the lending adjustments of German banks with credit relationships to corporates affected by the 2013 flooding of the river Elbe. The authors find that after the flooding, banks lend more to disaster-hit firms (in the form of emergency lending) than to non-affected firms. In addition, banks source their lending primarily through local savings deposits rather than through wholesale funding.

After differentiating between affected and non-affected banks, Schüwer et al. (2019) apply a similar approach to assess the adjustment strategies of US banks following a catastrophic event. Using Hurricane Katrina as a case study, they examine how natural disasters affect a bank's lending, asset allocation, and capital ratios. The authors further distinguish between independent banks and banks affiliated within bank holding companies (BHCs) and find evidence that suggests that independent banks increase their risk-based capital ratios. In another study in which they examine the impact of multiple disasters on banks in the US, Noth and Schüwer (2018) focus on bank stability and bank performance. They analyze bank accounting ratios such as the return-on-assets, z-score, and equity-to-assets and find that disasters weaken both bank performance and stability.

Previous studies on the effects of natural disasters and bank solvency take different approaches. Brei et al. (2019) investigate the effects of hurricanes on the aggregate banking system of seven countries in the Caribbean, and Nguyen et al. (2020) focus on the affectedness of individual banks from natural disasters, particularly earthquakes and tsunamis, in seven East-Asian countries. They find that the disasters hit bank liquidity via deposits, but do not observe negative effects on solvency. Nguyen et al. (2020) measure the default risk of banks using their z-score, and Brei et al. (2019) use in addition the tier 1 capital ratio of the banking system.

Typically, changes in financial regulation are driven by past experiences and aim to address the vulnerabilities that these experiences have revealed in the financial and economic system.[1] However, it is questionable if this approach is sufficient to avoid future financial crises. Rather, a complete approach that also includes emerging risks is called for. The current solvency requirements should be extended to ensure that banks introduce factors in their capital reserve calculations that account for their susceptibility to the increasing likelihood and severity of natural disasters, particularly with respect to their lending, financing, and investment activities. Accordingly, risk weighted assets should be adjusted while leaving the overall capital requirements at the same level (Van Gelder and Stichele, 2011). This approach is also propagated by Batten et al. (2016) who argue that weather-related natural disasters can trigger financial instability and may cause severe damages to the balance sheets of banks.

A recent report by the *Cambridge Institute for Sustainability Leadership* recommends that the Basel Committee should explicitly acknowledge environmental risk and their increasing impact on the stability of the financial system (CISL, 2016). The report encourages regulators and banking institutions to adopt new practices to address environmental issues and incorporate a forward-looking approach to ensure the sustainability of bank lending activities. From a more comprehensive perspective, Aiyar et al. (2015) argue that credit instruments that are not subject to capital regulation or constitute no risk weights will cause undesirable negative effects for the credit supply of banks. Credit risks from natural disasters as a more recent phenomenon might not yet be considered adequately in risk-weighted assets or regulatory requirements.

In addition to studies related to banks and banking regulations, recent work has investigated the effect of disasters on other types of institutions as well as on the financial value of investments. These studies emphasize potential channels of disaster risk transmission and frequently call for novel methodological approaches. Building on the new climate-economy literature, Balvers et al. (2017) posit that temperature shocks restrict the growth of companies and impose a higher cost of equity. Based on the arbitrage pricing theory and a specification for expected temperature levels, they consider temperature shocks as a systematic risk factor and examine the loading of asset prices to the temperature risk factor. The loading is negative and equates to a higher cost of equity capital of approximately 0.22%. Another consequence of climate change is the rise of sea

[1] For instance, the Basel III Accord was largely developed in response to the recent subprime mortgage crisis. In line with the accord, the European Union's Capital Requirements Directive (CRD) obliges banks to set aside a minimum percentage of their capital to cover any potential defaults on their loans and investments.

levels with further effects on the price of properties in coastal areas and their use as collateral. Bernstein et al. (2018) categorize properties into buckets of similar size, elevation, and zip code, yet with a different exposure to sea level rise. They find that properties exposed to sea level rise trade at a discount of 6.6% compared to those that are not exposed.

This study contributes to the literature by assessing whether and by how much bank solvency is affected by natural disasters. We provide a cross-country analysis based on individual banks worldwide and thus complement existing studies examining fewer countries (Brei et al., 2019; Nguyen et al., 2020) or focusing on aggregate system-wide evidence (Klomp, 2014). Specifically, we investigate how different characteristics, business models, and locations of banks affect their solvency following a natural disaster. Moreover, we assess the suitability of two alternative measures of bank solvency to reflect banks' sensitivity to natural disasters and their interaction with bank characteristics and locations.

3. Hypothesis development

Prior studies in this area discuss different measures of solvency and note that solvency can be expressed from a balance sheet perspective as a form of accounting equity or from a supervisory point of view as a more refined risk-based measure of regulatory capital (Flannery and Giacomini, 2015; Hogan, 2015). We thus employ two different types of bank capital ratios in our analysis: (1) the equity ratio (accounting capital ratio) and (2) the tier 1 capital ratio (regulatory capital ratio). Accounting equity comprises all balance sheet components of a bank's proprietary capital including both common equity and preferred equity (Cohen and Scatigna, 2016). It can be interpreted as an institution's risk bearing capacity based on standard accounting principles. In contrast, the tier 1 capital takes a regulatory and specific risk-based point of view, with tier 1 capital generally defined as high-quality equity capital (BCBS, 2011; BCBS, 2017).

In order to obtain numbers that are comparable across banks and years, we standardize the different types of capital. We use the volume of total assets (TA) to standardize the volume-based accounting equity (equity ratio), and the risk-weighted assets (RWA) to standardize tier 1 capital as risk-adjusted capital (tier 1 capital ratio). Risk-weighted assets are based on the Basel II regulation that in essence have also been retained in the Basel III Accord (Dermine, 2015). Risk-weighted assets do not comprise all balance-sheet assets of a bank, and the weight of included assets may be below 100% or even zero.

Our first hypothesis is in line with the general assumption that natural disasters have a negative impact on customers and bank operations and may thus cause losses (Benson and Clay, 2004; Brei et al., 2019; Ngyuen, 2020). Negative effects relate to the assets and/or counterparties of banks and to the banks' infrastructure. As natural disasters are a class of emerging risks, it is likely that banks have not yet priced them or built reserves. Specifically, we postulate that:

H_1: Natural disasters negatively affect the solvency of banks, measured via either the equity ratio (Hypothesis H_{1A}) or the tier 1 capital ratio (Hypothesis H_{1B}).

Because the two capital ratios are standardized using a different denominator, we can test the behavior of the simple volume-weighted equity ratio with respect to disasters and compare it to the behavior of the risk-weighted tier 1 capital ratio. On one hand, risk weights are calibrated depending on the type of assets and/or counterparty and considered more adequate for supervisory risk assessment; however, they may be more complex and less robust on the other hand (Dermine, 2015; Hogan, 2015). Moreover, because tier 1 capital is generally understood to be a more refined measure of a bank's capitalization, we further propose that:

H_2: The regulatory capital ratio is more sensitive to disaster risk than the accounting capital ratio.

There are also arguments in disfavor of this hypothesis. As regulators usually align the risk weights of assets based on experiences, they may not fully reflect the impact from emerging risks such as natural disasters and contribute to an "ill-defined concept of bank capital ratios" (Aiyar et al., 2015, p. 976). Bischof et al. (2020) argue that the tier 1 capital ratio is a license to operate, and banks manage it actively to keep it at a stable level. The authors further make the point that based on prudential filters regulators may add back some losses (e.g., unrealized fair value losses) in the calculation of regulatory capital. As risk weights of top-rated companies and countries are very low and often zero, this further obstructs the adaptability and sensitivity of the tier 1 ratio.

We further assume that the magnitude of effects on solvency depends on the characteristics and locations of individual banks. Particularly, the business model of banks and their size may affect the damage they are exposed to from natural disasters. Our third hypothesis, which we also test with respect to the accounting and regulatory capital ratio, therefore reads as follows:

H_3: Disasters affect banks differently depending on the individual banks' characteristics.

4. Data and data preparation

This study uses data from the Emergency Events Database (EM-DAT) and a merged data set of banks' financial statements from Bankscope and Fitch. EM-DAT is provided by the Centre for Research on the Epidemiology of Disasters (CRED) at the University of Leuven, and contains detailed data on damages and other relevant information about various types of catastrophes around the globe. The data is collected from a variety of public and private sources, and since 2000, the centre has enhanced the data by geocoding each disaster (CRED, 2016). Natural (non-technological) disasters include critical meteorological (e.g., droughts, floods, storms) and geo-physical events (e.g., earthquakes, volcanic eruptions). Figure 1 provides an overview of the average annual damages per country caused by recorded disasters during the period 2000–2017. The different shades refer to the weighted damage ratio of each country, i.e., the ratio of the total annual damages in a given country to the country's GDP, averaged across our sample period. Figure 2 provides an overview of the damages caused by different types of disasters during our sample period. The proportion of damages attributable to the three main categories of disasters (earthquakes/tsunamis, floods, and strong winds) varies considerably over time and often depends on one or two 'mega-disasters' that caused most of the damages during a given year. For instance, in 2005, Hurricane Katrina was responsible for a large proportion of the natural disaster-related damages during that year, while in 2011 the earthquake leading to the Fukushima nuclear catastrophe represented a mega-disaster.

***** Insert Figure 1 about here *****

***** Insert Figure 2 about here *****

Bureau van Dijk (Bankscope) and Fitch Solutions (Fitch) provide detailed data on banks' accounting and financial statements. Bankscope includes extensive information for the years 2000 to 2014 yet limits the range of data offered thereafter. Therefore, we merge data from Bankscope through the year 2014 with information from Fitch for the years 2013 to 2017. When matching the two databases, we perform numerous checks to ensure the consistency of institutions and parameters included. A first issue is that the names of banks in Bankscope can differ from those in Fitch. In some cases, banks with similar names may be located in different countries, or banks can have several subsidiaries that are located in different cities in a given country yet display the same name. Furthermore, for some variables, the way Bankscope records

or calculates the data can be different from Fitch, and thus variables with the same name in Bankscope and Fitch are not always identical.[2]

In a next step, we employ the year 2013 data on total assets from both Bankscope and Fitch (i.e., the year in which the two databases overlap) and calculate the following variable which we then use to further compare the banks in each database:

$$ADTA = \left| \frac{BTA - FTA}{BTA} \right| \quad (1)$$

where ADTA is the absolute difference in total assets between two banks, BTA is the value of total assets for a bank in Bankscope, and FTA is the value of total assets for a matched bank in Fitch.

The distribution of ADTA is shown in Appendix 1. If the absolute difference in the value of total assets is smaller than 0.1 (10%), we consider the match to be authentic. In contrast, if the absolute difference exceeds 0.1, we drop the matched bank pair.

In addition to total assets, we check the consistency of other variables in Bankscope and Fitch. We again examine the year 2013 data for 2,895 banks in Fitch, and compare the variable values with those of their matched counterparts in Bankscope. We use two different methods for our comparison (see Appendix 2). The first method is based on two correlation measures (the normal correlation and the correlation after trimming each variable at the 1% and 99% levels). The respective results are displayed in columns 1 and 2 of Appendix 2. The second method employs the absolute difference ratio, calculated in the same fashion as the absolute difference in total assets above. If the difference ratio is larger than 0.1 (i.e., a variable value in Fitch is ten percent larger or smaller than in Bankscope), we assign a value of "1" (wrong matching); if not, we assign a value of "0" (correct matching). In addition, if the value in Bankscope is 0 (making it impossible to be used as a denominator in our percentage difference calculation), then we assign a value of "0" if the value in Fitch is also 0 (correct matching); otherwise, we assign a value of "1" (wrong matching). The percentage of "1s" (i.e., the percentage of wrong matches) for each variable is shown in column 3 of Appendix 2. We mark the variables we use in this paper in bold

[2] We use the Stata command "matchit" to fuzzy-match the bank names (Stata, 2017). This command calculates similarity scores, ranging from 0 to 1, between every paired bank from Bankscope and Fitch. After matching the names, we ensure that the countries and cities provided as bank locations in the Bankscope database are exactly the same as the matched banks in Fitch. If the locations do not match, we delete the matched banks. Afterwards, we check the rest of the matched banks manually, to ensure that they are very likely to be the same banks.

and with grey shading. They exhibit good quality matching with a correlation higher than 0.99 and a percentage of difference ratio (at the 0.1 level) of less than 10%.

