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How do local banks respond to natural disasters?

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ABSTRACT

The increasing frequency and intensity of catastrophic natural disasters have the potential to stress and imperil banks to the point of compromised viability or even bankruptcy. Using data of approximately 907 domestic/local banks and Spatial Hazard Events and Losses Database for the United States during the period 2010–2019, we explore how natural disasters impact bank stability. Our main findings support the aforementioned hypothesis that natural disasters decrease bank stability because total deposit and equity (capital) become more volatile and the bank is prone to increased lending margins, as well as a provision of loan loss. Thus, banks lose their competitiveness, ROA deteriorates, and *Z*-score becomes lower. Strong corporate governance and healthy financial strategy, nevertheless, assist bank recovery in the aftermath of these weather extreme events. Last but not least, we find a non-linear relationship between natural disasters and bank stability and posit the role of indemnity paid out from the Federal insurance programme (after natural hazards) in the high-damage group.

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1. Introduction

Concurrently expanding with the awareness of adverse effects on smooth functioning of the various agents of the financial system, i.e. financial markets, and payments, settlement and clearing systems,[1] the literature on how climate hazards destabilize financial institutions is emerging (Batten, Sowerbutts, and Tanaka 2016 and Breitenstein, Nguyen, and Walther 2021 for details).

The growing trend of frequency and intensity of climate-related disasters, such as extreme weather events (i.e. droughts, floods, and heat waves), has stressed banking operation and performance, including reducing the total amount of deposits (Brei, Mohan, and Strobl 2019), increasing the share of non-performing loans (Brahmana, Puah, and Chai 2016), or even loan portfolio restructuring (Collier, Katchova, and Skees 2011). Specifically, disasters may subject banks to insolvency owing to one of the following mechanisms: bank run, immediate withdrawals to replace loss, excessive write-off of loan losses, and collateral destruction or offices damages. Therefore, after disaster event, banks may be exposed to short-term pressure on capital adequacy, asset quality, managerial qualities, and liquidity risk as uncertainty and repayment increase (Cetorelli and Goldberg 2011; Collier and Skees 2012; Klomp 2014; Noth and Schüwer 2018).

However, the existing empirical evidence is mixed because the impact of climate risks on financial soundness of banks goes beyond these direct impacts. The ultimate consequence of climatic events has shown both perils and opportunities to operation of financial institutions, among which banking and insurance industry are crucial. For instance, the credit demand shows a rising trend in the aftermath of volcanic activities (Berg and Schrader 2012), and banks in unaffected areas find opportunities by providing credits to businesses in disaster-stricken regions (Koetter, Noth, and Rehbein 2020). Further, those realized disaster-related damages are affected

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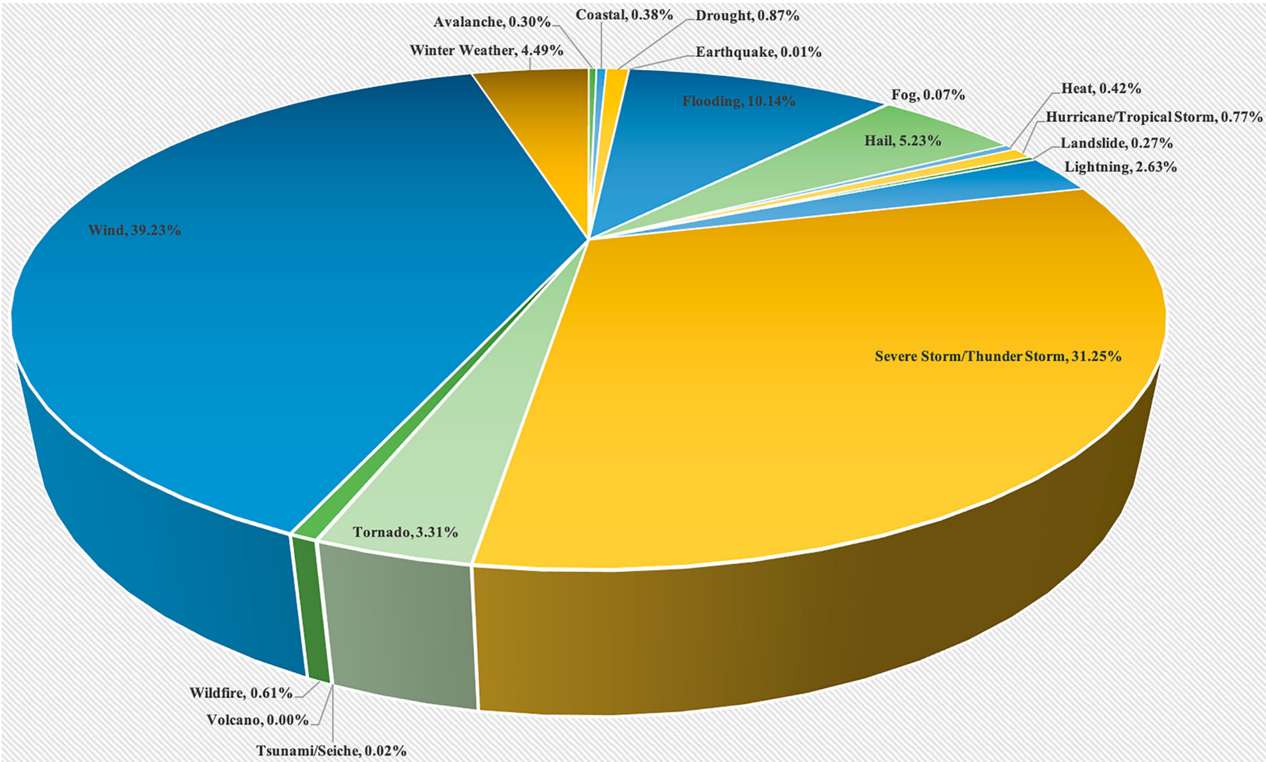

