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Natural Disasters and Banking Stability

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Abstract: This paper aims to examine the impact of natural disasters on banking stability across different levels of economic development. Utilizing bank-level data from 1242 banks in 72 countries, combined with natural disaster data from the Center for Research on the Epidemiology of Disasters, we contribute to the literature in three ways. Firstly, we directly assess the influence of natural disasters on banking stability. Secondly, we focus on bank-level data instead of country-level data. Thirdly, we expand on existing research by using different thresholds for the total number of people affected to population ratio, surpassing the previously suggested threshold of 0.5%. Our panel regression analysis with banks and year-fixed effects reveals that natural disasters significantly affect bank stability, particularly in middle- and low-income countries. These effects are robust across alternative measures and estimations, leading to higher non-performing loans, lower return on assets, and decreased capital and return on equity ratios, indicating a negative impact on bank performance.

Keywords: natural disasters; banking stability; bank performance; financial development; climate

1. Introduction

Natural disasters possess a remarkable capacity to inflict tremendous losses on human lives and economies. According to the UNDRR's 2019 report, disasters associated with extensive risk accounted for 68.5% of all economic losses between 2005 and 2017. As these catastrophes strike, they can dramatically impact various sectors, including the financial industry. The banking sector, which plays a vital role in the economy and society by providing essential intermediation services, is not immune to the disruptive forces of natural disasters. Recognizing their potential influence on banking stability becomes imperative to ensure the sector's resilience and continued effectiveness.

Studies have consistently demonstrated the positive contribution of banking stability to the real economy, fostering increased certainty in the real output growth (Jokipii and Monnin 2013; Creel et al. 2015; Wang et al. 2019). However, the stability of the banking sector remains vulnerable to a variety of factors. For instance, financial liberalization (Detragiache and Demirgüç-Kunt 1998; Laeven and Valencia 2013), banking sector concentration (Boyd and De Nicoló 2005; Beck et al. 2006), and interest rate volatility (Calvo et al. 1993; Demirgüç-Kunt and Detragiache 1998) have been identified as determinants of banking stability. However, among these factors, the potential influence of natural disasters on banking stability remains relatively understudied.

Disasters can significantly impact the stability of the banking sector by increasing the share of non-performing loans or raising the likelihood of bank runs, particularly in the immediate aftermath of the events. Notably, large-scale natural disasters exert adverse effects on the financial sector within the affected regions. Consequently, banking regulators require banks to maintain adequate capital reserves and acknowledge the systematic environmental risks that pose threats to banking stability (Alexander 2014). The examination of the effect of natural disasters on financial stability has yielded inconclusive findings. Klomp (2014) stands as the pioneering study to directly explore this effect, revealing the significant impact of large-scale disasters on financial stability. However, only a handful

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of subsequent studies have followed Klomp (2014) which have investigated the relationship using different samples and methodological approaches (Noth and Schüwer 2018; Albuquerque and Rajhi 2019; Brei et al. 2019).

Therefore, in this article, we aim to answer the question of whether there is a direct impact of natural disasters on the stability of the banks. Moreover, natural disaster shocks may differ in high-income and low-income countries. It is expected that natural disasters have a relatively lower effect on high-income countries since they may have a strong infrastructure in place, good credit ratings that permit sovereign borrowing, and a developed insurance industry that helps alleviate losses. Therefore, we also aim to answer the question of whether the effect of natural disasters has a different impact on low-income countries.

To answer the research questions, we utilize the total number of people affected by disasters as a measure of the exogenous shock of natural disasters. Additionally, our main dependent variable is the distance-to-default measure, or Z-score, commonly used in the literature to measure the stability of banks. We find that, by using a fixed effects estimator, the natural disaster variable has a significantly negative impact on the Z-score bank values, especially in middle- and low-income countries. Furthermore, we perform different robustness tests to consider other situations. Due to the overrepresentation of banks from high-income countries, we split our sample into two groups: high-income countries and middle- and low-income countries. We produce different results that show that the impact is only significant for middle- and low-income economies. Additionally, we utilize a different binary variable of natural disasters, and the results support our main findings. Lastly, we employ additional measures for the stability of banks and find that natural disasters affect non-performing loans, return on assets ratios, and capital ratios.

Our research reveals that the stability of the banking sector is negatively impacted by natural disasters. To ensure a representative sample, we divided our data into two groups primarily due to the predominant representation of high-income countries, influenced by data availability. Additionally, this division allows us to examine potential variations in effects based on countries' income levels. Our results indicate that, within high-income countries, natural disasters do not exert a statistically significant impact on banking stability. However, in middle- and low-income countries, the effect is both significant and negative.

To ensure the robustness of our findings, we employed alternative measures to test the relationship. Specifically, we utilized a binary variable based on McDermott et al.'s (2014) disaster variable, but with different thresholds. The results corroborated our primary variable's findings, demonstrating similar effects. Additionally, our findings indicate that for natural disasters to affect banking stability, the threshold of the affected population to the total population needs to be at least 5%.

Furthermore, we explore additional indicators of banks' performance. Our analysis revealed that natural disasters lead to a decrease in the return on assets, capitalization, and return on equity ratios, while increasing the percentage of non-performing loans. These effects were particularly significant in middle- and low-income countries.

This study contributes to the existing literature in three ways. First, it examines the direct impact of natural disasters on banking stability. The previous literature studying the same effect of natural disasters on banks has focused only on large-scale disasters in terms of the total damage caused by the events (Klomp 2014). Thus, our study expands this scope by including more disasters and using the total number of people affected as a main proxy for natural disasters, as the total cost of disasters can be manipulated or miscalculated (Noy 2009; Keerthiratne and Tol 2017). While total monetary damages directly measure the financial losses caused by natural disasters, they may not capture the full extent of their impact on the banking sector. The total monetary damage may be gathered by inexperienced individuals who attend to the affected areas to provide medical assistance; therefore, they may lack the expertise to evaluate the economic losses correctly, especially in poorer countries (Noy 2009; McDermott et al. 2014; Keerthiratne and Tol 2017). Though both measures of natural disasters may have a similar limitation when it comes to the accuracy of reported data, the total number of people affected is a more straightforward measure even for low-income countries, as they can still estimate the number of people affected with surveys, census or population data, and reports from relief agencies. In addition, natural disasters can have indirect financial consequences, such as increased loan defaults, higher credit risk, reduced economic growth, and increased operational costs for banks. These indirect effects may not be fully reflected in the monetary damages alone. By considering the number of people affected, we are accounting for the broader socioeconomic impact, which can indirectly influence the stability of the banking sector. Therefore, the total number of people affected is more suitable for this study as it reflects the scale of social and economic disruptions caused by natural disasters. When a large number of people are affected, it indicates significant disruptions in various sectors, including housing, transportation, healthcare, education, and commerce. Such disruptions can have knock-on effects on the stability and functioning of the banking sector. For example, if a substantial portion of the population is displaced or faces financial hardships due to a disaster, it may lead to increased loan provisions, reduced consumer spending, and a decline in economic activity, all of which can affect the stability of banks.

Second, this article provides bank-level evidence of the effect of natural disasters on banking stability. Most natural disaster studies use country-level data (Noy 2009; McDermott et al. 2014; Klomp 2014; Keerthiratne and Tol 2017; Albuquerque and Rajhi 2019). Though the use of macro-level variables can be expected when studying the effect on the economy, it is imperative to examine the bank-level variations and the impact on banks directly. Bank-level data allows for analysis of disaster effects on individual banks' stability indicators, like non-performing loans, profitability, and liquidity ratios, which provides more nuanced evidence than aggregate system-wide data. It allows for an assessment of risk management practices and preparedness measures implemented by individual banks in response to natural disasters. Keerthiratne and Tol (2017) suggest that using micro-level data to study the effect of natural disasters can be more helpful, as macro-level data are open to misinterpretation, which may disguise the actual mechanisms. Therefore, bank-level data helps to isolate variations in banking stability arising from (unobserved) heterogeneity of banks and ensures that individual banks' reactions to natural disasters are not confounded by aggregate variation in the stability of the banking sector (Skidmore 2001; Kellenberg and Mobarak 2008; Fosu 2014).

Finally, we contribute to the literature by introducing a new threshold that determines the natural disasters magnitude that affect banks' stability. McDermott et al. (2014) have constructed a binary variable of natural disasters where the threshold of the total people affected to the population is 0.5%. However, as the threshold is somewhat arbitrary, we expand our scope by testing different thresholds. In particular, we test for different thresholds of the ratio of total number of people affected to the total population, namely 0.5%, 1%, 2.5%, 5%, 7%, and 10%. By setting a threshold based on the share of the population affected by disasters, we provide a clear criterion for determining when natural disasters are considered to have a significant impact on the banking stability. This threshold can help identify situations where the severity or scale of the disaster is substantial enough to potentially affect the stability of the banking sector. It allows for a more nuanced analysis by distinguishing between low-impact and high-impact events. Additionally, it can help policymakers and stakeholders identify critical thresholds at which interventions and policy responses may be necessary to safeguard banking stability.