The Bankscope and Fitch databases include banks from around the world that file their financial statements in different currencies. In total, we have 9,928 banks in our sample with complete data on all variables. These banks are located across 149 different countries. Table 1 reports the geographical distribution.

***** Insert Table 1 about here *****

Some authors suggest keeping data in the original currency and thus avoid translation effects (Cohen and Scatigna, 2016). However, in order to achieve better comparability (e.g., in terms of size), we convert all non-US$ figures at the respective exchange rate at the end of the accounting period. For most of our variables, potential biases caused by exchange rate fluctuations are avoided as we work with standardized data (e.g., capital in absolute terms divided by assets in absolute terms). Hence, any potential biases arising from currency fluctuations in the nominator and denominator should compensate each other.

Appendix 3 provides definitions for all variables used in our analysis and Table 2 reports summary statistics for the variables. The number of observations of the tier 1 capital ratio (124,997) is considerably smaller than that of the equity ratio (164,046). The discrepancy is due to the fact that banks have not always been obliged to publish regulatory capital ratios. It is worth noting that the tier 1 capital ratio (tier 1 capital divided by risk-weighted assets) has a median of 14.50%, much higher than the 6% required by Basel III.

***** Insert Table 2 about here *****

5. Methodology

We assess a bank's sensitivity to risk based on a series of ordinary least squares (OLS) and quantile regression approaches. We employ alternative measures of disaster damages as our main independent variables and different specifications of bank solvency as our dependent variables. A major challenge in our analysis is to relate the two types of variables in a meaningful way. For instance, the EM-DAT database we use to assess damages from natural disasters reports disasters over periods of different length, e.g., single-day tornados or blizzards versus longer periods for floods and droughts. In addition, the impact of disasters on banks may be immediate, e.g., if they

expose banks to operational risks, or long-term if disasters first affect the banks' customers and then gradually transform into credit risks.

To address these issues, we follow Klomp (2014) and design our main explanatory variable of interest (*Damage Ratio*) as follows: We assume that all banks in one country experience the same repercussions from a given disaster, and further that the impact of the disaster fully materializes and affects banks within one single year or two consecutive years.[3] For example, we assume that the shortest period during which a given disaster occurs and affects a bank is two months (60 days). In addition, we assume that disaster *j* affects country *i* approximately *m* days before the end of year *t*, and that the total number of disasters that occur in year *t* for country *i* is *n*. The proportion of damages attributed to year *t* ($damage_{ijt}$) and year *t+1* ($damage_{ij(t+1)}$) is thus calculated as follows:

$$If\ m \geq 60: damage_{ijt} = total\ damage\ of\ disaster\ j\ in\ country\ i$$

$$Otherwise(\ m < 60): \begin{cases} damage_{ijt} = \left(\frac{m}{60}\right) * total\ damage\ of\ disaster\ j\ in\ country\ i \\ damage_{ij(t+1)} = \left(\frac{60-m}{60}\right) * total\ damage\ of\ disaster\ j\ in\ country\ i \end{cases} \quad (2)$$

$$DamageRatio_{it} = (\sum_{j=1}^{n} damage_{ijt})/GDP_{it}$$

To account for the different time patterns that characterize both disasters themselves and their effects, we consider periods of varying length during which damages may materialize. Specifically, in addition to the aforementioned 60 days, we also assume that damages manifest within 90 days and 180 days after the beginning of the disaster. Because the results for the different periods are very similar, we only report the results for an impact period of 60 and 180 days, and consider other periods as part of our robustness tests.

Following the prior literature on bank capitalization, we control for several characteristics of banks: Size, measured as the natural logarithm of total assets (Barrios and Blanco, 2003; Brewer et al., 2008; Schepens, 2016), the loan ratio, measured as net loans over total assets (Altunbas et al., 2007; Demirgüç-Kunt et al., 2013; Schepens, 2016), profitability, measured as the ratio of net income over equity (Brewer et al., 2008; Schaeck and Cihák, 2012), and the deposit level,

[3] Klomp (2014) also allocates disaster damages to two different years. However, he only uses large-scale disasters and equally assigns 50% of the damage to the disaster year and the subsequent year. In contrast, we include all disasters listed in the EM-DAT database and divide the damages resulting from each disaster into two years based on the specific timing of the disaster during a given year.

measured as the ratio of total customer deposits over total assets (Barrios and Blanco, 2003; Demirgüç-Kunt et al., 2013).

Furthermore, because country-specific variables can affect each nation's banking system, we include several country-levels controls that have been used in previous research in this area. These include: the level of national development, measured as the natural logarithm of a country's annual real GDP per capita; economic growth, measured as the annual growth in the real GDP, and the credit activity of a country measured as the growth of credit to the private sector. We also examine other country-specific control variables such as the world government index (Kaufmann et al., 2011), a country's trade balance, and changes in each country's exchange rate. The resulting models either suffer from multicollinearity problems or are associated with large reductions in our sample size due to missing values. We thus decided not report the respective regressions here. However, even with these variables included, the results remain similar.

Our resultant regression model can be written as follows:

$$\Delta\, ratio_{kit} = \mu * ratio_{kit-1} + \beta * \mathrm{DR}_{it} + \alpha_m * B^s_{kit} + \gamma_h * C^h_{it} + \\ + \theta_t + \varphi_i + \delta_{kit} + \omega_{kit} + \varepsilon_{kit} \quad (3)$$

and

$$\Delta\, ratio_{kit} = ratio_{kit} - ratio_{kit-1} \quad (4)$$

where $ratio_{kit}$ represents the equity ratio or tier 1 capital ratio for bank *k* in country *i* in year *t*, and $ratio_{kit-1}$ is the corresponding ratio in the preceding year. DR_{it} is our explanatory variable of interest (in this case the weighted damage ratio during the 60 days (or 180 days) following a disaster). B^s_{kit} is a vector of *s* bank-specific control variables, and C^h_{it} is a vector of *h* country-specific control variables. θ_t represents time fixed effects, and φ_i the country fixed effects. δ_{kit} are the accounting standard fixed effects, and ω_{kit} are the bank specialization fixed effects.

6. Results

Before commencing with our multivariate analysis, we first examine the Pearson correlation coefficients for all variable pairs in Table 3. All correlations – except for two – between the variables are well below 0.5. Exceptions include the correlation between the lagged tier 1 capital ratio and the lagged equity ratio (0.8206), where a high correlation is expected. However, the two variables are never employed in the same model, thus mitigating any multicollinearity concerns

in our multivariate analysis. Similarly, and again as expected, the damage ratio (60 days) and the damage ratio (180 days) exhibit a high correlation (0.9425). The two variables are used as alternative damage proxies and thus never coexist in one model, again mitigating any multicollinearity concerns.

***** Insert Table 3 about here *****

We next commence our multivariate analysis by examining how banks' solvency ratios are affected by natural disasters (Hypotheses H_{1A} and H_{1B}). In addition, we explore whether the relationship is different when employing the tier 1 capital ratio, instead of the equity ratio, as a dependent variable (Hypothesis H_2). Because the sensitivity to natural hazards is unlikely to be uniform across institutions, we differentiate between banks located in countries with different land masses as well as between different types of banks (based on their business model) as well as different ex-ante capitalization levels of banks.

6.1 The sensitivity of banks' equity capital to natural disasters

Table 4 provides our regression results for Hypothesis H_1. To ensure the robustness of our results, we perform separate regressions for our full (worldwide) sample of banks, banks in the United States (US only), and banks in other countries (non-US). Columns 1 to 4 of Table 4 show how the weighted 60-day damage ratio affects the equity ratio ($\Delta E/TA$) for the three geographical subsamples (with column 4 repeating the full-sample analysis of column 3, but employing a non-winsorized sample). The coefficients for the damage ratio are consistently negative and significant, suggesting that natural disasters indeed have a detrimental effect on banks' capital ratios. Columns 5 to 8 of Table 4 employ the same model specifications as those employed in columns 1 to 4, but use the weighted damage ratio measured over a period of 180 days as the main variable of interest. The results are qualitatively and quantitatively very similar to those in the first four columns.

There are likely several reasons why natural disasters affect a bank's capital ratio. One explanation is that while banks protect their lending activities by requiring assets as collateral, the occurrence of natural disasters may destroy or at least reduce the value of the assets in question, hence reducing the bank's capacity to recover the outstanding loan balance via its collateral. Accordingly, if a borrower defaults on his/her loan and the bank manager realizes that the bank cannot recover the borrowed money through the collateral, the bank has to write off the borrowed

amount from its books and, by extension, the bank equity. Consequently, losing collateral as a result of a natural disaster is likely the main channel through which natural disasters affect a bank's equity. Furthermore, disasters may affect banks directly, for instance by damaging a bank's offices or its technical infrastructure. In summary, there is a multitude of reasons why banks that lend in high-risk areas should prepare for and create reserves to protect themselves against natural disasters and prevent any associated deterioration in their capital ratios.[4]

When examining the other explanatory variables, we observe that bank size (measured by the *natural log of total assets*) negatively correlates with the bank equity ratio, which is in line with prior research on bank solvency (Barrios and Blanco, 2003; Altunbas et al., 2007; Schaeck and Cihák, 2012; Schepens, 2016). Similarly, and also in line with the extant literature, we observe that profitability (measured by the *lagged net income to equity ratio*) is positively related to the equity ratio (Brewer et al., 2008; Schaeck and Cihák, 2012; Panier et al., 2013; Berger et al., 2018); and that the *net loan ratio* (net loans/total assets) is, generally, negatively correlated with the equity ratio (Altunbas et al., 2007; Schepens, 2016).

The prior banking literature exhibits mixed evidence regarding the effect of disruptions on the equity ratio of banks. Studies on financial crises (De Jonghe and Öztekin, 2015, and Gambacorta and Shin, 2018) suggest that the equity ratio of banks is procyclical: when a financial crisis hits the market, the equity ratio of banks increases (likely due to capital injections). Similarly, Koetter et al. (2016) and Bos et al. (2018) argue that capital adequacy (as proxied by the equity ratio) and lending (in the form of total outstanding loans) increase after large-scale natural disasters. In contrast, Noth and Schüwer (2018) find evidence that suggests that US banks that engage in mortgage lending experience a decline in bank capital following a natural disaster. Klomp (2014) shows that banks' default risk increases (and the equity ratio decreases) in the years following a large natural disaster. Brei et al. (2019) analyze a sample of seven countries in the Caribbean and find that banks experience changes in funding and lending after hurricanes, yet they do not detect any effects on risk and equity. Nguyen et al. (2020) confirm this result for banks operating in East-Asia. Our results complement this research.

***** Insert Table 4 about here *****

[4] It is worth noting here that higher capital requirements (e.g., those mandated by Basel III) have been shown to increase banks' lending rates and, consequently, have been blamed for the comparatively slow economic recovery following the 2008/2009 financial crisis and a reduction in global GDP growth, estimated at approximately 0.3% per year. A well-measured response to climate change with appropriately defined natural disaster prone risk weightings for banks' assets is therefore called for.