Figure 1. Summary of natural disasters in the US from 2000 to 2019.

by local economic structure and disaster management, such as public financial aid programmes supporting corporations and individuals in affected regions, and thus endogenous within local economic conditions. Additionally, banks are often a part of a larger financial conglomerate including an insurance branch, which may also incur substantial losses after a disaster. Hence, banks may choose their business regions and counties with more or less disaster risks for their business activities.

Different kinds of natural hazards may have different effects across different geographical regions (Skidmore and Toya 2002; Gassebner, Keck, and Teh 2010) since large countries tend to have a higher probability of experiencing a natural event. In particular, the United States (US) would offer an interesting case study of the effects of natural hazards on banking stability because it is one of the top countries which suffers from natural disasters[2], and due to the fact that US banking financial system exhibits the strong influence over the global banking sector. In this study, we, thus, use the Spatial Hazard Events and Losses Database for the United States (SHELDUS)[3] (Figure 1) alongside the S&P COMPUSTAT to investigate the impact of natural disaster on banking system as well as providing underlying mechanisms driving the results. Those mechanisms can be both banking financial and governance strategies. As board plays a pivotal role in setting policies, level of corporate governance is usually linked with board characteristics (Iliev and Roth 2021). The study highlights the role of corporate governance on bank stability upon the occurrence of natural disasters.

Despite climate change opponents, greenhouse gas, among which CO_2 plays the dominant role, emissions are believed to be assertively blamed for the severe changes in weather patterns, e.g. intensity and frequencies of weather extremes. While climate finance is burgeoning (Hong, Li, and Xu 2019; Bernstein, Gustafson, and Lewis 2019; Hong, Karolyi, and Scheinkman 2020; Baldauf, Garlappi, and Yannelis 2020; Murfin and Spiegel 2020), studies that explore the causality of CO_2 emission and natural disasters and their detrimental impact on financial stability are scant. Moreover, United States is the second-largest emitter of greenhouse gas emissions per person in the world. Therefore, it is necessary to consider the effects of consumption-based carbon emission alongside the impact of weather extremes in the causal settings. We employ CO_2 emission as an instrument in IV-GMM models.[4]

Our findings suggest that banks often recover from negative impacts caused by weather-related natural calamities on their stability and performance. Our approach, which uses two-stage least square, adds to the body of knowledge about how CO_2 affects the financial stability in the long run. By looking at the process of how natural disasters affect bank risk, we discover that increasing the interest rate spread does not sufficiently compensate for the risk of natural disasters, but instead induces worse lending activity in the future. Good operating strategy, a sufficient loss buffer, and a strong loan portfolio are all important considerations in ensuring that banks remain resilient in the face of natural disasters. Sub-sample analyses illustrate that those banks unfamiliar with dealing with the aftermath of natural disasters are less equipped to climate risk, whereas those who are more likely to be exposed to disasters are better at effective forecast and preparation.[5]