The remainder of this paper consists of eleven sections. In Sections 2 and 3, we present the literature review and the primary studies that have examined the relationship between natural disasters and banking stability. Sections 4–7 show the data we use in this study, while Section 8 outlines the methodology. Section 9 then presents the results, main findings, and discussion. Finally, Section 11 offers our conclusion and a discussion of our recommendations and limitations.

2. Literature Review

Various factors play essential roles in increasing the banking sector's fragility. For example, financial liberalization can cause markets to become more unstable, and banking crises occur more frequently in liberalized economies. However, a robust institutional environment can limit the adverse effects of liberalization on the financial system (Detragiache and Demirgüç-Kunt 1998). Likewise, Ranciere et al. (2006) find that financial liberalization leads to financial instability and crises; however, they argue that financial liberalization is also beneficial for faster average long-run growth. Additionally, Laeven and Valencia (2013) highlight recent data showing that costly banking crises occur in advanced economies and not only in emerging economies. A possible explanation is that financial deregulation or innovation has led to increased financial fragility in developed economies.

Moreover, numerous studies have examined the effects of bank concentration and competition on financial stability. For example, Boyd and De Nicoló (2005) assert that concentrated banking systems increase bank market power and interest rates, which may lead firms to take additional risks as a result. Thus, they argue that there is a positive relationship between concentration and banks' fragility. Similarly, Caminal and Matutes (2002) argue that while there is no clear relationship between bank concentration and exposure to risks, a lack of competition may result in less credit rationing, larger loans, and an increased likelihood of failure. In contrast to the above findings, Beck et al. (2006) suggest that relatively concentrated banking systems are less prone to banking crises after controlling for different regulatory policies and macroeconomic conditions. Their analyses indicate that bank concentration tends to reduce banking fragility.

Furthermore, central banks determine the interest rates in the economy, which has serious consequences for banks. For instance, if banks are unable to increase their lending rates quickly, they can be negatively affected by high interest rates (Demirgüç-Kunt and Detragiache 1998). Moreover, Calvo et al. (1993) argue that the volatility of interest rates plays a vital role in capital flows, which impacts the financial industry's stability. Similarly, Frankel (1999, cited in Klomp 2014) states that the increased capital flows since 1990 have led to the financial sector's vulnerability and financial crises.

Nevertheless, an increased lending rate for banks is not always beneficial. In recent studies, the effect of having increased finance in the economy has been proven to harm economic growth. For example, Arcand et al. (2015) and Law and Singh (2014) argue that financial deepening can be beneficial up to a certain threshold; beyond this threshold, however, increased finance hurts the economy. However, the income level of countries is a crucial factor, as Beck et al. (2014) find that increased finance in high-income countries increases volatility over the short- and medium terms. Similarly, Berger et al. (2019) argue that a bank's liquidity creation level is associated with financial crises and negative financial stability. They also differentiate between Islamic and commercial banks to find that the latter's liquidity creation negatively affects financial stability in high-income countries, while the former's liquidity creation promotes financial stability in low-income countries. Furthermore, it is important to note that conventional and Islamic banks can have very different risk profiles, impacting their resilience to natural disasters. Albaity et al. (2019) and Bilgin et al. (2021) highlight potential differences in risk and resilience between conventional and Islamic banks, emphasizing the need for further exploration in this area.

The abovementioned factors that might affect banks' stability have been well-studied in the literature. However, a potential exogenous factor that may influence the banking sector's stability is natural disasters. Natural disasters result in a tremendous loss not only in terms of human lives but also to the economy. There are around 350 million people affected by natural disasters each year, which can affect a country's plans for development, especially for poorer nations (United Nations 2019). Furthermore, the economic damage from disasters can be catastrophic; in the past three decades, the estimated damages from natural disasters have been over USD 2 trillion (Klomp 2014). Additionally, 68.5% of all economic losses over the period from 2005 to 2017 were caused by disasters associated with extensive risk (UNDRR 2019). Lastly, according to Alexander (2014), natural disasters can significantly increase the instability of banks unless sufficient precautions are taken, and they argue that banking regulations must recognize systemic environmental risks because they pose a potential threat to banking stability.

The literature on the effect of natural disasters on the economy has been growing in the past two decades (Klomp and Valckx 2014). One of the first attempts to empirically examine the impact was made by Albala-Bertrand (1993). In this study, he discusses the pre- and post-disaster effects using data from 28 disasters in 26 countries during 1960–1979. The results show that the GDP, capital formation, and agricultural output increased, while there was no effect on inflation and exchange rates. However, Skidmore and Toya (2002) argue that the short-term increase in the GDP is due to how disasters destroy the capital stock, and the capital stock is not measured in the GDP. Therefore, replacing them with investing in disaster mitigation and recovery efforts increases the GDP in the periods immediately following the disasters. Consequently, they extend their study to measure the long-term impact of disasters on economic growth. Their cross-country analysis for the period of 1960–1990 shows that higher frequencies of natural disasters positively affect human capital accumulation, total factor productivity, and economic growth.

Moreover, further research has been carried out to investigate the effect by examining the differences between developed and developing countries. Raddatz (2007) argues that external shocks, including natural disasters, have an adverse short-term impact on the GDP of low-income countries. However, the results suggest that other internal factors play an essential role in the economic instability experienced by these countries. This claim is supported by Noy's (2009) findings, through which they conclude that developing countries are more vulnerable to disasters. In particular, Noy (2009) finds that developing countries face much larger shocks to their macro economies than developed economies for relatively similar disaster magnitudes. Additionally, while the effects of natural disasters hurt the GDP per capita for developing countries in the short term, the growth returns to its original path in the long term (Klomp and Valckx 2014). However, natural disaster events do not necessarily have a damaging effect on the economy of all developing countries. Cavallo et al. (2013) state that there must be a radical political revolution that severely affects the institutional organization of society for a disaster to harm the growth of the countries in their sample. Therefore, they argue that disasters have no significant effect on economic growth unless they are combined with political distress. In addition, according to Felbermayr and Gröschl (2014), the empirical literature does not provide conclusive evidence of the effects of natural disasters on the economy because most studies use disaster data from insurance company records or news stories. In response, the authors build a comprehensive database of disaster events from primary geophysical and meteorological information instead. They have found a significant and negative impact of natural disasters on growth; more specifically, low-income countries are more affected by geophysical disasters and high-income countries are more affected by meteorological events.

Furthermore, it is expected that disasters both affect the abilities of individuals and small firms to pay back loans and sharply increase the cash demand to cover unexpected losses, especially in developing countries. As Alexander (2014) shows, natural disasters can then lead to the instability of the banking sector, as they increase the share of non-performing loans and bank runs. Therefore, banks can become insolvent following a catastrophe as a result of one of the following mechanisms: bank run or immediate withdrawals to replace losses, excessive provisions for loan losses, and increased borrowing demand and lower creditworthiness (Do et al. 2023).

An early attempt to examine the effects of disasters on banks' liquidity was made by Steindl and Weinrobe (1983). They study the deposit experiences of individual savings, loan associations, and commercial banks in the US following a sizable natural disaster. Their findings suggest no evidence of significant changes or bank runs; conversely, there is a substantial increase in deposits. They believe that the rise in deposits can be explained by different factors, such as direct government support to facilitate the issues arising from disasters, insurance claims, or individual deposits to insure themselves against any further disruption. Similarly, Skidmore (2001) examines the savings behaviors in cases of natural catastrophes, and he finds that there is an increase in savings rates in cases where the chances of natural disasters are higher. He argues that households tend to self-insure against catastrophic events, especially when insurance claims and government policies do not provide enough protection against possible losses. Ultimately, he argues that natural disasters increase household saving rates. Additionally, Skoufias (2003) argues that many of the informal mechanisms to cope with risk become less effective during economic crises and natural disasters, which leads households to rely on self-insurance strategies. However, these strategies would be costly in terms of current as well as future welfare. Similarly, a recent study using contemporary data was made by Chamberlain et al. (2019) to examine the impact of natural disasters on bank liquidity. They find that banks face a significant decline in deposits following a disaster, which can affect the supply of funds available to support loan growth.

Natural disasters can also affect the banking sector in terms of loans and access to credit. Collier et al. (2011) survey the effect of El Niño events on microfinance institutions in Northern Peru, where they face severe flooding disasters. They have found that the events significantly increased the proportion of restructured loans by 3.6% of the total value of the loan portfolio. Moreover, Berg and Schrader (2012) analyzed the impact of natural disaster events in Ecuador on loan demand and access to credit. They find that, during the period following a disaster, the demand for loans increases. However, there is a considerable decrease in the probability for individual clients to be approved for a loan. In addition, Yang (2008) argues that there is a decline in commercial lending after disasters, which can be explained by declines in rates of return or increased risk perceptions on the part of international lenders and investors. Furthermore, Dafermos et al. (2018) analyze the effect of climate change on financial stability using global data and simulations conducted for the period 2016–2120. They argue that due to climate change events, the liquidity and profitability of firms would decrease. As a result, the default rate of corporate loans would increase, which can harm the stability of the banking system. Moreover, catastrophic events might affect credit expansion, which would aggravate the adverse impact of disasters on the economy.