6.2 The sensitivity of banks' tier 1 capital to natural disasters

In order to compare the sensitivity of our two solvency measures, we re-estimate the same regressions we employed in Table 4 with the *tier 1 capital ratio* as the independent variable. We thus address our hypothesis (H_2) that suggests that regulatory capital ratios more distinctly reflect changes in risk than accounting based measures of capital. Columns 1 to 3 (4 to 6) of Table 5 show how the weighted 60-day (180-day) damage ratio affects the tier 1 capital ratio of banks in our three geographical subsamples (US banks, non-US banks, and the full sample). Except for the US, the coefficients are not significant and not always negative, suggesting that natural disasters have a smaller effect on regulatory capital ratios than they have on the accounting based equity ratios we examined in Table 4.

***** Insert Table 5 about here *****

For the subsample of US banks, the coefficients for the damage ratio in our accounting equity analyses (Table 4) are considerably larger than those in our regulatory capital regressions (Table 5). We also find that, in general, disasters have a larger impact on the equity ratio of US banks than on the equity ratio of non-US banks. This is likely driven by the fact that since about the 1980s, the damages caused by disasters in the US increased considerably more than those in other countries. For instance, in 2017, the US accounted for 83% of damages from storms worldwide (Munich Re, 2018, p. 52; WEF, 2018, p. 12).

Contrary to Hypothesis H_2, we note that disasters do not have a large impact on the tier 1 capital ratio. If anything, our results show that, in comparison with the equity ratio, the tier 1 capital ratio is less significantly and uniformly influenced by natural disasters. There are several possible reasons: first, regulations may force banks to keep the required amount of tier 1 capital at a specific and constant level; second, in order to protect against failure, bank management will, by itself, have an incentive to keep the tier 1 capital ratio at a safe level (Abou-El-Sood, 2015; Bischof et al., 2020); third, the denominator of the tier 1 capital ratio (a bank's risk-weighted assets), does not sufficiently take natural disaster risk into account, causing regulatory weightings to remain largely unaffected by disasters. Our lack of support for Hypothesis H_2 is in line with prior research findings in this area. For instance, Schüwer et al. (2019) document that the regulatory capital ratio increases (rather than decreases) after a disaster.[5]

[5] The authors show that higher risk-based capital ratios are the result of banks prioritizing lower risk-weighted assets such as government securities.

We conclude that we cannot find clear evidence of a higher risk sensitivity of the tier 1 capital ratio. Rather, the equity ratio appears to be a more appropriate measure of natural disaster risk and should be considered for regulatory purposes. In addition, as noted above, a revised risk-weighting of assets that does not only take historical credit and liquidity into consideration (as per Basel III), but weighs assets based on their expected susceptibility to natural disasters, may lead to a better inclusion of natural disaster risks in banking regulations. Similar results should be achieved from a fairer risk weighting of assets that takes the geographical lending habits (and thus the proneness to natural disasters) of a given bank into consideration.

With respect to our other explanatory variables, we observe that – in line with previous research in this area (e.g., Brewer et al., 2008) – bank size negatively correlates with the tier 1 capital ratio, and that profitability (the *lagged net income to equity ratio*) positively relates to the equity ratio.

6.3 Bank solvency strategies to prepare for natural disasters (ex-ante tests)

It is plausible that banks may anticipate natural disasters and respond in advance. To address this possibility, we perform a series of tests in which we include the forward damage ratio (damage ratio one year ahead) among our explanatory variables. Assuming that banks can correctly predict upcoming challenges from natural disasters, they should be able prepare themselves by increasing their equity and raising their risk premiums to build reserves. However, our full sample results in Table 6 provide little evidence for this conjecture and suggest no significant change in banks' equity ratio (column 3), tier 1 capital ratio (column 6) or net interest margin (column 9) in the year preceding a given disaster. However, banks in the US (columns 1, 4, and 7), appear to be more forward-looking and show signs of strengthening their balance sheet by increasing (reducing) equity (debt), injecting liquidity, and expanding their profit margin.

These results have several implications. First, the forward damage ratio significantly affects the asset structure of US banks, which indicates the quality of their prediction and the actions taken to prepare for natural disasters. Second, as can be observed in the aftermath of natural disasters, some governments tend to adopt relatively loose credit policies to support post-disaster reconstruction, which may lead to an increase in banks' bad debt thereafter. However, US banks can effectively mitigate the impact of natural disasters on loan quality and credit risk by raising the lending rate in advance and increasing cash reserves, thereby alleviating panic in the capital

market and reducing market risks.

***** Insert Table 6 about here *****

6.4 The influence of bank characteristics

The results up to now provide evidence for our full sample of banks. However, banks around the globe operate under different conditions, pursue divergent business models, and are subject to differing types of disasters as well as variations in country-level factors characterizing each country's legal environment, economic development, and banking regulations. To address these issues, we perform a series of robustness tests in which we examine whether our results hold for different subsamples of our data based on the characteristics of both banks and/or the countries they operate.

6.4.1 Business models

Banks vary considerably with respect to the way they conduct their business, and it is important to explore whether a bank's business model affects its susceptibility to adverse consequences from a natural disaster. We therefore investigate if the risk sensitivity of banks to catastrophic events depends on their respective business models, i.e., their strategy towards customers, products, and regions, and the associated diversification potential. The assumption is that more diversified institutions (whose lending and investment portfolio includes claims with low correlations) are better able to absorb and deal with large damages than undiversified banks. In this respect, damages from disasters may be considered a specific class of risk that allows for diversification effects.

Our analysis focuses on the three predominant business models, namely bank holding companies (BHCs), commercial banks, and savings banks. A bank holding company typically operates across multiple regions and product markets through the participation in different entities. As a result, the potential for geographical diversification is generally higher for BHCs than for commercial banks that also have a broad product portfolio, yet display a smaller network of national and international branches. Savings banks operate under a third type of business model. Their lending portfolio is often regionally focused and they tend to be smaller, increasing their exposure to local disasters. In summary, we expect more diversified (and less concentrated)

banks such as BHCs to be less affected by disasters than commercial banks and, in particular, savings banks.

Although our results are not fully as expected, our assumption that a banks' business model matters is confirmed. Table 7 shows that in our global sample, only BHCs exhibit a significant and negative coefficient. In the US sub-sample, BHCs experience the most negative effect from natural disasters whereas commercial banks have a lower, albeit still significant, coefficient. US savings banks exhibit a non-significant and economically small coefficient. Further investigation is needed to explore the causes. In particular, it is likely that a more refined geographical matching of disasters and bank lending activities will affect our results. For instance, there are several thousand savings banks that operate across the US and while a certain proportion of these banks is likely to be severely affected by a disaster, the remainder are likely to be unaffected because they are geographically removed from the disaster. On average, this makes savings banks appear unexposed on average, even though the individual exposures within this group may vary widely. Future research may also consider if business models are still to be conceived as a proxy for diversification as far as damages from natural disasters are concerned. Natural catastrophes represent to a certain extent a systemic risk and traditional patterns of diversification may fail to sufficiently protect the institutions. In addition, it is worth exploring if the benefits from diversification are potentially overcompensated by higher idiosyncratic risks institutions assume with respect to natural disasters.

***** Insert Table 7 about here *****

6.4.2 Ex-ante capitalization levels

Another attribute that may affect the sensitivity of banks to disasters is the extent of their ex-ante capitalization. We expect that banks with higher capital can better mitigate and control damages from disasters as they are better equipped to offset losses. Particularly, single losses may affect large and well-capitalized banks to a lesser extent than smaller institutions with less capital. We consider a bank's total equity as a proxy for size and the equity ratio as a proxy for the bank's equity base. We then use a series of quantile regressions to examine whether our results differ across banks with different ex-ante equity ratios.

Table 8 provides the results for the 0.25, 0.50 and 0.75 quantiles. When examining the coefficients for the damage ratio across all countries and for the US only, we observe that banks

with a lower equity ratio (i.e., the 0.25 quantile) exhibit a higher (negative) sensitivity to damages than banks at the 0.75 quantile. The sensitivity decreases continuously from the 0.25 quantile to the 0.75 quantile. In the sub-sample of non-US banks, the coefficients of the damage ratio in the 0.25 and 0.50 quantile regressions are not significant, but become significantly negative in the 0.75 quantile. Overall, these results suggest that higher ex-ante equity ratios appear to reduce the impact of natural disasters on a bank's solvency. Another potential explanation is that banks with a higher capitalization have been hit less frequently by disasters in the past and therefore have been able to maintain higher levels of equity capital.

***** Insert Table 8 about here *****

6.4.3 Bank location

From a spatial perspective, the severity of disasters and the magnitude of the associated damages may vary among countries and affect some banks more than others based on their location. In addition, natural disasters of the same magnitude may hit smaller countries more extensively while their impact on large countries may be comparatively small. For example, a single tsunami may destroy much of the infrastructure of any Caribbean state. In contrast, the 2008 earthquake in China's Sichuan province had a destructive effect on this province, but had a relatively small impact on banks in surrounding provinces, because they are geographically far removed.

For smaller countries, the reduced land mass increases the likelihood that a disaster affects one or more of a bank's clients. Second, banks in smaller countries are less likely to be diversified. As a result, a country's land mass should be negatively related to a bank's post-disaster solvency.

Table 9 provides empirical evidence for several tests that address this issue. We divide our sample into two subsamples based on whether the land mass of their respective countries falls above or below the sample median. In column 1, we can see that disaster damages have a significantly negative impact on the equity ratio of banks in countries with a comparatively small land size. However, regardless of whether we include banks in the US, the results are insignificant for larger countries (see columns 2 and 3). As before, disasters appear to have no impact on the tier 1 capital ratio for either small or large countries.

***** Insert Table 9 about here *****

We further estimate a weighted regression in which we assign a weight equal to one divided by the square root of a country's 2017 surface area based on data from the World Bank Indicators

Database (https://data.worldbank.org/indicator) to all damage observations in that country. Our results remain robust with respect to this methodological variation.

Ceteris paribus, as the size of a country increases, it is more likely to be affected by a natural disaster. We thus adjust the natural disaster variable for a country's surface area to rule out any endogeneity bias, and the results remain robust. In the full sample, the banks' equity ratio is significantly reduced after they experience a natural disaster (columns 1 and 2 in Table 10), but the capital adequacy ratio is not significantly curtailed (column 3).

***** Insert Table 10 about here *****

Next, we group countries into quintiles based on the 2017 GDP per capita in each country, again employing data provided by the World Bank Indicators Database. In rare instances where 2017 data was not available, we employ the most recent available GDP per capita for that country and then extrapolate it to the year 2017 (i.e., to the end of our sample period) using the GDP per capita growth rate during the previous five years as a growth factor. We then assign dummy variables to each of the five quintiles and estimate a 'wealth fixed effect regression' in which we include dummy variables for four of the five quintiles in our model (excluding the center quintile). The coefficients for the dummy variables denoting the lowest two GDP per capita quintiles are significantly negative, suggesting that banks in poorer countries (i.e., countries with lower GDP per capita figures) experience larger declines in solvency following a natural disaster (see Table 11).

***** Insert Table 11 about here *****

Considering that the occurrence of natural disasters closely relates to the geographical location of banks, we divide the sample into six groups based on the continent on which they are located. The results show that the equity ratio of banks in Africa exhibits the strongest negative effects (column 1 in Table 12), which may be attributed to an overall less resilient banking system in that region, followed by smaller adjustments in bank assets in Oceania and North America (columns 5 and 4). Even so, there is no significant change in the tier 1 capital ratio on any continent, supporting our main hypothesis (columns 7-12). In other words, banks on all continents appear to meet the of capital adequacy requirements for regulatory purposes, with little variation following a natural disaster. However, this finding also reveals that the Basel Accords fail to take into account the adequacy of capital requirements in the case of natural disasters.