We also perform additional tests utilizing interaction terms of governance traits and natural hazard dummy to gain a better understanding of how different board personalities contribute to the process of addressing climate change problems. Our results show that board characteristics do have influence on bank soundness. Particularly, gender diversification within board members helps banks stabilize better, in which 1% increase in female director helps explain 17% of bank stability improvement. Although board busyness shows a marginal net effect when banks are hit by natural disasters, board networks prove to increase bank stability, consistent with reputation hypothesis. Last but not least, the number of board members show a significant impact on bank stability, sharing the same results with Coles, Daniel, and Naveen (2008) and Pathan and Faff (2013). Therefore, we contribute to corporate governance literature by showing that board characteristics (e.g. gender diversity, board networks, and board size) reinforce banks stability against non-fundamental risk.

Additionally, we contribute to the literature of natural disaster by providing evidence of a U-shaped relationship between weather extreme damage and bank stability. Particularly, the Z-score initially reduces as natural hazards cause increasing damage up to a threshold; but when the total damage exceeds that threshold, the Z-score starts improving. This may be explained by the jointly effect of government aid programmes, such as the Federal Crop Insurance programmes administered by the Risk Management Agency (RMA). However, we also find that indemnity does not contribute to Z-score recovery in the low-damage group whereas the non-linear effect of indemnity on Z-score in the high-damage group is significant. We believe this result may refer to the situation when natural hazards severely damage a region to such a certain threshold that the indemnity is unable to recover the loss caused by hazards.

Our study though closely aligns with the other papers, Klomp (2014), Noth and Schüwer (2018) and Brei, Mohan, and Strobl (2019) provide novel findings surrounding the association between 'anthropogenic' (human-induced) factors and weather extremes. Particularly, Klomp (2014) is the first study that explores the relationship of large-scale natural hazards and banking Z-score on the global scale (1997–2010), using explanations such as country financial regulation strength, economic growth, credit to GDP and trade openness to gauge the recovery of commercial bank stability. While Noth and Schüwer (2018) explores the impact of natural disasters on the US banking Z-score in 1994–2012 period, using derived proxies of natural disasters to assert the real effects, the authors neither concern about mediating mechanisms, such as corporate governance, nor emphasize about bank fundamental characteristics. Recently, Brei, Mohan, and Strobl's (2019) study explores the effect of hurricane on different components of bank balance sheets, through which they reveal the mechanism of how commercial banks from seven Eastern Caribbean countries experienced negative shocks over the period 2001–2012. However, their study does not cover other types of hazards, only concerns about hurricane even though the merit of this study is to build a hurricane index which considers the physical characteristics of hurricanes, and the ex-ante economic exposure to damage. Overall, those three studies cover the time period from mid-90s up to 2010/2012, coinciding with Kyoto Agreement (from first signed time-point (1997) to first commitment in 2012). While Kyoto Agreement calls for reducing greenhouse gas emission compared to pre-1990 levels, much attention has been shifted on multifaceted adverse impacts of climate change after Paris Agreement in 2016. Hence, our study not only adds to the literature by providing evidence for more recent period (i.e. 2010–2019) tallying with the worldwide attention on climate change, but also is different from their studies in several perspectives: (i) this study makes use of the concept of instrumental variable and a two-stage least square technique to explore the relationship of CO_2 emission and natural disasters, (ii) we also explore how different bank's fundamental channels and governance help mitigate the risk of natural disasters, and (iii) this study is one of the first pioneers investigating the non-linear effect of natural disasters on financial stability.

This paper proceeds as follows: Section 2 presents the literature review of our study. Section 3 describes the Data while Methodology and Identification strategy are presented in Section 4. Section 5 reports the empirical results. Section 6 shows further robust tests. Section 7 concludes, and Section 8 provides limitation and future research.