Therefore, Dal Maso et al. (2022) argue that banks need to recognize natural disaster risk, and one of the effective ways for banks to do that is to enhance their credit risk management through loan loss provisions. They claim that a higher level of loan loss provisions is required by banks in the current period to build reserves in anticipation of future write-offs. Moreover, they empirically demonstrate that natural disasters positively affect loan loss provisions, with a one standard deviation change in disaster risk resulting in a 5.4% to 7% increase in loan loss provisions, resulting in a 1.2% to 1.6% reduction in earnings. Likewise, Lambert et al. (2012) study how banks react to natural disasters by comparing banks in affected locations to other banks. They find that loan loss provisions for banks in locations affected by natural disasters increased sharply following disaster events in comparison to unaffected banks.

Similarly, Chamberlain et al. (2019) argue that banks need to have more conservative policies when it comes to loan loss provisions, especially in regions that are more vulnerable to natural disasters. They find that, in the period preceding disasters, banks that make prudent or timely provisioning decisions can respond more quickly to the new loan demands that are created by disasters and experience greater growth in their loan portfolios. Furthermore, Do et al. (2023) state that banks become vulnerable when disasters occur due to the volatility of total deposits and liquidity and that banks are prone to increased provisions of loan loss which may lead to loss of their competitiveness. However, they strongly suggest that appropriate loan loss provision levels prior to disasters help mitigate climate risks without impairing capital during disasters.

One of the first attempts to directly study the effect of natural disasters on bank stability was developed by Klomp (2014). He uses data consisting of 170 natural disasters in 160 countries from 1997 to 2010. The findings suggest that large-scale disasters increase the likelihood of bank defaults and adversely affect financial stability, especially geophysical and meteorological disasters due to their high damage costs. Additionally, Klomp (2014) argues that while natural disasters may be a substantial threat to liquidity, there is no evidence of their impact on the solvency of the banking sector. However, in contrast to Klomp (2014), Noth and Schüwer (2018) have found that disasters have a significant negative impact on banks in the US. They use a sample of more than 6000 banks in the US from 1994 to 2012 and prove that natural disasters result in a reduction in banks' Z-score values and other performance ratios. Moreover, Albuquerque and Rajhi (2019) have examined the effect of natural disasters and state fragility on banking stability. They use a sample of 66 developing countries from 1995 to 2011, finding that the effects of natural disasters are temporary and detrimental only to non-performing loans. Similarly, Brei et al. (2019) test this same relationship by using a sample of seven Eastern Caribbean countries throughout 2001–2012. They have found that there is a decrease in deposits after disasters, which results in a reduction in credit and other investments by banks. Furthermore, they note that disasters lower the Z-scores, which they assume is due to the relatively lower bank profitability.

Therefore, based on the literature presented in this section, it is clear that there is a demanding gap in the natural disasters and banking stability literature, which we aim to fulfil by testing the research hypotheses addressed in the next section.

3. Research Hypotheses

Based on the literature review, it is clear that natural disasters have different effects on the economy and financial sector, and these effects differ depending on the development level of countries. Hence, we discuss the relative literature to build our four research hypotheses for this study.

Natural disasters cause massive losses to the economy and, more importantly, to human lives. The natural disaster literature has shown differing results regarding the effect of these disasters on the economy both before and after the events themselves. Scholars argue that when disasters happen in a country, there is an increase in the economic output immediately after the event due to the increase in mitigation and recovery investment (Albala-Bertrand 1993; Skidmore and Toya 2002). In contrast, more recent studies argue that disasters harm the economy, especially in the periods immediately after the event (Noy 2009; Klomp and Valckx 2014; Felbermayr and Gröschl 2014). Therefore, natural disasters have a direct impact on the economy, which in turn would have some effect on the banking sector and the profitability of firms in general. In the case of a major disaster, there would be an effect on local firms and households, which would increase the probability of corporate loan defaults (Dafermos et al. 2018). This can then affect the stability of the banking sector, as it threatens the liquidity of banks and increases the likelihood of bank defaults (Klomp 2014; Noth and Schüwer 2018; Brei et al. 2019). Thus, we test for the following hypotheses:

H_1: *Natural disasters have a significant negative impact on the Z-scores of banks.*

H_2: *Natural disasters increase the shares of non-performing loans.*

Moreover, natural disasters affect the bank's performance. Even though it is assumed that natural disasters increase banks deposits (e.g., Steindl and Weinrobe 1983; Skidmore 2001), there is some evidence suggesting that disasters lead to an increase in the non-performing loans, thereby harming the profitability of banks and potentially leading to bank runs (Alexander 2014). Additionally, large-scale disasters cause massive losses to firms and individuals, which increases the demand for credit. However, due to the decline in rates of return or increased risk, access to credit declines (Yang 2008). Consequently, banks face adverse selection issues, which can affect bank performance. Thus, we test for the following hypothesis:

H_3: *There is a significant effect of natural disasters on banks' return on assets ratio (ROA).*

4. Data

In this study, we utilize DataStream as a primary source of banks' data. We use a panel dataset from 1999 to 2018 for 1242 banks. The study focuses on bank-level data to measure the effect of natural disasters on banks' stability. Hence, our sample comprises 19,733 bank-year observations, which is all the available banks' data on DataStream for the countries with natural disaster data. There are other country-level factors to be considered in the study, since the banks come from countries with different levels of economic development. The number of countries represented in the sample is 72, where the majority of the sample, 67% of banks, belong to high-income economies due to the availability of the data. The United States banks represent the vast majority of the sample, with 41% (513 banks) of the total number of banks. Additionally, Japan and China come after the United States in terms of the number of banks, with 7% (83 banks) and 3% (37 banks) of the total number of banks, respectively. The rest of the sample countries represent between 0.08% to 2.72%. This type of distribution is common in the banking literature (Mollah and Liljeblom 2016). However, we try to overcome this issue by splitting the sample into different categories so that the results are not only driven by those countries. The full distribution of banks among countries is available in Table 1.

Table 1. Country distribution.

Number	Country	Number of Banks	Percent	Number	Country	Number of Banks	Percent
1	Argentina	7	0.56	37	Korea (the Republic of)	9	0.72
2	Australia	8	0.64	38	Lebanon	6	0.48
3	Austria	7	0.56	39	Malawi	4	0.32
4	Bangladesh	28	2.25	40	Malaysia	10	0.8
5	Belgium	2	0.16	41	Mexico	4	0.32
6	Bolivia (Plurinational State of)	2	0.16	42	Morocco	6	0.48
7	Bosnia and Herzegovina	9	0.72	43	Netherlands	4	0.32
8	Botswana	3	0.24	44	Nigeria	12	0.96
9	Brazil	18	1.44	45	Norway	23	1.85
10	Bulgaria	4	0.32	46	Oman	6	0.48
11	Canada	9	0.72	47	Pakistan	20	1.61
12	Chile	5	0.4	48	Peru	7	0.56
13	China	36	2.89	49	Philippines (the)	16	1.28
14	Colombia	8	0.64	50	Poland	12	0.96
15	Costa Rica	2	0.16	51	Portugal	1	0.08
16	Croatia	8	0.64	52	Romania	1	0.08
17	Cyprus	2	0.16	53	Russian Federation (the)	17	1.36
18	Czech Republic (the)	2	0.16	54	Saudi Arabia	11	0.88
19	Denmark	19	1.52	55	Serbia	2	0.16
20	Ecuador	4	0.32	56	Singapore	3	0.24
21	Egypt	12	0.96	57	Slovakia	3	0.24
22	Estonia	1	0.08	58	South Africa	8	0.64
23	France	18	1.44	59	Spain	8	0.64
24	Germany	10	0.8	60	Sri Lanka	13	1.04
25	Ghana	6	0.48	61	Sweden	4	0.32
26	Greece	6	0.48	62	Taiwan	19	1.52
27	Hong Kong	7	0.56	63	Tanzania, United Republic of	4	0.32
28	Hungary	1	0.08	64	Thailand	11	0.88
29	India	33	2.65	65	Turkey	13	1.04
30	Indonesia	34	2.73	66	Uganda	2	0.16
31	Ireland	3	0.24	67	Ukraine	7	0.56
32	Israel	8	0.64	68	United Kingdom of Great Britain and Northern Ireland (the)	13	1.04
33	Italy	14	1.12	69	United States of America (the)	513	41.17
34	Japan	83	6.66	70	Venezuela (Bolivarian Republic of)	6	0.48
35	Jordan	11	0.88	71	Vietnam	8	0.64
36	Kazakhstan	7	0.56	72	Zambia	3	0.24
					Total	1246	100

The data on natural disasters are gathered from the International Disaster Database, EM-DAT, provided by the Centre for Research on the Epidemiology of Disasters (CRED) at the Université Catholique de Louvain in Brussels, Belgium (EM-DAT 2020). The database is gathered from various sources, including UN agencies, non-governmental organizations, insurance companies, research institutions, and press agencies. The EM-DAT database contains essential data on natural disasters and the occurrences and effects of more than

14,000 events from 1900 to 2020 worldwide. Moreover, at least one of the following criteria must be fulfilled for a disaster to be entered into the EM-DAT database: (1) 10 or more people reported killed; (2) 100 people reported affected; (3) declaration of a state of emergency; (4) call for international assistance. However, according to Cavallo et al. (2013) and Noy (2009), these requirements are quite low, which increases the number of small disasters in the sample. Still, the EM-DAT database has been used the most in recent investigations on the effect of natural disasters (Yang 2008; Gassebner et al. 2010; Klomp 2014; Miao and Popp 2014; Keerthiratne and Tol 2017).