***** Insert Table 12 about here *****

6.5 Different types of disasters

Finally, we aim to analyze the consequences of different types of disasters on bank solvency. Among all disaster types, floods have the most significant impact on capital (column 2 in Table 13), followed by storms (column 1), while earthquakes have no significant impact (column 3). As Benson and Clay (2004) point out, geological disasters such as earthquakes are likely to cause Schumpeter's "creative destruction" and thus stimulate post-disaster economic development. Yet meteorological and hydrological disasters such as storms and floods that occur more frequently are likely to have a pronounced negative effect on the local economy, leading to a significant contraction in the equity ratio.

***** Insert Table 13 about here *****

7 Additional robustness tests

To further ensure the robustness of our results, we perform some additional sensitivity checks. First, we are interested whether and how much any potential damages from the previous year can influence the equity ratio of the current year. We therefore regress the change in the equity ratio of the current year against the damage ratio of the previous year (Damage ratio_{t-1}). Our results, presented in columns 1 and 2 of Table 14, show that, regardless of whether we use the damage ratio over 60 or 180 days, its significance level decreases relative to our main regression results in Table 4, although the coefficient remains negative. This suggests that damages affect a bank's capitalization relatively quickly and that, as time passes, the impact decreases.

***** Insert Table 14 about here *****

Next, we examine whether our results stay robust if we do not control for the equity ratio in the previous year. We estimate the respective regressions in column 3 and 4. The coefficients of both the 60- and 180-day damage ratio remain negative and highly significant. Moreover, we employ a system GMM approach to estimate our regressions. The coefficients are still significantly negative. However, it is worth noting in this context that with fixed effect dummies (or any other dummy with many 0s or 1s), the results of a system GMM can be biased.[6]

Finally, our results remain robust after standardizing all variables. When doing so, we observe that for every standard deviation change in the damage ratio, the equity ratio decreases by 0.004

[6] For additional details, please refer to Roodman (2009).

standard deviations (column 3 in Table 15). Although 0.004 is a small number, the damages from disasters can be surprisingly large: the highest damage ratio is 148.38%, which corresponds to approximately 192.70 standard deviations (0.77%).

***** Insert Table 15 about here *****

8 Conclusion

This paper examines whether and how natural disasters affect bank solvency. Specifically, using a sample of 9,928 banks located in 149 countries and data on natural disasters that occurred around the globe during the period 2000–2017, we examine how natural disaster damages affect banks' equity ratios and tier 1 capital ratios.

Our major finding is that damages from natural disasters negatively affect bank solvency. The relationship varies across regions and among different types of banks, but provides compelling evidence that natural disasters represent a significant threat for the financial soundness of individual banks and, by extension, the stability of our financial system as a whole.

We hypothesized that the tier 1 capital ratio – as a regulatory measure of bank solvency – would be more sensitive to natural disaster damages than the accounting based equity ratio. However, natural disasters appear to affect the tier 1 capital ratio to a lesser extent than the corresponding accounting ratio. Although this issue calls for further investigation, we conclude that the regulatory weights attributed to risky assets in the tier 1 capital ratio specification are not adequate in capturing a bank's exposure to natural disasters. The regulatory risk weights stem from historical evidence and rely primarily on economic drivers of risk. However, the observable increase in the frequency and severity of natural disasters is a more recent phenomenon with roots that largely lie outside the financial system.

The results of our study have important implications for financial regulators and risk managers. In particular, financial regulators should consider modifying the assessment and weighting of solvency risks in light of the increasing damages caused by natural disasters. For instance, they may consider explicitly including disasters as a source of operational risk and to increase the risk weights for customers, which are particularly exposed to these risks. Similarly, managers of institutions that lend in disaster-prone areas should include the expected damages from disasters in their calculations of the risk premium of loans. If the premium is priced correctly, i.e., when it accounts for higher damages from natural disasters, any losses in a bank's lending business should be largely compensated by the premium.

The negative effect of natural disasters on bank solvency varies depending on the specific profile of banks. Banks located in countries where damages from natural disasters have a relatively high impact (as compared to the GDP) show a higher degree of affectedness. This is also the case for banks with a low ex-ante capitalization. In contrast, our study does not find significant and consistent results for banks with different business models. We conclude that natural disasters may exhibit a different propagation pattern and may affect regions, infrastructures, and institutions as a whole. Consequently, traditional diversification patterns appear to be irrelevant in this case.

A potential direction for further research on the link between bank solvency and natural disasters is to address the underlying transmission process of damages. This is challenging as causes and effects may unfold in various forms. Natural disasters primarily affect a bank's customers but may, at the same time, jeopardize the infrastructure of banks themselves. Depending on the risk management strategies both banks and their customers employ, the effect of disasters on bank solvency may be different. In addition, the frequency and magnitude of disasters may change over time. Future research has to cope with this high degree of complexity and the dynamic nature of disasters.

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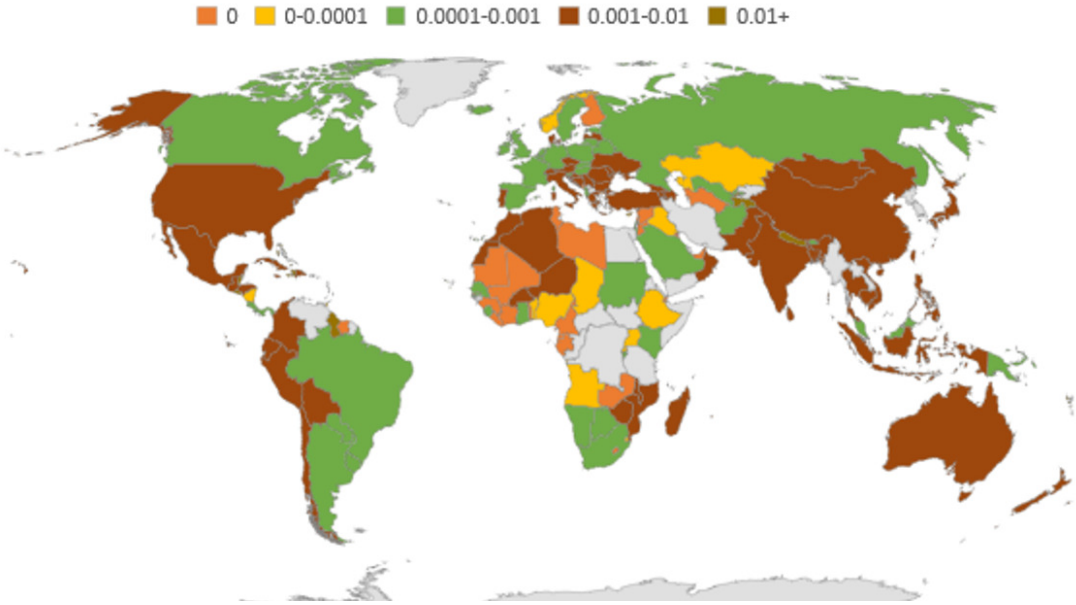

Figure 1: Ratios of disaster damages/GDP – Country-level averages for the 18-year period (2000–2017), grey indicates that no data is available

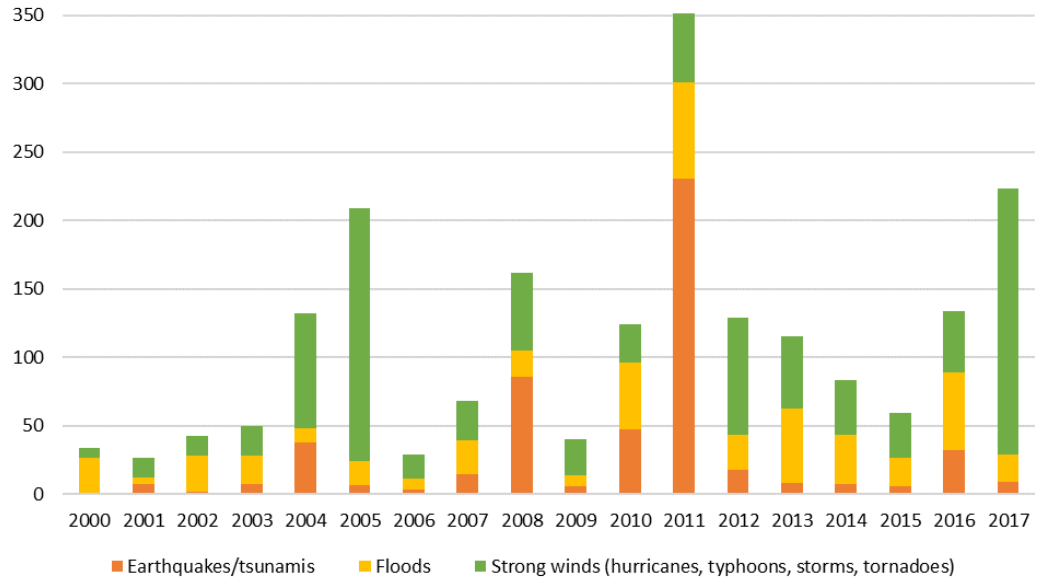

Figure 2: Distribution of worldwide disaster damages across different types of disasters, by year (US$ billion)

Table 1: Sample distribution: The number of banks per country

This table reports the distribution of our sample of 9,928 banks across 149 countries. We list countries alphabetically and report the number of banks (N) for each country.

Seq	Country	N	Seq	Country	N	Seq	Country	N	Seq	Country	N
1	Afghanistan	5	39	Egypt	19	76	Liberia	1	113	Romania	17
2	Albania	12	40	El Salvador	9	77	Libya	2	114	Russian	54
3	Algeria	2	41	Estonia	8	78	Lithuania	6	115	Rwanda	6
4	Angola	4	42	Ethiopia	1	79	Luxembourg	27	116	Saint Kitts	1
5	Antigua	1	43	Finland	23	80	Macau	5	117	Saint Lucia	1
6	Argentina	1	44	France	33	81	Madagascar	1	118	Saudi Arabia	10
7	Armenia	11	45	Gabon	2	82	Malawi	6	119	Senegal	4
8	Australia	23	46	Gambia	2	83	Malaysia	43	120	Serbia	10
9	Austria	119	47	Georgia	11	84	Maldives	2	121	Seychelles	3
10	Azerbaijan	22	48	Germany	1,211	85	Mali	3	122	Sierra Leone	3
11	Bahamas	6	49	Ghana	20	86	Malta	4	123	Singapore	12
12	Bahrain	15	50	Greece	5	87	Mauritania	1	124	Slovakia	8
13	Bangladesh	38	51	Grenada	1	88	Mauritius	11	125	Slovenia	12
14	Barbados	1	52	Guatemala	2	89	Mexico	20	126	South Africa	12
15	Belarus	10	53	Guinea	1	90	Moldova	7	127	Spain	49
16	Belgium	13	54	Guyana	3	91	Mongolia	2	128	Sri Lanka	15
17	Benin	1	55	Haiti	1	92	Montenegro	6	129	Sudan	5
18	Bhutan	2	56	Honduras	1	93	Morocco	4	130	Suriname	3
19	Bolivia	6	57	Hong Kong	16	94	Mozambique	10	131	Sweden	66
20	Bosnia	16	58	Hungary	15	95	Namibia	7	132	Switzerland	79
21	Botswana	7	59	Iceland	2	96	Nepal	2	133	Tajikistan	2
22	Brazil	59	60	India	9	97	Netherlands	22	134	Thailand	21
23	Bulgaria	15	61	Indonesia	56	98	New Zealand	4	135	Togo	1
24	Burundi	1	62	Iraq	1	99	Nicaragua	4	136	Trinidad	4
25	Cambodia	15	63	Ireland	9	100	Niger	1	137	Tunisia	3
26	Canada	3	64	Israel	7	101	Nigeria	15	138	Turkey	18
27	Cape Verde	3	65	Italy	338	102	Norway	93	139	Uganda	13
28	Chile	18	66	Jamaica	5	103	Oman	9	140	Ukraine	6
29	China	104	67	Japan	231	104	Pakistan	21	141	Emirates	22
30	Congo	2	68	Jordan	14	105	Panama	18	142	United Kingdom	95
31	Costa Rica	11	69	Kazakhstan	24	106	New Guinea	2	143	United States	6,010
32	Croatia	24	70	Kenya	24	107	Paraguay	2	144	Uruguay	14
33	Cyprus	8	71	South Korea	7	108	Peru	3	145	Vanuatu	2
34	Denmark	53	72	Kuwait	3	109	Philippines	11	146	Venezuela	14
35	Djibouti	2	73	Latvia	14	110	Poland	23	147	Vietnam	8
36	Dominica	1	74	Lebanon	19	111	Portugal	77	148	Yemen	5
37	Dominican Rep.	24	75	Lesotho	2	112	Qatar	10	149	Zambia	13
38	Ecuador	15								Total	9,928

Table 2: Summary statistics

This table provides summary statistics for our sample. For each variable, we report the number of bank-year observations, together with the mean, standard deviation, median, 5th percentile, and 95th percentile. The number of bank-year observations varies due to missing data for some banks.

Variable name	No. of Observations	Mean	Std. Dev.	Median	5th Percentile	95th Percentile
Equity ratio	164,046	0.1166	0.0945	0.0973	0.0448	0.2253
Tier 1 capital ratio	124,997	0.1812	0.1359	0.1450	0.0914	0.3688
Damage ratio (60 days)	194,186	0.0023	0.0078	0.0009	0.0000	0.0072
Damage ratio (180 days)	194,186	0.0022	0.0068	0.0010	0.0000	0.0097
Total assets (in US$ billion)	164,056	3.2179	11.3531	0.2753	0.0295	14.9945
Net loans ratio	163,168	0.5978	0.1853	0.6258	0.2363	0.8522
Customer deposits ratio	161,893	0.7581	0.1744	0.8127	0.3893	0.9105
Net income to equity ratio	163,865	0.0730	0.0892	0.0705	-0.0467	0.2075
Real GDP growth rate	194,157	0.0204	0.0675	0.0227	-0.1035	0.1260
Growth rate of credit to private sector	172,545	0.0128	0.0619	0.0097	-0.0886	0.0920
Real GDP per capita (in US$ thousands)	194,186	32.0650	14.0286	37.0949	0.7586	42.0992

Table 3: Correlation matrix

This table presents the Pearson correlation coefficients between the dependent variables (the annual change in the equity ratio and the annual change in the tier 1 capital ratio), and the explanatory variables. Although the lagged tier 1 capital ratio is highly correlated (**0.8206**) with the lagged equity ratio, they do not coexist in any model. Similarly, the damage ratio (60 days) and the damage ratio (180 days) exhibit a high correlation (**0.9425**), but are not jointly used in any model. * indicates significance at the 10% level.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1)	Change in equity ratio	1											
(2)	Lagged equity ratio	-0.3068*	1										
(3)	Lagged tier 1 capital ratio	-0.2712*	**0.8206***	1									
(4)	Damage ratio (60 days)	-0.0036	0.0050*	0.0111*	1								
(5)	Damage ratio (180 days)	-0.0046*	0.0057*	0.0094*	**0.9425***	1							
(6)	Log (total assets)	0.0414*	-0.2452*	-0.2774*	-0.0328*	-0.0352*	1						
(7)	Net loans ratio	-0.0045*	-0.2795*	-0.4838*	0.0062*	0.0056*	0.0304*	1					
(8)	Customer deposits ratio	-0.0138*	-0.3933*	-0.3165*	0.0468*	0.0498*	-0.2616*	0.1929*	1				
(9)	Lagged net income to equity ratio	0.0999*	-0.0505*	-0.1180*	0.0266*	0.0295*	0.0508*	0.0209*	0.0237*	1			
(10)	Real GDP growth rate	-0.0072*	-0.0304*	0.0203*	0.0272*	0.0289*	0.0019	0.0153*	0.0264*	0.0464*	1		
(11)	Growth rate of credit to private sector	-0.0340*	0.0851*	0.0315*	-0.0163*	0.0074*	-0.0339*	-0.0020	-0.0590*	0.1581*	0.0955*	1	
(12)	Log (real GDP per capita)	0.0264*	-0.1599*	-0.0262*	-0.0056*	-0.0111*	-0.1318*	0.1866*	0.2486*	-0.1112*	0.0737*	-0.2081*	1

Table 4: The effect of natural disasters on banks' equity ratios, employing damage ratios calculated over 60 and 180 days

This table presents the results for a series of models in which we regress the equity ratio of banks on the weighted damage ratio and other control variables over the 2000–2017 period for the 142,063 firm-year observations in our sample for which data on the equity ratio is available. The dependent variable in columns (1) to (3) and (5) to (7) is the change in the equity ratio (winsorized). The dependent variable in columns (4) and (8) is the change in the equity ratio (not winsorized). In columns (1) to (4), the independent variable of interest is the damage ratio calculated over a period of 60 days; in columns (5) to (8), the independent variable of interest is the damage ratio calculated over a period of 180 days. Columns (1) and (5) report results for the US-only subsample; columns (2) and (6) report results for the non-US subsample; and columns (3), (4), (7), and (8) report results for the full sample. Robust p-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Damage Period: 60 Days				Damage Period: 180 Days			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable: ΔE/TA	US Only	Non-US	Full Sample	Full Sample	US Only	Non-US	Full Sample	Full Sample
	ΔE/TA winsorized			ΔE/TA not winsorized	ΔE/TA winsorized			ΔE/TA not winsorized
Damage ratio	-0.359***	-0.012**	-0.016**	-0.018**	-0.522***	-0.013*	-0.019***	-0.022**
	(0.000)	(0.037)	(0.011)	(0.016)	(0.000)	(0.051)	(0.007)	(0.011)
Lagged equity ratio	-0.304***	-0.187***	-0.222***	-0.237***	-0.304***	-0.187***	-0.222***	-0.237***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log (total assets)	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Net loans ratio	-0.024***	-0.006***	-0.015***	-0.023***	-0.024***	-0.006***	-0.015***	-0.023***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Customer deposits ratio	-0.112***	-0.032***	-0.059***	-0.083***	-0.112***	-0.032***	-0.059***	-0.083***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged net income to equity ratio	0.029***	0.025***	0.036***	0.001	0.029***	0.025***	0.036***	0.001
	(0.000)	(0.000)	(0.000)	(0.500)	(0.000)	(0.000)	(0.000)	(0.500)
Real GDP growth rate	0.068***	0.001	-0.004**	-0.002	0.063***	0.001	-0.004**	-0.002
	(0.000)	(0.714)	(0.047)	(0.390)	(0.000)	(0.751)	(0.042)	(0.395)
Growth rate of credit to private sector	-0.012***	-0.018***	-0.016***	0.000	-0.008***	-0.019***	-0.017***	0.000
	(0.000)	(0.000)	(0.000)	(0.453)	(0.000)	(0.000)	(0.000)	(0.452)
Log (real GDP per capita)	0.048***	0.003**	0.003**	0.003**	0.050***	0.003**	0.003**	0.003**
	(0.000)	(0.016)	(0.022)	(0.040)	(0.000)	(0.017)	(0.024)	(0.041)
Country FE		Yes	Yes	Yes		Yes	Yes	Yes
Year FE		Yes	Yes	Yes		Yes	Yes	Yes
Specialization FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Accounting standard FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	88,918	53,145	142,063	142,063	88,918	53,145	142,063	142,063
Adjusted R^2	0.316	0.154	0.217	0.215	0.316	0.154	0.217	0.215

Table 5: The effect of natural disasters on banks' tier 1 capital ratios, employing damage ratios calculated over 60 and 180 days

This table presents the results for a series of models in which we regress the tier 1 capital ratio of banks on the weighted damage ratio and other control variables over the 2000–2017 period for the 107,832 firm-year observations in our sample for which data on the tier 1 capital ratio is available. The dependent variable is the change in the tier 1 capital ratio (winsorized). In columns (1) to (3), the independent variable of interest is the damage ratio calculated over a period of 60 days; in columns (4) to (6), the independent variable of interest is the damage ratio calculated over a period of 180 days. Columns (1) and (4) report results for the US-only subsample; columns (2) and (5) report results for the non-US subsample; columns (3) and (6) report results for the full sample. Robust p-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dependent variable: ΔT1R/TA (winsorized)	Damage Period: 60 Days			Damage Period: 180 Days		
	(1) US Only	(2) Non-US	(3) Full Sample	(4) US Only	(5) Non-US	(6) Full Sample
Damage ratio	-0.292***	0.003	-0.019	-0.407***	-0.003	-0.024
	(0.000)	(0.935)	(0.625)	(0.000)	(0.954)	(0.582)
Lagged tier 1 capital ratio	-0.217***	-0.183***	-0.192***	-0.218***	-0.183***	-0.192***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log (total assets)	-0.004***	-0.003***	-0.004***	-0.004***	-0.003***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Net loans ratio	-0.089***	-0.044***	-0.074***	-0.089***	-0.044***	-0.074***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Customer deposits ratio	-0.121***	-0.024***	-0.086***	-0.121***	-0.024***	-0.086***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged net income to equity ratio	0.041***	0.028***	0.054***	0.041***	0.028***	0.054***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Real GDP growth rate	0.083***	0.009	-0.005	0.078***	0.009	-0.005
	(0.000)	(0.181)	(0.287)	(0.000)	(0.180)	(0.285)
Growth rate of credit to private sector	-0.016***	-0.048***	-0.035***	-0.013***	-0.048***	-0.035***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log (real GDP per capita)	0.064***	-0.004	-0.009***	0.066***	-0.004	-0.009***
	(0.000)	(0.177)	(0.000)	(0.000)	(0.175)	(0.000)
Country FE		Yes	Yes		Yes	Yes
Year FE		Yes	Yes		Yes	Yes
Specialization FE	Yes	Yes	Yes	Yes	Yes	Yes
Accounting standard FE	Yes	Yes	Yes	Yes	Yes	Yes
N	86,231	21,601	107,832	86,231	21,601	107,832
Adjusted R^2	0.238	0.265	0.177	0.238	0.265	0.177