For the period of this study, from 1999 to 2018, the database contains data on about 8000 natural disaster events that have occurred in 215 countries. However, due to the availability of banks' data on DataStream, the natural disaster sample for this study contains information about 4935 disaster events that have occurred in the 72 countries from 1999 to 2018 that have affected at least one person.

EM-DAT categories natural disasters into sub-groups, namely geophysical, meteorological, hydrological, climatological, biological, and extraterrestrial disasters, and each sub-group has different types and sub-types of the event. However, this paper excludes biological disasters, as their economic effects differ systematically from other natural disasters (Gassebner et al. 2010). Hydrological and meteorological disasters are the most common natural disasters, with 46.22% and 37.37% of total disaster events, respectively. Even though hydrological and meteorological disasters are more likely to occur, they do not affect as many people as climatological disasters or cause as many deaths as geophysical hazards. Additionally, the impact of disasters differs among regions. Asia has more people affected by disasters than the global average in the sample, followed by Africa and both Americas. Although Europe has a meagre average of people affected by disasters, the average of total deaths from disasters is higher than the sample average and higher than the average of Africa, the Americas, and Oceania combined. Details of the distribution of disasters among continents are in Table 2. The high number of people affected in Asia specifically could be explained by the population density in the region and the sizeable geographical landscape. Therefore, we can assume that the location and the magnitude of natural disaster events have some randomness associated with them.

Table 2. Natural disasters' distribution.

	Total Number of People Affected		**Total Number of Deaths**	
Continent	**Mean**	**Freq.**	**Mean**	**Freq.**
Africa	259,025.14	273	32.04	199
Americas	230,078.02	896	65.01	845
Asia	1,670,903.00	2060	308.12	1980
Europe	28,083.80	487	253.22	576
Oceania	5473.33	81	16.94	49
Total	983,156.23	3797	224.19	3649

5. Measures for Dependent Variables

The primary dependent variable for this study is the Z-score values of banks. The Z-score is a commonly used measure of banks' stability as it accounts for a bank's probability of insolvency (Lepetit and Strobel 2013). The Z-score measure captures the distance to a default of banks. A higher Z-score indicates a lower likelihood of a bank failing, as it has enough capital to withstand adverse shocks. Low Z-score values suggest undercapitalized, risky banks. In addition, a Z-score value of 0 means a bank is insolvent, and the Z-score measures the number of standard deviations ROA needs to fall to wipe out all bank capital. According to Laeven and Levine (2009), insolvency is the state where losses overcome equity ($E < -\pi$), where E is equity and π is profits. Therefore, insolvency can be expressed as the probability of ($-ROA < CAR$), where ROA ($=\pi/A$) is the return on assets and CAR ($=E/A$) is the capital assets ratio. Thus, the Z-score can be measured by the following equation:

$$Z_{i,t} = \frac{(ROA_{i,t} + CAR_{i,t})}{\sigma(ROA_i)} \quad (1)$$

where σ (ROA) is the standard deviation of ROA for bank i.

Moreover, to test the robustness of our estimations, we introduce other measures of banks' stability as dependent variables. We use return on assets (ROA) as a proxy for the banks' performance and profitability. The ROA measure is widely used in the literature to evaluate the performance of banks (Mollah and Liljeblom 2016). Return on assets measures how well a bank uses its assets to generate profits. Higher ROAs indicate more efficient asset use. Therefore, the annual ROA values are collected from DataStream for all banks in the sample. In addition, we test the impact of natural disasters on the non-performing loan ratio (NPL). We aim to identify if the disaster events increase the ratio of loan repayment defaults and, therefore, increase the instability of banks. Finally, we include the capital ratio (Cap ratio) of banks as our dependent variable as a robustness check. Capital ratio is a key measure of banks' financial strength and their ability to absorb losses during catastrophes; hence, we examine how natural disasters affect the capital ratio of banks.

6. Measures for Independent Variables

The primary independent variable is natural disasters. The EM-DAT provides data on natural disasters based on the total monetary damages, number total of deaths, and the total number of people affected (injured, became homeless, displaced, or otherwise affected) by the disasters.

The total monetary damage may be gathered by inexperienced individuals who attend to the affected areas to assist; also, some developing countries may inflate the reported damages to receive higher support from international organizations and governments (Noy 2009; Keerthiratne and Tol 2017; McDermott et al. 2014). Additionally, the total number of deaths does not measure the effect of natural disasters directly, as many disasters may not kill any individuals, especially in wealthier countries, which would create a selection bias in the data (Gassebner et al. 2010; McDermott et al. 2014). Therefore, in this study, the total number of people affected is the primary indicator of the impact of natural disasters.

The effects of disasters, in terms of the number of people killed or affected, depend on other factors, such as socioeconomic status, which may lead to endogeneity in the models (Kellenberg and Mobarak 2008). Therefore, McDermott et al. (2014) construct a binary variable of disasters where it takes a value of one if the ratio of people affected by a disaster to the population exceeds the 0.5% threshold. However, they acknowledge that using a binary variable reduces the variation in the data and the explanatory power of the data. Nevertheless, using a binary variable would equalize more minor disasters affecting fewer people and large-scale disasters involving hundreds of thousands of people. However, the binary variable is used in this analysis as a robustness test. Also, we test different thresholds to examine the effect of large disasters on high-income and middle- and low-income economies.

Therefore, a continuous measure of the number of people affected is employed for this study. However, to avoid the differences in population density in some regions, as we can see from Table 2, we follow Noy (2009) and Keerthiratne and Tol (2017) by taking the percentage of people affected to the population, using the population of the year before the disasters' events, as the current year's population has been affected by the disaster already (Dis%).

7. Measures for Control Variables

To improve the model, we use the control variables employed by previous studies in the banking stability literature. The variables are utilized to control for bank-specific characteristics, macroeconomic indicators, and financial development variables.

Adverse shocks affect financial stability by affecting the solvency of borrowers; also, there are differences in the level of development among countries. Therefore, we control for that notion by employing GDP per capita using the World Development Indicators database. It helps to account for cross-country differences in development levels and productivity. GDP per capita measures the average income per person in a country and helps to control for differences in economic development. Additionally, the level of financial development plays a vital role in the financial stability (Loayza and Ranciere 2006). Well-developed financial systems channel more credit to productive uses and support economic growth. Thus, private credit to GDP (credit) is used to account for the country's financial development level. Credit to GDP measures financial development and it is commonly used in the literature (Rewilak 2013).

Furthermore, Cavallo et al. (2013) argue that natural disasters only affect financial development or economic growth if there is political turmoil. Similarly, Demirgüç-Kunt and Detragiache (1998) state that financial fragility is positively related to weaker institutions. Moreover, political institutions are vital in the mitigation process after disasters occur. To capture the different country effects that might affect banking stability, we construct a binary variable that takes a value of 1 if a significant event happens in the relative country during that year. Major events comprise different political and economic factors. Political factors include civil wars (Marshall 2019) and coups (Elzinga-Marshall and Elzinga-Marshall 2019). In addition, the country effect variable takes a value of 1 if a country faces a banking crisis, liquidity crisis, or sovereign debt crisis that year; the crisis data are provided by Laeven and Valencia (2020). We name the binary variable (country effect) for simplicity.

Moreover, some developing countries receive financial assistance from different countries or organizations, especially during crises. Financial aid can be crucial for the banking sector's stability since it can help maintain certain aspects of economic development, enhancing banking stability by reducing credit risk. Thus, we control for that by including the percentage of the official development assistance (ODA) to gross national income (GNI). Official development assistance (ODA) consists of grants or loans to developing countries, from both bilateral and multilateral sources, that are undertaken by the official sector to promote economic development and welfare.

One of the main risks that banks face is liquidity risk; therefore, we include a binary variable of whether a country has deposit insurance as it prevents bank runs and ensures stability (Diamond and Dybvig 1983). Additionally, banking sector concentration affects the banking sector fragility (Beck et al. 2006). High concentration may hinder competition but also facilitate risk monitoring in banking. Trade-offs exist between concentration and stability. The data are collected from the financial development and structure dataset (Beck et al. 2019).