Table 6: Ex-ante tests

This table presents the results for a series of models in which we regress changes in the equity ratio, tier 1 capital ratio, and net interest margin of banks on the forward damage ratio and other control variables over the 2000–2017 period for different subsamples of our dataset. The dependent variable in columns (1) to (3) is the change in the equity ratio (winsorized). The dependent variable in columns (4) to (6) is the change in the tier 1 capital ratio (winsorized). The dependent variable in columns (7) to (9) is the change in the net interest margin (winsorized). Columns (1), (4), and (7) report results for the US-only subsample; columns (2), (5), and (8) report results for the non-US subsample; and columns (3), (6), and (9) report results for the full sample. Robust p-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: ΔE/TA (winsorized)			Dependent variable: ΔT1R/TA (winsorized)			Dependent variable: ΔNIM (winsorized)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	US Only	Non-US	Full Sample	US Only	Non-US	Full Sample	US Only	Non-US	Full Sample
Lagged equity ratio	-0.305***	-0.195***	-0.228***						
	(0.000)	(0.000)	(0.000)						
Lagged tier 1 capital ratio				-0.257***	-0.226***	-0.235***			
				(0.000)	(0.000)	(0.000)			
Lagged net interest margin							-0.032	-0.012**	-0.016***
							(0.182)	(0.010)	(0.003)
Forward 1 damage ratio	0.038*	0.006	0.006	0.210***	0.069	0.043	0.090***	-0.010	-0.009
	(0.084)	(0.335)	(0.352)	(0.000)	(0.326)	(0.482)	(0.000)	(0.175)	(0.228)
Log (total assets)	-0.003***	-0.003***	-0.003***	-0.004***	-0.004***	-0.004***	-0.000***	-0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.280)	(0.000)
Net loans ratio	-0.024***	-0.006***	-0.016***	-0.091***	-0.047***	-0.078***	0.004***	0.002***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Customer deposits ratio	-0.112***	-0.031***	-0.060***	-0.091***	-0.023***	-0.071***	-0.002***	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.559)	(0.148)
Lagged net income to equity ratio	0.029***	0.025***	0.036***	0.040***	0.030***	0.051***	-0.010***	-0.006***	-0.009***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Real GDP growth rate	0.045***	-0.000	-0.006***	0.055***	0.011	-0.005	-0.002	-0.003**	-0.002***
	(0.000)	(0.933)	(0.009)	(0.000)	(0.138)	(0.317)	(0.252)	(0.015)	(0.000)
Growth rate of credit to private sector	-0.008***	-0.017***	-0.015***	-0.013***	-0.048***	-0.033***	-0.001**	0.001	0.002**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.026)	(0.286)	(0.019)
Log (real GDP per capita)	0.047***	0.004***	0.003***	0.061***	-0.003	-0.008***	-0.016***	-0.000	0.000
	(0.000)	(0.008)	(0.007)	(0.000)	(0.375)	(0.009)	(0.000)	(0.615)	(0.874)
Country FE		Yes	Yes		Yes	Yes		Yes	Yes
Year FE		Yes	Yes		Yes	Yes		Yes	Yes
Specialization FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Accounting standard FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	88,918	53,145	142,063	86,231	21,601	107,832	87,636	48,767	136,403
Adjusted R^2	0.317	0.162	0.224	0.254	0.192	0.240	0.065	0.038	0.075

Table 7: The effect of natural disasters on banks' equity ratios – Commercial banks vs. bank holding companies and savings banks

This table presents the results for a series of models in which we regress the equity ratio of banks on the weighted damage ratio and other control variables over the 2000–2017 period, for different subsamples of our dataset based on the business model of each bank. The dependent variable is the change in the equity ratio (winsorized). The independent variable of interest is the damage ratio calculated over a period of 60 days. Columns (1) to (3) report the result for the subsample of commercial banks. Columns (4) to (6) report the result for the subsample of bank holding companies, and columns (7) to (9) report the result for the subsample of savings banks. Columns (1), (4), and (7) report results for the US sample; columns (2), (5), and (8) report results for the non-US sample; and columns (3), (6), and (9) report results for the full sample. Robust p-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dependent variable: ΔE/TA (winsorized)	Commercial banks			Bank holding companies			Savings banks		
	(1) US Only	(2) Non-US	(3) Full Sample	(4) US Only	(5) Non-US	(6) Full Sample	(7) US Only	(8) Non-US	(9) Full Sample
Damage ratio	-0.360***	-0.012**	-0.014**	-0.406***	0.062	0.120	-0.083	-0.157***	-0.022
	(0.000)	(0.047)	(0.021)	(0.000)	(0.478)	(0.274)	(0.359)	(0.008)	(0.721)
Lagged equity ratio	-0.346***	-0.235***	-0.267***	-0.142***	-0.175***	-0.146***	-0.189***	-0.052***	-0.120***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log (total assets)	-0.003***	-0.006***	-0.003***	-0.001***	-0.006***	-0.002***	-0.003***	-0.000**	-0.002***
	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)	(0.000)	(0.000)	(0.012)	(0.000)
Net loans ratio	-0.025***	-0.005**	-0.017***	-0.012***	0.012	-0.008***	-0.021***	-0.002**	-0.014***
	(0.000)	(0.012)	(0.000)	(0.000)	(0.202)	(0.000)	(0.000)	(0.014)	(0.000)
Customer deposits ratio	-0.132***	-0.041***	-0.079***	-0.033***	-0.058***	-0.041***	-0.077***	-0.003**	-0.037***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.038)	(0.000)
Lagged net income to equity ratio	0.029***	0.025***	0.036***	0.014***	0.037	0.022***	0.019**	0.009*	0.022***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.202)	(0.000)	(0.015)	(0.059)	(0.000)
Real GDP growth rate	0.071***	0.004	0.000	0.018	0.012	-0.009	0.078***	0.019**	-0.005
	(0.000)	(0.273)	(0.973)	(0.111)	(0.448)	(0.534)	(0.000)	(0.018)	(0.150)
Growth rate of credit to private sector	-0.014***	-0.021***	-0.022***	-0.011***	-0.031*	-0.042***	0.016**	-0.010	0.002
	(0.000)	(0.000)	(0.000)	(0.002)	(0.054)	(0.001)	(0.015)	(0.166)	(0.606)
Log (real GDP per capita)	0.048***	0.003	-0.000	0.021***	0.017	0.006	0.056***	-0.008**	0.005**
	(0.000)	(0.118)	(0.900)	(0.000)	(0.140)	(0.476)	(0.000)	(0.033)	(0.011)
Country FE		Yes	Yes		Yes	Yes		Yes	Yes
Year FE		Yes	Yes		Yes	Yes		Yes	Yes
Accounting standard FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	71,106	20,985	92,091	10,314	1,060	11,374	7,423	11,206	18,629
Adjusted R^2	0.370	0.182	0.264	0.097	0.108	0.114	0.168	0.122	0.119

Table 8: The effect of natural disasters on banks' equity ratios – Quantile regression results for the 0.25, 0.50, and 0.75 quantiles

This table presents the results for a series of models in which we regress (using quantile regressions) the equity ratio of banks on the weighted damage ratio and other control variables over the 2000–2017 period for the 142,063 firm-year observations in our sample for which data on the equity ratio is available. The dependent variable in all models is the change in the equity ratio (winsorized). The independent variable of interest is the damage ratio calculated over a period of 60 days. Columns (1) to (3) provide the results for the 0.25 quantile regression, columns (4) to (6) provide the results for the 0.50 quantile regression, and columns (7) to (9) provide the results for the 0.75 quantile regression. Columns (1), (4), and (7) report results of the US sample, columns (2), (5), and (8) report results of the non-US sample, and columns (3), (6), and (9) report results for the full sample. P-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dependent variable: ΔE/TA (winsorized)	0.25 Quantile			0.5 Quantile			0.75 Quantile		
	(1) US Only	(2) Non-US	(3) Full Sample	(4) US Only	(5) Non-US	(6) Full Sample	(7) US Only	(8) Non-US	(9) Full Sample
Damage ratio	-0.294***	-0.003	-0.022***	-0.243***	-0.006	-0.018***	-0.190***	-0.012**	-0.014***
	(0.000)	(0.688)	(0.002)	(0.000)	(0.244)	(0.000)	(0.000)	(0.046)	(0.002)
Lagged equity ratio	-0.139***	-0.135***	-0.132***	-0.051***	-0.038***	-0.031***	-0.056***	-0.017***	-0.032***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log (total assets)	-0.001***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.001***	-0.001***
	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Net loans ratio	-0.004***	0.005***	0.001*	-0.003***	0.001***	-0.001***	-0.004***	-0.003***	-0.002***
	(0.000)	(0.000)	(0.098)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Customer deposits ratio	-0.019***	0.001	-0.004***	-0.023***	-0.002***	-0.009***	-0.025***	-0.007***	-0.012***
	(0.000)	(0.126)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged net income to equity ratio	0.020***	0.015***	0.020***	0.008***	0.006***	0.010***	-0.001***	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	(0.790)	(0.654)
Real GDP growth rate	0.063***	0.002*	-0.006***	0.050***	0.002*	-0.005***	0.034***	0.000	-0.006***
	(0.000)	(0.076)	(0.000)	(0.000)	(0.073)	(0.000)	(0.000)	(0.712)	(0.000)
Growth rate of credit to private sector	-0.015***	-0.011***	-0.013***	-0.015***	-0.011***	-0.013***	-0.015***	-0.010***	-0.013***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log (real GDP per capita)	0.017***	0.000	0.002***	0.006***	-0.000	0.001***	0.004***	-0.001	0.002***
	(0.000)	(0.852)	(0.000)	(0.000)	(0.703)	(0.000)	(0.000)	(0.360)	(0.000)
Country FE		Yes	Yes		Yes	Yes		Yes	Yes
Year FE		Yes	Yes		Yes	Yes		Yes	Yes
Specialization FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Accounting standard FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	88,918	53,145	142,063	88,918	53,145	142,063	88,918	53,145	142,063

Table 9: The effect of natural disasters on banks' equity and tier 1 capital ratios – Small vs. large countries

This table presents the results for a series of models in which we regress the capital ratio (i.e., either the equity ratio or the tier 1 capital ratio) of banks on the weighted damage ratio and other control variables over the 2000–2017 period for different subsamples of our dataset based on the size of the country in which each bank is headquartered. The dependent variable in columns (1) and (2) is the change in the equity ratio (winsorized). The dependent variable in columns (3) and (4) is the change in the tier 1 capital ratio (winsorized). The independent variable of interest is the damage ratio calculated over a period of 60 days. Columns (1) and (3) report the result for the subsample of banks in countries whose land mass is smaller than the median of all countries. Columns (2) and (4) report the result for the subsample of banks in countries (including the US) whose land mass is larger than the median of all countries. Robust p-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: ΔE/TA (winsorized)		Dependent variable: ΔT1R/TA (winsorized)	
	(1) Small countries	(2) Large countries (incl. US)	(3) Small countries	(4) Large countries (incl. US)
Damage ratio	-0.018***	-0.011	-0.101	-0.013
	(0.010)	(0.499)	(0.522)	(0.725)
Lagged equity ratio	-0.213***	-0.228***		
	(0.000)	(0.000)		
Lagged tier 1 capital ratio			-0.224***	-0.235***
			(0.000)	(0.000)
Log (total assets)	-0.005***	-0.003***	-0.005***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
Net loans ratio	-0.007***	-0.016***	-0.032***	-0.080***
	(0.004)	(0.000)	(0.000)	(0.000)
Customer deposits ratio	-0.041***	-0.063***	-0.035***	-0.073***
	(0.000)	(0.000)	(0.000)	(0.000)
Lagged net income to equity ratio	0.023***	0.038***	0.025***	0.052***
	(0.000)	(0.000)	(0.008)	(0.000)
Real GDP growth rate	0.006	-0.005**	0.017	0.002
	(0.373)	(0.017)	(0.323)	(0.699)
Growth rate of credit to private sector	-0.019***	-0.015***	-0.061***	-0.023***
	(0.001)	(0.000)	(0.000)	(0.000)
Log (real GDP per capita)	0.004	0.003**	-0.011	-0.011***
	(0.105)	(0.037)	(0.242)	(0.000)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Specialization FE	Yes	Yes	Yes	Yes
Accounting standard FE	Yes	Yes	Yes	Yes
N	13,471	128,592	4,681	103,151
Adjusted R^2	0.180	0.228	0.199	0.239

Table 10: The effect (area-adjusted) of natural disasters on banks' equity and tier 1 capital ratios