Finally, our data comprise mainly bank-level data, and, therefore, we need to control for bank-specific factors commonly used in the stability literature. For example, we control for capital adequacy by including the capital ratio (cap ratio). The capital adequacy ratio aims to protect depositors by ensuring banks have sufficient capital buffers. Also, we control for asset quality by looking into the non-performing loans (NPLs), as high NPLs erode bank capital and signify weak underwriting and risk management practices. Sustainable NPLs are important for banking system stability. In addition, we count for management quality via the cost-to-income ratio (cost–income), as this ratio benchmarks a bank's operational efficiency, and lower ratios indicate greater efficiency. Finally, we control for profitability by using the return on assets ratio (ROA), and bank size by including total assets (assets). Larger banks may benefit from economies of scale but also pose greater systemic risk. All the variable definitions, sources, and how they are calculated are presented in Table 3.

Table 3. Variable definitions and sources.

Variable Name	Definition	Source
Z-score	A measure of bank solvency calculated based on return on assets, equity/assets ratio, and standard deviation of return on assets. $Z_{i,t} = \frac{(ROA_{i,t}+CAR_{i,t})}{\sigma(ROA_i)}$	DataStream
Dis%	Percentage of the total number of people affected by disasters to total population.	(EM-DAT 2020)
ROA	Return on assets, measured as net income divided by total assets. Indicates bank profitability.	DataStream
Cap ratio	Capital ratio, measured as equity divided by total assets. Indicates bank capital adequacy.	DataStream
Ln (Assets)	Natural log of total assets. Used to control for bank size.	DataStream
Ln (NPL)	Natural log of ratio of nonperforming loans to total loans. Indicates asset quality.	DataStream
Ln (Cost–income)	Natural log of ratio of total costs to total income. Indicates operational efficiency.	DataStream
Ln (GDP)	Natural log of gross domestic product per capita. Controls for macroeconomic environment.	World Development Indicators database
Concentration	Asset concentration ratio of the 3 largest banks as a share of assets of all commercial banks. Indicates market structure.	Financial development and structure dataset (Beck et al. 2019)
Ln (Credit)	Natural log of domestic credit provided by financial sector as % of GDP. Indicates financial depth.	World Development Indicators database
Deposit Insurance	Dummy variable for existence of explicit deposit insurance scheme	Financial development and financial structure dataset (Beck et al. 2019)
Country effect	Dummy variables for each country. Control for unobserved heterogeneity. It takes a value of 1 if a country faced systematic risks, such as financial crises or political instability.	(Marshall 2019; Elzinga-Marshall and Elzinga-Marshall 2019; Laeven and Valencia 2020)
ODA	Comprises disbursement of concessional finance from both bilateral and multilateral sources. Received as % of GNI. Indicates reliance on foreign aid flows.	World Development Indicators database

Table 4 presents the descriptive statistics of the main and control variables. Due to the availability of data, there is inconsistency in the number of observations for different variables. The total number affected variable shows the number of people affected by disasters during a year. It offers huge variations ranging from 1 to 347 million people affected by disasters in a single year, which happened in India in 2015. Moreover, our main dependent variable, the percentage of the total number of people affected by the total population, shows similar variation from a very small percentage to about 45% of the population—however, most of the sample experienced disasters that affected a small portion of their population, as expected. In addition, the top 1% of the observations come from different geographical locations and development levels. For example, Malawi experienced disasters in 2015 and 2005 that affected about 45% and 41% of its population, respectively. Also, South Africa faced events in 2004 that affected 32% of the population, India faced events in 2004 that affected around 32% of the population, and the United States faced events in 2016 that affected about 27% of its population. This shows that even though disasters might occur more frequently in some areas of the world, when and where they occur and the magnitude of the events have some randomness associated with them.

Table 4. Descriptive statistics.

Variable	Observations	Mean	Std. Dev.	Min	Max
Total affected	9029	7,486,101	30,367,493	1.00	346,600,000 *
Dis%	9029	0.02	0.05	0.00	0.32
Z-score	9029	50.27	38.75	−0.31	244.87
Ln(Z-score)	9029	0.38	0.23	0.00	1.24
ROA	9029	1.25	1.07	−14.80	44.48
Cap ratio	9029	0.16	0.09	−0.04	0.98
Ln (Assets)	9029	15.23	2.10	10.70	22.13
Ln (NPL)	9029	10.39	2.78	0.00	20.17
Ln (Cost–income)	9029	1.47	0.80	−0.83	8.14
Ln (GDP)	9029	10.10	1.22	6.09	11.13
Interest rates	9029	0.04	0.05	0.00	0.67
Concentration	9029	0.38	0.14	0.21	1.00
Ln (Credit)	9029	4.03	0.43	2.31	5.25
ODA	9029	0.00	0.00	0	0.07

* The maximum number of people affected occurred in India in 2015, as India experienced a drought that affected more than 346 million people that year.

The primary dependent variable in this study is Z-scores. The values of Z-score of banks vary in the sample, from a minimum of −30.39 to 245; the variation in the values is expected since the data contains bank-level observations from various countries. Therefore, we take the logarithm of the Z-scores, as explained earlier, and it ranges between −0.36 to 1.24, with a mean of 0.36.

8. Methodology

We estimate our models using a panel regression estimator with bank and year fixed effects. A fixed effects estimator is chosen to prevent any selection biases in the data due to the overrepresentation of disaster data in developing countries as a result of vulnerability to disasters (Keerthiratne and Tol 2017). Moreover, we estimate the year-fixed effects to control for common shocks across all banks, such as global warming, the increasing number of disasters, and global financial crises. Standard errors are clustered at the bank level.

Therefore, the baseline model of the panel regression is as follows:

$$\begin{aligned} ln\ Z\_score_{i,t} = \alpha_i + \beta_1 Dis\%_{i,t} + \beta_2 ROA_{i,t} + \beta_3 Cap\ ratio_{i,t} + \beta_4\ assets_{i,t} + \beta_6 NPL_{i,t} + \ \ \beta_7 cost_{i,t} + \\ \beta_8 GDP_{i,t} + \beta_9\ Interest\ rates_{i,t} + \beta_{10}\ Concentration_{i,t} + \beta_{11} Credit_{i,t} + \beta_{12} Deposit\_insurance_{i,t} + \\ \beta_{13} Country\_effect_{i,t} + \beta_{14} ODA_{i,t} + \tau_t + \varepsilon_{i,t} \end{aligned} \tag{2}$$

where *ln Z_score* is the distance-to-default taken in natural logarithms for bank *i* for year *t*. The Z-score values were divided by 100, then added by 1 before taking the logarithm to prevent losing any negative values and smoothing out higher values (Klomp 2014).

Moreover, *Dis%* is our primary independent variable in this study. This natural disaster variable is the total number of people affected divided by the previous year's population. Disaster events occur randomly, especially since we might know the geographic locations of more vulnerable areas; however, the timing of the events is random. Additionally, as the share of the population affected by disasters increases, we would expect that there would be some defaults in loan repayments, especially from businesses that were hurt because of the disasters. Also, individuals and small firms may lose income during that period, which could decrease banks' stability in terms of their z-scores.

Bank-level control variables are added to the baseline model to capture the differences across banks. Therefore, we include $ROA_{i,t}$ which is the return on asset ratio. Additionally, $Cap\ ratio_{i,t}$ is the capital to assets ratio of bank *i* for year *t*. The ratio is important to control for as it shows the level of capital at the banks, and if they have enough liquidity to absorb losses during crises before they become insolvent. Also, $assets_{i,t}$ is the log of total assets of bank *i* at time *t* to control for the bank size. $NPL_{i,t}$ is the logged non-performing loans of bank i at time t. Finally, to control for the management differences, we add $cost_{i,t}$, which is the cost to income ratio of bank i at time t.

Furthermore, countries have different characteristics and levels of development and income. Therefore, we capture those differences by including macro-level control variables. $GDP_{i,t}$ is the logarithm of the GDP per capita for in country i at time t in constant 2010 USD. It is essential to control for the levels of income, as it is expected that banks in countries where the GDP per capita is relatively higher than other countries would not be as affected because they would have a stronger financial position to cope with the consequences of the disasters. $Interest\ rates_{i,t}$ captures the interest rates, since they can affect the banking stability through their lending rates and capital flows. $Concentration_{i,t}$ controls for the concentration of the banking system, and is calculated as the assets of the three largest banks as a share of assets of all commercial banks (Beck et al. 2019). $Credit_{i,t}$ captures the different levels of financial development, which is the ratio of credit to private sector to GDP taken into the logarithm. Additionally, $Deposit\ Insurance_{i,t}$ is a binary variable to capture whether the country has a deposit insurance scheme. $Country\_effect_{i,t}$ is a binary variable to capture time-varying effects that may impact bank stability within a country; it takes a value of 1 if a country experiences a banking crisis, a liquidity crisis, a sovereign debt crisis, coups, or civil wars. Lastly, the official development assistance (ODA) is important during disasters, especially for low-income countries, as it helps to alleviate the disasters' consequences; therefore, it is captured by including the variable $ODA_{i,t}$ which is the percentage of the ODA to GNI.

In our estimation, we split the sample into two groups, high-income countries (HIC) and middle- and low-income countries (L&M). The banks from high-income countries are overrepresented in the sample; therefore, we estimate the models for the full sample and for the two groups to overcome this issue.

Moreover, we use other metrics of banking stability. As robustness tests, we use the non-performing loans ratio (NPL) as the dependent variable to test the effects of natural disasters on loan repayments and if that affects banks' liquidity. We include the ratio of non-performing loans to net loans as our measure of impaired loans. Also, we include the return on assets ratio (ROA) as the primary dependent variable to check the effects of disasters on the banks' performance. Finally, following McDermott et al. (2014) and Keerthiratne and Tol (2017), we use a binary variable of the natural disasters with different thresholds. McDermott et al. (2014) suggest that the threshold is 0.5% of the total population. However, following Keerthiratne and Tol (2017), we use different thresholds of the number of people affected by disasters to the total population to reduce any endogeneity problems and to avoid the possibility of results being driven by outliers.

9. Results and Discussion

The results of our baseline model are presented in Table 5. In column 1, we estimate our model using all control variables on the full sample. In columns 2 and 3, we split our sample into two groups; one includes only high-income countries (HIC) and the other consists of middle- and low-income countries (L&M). We include middle- and low-income countries in the same category since low-income countries have minimal bank data availability on DataStream. However, as mentioned earlier, due to the availability of banks' data, the majority of our sample comprises high-income countries. Therefore, to avoid the results being driven by high-income countries, we estimate the models using the full sample and the split of the two groups.

Table 5. Benchmark results.

Dependent Variable: Ln (Z-score)							
	Independent Variable: %Affected				Independent Variable: BINARY 0.5%		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	Full sample	HIC	L&M	Excluding U.S. Banks	Full sample	HIC	L&M
Dis%	−0.045 ***	−0.012	−0.044 **	−0.027 *			
	(0.012)	(0.014)	(0.017)	(0.016)			
Dis-binary					−0.002	−0.002	−0.006 ***
					(0.001)	(0.001)	(0.002)
Bank characteristics							
ROA	0.002	−0.001	0.007 ***	0.005 **	0.002	−0.001	0.006 ***
	(0.003)	(0.006)	(0.002)	(0.002)	(0.003)	(0.006)	(0.002)
Cap ratio	1.275 ***	1.498 ***	0.852 ***	1.043 ***	1.283 ***	1.499 ***	0.863 ***
	(0.067)	(0.093)	(0.057)	(0.070)	(0.068)	(0.093)	(0.056)
Ln (Assets)	0.014 *	0.012	0.019 *	0.025 ***	0.013 *	0.012	0.017 *
	(0.008)	(0.010)	(0.010)	(0.007)	(0.007)	(0.010)	(0.009)
Ln (NPL)	−0.003 **	−0.004 **	−0.002	−0.002	−0.004 ***	−0.004 **	−0.002
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Ln (Cost–income)	−0.002	−0.005 **	0.002	−0.003	−0.002	−0.005 **	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Macroeconomic indicators							
Ln (GDP)	0.011	−0.046 *	0.034 **	−0.004	−0.006	−0.047 *	0.010
	(0.011)	(0.025)	(0.016)	(0.011)	(0.013)	(0.027)	(0.012)
Ln (Interest rates)	−0.007 ***	−0.003 **	−0.007 ***	−0.009 ***	−0.004 ***	−0.003 **	−0.008 ***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Concentration	−0.014	0.056 ***	−0.027 *	0.005	−0.021	0.057 ***	−0.012
	(0.011)	(0.018)	(0.014)	(0.012)	(0.013)	(0.018)	(0.014)
Ln (Credit)	−0.010	0.009	−0.012	−0.017 **	0.006	0.010	−0.014
	(0.009)	(0.009)	(0.012)	(0.008)	(0.009)	(0.010)	(0.011)
Deposit insurance	0.009	0.039 ***	0.001	−0.001	0.011	0.040 ***	−0.004
	(0.009)	(0.014)	(0.008)	(0.008)	(0.010)	(0.015)	(0.008)
Country effect	0.004	0.003	0.007 **	0.002	0.006 ***	0.003	0.005
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
ODA	0.065	6.119	1.060 **	0.497	0.022	4.999	0.976 *
	(0.650)	(12.273)	(0.526)	(0.580)	(0.650)	(12.118)	(0.532)
Constant	−0.100	0.424 ***	−0.398 ***	−0.166 ***	0.038	0.439 ***	−0.202 ***
	(0.084)	(0.145)	(0.125)	(0.052)	(0.059)	(0.155)	(0.060)
Observations	9029	7072	1957	3374	9029	7072	1957
R-squared	0.713	0.755	0.726	0.662	0.707	0.755	0.717
Number of ID	907	652	255	422	907	652	255

Notes: All estimates are using fixed effects, and each column contains a different regression. Standard errors are reported in parentheses, where *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. The time dummies are included in the specification but are unreported for brevity.

The results in column 1 show that the disaster variable has a statistically significant negative impact on the Z-scores. It is significant at the confidence level of 1%, and the result suggests that an increase in the share of people affected by natural disasters to the total population leads to a decrease in the z-scores of banks and, therefore, a reduction in the banking system stability. The results support the findings of Klomp (2014), who examines only large-scale disasters based on the total monetary damages. However, Klomp (2014) finds that there is no significant effect of disasters when considering all disasters during the period of his study and assumes that there is a certain threshold of the monetary damage to GDP for disasters to affect the distance-to-default measure. Therefore, we expand on his findings using contemporary data, and different measures of natural disasters, by finding that natural disasters have a significant negative impact on z-scores. In addition, given that the U.S. banks are the majority in our sample, about 41% of banks, we exclude banks from the U.S. in our baseline estimation to ensure that our results are not driven solely by one country. We present the results in column 4, finding that the results remain consistent and unchanged even after removing U.S. banks. Based on these findings, the results support the hypothesis (H1) that natural disasters have a significant negative impact on the Z-scores of banks.

Nevertheless, the effect differs when we split our sample. Even though it shows a negative sign, the impact of natural disasters on z-scores is insignificant in high-income countries. High-income countries might be better prepared for such events than middle- and low-income countries in terms of infrastructure and financial strength, enabling them to alleviate the consequences of disasters.

In column 3, we split the sample and present the results considering only middle- and low-income countries (L&M). The results indicate that natural disasters have a statistically significant negative effect on Z-scores. Moreover, by splitting the sample, we are able to see that an increase in the share of people affected by disasters to population decreases the Z-scores of banks in that category. The coefficient is even higher than when we estimated the model on the full sample. The results suggest that banks in middle- and low-income countries are more vulnerable to natural disasters.

Endogeneity is one of the main issues when using a continuous variable of natural disasters. According to Kellenberg and Mobarak (2008), the consequences of natural disasters might depend on different socioeconomic aspects. Therefore, following McDermott et al. (2014), we use a binary variable of disasters where it takes a value of 1 if the percentage of the total people affected by disasters to the population is greater than 0.5% and 0 otherwise. The binary variable limits the variation in the data and focuses only on large disasters. In Table 5, columns 4–6 show our estimation results using a binary disasters variable for the entire sample and the split based on income. The results indicate that natural disasters have an insignificant impact on banks' stability when applying that to the whole sample. However, when we split the sample between high-income and middle- and low-income countries, the results are consistent with our findings using the continuous variable. It appears that, even when we focus on disasters that affect more than 0.5% of the population, natural disasters do not affect the stability of banks in high-income countries. Conversely, middle- and low-income countries appear to be more vulnerable to disasters. The results indicate that natural disasters have a significant negative impact on banks' stability at a 1% confidence level.

In addition, in column 1, the coefficients' signs of the control variables are as expected. The non-performing loans ratio shows a significant negative impact on banks' stability. Furthermore, the bank's size, as indicated by the logarithm of total assets, has a significant and positive effect on the Z-score values; however, only in the full-sample estimation and L&M sample, and the effect is insignificant in the HIC sample. Moreover, the interest rate has a steady significant and negative impact on banks' stability in all our estimations, which is expected based on the findings of the earlier literature (Demirgüç-Kunt and Detragiache 1998; Calvo et al. 1993). Finally, the private credit to GDP ratio shows an insignificant impact on the stability of banks. The result indicates that the level of financial development does not affect banks' stability in all our samples, except for in our sample that excludes the U.S. banks, where it is significant and negative at a 5% confidence level. That negative or insignificant effect of the credit variable is similar to the recent findings that the generally positive impact of financial development is changing or even vanishing in recent years (Arcand et al. 2015; Law and Singh 2014; Berger et al. 2019).