This table presents the results for a series of models in which we regress changes in the equity ratio and tier 1 capital ratio of banks on the damage ratio (adjusted for the landmass of the country in which a given bank is headquartered) and other control variables over the 2000–2017 period for different subsamples of our dataset. The dependent variable in columns (1) and (2) is the change in the equity ratio (winsorized). The dependent variable in columns (3) and (4) is the change in the tier 1 capital ratio (winsorized). Columns (2) and (4) report results with country, year, specialization, and accounting standard fixed effects. Robust p-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: ΔE/TA (winsorized)		Dependent variable: ΔT1R/TA (winsorized)	
	(1)	(2)	(3)	(4)
	Full Sample	Full Sample	Full Sample	Full Sample
Lagged equity ratio	-0.191***	-0.223***		
	(0.000)	(0.000)		
Lagged tier 1 capital ratio			-0.205***	-0.231***
			(0.000)	(0.000)
Damage ratio（/area）	-0.002***	-0.003**	-3.581	-7.203*
	(0.009)	(0.013)	(0.112)	(0.085)
Log (total assets)	-0.002***	-0.003***	-0.003***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
Net loans ratio	-0.014***	-0.015***	-0.068***	-0.077***
	(0.000)	(0.000)	(0.000)	(0.000)
Customer deposits ratio	-0.040***	-0.059***	-0.051***	-0.069***
	(0.000)	(0.000)	(0.000)	(0.000)
Lagged net income to equity ratio	0.034***	0.036***	0.035***	0.050***
	(0.000)	(0.000)	(0.000)	(0.000)
Real GDP growth rate	-0.011***	-0.004**	-0.004	-0.004
	(0.000)	(0.042)	(0.202)	(0.379)
Growth rate of credit to private sector	-0.011***	-0.017***	-0.028***	-0.033***
	(0.000)	(0.000)	(0.000)	(0.000)
Log (real GDP per capita)	0.000	0.003**	0.003***	-0.007***
	(0.134)	(0.011)	(0.000)	(0.003)
Country FE		Yes		Yes
Year FE		Yes		Yes
Specialization FE		Yes		Yes
Accounting standard FE		Yes		Yes
N	142,063	142,063	107,832	107,832
Adjusted R^2	0.178	0.217	0.189	0.233

Table 11: The effect of natural disasters on banks' equity and tier 1 capital ratios – Wealthy vs. poor countries

This table presents the results for a series of models in which we regress changes in the equity ratio and tier 1 capital ratio of banks on the damage ratio and other control variables over the 2000–2017 period for different subsamples of our dataset based on the GDP per capita of the country in which a bank is headquartered. The dependent variable in columns (1) and (2) is the change in the equity ratio (winsorized). The dependent variable in columns (3) and (4) is the change in the tier 1 capital ratio (winsorized). Columns (1) and (3) report results for the lower GDP per capita subsample (with a GDP per capita below the full sample median); columns (2) and (4) report results for the higher GDP per capita subsample. Robust p-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: ΔE/TA (winsorized)		Dependent variable: ΔT1R/TA (winsorized)	
	(1)	(2)	(3)	(4)
	GDP low	GDP high	GDP low	GDP high
Lagged equity ratio	-0.197***	-0.259***		
	(0.000)	(0.000)		
Lagged tier 1 capital ratio			-0.217***	-0.245***
			(0.000)	(0.000)
Damage ratio	-0.113*	-0.539*	-0.126	-0.366
	(0.059)	(0.088)	(0.775)	(0.559)
Log (total assets)	-0.004***	-0.003***	-0.004***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
Net loans ratio	-0.006***	-0.019***	-0.048***	-0.083***
	(0.000)	(0.000)	(0.000)	(0.000)
Customer deposits ratio	-0.035***	-0.086***	-0.026***	-0.087***
	(0.000)	(0.000)	(0.000)	(0.000)
Lagged net income to equity ratio	0.031***	0.035***	0.036***	0.051***
	(0.000)	(0.000)	(0.000)	(0.000)
Real GDP growth rate	0.001	-0.008***	0.009	-0.031***
	(0.799)	(0.005)	(0.265)	(0.000)
Growth rate of credit to private sector	-0.020***	-0.020***	-0.051***	-0.017*
	(0.000)	(0.000)	(0.000)	(0.056)
Log (real GDP per capita)	0.004***	-0.004**	-0.004	-0.004
	(0.005)	(0.047)	(0.229)	(0.379)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Specialization FE	Yes	Yes	Yes	Yes
Accounting standard FE	Yes	Yes	Yes	Yes
N	41,194	100,869	17,409	90,423
Adjusted R^2	0.160	0.274	0.185	0.254

Table 12: The effect of natural disasters on banks' equity and tier 1 capital ratios – Banks from different continents

This table presents the results for a series of models in which we regress changes in the equity ratio and tier 1 capital ratio of banks on the damage ratio and other control variables over the 2000–2017 period for different subsamples of our dataset based on the continent on which a given bank is headquartered. The dependent variable in columns (1) to (6) is the change in the equity ratio (winsorized). The dependent variable in columns (7) to (12) is the change in the tier 1 capital ratio (winsorized). Columns (1) and (7), (2) and (8), (3) and (9), (4) and (10), (5) and (11), (6) and (12) report results for banks headquartered in Africa, Asia, Europe, North America, Oceania, and South America, respectively. Robust p-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: ΔE/TA (winsorized)						Dependent variable: ΔT1R/TA (winsorized)					
	(1) Africa	(2) Asia	(3) Europe	(4) N. Amer.	(5) Oceania	(6) S. Amer.	(7) Africa	(8) Asia	(9) Europe	(10) N. Amer.	(11) Oceania	(12) S. Amer.
Lagged equity ratio	-0.320***	-0.242***	-0.158***	-0.298***	-0.070	-0.184***						
	(0.000)	(0.000)	(0.000)	(0.000)	(0.229)	(0.000)						
Lagged tier 1 capital ratio							-0.483***	-0.218***	-0.160***	-0.255***	-0.202***	-0.385***
							(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Damage ratio	-0.376***	0.044	-0.028	-0.010**	-0.030***	-0.021	0.001	0.028	-0.071	-0.406	0.176	0.018
	(0.005)	(0.365)	(0.702)	(0.021)	(0.007)	(0.174)	(0.998)	(0.629)	(0.615)	(0.125)	(0.413)	(0.769)
Log (total assets)	-0.006***	-0.004***	-0.002***	-0.003***	-0.001*	-0.008***	-0.012***	-0.006***	-0.002***	-0.004***	-0.002	-0.021***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.055)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.138)	(0.000)
Net loans ratio	0.021***	-0.013***	-0.005***	-0.020***	-0.005	-0.010	-0.133***	-0.063***	-0.031***	-0.087***	0.004	-0.120***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.469)	(0.142)	(0.000)	(0.000)	(0.000)	(0.000)	(0.849)	(0.000)
Customer deposits ratio	-0.063***	-0.050***	-0.025***	-0.111***	-0.002	-0.053***	-0.130***	-0.027***	-0.014***	-0.096***	-0.004	-0.092***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.661)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.821)	(0.000)
Lagged net income to equity ratio	0.042***	0.024***	0.020***	0.036***	0.021	0.030**	0.082***	0.048***	0.019**	0.052***	-0.017	0.040
	(0.000)	(0.000)	(0.000)	(0.000)	(0.197)	(0.013)	(0.005)	(0.000)	(0.012)	(0.000)	(0.528)	(0.225)
Real GDP growth rate	0.011	-0.004	0.013	0.008	-0.051**	-0.015	0.042	-0.010	0.012	-0.079	-0.030	0.054
	(0.152)	(0.484)	(0.139)	(0.515)	(0.027)	(0.225)	(0.196)	(0.323)	(0.479)	(0.318)	(0.517)	(0.121)
Growth rate of credit to private sector	-0.024***	-0.014*	-0.017***	-0.001	0.028	-0.037***	-0.025	-0.038***	-0.038***	-0.048	-0.073	0.014
	(0.001)	(0.088)	(0.005)	(0.919)	(0.234)	(0.009)	(0.390)	(0.001)	(0.001)	(0.352)	(0.373)	(0.823)
Log (real GDP per capita)	0.004	0.001	-0.001	0.014**	0.017	0.011***	0.005	-0.005	0.001	0.005	0.044	0.017
	(0.375)	(0.668)	(0.787)	(0.040)	(0.513)	(0.004)	(0.821)	(0.252)	(0.834)	(0.851)	(0.626)	(0.412)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Specialization FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Accounting standard FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3,137	10,048	35,893	90,680	294	2,011	962	5,244	14,261	86,597	184	577
Adjusted R^2	0.301	0.205	0.122	0.319	0.193	0.144	0.355	0.195	0.133	0.265	0.187	0.274

Table 13: The effect of natural disasters on banks' equity and tier 1 capital ratios – Different types of disasters

This table presents the results for a series of models in which we regress changes in the equity ratio of banks on the damage ratio associated with various types of natural disasters and other control variables over the 2000–2017 period for the 142,063 firm-year observations in our sample for which data on the equity ratio is available. The dependent variable in all columns is the change in the equity ratio (winsorized). Columns (1), (2), and (3) report results for storm, flood, and earthquake damages, respectively. Robust p-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: ΔE/TA (winsorized)		
	(1) Full Sample	(2) Full Sample	(3) Full Sample
Lagged equity ratio	-0.222***	-0.222***	-0.222***
	(0.000)	(0.000)	(0.000)
Storm damage ratio	-0.011*		
	(0.087)		
Flood damage ratio		-0.050*	
		(0.060)	
Earthquake damage ratio			-0.009
			(0.418)
Log (total assets)	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)
Net loans ratio	-0.015***	-0.015***	-0.015***
	(0.000)	(0.000)	(0.000)
Customer deposits ratio	-0.059***	-0.059***	-0.059***
	(0.000)	(0.000)	(0.000)
Lagged net income to equity ratio	0.036***	0.036***	0.036***
	(0.000)	(0.000)	(0.000)
Real GDP growth rate	-0.004**	-0.004**	-0.004**
	(0.038)	(0.040)	(0.040)
Growth rate of credit to private sector	-0.017***	-0.016***	-0.017***
	(0.000)	(0.000)	(0.000)
Log (real GDP per capita)	0.003**	0.002**	0.003**
	(0.022)	(0.027)	(0.022)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Specialization FE	Yes	Yes	Yes
Accounting standard FE	Yes	Yes	Yes
N	142,063	142,063	142,063
Adjusted R^2	0.217	0.217	0.217

Table 14: The effect of natural disasters on banks' equity ratios – Additional robustness tests

This table presents the results for a series of models in which we regress changes in the equity ratio of banks on the weighted damage ratio and other control variables over the 2000–2017 period for the 142,063 firm-year observations in our sample for which data on the equity ratio is available. The dependent variable in all models is the change in the equity ratio (winsorized). In columns (1) and (2), the independent variable of interest is the lagged damage ratio. In columns (3) and (4), the independent variable of interest is still the damage ratio, but the lagged equity ratio is excluded from the control variables. In columns (5) and (6), the independent variable of interest is also the damage ratio, but we use system GMM regressions. In columns (1), (3), and (5), we use the damage ratio calculated over a period of 60 days, and in columns (2), (4) and (6), we use the damage ratio calculated over a period of 180 days. P-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dependent variable: ΔE/TA (winsorized)	OLS Regressions				System GMM Regressions	
	(1) Damage Period: 60 Days	(2) Damage Period: 180 Days	(3) Damage Period: 60 Days	(4) Damage Period: 180 Days	(5) Damage Period: 60 Days	(6) Damage Period: 180 Days
Lagged Damage ratio	-0.015*	-0.011				
	(0.050)	(0.229)				
Damage ratio			-0.016***	-0.019***	-0.789**	-0.807**
			(0.010)	(0.008)	(0.016)	(0.037)
Lagged equity ratio	-0.222***	-0.222***			-0.725***	-0.689***
	(0.000)	(0.000)			(0.000)	(0.000)
Log (total assets)	-0.003***	-0.003***	0.000***	0.000***	-0.012***	-0.012***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Net loans ratio	-0.015***	-0.015***	-0.001	-0.001	-0.000	-0.002
	(0.000)	(0.000)	(0.235)	(0.235)	(0.977)	(0.833)
Customer deposits ratio	-0.059***	-0.059***	-0.005***	-0.005***	0.054***	0.046***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged net income to equity ratio	0.036***	0.036***	0.048***	0.048***	-0.362***	-0.332***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Real GDP growth rate	-0.004**	-0.004**	-0.004	-0.004	0.056***	0.052***
	(0.045)	(0.042)	(0.106)	(0.108)	(0.001)	(0.000)
Growth rate of credit to private sector	-0.016***	-0.016***	-0.021***	-0.021***	-0.062**	-0.046**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.040)	(0.032)
Log (real GDP per capita)	0.003**	0.003**	-0.000	-0.000	-0.032	-0.053
	(0.023)	(0.023)	(0.872)	(0.867)	(0.456)	(0.167)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Specialization FE	Yes	Yes	Yes	Yes	Yes	Yes
Accounting Standard FE	Yes	Yes	Yes	Yes	Yes	Yes
N	142,063	142,063	142,063	142,063	142,063	142,063
Adjusted R^2	0.217	0.217	0.034	0.034		
Hansen's p-value					0.360	0.148
Arelanno–Bond AR(1) p-value					0.000	0.000
Arelanno–Bond AR(2) p-value					0.557	0.086