Nevertheless, McDermott et al. (2014) argue that the 0.5% threshold of the total population might be somewhat arbitrary. Therefore, we run our fixed effects model using the binary variable, but with different thresholds of the share of the total number of people affected by natural disasters to the population. We present our estimation results using different thresholds of 1%, 2.5%, 5%, 7%, and 10% of the disasters variable in Table 6. The coefficients' signs of the binary variable are all negative under different thresholds.

However, the effect becomes significant when the event affects 5% or more of the population. The results are similar to Keerthiratne and Tol's (2017) findings, where they find that disasters have a significant impact on financial development when the percentage of people affected by natural disasters is 5.5% or higher of the population.

Table 6. Different thresholds of the disasters' binary variable.

	Dependent Variable: Ln (Z-score)					
Variables	(1) 0.5%	(2) 1%	(3) 2.5%	(4) 5%	(5) 7%	(6) 10%
Dis-binary	−0.002	−0.001	−0.001	−0.008 ***	−0.008 ***	−0.006 **
	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)	(0.003)
Bank characteristics						
ROA	0.002	0.002	0.002	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Cap ratio	1.283 ***	1.283 ***	1.283 ***	1.275 ***	1.275 ***	1.282 ***
	(0.068)	(0.069)	(0.068)	(0.068)	(0.067)	(0.069)
Ln (Assets)	0.013 *	0.013 *	0.013 *	0.014 *	0.014 *	0.013 *
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)
Ln (NPL)	−0.004 ***	−0.004 ***	−0.004 ***	−0.003 **	−0.003 **	−0.004 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ln (Cost–income)	−0.002	−0.002	−0.002	−0.002	−0.002	−0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Macroeconomic indicators						
Ln (GDP)	−0.006	−0.006	−0.006	0.010	0.011	−0.006
	(0.013)	(0.013)	(0.013)	(0.011)	(0.011)	(0.012)
Ln(Interest rates)	−0.004 ***	−0.004 ***	−0.004 ***	−0.007 ***	−0.007 ***	−0.004 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Concentration	−0.021	−0.021	−0.021	−0.016	−0.015	−0.019
	(0.013)	(0.013)	(0.013)	(0.012)	(0.011)	(0.013)
Ln (Credit)	0.006	0.006	0.006	−0.009	−0.010	0.006
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Deposit insurance	0.011	0.010	0.010	0.009	0.009	0.011
	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)	(0.010)
Country effect	0.006 ***	0.006 ***	0.006 ***	0.004	0.004	0.005 **
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ODA	0.022	0.024	0.004	0.007	0.069	0.019
	(0.650)	(0.653)	(0.656)	(0.655)	(0.652)	(0.650)
Constant	0.038	0.036	0.036	−0.097	−0.101	0.032
	(0.059)	(0.059)	(0.058)	(0.084)	(0.084)	(0.058)
Observations	9029	9029	9029	9029	9029	9029
R-squared	0.707	0.707	0.707	0.712	0.712	0.708
Number of ID	907	907	907	907	907	907

Notes: All estimates are using fixed effects, and each column contains a different regression. Standard errors are reported in parentheses, where *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. The time dummies are included in the specification but are unreported for brevity.

10. Robustness Tests

Another measure of banks' performance is their non-performing loans ratio (NPL). Non-performing loans can be used as a measure of the overall quality of the bank's credit portfolio. We calculate the NPL by dividing the non-performing loans by net loans. An increase in the NPL indicates a lower asset quality of the bank and increases the probability of bank failure (Chiaramonte et al. 2016). Hence, we aim to test not only the distance-to-default of banks but also whether they are affected in terms of their loan repayment by natural disasters. In Table 7, in columns 1–3, we present the results of the regression models where the non-performing loans ratio is the dependent variable. The results in column 1 show that natural disasters have a statistically significant impact on the repayment of loans. Although it is only significant at the 5% confidence level, we can see that an increase in the percentage of the total people affected by disasters would lead to a rise in the non-performing loans ratio. The results support Noth and Schüwer's (2018) findings, where they test the effects of natural disasters on banks' performance using a sample of U.S. banks only, and they find that natural disasters have a significant positive impact on non-performing loan ratios. The results support hypothesis (H2) that natural disasters increase the shares of non-performing loans.

Table 7. Different measures of banks' stability.

	Dependent Variable: NPL			Dependent Variable: ROA		
Variables	(1) Full sample	(2) HIC	(3) L&M	(4) Full sample	(5) HIC	(6) L&M
Dis%	0.523 **	0.090	0.730 *	−0.541 ***	−0.521 ***	−0.582 *
	(0.224)	(0.181)	(0.418)	(0.108)	(0.074)	(0.341)
Bank Characteristics						
ROA	−0.012	−0.071	0.022			
	(0.028)	(0.043)	(0.043)			
Ln (NPL)				−0.018	−0.018 *	0.024
				(0.012)	(0.010)	(0.046)
Cap ratio	0.004	0.306	−1.046	2.929 ***	2.602 ***	3.530 ***
	(0.772)	(0.882)	(1.445)	(0.555)	(0.652)	(1.065)
Ln (Assets)	1.100 ***	1.140 ***	0.858 ***	−0.157 ***	−0.109	−0.103
	(0.094)	(0.099)	(0.192)	(0.059)	(0.077)	(0.123)
Ln (Cost–income)	0.307 ***	0.366 ***	0.234 ***	−0.352 ***	−0.299 ***	−0.556 ***
	(0.026)	(0.030)	(0.064)	(0.020)	(0.020)	(0.051)
Macroeconomic indicators						
Ln (GDP)	−0.774 ***	1.013 ***	−0.239	−0.161	−0.305	−0.077
	(0.183)	(0.310)	(0.277)	(0.127)	(0.208)	(0.209)
Ln(Interest rates)	−0.074 ***	−0.271 ***	0.002	0.070 ***	0.096 ***	−0.001
	(0.027)	(0.035)	(0.027)	(0.011)	(0.012)	(0.020)
Concentration	1.249 ***	0.709	0.462 *	−0.751 ***	−0.687 ***	−0.169
	(0.314)	(0.712)	(0.239)	(0.168)	(0.221)	(0.287)
Ln (Credit)	−0.682 ***	−2.393 ***	0.249	0.047	0.252 ***	−0.523 ***
	(0.195)	(0.223)	(0.273)	(0.110)	(0.076)	(0.201)
Deposit insurance	−0.032	0.161	−0.216	−0.026	−0.034	−0.089
	(0.249)	(0.495)	(0.228)	(0.122)	(0.141)	(0.150)
Country effect	0.513 ***	0.614 ***	0.172 ***	−0.026	−0.082 ***	0.112
	(0.052)	(0.047)	(0.065)	(0.027)	(0.022)	(0.133)
ODA	5.178	−230.629	5.744	−0.571	274.260	−1.788
	(12.449)	(232.635)	(11.421)	(8.232)	(249.202)	(7.799)
Constant	2.472 *	−10.214 ***	−1.134	5.882 ***	5.761 ***	6.411 ***
	(1.402)	(2.168)	(1.415)	(0.770)	(1.217)	(1.045)
Observations	9073	7112	1961	9073	7112	1961
R-squared	0.445	0.465	0.273	0.224	0.269	0.208
Number of ID	911	654	257	911	654	257

Notes: All estimates are using fixed effects, and each column contains a different regression. Standard errors are reported in parentheses, where *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. The time dummies are included in the specification but are unreported for brevity.

However, the effects differ when we split the sample. In column 2, we can see that natural disasters do not significantly impact non-performing loans in high-income countries. On the contrary, in column 3, middle- and low- income countries appear to be affected by disasters in terms of loan repayments. Our disasters variable shows a significant positive effect on the non-performing loans ratio. Moreover, similar to the whole sample, it is only significant at a 5% confidence level, but the coefficient is higher than that of the full sample.

Additionally, the return on assets ratio (ROA) is a commonly used variable in the banking literature to count for banks' performance. By definition, the Z-score is sensitive to the standard deviation of ROA, and, hence, it has a role in the stability of the banks (Chiaramonte et al. 2016). We present the results of our main independent and control variables estimations while using the ROA ratio as the dependent variable in columns 4–6 in Table 7. The results yield some interesting findings. Our disasters variable significantly and negatively impacts ROA in the full sample model and the other two split samples. They are all statically significant at a 1% confidence level, except for middle- and low- income countries, which are significant at a 5% level. However, the coefficient of middle- and low-income countries is higher than high-income countries. Additionally, the R-squared of all the models is lower than the R-squared values of the models where the Z-score is the main dependent variable. The results support our main findings in our benchmark model that natural disasters negatively affect banks' stability. Based on these findings, the results support hypothesis (H3) that there is a significant effect of natural disasters on banks' performance.

We can see from our benchmark results that natural disaster events affect banks' stability and performance. However, we want to explore whether the relationship between the disasters variable and the distance-to-default varies with the different levels of z-scores of banks. Therefore, we divide our z-score values into five quantiles. We present the results of the quantile regression in Table 8. We can see that natural disasters have a significant negative impact on z-scores in the first three quantiles, up to the Z-score value of 45, while, higher than that, the impact becomes insignificant. However, in the final quantile where the z-score values are higher than 73, disasters negatively and significantly affect their values, but only at a confidence level of 10%. An explanation for this result could be that banks with very high z-scores are more willing to lend and take risks during turbulent times.

Table 8. Quantile regression.

	Dependent Variable: Ln (Z-score)				
Variables	(1) 1st Quantile	(2) 2nd Quantile	(3) 3rd Quantile	(3) 4th Quantile	(3) 5th Quantile
Dis%	−0.012 **	−0.015 **	−0.014 **	−0.005	−0.018 *
	(0.005)	(0.006)	(0.006)	(0.006)	(0.009)
Bank characteristics					
ROA	0.379 ***	0.823 ***	1.350 ***	1.750 ***	2.276 ***
	(0.031)	(0.063)	(0.054)	(0.090)	(0.075)
Cap ratio	0.003	0.001	0.002	0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.003)	(0.006)
Ln (Assets)	0.023 ***	0.015 *	0.002	−0.005	0.026
	(0.008)	(0.008)	(0.007)	(0.009)	(0.016)
Ln (NPL)	−0.000	−0.002 ***	−0.001 *	−0.003 ***	−0.001
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
Ln (Cost–income)	−0.002 ***	−0.004 ***	−0.006 ***	−0.006 ***	−0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Macroeconomic indicators					
Ln (GDP)	−0.003	0.005	−0.005	−0.002	−0.011
	(0.004)	(0.005)	(0.005)	(0.009)	(0.018)
Ln(Interest rates)	−0.001 ***	0.000	−0.000	0.001	−0.003
	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)
Concentration	0.003	−0.003	−0.017 **	0.003	−0.011
	(0.008)	(0.006)	(0.007)	(0.011)	(0.021)
Ln (Credit)	0.007 *	−0.006 *	−0.006	−0.001	−0.005
	(0.004)	(0.004)	(0.005)	(0.009)	(0.023)
Deposit insurance	−0.004	0.005	0.010 **	−0.001	0.020 *
	(0.003)	(0.003)	(0.005)	(0.012)	(0.013)
Country effect	−0.004 ***	0.001	0.002	0.004 ***	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
ODA	0.129	0.586	0.447	−1.760	0.235
	(0.203)	(0.469)	(0.442)	(1.142)	(2.043)
Constant	−0.019	0.048	0.171 ***	0.209 ***	0.359 **
	(0.023)	(0.031)	(0.038)	(0.051)	(0.143)
Observations	1202	1611	1707	1976	1859
R-squared	0.674	0.764	0.818	0.823	0.902

Notes: All estimates are using fixed effects, and each column contains a different regression. Standard errors are reported in parentheses, where *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. The time dummies are included in the specification but are unreported for brevity.

Moreover, we include the first lag of all our independent and explanatory variables. Including lags is a common practice in the literature. The results are in column 2 in Table 9. We find that, even when including a first lag of all right-hand-side variables, our disasters variable has a significant negative impact on banks' stability. Although the R-squared value is smaller with lags than our benchmark estimation, the coefficient is slightly higher, and it is overall consistent with our benchmark results.

Table 9. Robustness checks.

	Dependent Variable: Ln (Z-score)	Dependent Variable: Capital Ratio	Dependent Variable: Return on Equity (ROE)
	(1)	(2)	(3)
Variables	First Lag	Cap ratio	Cap ratio
Dis%	−0.050 ***	−0.031 **	−0.018 ***
	(0.012)	(0.016)	(0.005)
Bank Characteristics			
Cap ratio	0.840 ***		−0.208 ***
	(0.044)		(0.020)
ROA	0.003	0.019 ***	
	(0.002)	(0.003)	
Ln (Assets)	0.013 ***	0.001	−0.015 ***
	(0.005)	(0.008)	(0.003)
Ln (NPL)	−0.006 ***	0.000	−0.002 **
	(0.001)	(0.002)	(0.001)
Ln (Cost–income)	−0.000	0.004 **	−0.027 ***
	(0.002)	(0.002)	(0.001)
Macroeconomic indicators			
Ln (GDP)	−0.002	−0.004	0.002
	(0.010)	(0.011)	(0.006)
Ln (Interest rates)	0.000	−0.000	0.003 ***
	(0.002)	(0.001)	(0.001)
Concentration	−0.043 **	−0.040 ***	−0.003
	(0.017)	(0.013)	(0.007)
Ln (Credit)	0.020 ***	0.042 ***	−0.005
	(0.007)	(0.010)	(0.006)
Deposit insurance	0.001	−0.008	0.004
	(0.010)	(0.012)	(0.005)
Country effect	−0.002	0.008 ***	−0.004 ***
	(0.002)	(0.003)	(0.001)
ODA	0.599	1.407 *	0.155
	(0.583)	(0.725)	(0.639)
Constant	0.065	−0.009	0.392 ***
	(0.063)	(0.091)	(0.034)
Observations	8642	9073	9970
R-squared	0.335	0.088	0.316
Number of ID	891	911	937

Notes: All estimates are using fixed effects, and each column contains a different regression. Standard errors are reported in parentheses, where *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. The time dummies are included in the specification but are unreported for brevity.

Furthermore, we use other metrics of how healthy banks are after natural disasters' events. Therefore, we estimate our model using the capital ratio and return on equity ratio (ROE) as the dependent variables. The capital ratio is calculated by dividing the total equity by the total assets, and the ROE by dividing net income by shareholders' equity. Both measures are in line with common practice in the literature, and they are essential predictors of the healthiness of banks and how far they are from failure (Chiaramonte et al. 2016; Noth and Schüwer 2018). We find that natural disasters affect the capital ratio, as presented in column 2. The effect is significant at the 5% confidence level, and it shows that natural disasters significantly negatively impact banks' capital ratio. In addition, column 3 shows the results of our estimation when ROE is the main dependent variable. The results show that natural disasters affect the return on equity ratio negatively with 1% significance level. The results support our main findings from our benchmark estimation that natural disasters negatively affect banks' stability.

11. Conclusions

This study shows that natural disasters significantly negatively impact banking stability, specifically in middle- and low-income countries. The examination of the effect of natural disasters on banking stability is limited but growing (Klomp 2014; Noth and Schüwer 2018; Albuquerque and Rajhi 2019; Brei et al. 2019). The literature on natural disasters mainly centers on their macroeconomic consequences. Thus, this study adds to the natural disasters and banking stability literature, primarily by using bank-level data of 1248 banks from 72 countries for the period from 1999 to 2018. Moreover, we employ a commonly used measure of natural disasters, the number of people affected, in our models to examine the effect of disaster events that distress people rather than using the cost of damages. Additionally, we use the commonly used measure of banking stability, which is the distance-to-default measure, also known as the Z-score.

Our findings suggest that natural disasters affect the distance-to-default values negatively. We split our sample into two groups for two reasons. First, the vast majority of the banks in our sample represent high-income countries due to the data availability. The second reason was to test whether the effects differ among countries based on income levels. After splitting the data, we find that natural disasters have no significant impact on banking stability in high-income countries. However, the effect is significant and negative for middle- and low-income countries.

We use other measures to test the relationship and ensure our results are robust. Therefore, we use a binary variable of the disaster's variable introduced by McDermott et al. (2014) but with different thresholds. The results show similar effects to our primary variable of natural disasters. Moreover, the findings indicate that the threshold of the ratio of the total number of people affected by natural disasters to population needs to be at least 5% of the total population to affect banks' stability.

Moreover, we test other measures of banks' performance. We find that natural disasters decrease the ROA, the capitalization, and ROE ratios and increase the percentage of non-performing loans. These effects are significant mainly in middle- and low-income countries. This supports our main findings that natural disasters adversely impact the banking system's stability.

The outcome of this study provides valuable insights into the effects of natural disasters on banking stability to policymakers, academics, and other parties who may be interested in the factors that may affect financial stability or the direct impact of natural disasters. Based on the study's findings, two key recommendations can be made to bank managers aiming to enhance bank stability in the face of natural catastrophe. Bank managers should prioritize the development of comprehensive disaster preparedness plans and risk management strategies. This includes conducting thorough risk assessments, implementing robust contingency plans, and establishing effective communication channels for swift response and recovery. Additionally, diversification of assets and investments should be considered to mitigate the adverse impact of natural disasters, especially for banks located in more vulnerable regions. By spreading risk across different sectors and geographic locations, banks can minimize vulnerability and enhance overall stability. These key recommendations provide actionable steps for bank managers to improve their institutions' resilience in the context of natural disasters.

There are a number of limitations of this study that need to be addressed for future research. First, the availability of bank-level data is minimal, particularly for low-income countries. Second, we need to consider the time and location of each disaster. For example, an event that occurs in January has a different impact on the annual Z-scores than another event that occurs in the last quarter of the year, mainly because we use annual data. Finally, we need to understand the reasons behind the impact of disasters on banking stability and what drives that negative effect to understand if the impact is because of no access to credit, bank runs, or loss of property.

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