Table 15: Economic significance

This table presents the results for a series of models in which we regress standardized changes in the equity ratio and tier 1 capital ratio of banks on the standardized damage ratio and other control variables over the 2000–2017 period for different subsamples of our dataset. The dependent variable in columns (1) to (3) is the change in the equity ratio (winsorized). The dependent variable in columns (4) to (6) is the change in the tier 1 capital ratio (winsorized). Columns (1), (4), and (7) report results for the US-only subsample; columns (2), (5), and (8) report results for the non-US subsample; and columns (3), (6), and (9) report results for the full sample. All variables are standardized. Robust p-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: ΔE/TA (winsorized)			Dependent variable: ΔT1R/TA (winsorized)		
	(1) US Only	(2) Non-US	(3) Full Sample	(4) US Only	(5) Non-US	(6) Full Sample
Lagged equity ratio	-0.832***	-0.510***	-0.607***			
	(0.000)	(0.000)	(0.000)			
Lagged tier 1 capital ratio				-0.668***	-0.552***	-0.605***
				(0.000)	(0.000)	(0.000)
Damage ratio	-0.096***	-0.003**	-0.004**	-0.049***	-0.000	-0.003
	(0.000)	(0.037)	(0.011)	(0.000)	(0.935)	(0.625)
Log (total assets)	-0.169***	-0.217***	-0.186***	-0.157***	-0.163***	-0.167***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Net loans ratio	-0.151***	-0.035***	-0.098***	-0.402***	-0.198***	-0.339***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Customer deposits ratio	-0.660***	-0.190***	-0.347***	-0.374***	-0.099***	-0.285***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged net income to equity ratio	0.110***	0.105***	0.128***	0.104***	0.072***	0.117***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Real GDP growth rate	0.091***	-0.001	-0.011***	0.072***	0.012	-0.010
	(0.000)	(0.714)	(0.047)	(0.000)	(0.181)	(0.287)
Growth rate of credit to private sector	-0.025***	-0.038***	-0.032***	-0.022***	-0.062***	-0.042***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log (real GDP per capita)	1.990***	0.152**	0.103**	1.831***	-0.110	-0.208***
	(0.000)	(0.016)	(0.022)	(0.000)	(0.177)	(0.000)
Country FE		Yes	Yes		Yes	Yes
Year FE		Yes	Yes		Yes	Yes
Specialization FE	Yes	Yes	Yes	Yes	Yes	Yes
Accounting standard FE	Yes	Yes	Yes	Yes	Yes	Yes
N	88,918	53,145	142,063	86,231	21,601	107,832
Adjusted R^2	0.316	0.154	0.217	0.238	0.265	0.177

Appendix 1: Absolute differences in total assets (ADTA) between Fitch and Bankscope

This table examines differences in observations between the two databases (Fitch and Bankscope) used in our paper. We match banks by name and then employ a variable that measures the absolute difference in total assets (ADTA) to compare each match, where $ADTA = |BTA - FTA|/BTA$, BTA is the value of total assets of a given bank in Bankscope, and FTA is the value of total assets of the same bank in Fitch. Matches whose ADTA exceed 0.1 are excluded from our sample. Column (1) reports the number of banks whose ADTAs fall within each range bracket. Column (2) shows the percentage distribution of our sample across the different brackets. Due to missing data for several of our dependent and independent variables, the total number of observations reported here (11,881) decreases to 9,928 in Table 1.

Range of ADTA	(1)	(2)
	Frequency	Percentage
0	9,803	82.51
0 – 0.0000001	723	6.09
0.0000001 – 0.000001	273	2.30
0.000001 – 0.00001	19	0.16
0.00001 – 0.0001	33	0.28
0.0001 – 0.001	76	0.64
0.001 – 0.01	168	1.41
0.01 – 0.1	468	3.94
0.1 +	318	2.68
Total	11,881	100

Appendix 2: Correlation between matched banking variables from Fitch and Bankscope

This table examines the correlation between various variables reported by Fitch and Bankscope for the year in which the two databases overlap (year 2013). Column (1) reports the Pearson correlation coefficients between the variable values in Fitch and the corresponding values in Bankscope. Column (2) reports the same correlations, except that variables are trimmed at the 1% and 99% level. Column (3) reports the mean percentage difference between the paired variables. Difference ratios are calculated as (the value in Bankscope – the value in Fitch)/the value in Bankscope. The variables we use in our paper (i.e., variables which exhibit a maximum difference of 10%) are bolded and highlighted in grey.

	(1)	(2)	(3)
Variable Name	Correlation	Trimmed correlation	Percentage of difference ratio > 0.1
Total Liabilities & Equity	1	0.9999	0.00%
Total Assets	**1**	**0.9999**	**0.00%**
Net Interest Revenue	1	0.9999	4.21%
Number of Branches	1	0.9996	0.81%
Deposits & Short-term Funding	0.9999	0.9997	1.29%
Fixed Assets	0.9999	0.9997	4.13%
Gross Loans	0.9999	0.9999	1.78%
Net Loans	**0.9999**	**0.9999**	**1.71%**
Number of Employees	0.9998	0.9999	1.30%
Total Customer Deposits	**0.9998**	**0.9997**	**0.81%**
Net Income	**0.9998**	**0.9981**	**5.62%**
Tier 1 Capital	**0.9997**	**0.9990**	**1.23%**
Intangibles	0.9997	0.9999	6.97%
Profit before Tax	0.9996	0.9990	5.52%
Derivatives	0.9996	0.9978	2.91%
Reserves for Impaired Loans/NPLs	0.9995	0.9967	6.54%
Loan Loss Reserves	0.9995	0.9965	8.90%
Total Earning Assets	0.9994	0.9994	2.04%
Impaired Loans	0.9991	0.9959	9.34%
Net Fees and Commissions	0.9990	0.9891	5.96%
Equity	**0.9987**	**0.9985**	**4.39%**
Long term Funding	0.9981	0.9894	14.27%
Loan Loss Reserves/Gross Loans	**0.9979**	**0.9957**	**7.94%**
Equity/Net Loans	0.9976	0.9915	4.95%
Equity/Total Assets	**0.9976**	**0.9954**	**4.18%**
Equity/Liabilities	0.9969	0.9920	5.48%
Tier 1 Capital Ratio	**0.9963**	**0.9952**	**1.38%**
Equity/Customer & Short Term Funding	0.9959	0.9806	5.29%
Net Loans/Total Assets	0.9957	0.9951	0.80%
Trading Liabilities	0.9949	0.9853	2.96%
Tax	0.9948	0.9990	6.14%
Dividend Paid	0.9917	0.9803	13.46%
Subordinated Debts	0.9878	0.9574	4.36%
Impaired Loans/Gross Loans	0.9792	0.9865	7.94%
Net Loans/Deposits & ST Funding	0.9765	0.9933	1.90%
Net Interest Revenue/Average Assets	0.9762	0.9955	2.77%
Impaired Loans/Equity	0.9755	0.9750	11.90%

Net Charge-Offs	0.9683	0.9801	6.14%
Dividend Pay-Out	0.9571	0.9507	14.04%
Unreserved Impaired Loans/Equity	0.9487	0.9712	14.62%
Other Deposits and Short-term Borrowings	0.9484	0.9554	8.78%
Non Interest Expenses/Average Assets	0.9416	0.8846	51.47%
Net Interest Margin	0.8854	0.9637	34.14%
Other Operating Income/Average Assets	0.8801	0.5014	95.67%
Loan Loss Reserves/Impaired Loans	0.8612	0.9341	8.98%
Deposits from Banks	0.8459	0.8468	17.75%
Loans and Advances to Banks	0.8446	0.7786	17.12%
Liquid Assets	0.8369	0.7956	93.69%
Other Operating Income	0.6763	0.6308	95.42%
Return On Average Assets (ROAA)	0.6539	0.9895	8.30%
Return On Average Equity (ROAE)	0.6366	0.9812	10.27%
Other Securities	0.6242	0.4288	56.47%
Liquid Assets/Deposits & ST Funding	0.5550	0.4393	93.93%
Loan Loss Reserves	0.5016	0.4697	97.81%
Other Earning Assets	0.4416	0.3688	99.35%
NCO/Average Gross Loans	0.2672	0.9779	13.43%
Interbank Ratio	0.0548	0.1847	22.31%

Appendix 3: Definitions and descriptions of variables

Name	Description	Sources
Equity ratio	Equity/total assets, winsorized at the 1.5% – 98.5% level	Bankscope & Fitch
Tier 1 capital ratio	Tier 1 capital/risk weighted assets, winsorized at the 1.5% – 98.5% level	Bankscope & Fitch
Damage ratio	Total damages caused by natural disasters in a given country in year *t*, distributed across year *t* and year *t+1* following equation (2) and divided by the gross domestic product (GDP) of each country.	EM-DAT international disaster database
Log (total assets)	Natural log of total assets, winsorized at the 1.5% – 98.5% level	Bankscope & Fitch
Net loans ratio	Net loans/total assets, winsorized at the 1.5% – 98.5% level	Bankscope & Fitch
Customer deposits ratio	Total customer deposits/total assets, winsorized at the 1.5% – 98.5% level	Bankscope & Fitch
Net income to equity ratio	Net income/equity, winsorized at the 1.5% – 98.5% level	Bankscope & Fitch
Real GDP growth rate	Annual growth of the real GDP of a given country	World Bank
Growth rate of credit to private sector	Annual growth of domestic credit to the private sector (expressed as a percentage of GDP) in a given country, winsorized at the 1.5% – 98.5% level	World Bank
Log (real GDP per capita)	Natural log of the real GDP per capita of a given country	World Bank
Year FE	Binary variables that take on a value of 1 if a given observation falls within a year from 2000 to 2017, 0 otherwise	Bankscope & Fitch
Country FE	Binary variables that take on a value of 1 if a bank operates in one of 149 countries, 0 otherwise	Bankscope & Fitch
Specialization FE	Binary variables that take on a value of 1 if a bank operates under one of seven business models/specializations (bank holding companies, commercial banks, cooperative banks, investment banks, Islamic banks, real estate and mortgage banks, and savings banks), 0 otherwise	Bankscope & Fitch
Accounting Standard FE	Binary variables that take on a value of 1 if a bank employs one of five accounting standards (IAS, IFRS, Local GAAP, Regulatory, and US GAAP) in a given year, 0 otherwise	Bankscope & Fitch