2. Literature review

2.1. A framework about natural disaster and financial stability

The number and cost of climatic disasters are elevating at global scale due to a combination of increasing various constituents, such as exposure (i.e. more assets at risk) and vulnerability (i.e. how much damage a hazard of given intensity – wind speed or flood depth, for example – causes at a location).[6] Natural catastrophes are more likely to cause financial sectors to be in difficult situation if they misjudge risk ex-ante and hold insufficient capital (Batten, Sowerbutts, and Tanaka 2016). The diversity of natural hazards also have varying consequences across distinct geographical locations, yet large countries like the US have a larger possibility of encountering a natural catastrophe. Adverse shocks caused by natural disasters may affect the default risk of banks through various ways. On the one hand, catastrophic events can immediately affect banks' deposits and lending operations, resulting in bank runs, urgent withdrawals to replace lost funds, excessive loan loss write-offs, an increase in non-performing loans, collateral destruction, or office damage inside disaster zones (Faiella and Natoli 2018; Barth, Sun, and Zhang 2019; Koetter, Noth, and Rehbein 2020).

For example, Brei, Mohan, and Strobl (2019) find that the hurricane strike significantly deteriorates the total deposits of the Eastern Caribbean banks by 8%, of which 6% was the decrease in household deposits.[7] Collier and Skees (2012) indicates that there is a drop in the equity ratio immediately following the El Nino happened in Peru. In addition, Brahmana, Puah, and Chai (2016) shows that the Nias Tsunami caused a huge negative impact to the non-performing loans (NPL) of Indonesian banks. In practice, the NPL of Indonesian banks increased dramatically by around 10% after the Nias Tsunami occurred in 2004.

Nevertheless, as per Cortés and Strahan (2017) after the natural disaster happens, bank lending, especially in form of home mortgage, seems moderately increasing in the post natural hazards period. As a result, it is reasonable to expect banks to increase their lending spreads in order to hedge against future climate hazards, such that banks and lenders charge higher interest rates on mortgages and loans in areas prone to sea-level rise and natural disasters (see Correa et al. 2020 and Nguyen et al. 2020). Additionally, Huynh, Nguyen, and Truong (2020) confirm the significant correlation between the higher cost of equity capital and drought risk. Thus we wonder whether this is sufficient or whether rising spreads would ultimately be detrimental or beneficial in a competitive business-like banking.

On the other hand, the ex-post effect of natural disaster materializes in increasing conflict of interest problem intervening the relationship between banks and customers, such as earnings management in post-disaster period (Cheng et al. 2019; Wu et al. 2021), spill-over effect onto lending activities in non-disaster areas (Rehbein and Ongena 2020; Koetter, Noth, and Rehbein 2020), alternation in bank operation (Chavaz 2016; Cortés and Strahan 2017; Bos et al. 2017; Ivanov, Macchiavelli, and Santos 2020; Ivanov et al. 2020), and biases in lending activities (Garbarino and Guin 2021; Kong et al. 2021). For instance, the credit demand after hazards is increasing whereas the access to credit is more likely to be limited as bank changes their operations according the record of risks (Berg and Schrader 2012; Gallagher and Hartley 2017). Consequently, Hosono et al. (2016) find that an adverse natural disaster shock to bank lending capacity reduces client firms' activity even in an economy with well-developed financial markets and institutions. In contrast, for those banks with multi-market branches, their response is to reallocate funds towards markets with high credit demand and away from other markets ('connected markets') in which they lend (Cortés and Strahan 2017). Nguyen and Wilson (2020) emphasize the importance of bank existence at the affected regions in alleviating adverse lending effects. Simply said, natural catastrophes not only subject banks to short-term onerous strain on capital adequacy, asset quality, management qualities, and liquidity risk as uncertainty and payback increase, but also may lead to moral hazard and adverse selection in aftermath lending strategies.

The heterogeneous interaction between local economic structure and disaster management programme yields mixed findings, thus may pose difficulty in causally identifying the impact of natural disaster on bank risk. Klomp (2014) suggests that large-scale weather-related disasters, on average, have no significant negative effect on the stability of the banking sector in developed countries, but rather only in emerging countries, indicating heterogeneous effects of extreme weather events in different countries. Noy's (2009) study also shows that countries with more developed credit markets appear to be more robust and better able to endure natural disasters, while Strömberg (2007) points out that bank lending activities reduce rapidly after a climatic disaster in developing countries.

It is worth noting that the insurance programme plays a critical role in improving resilience to natural hazards or climate-related events by both promoting recovery and providing incentives for investments in hazard mitigation insurance programme (Kousky 2019). In particular, it helps households recover from natural disasters (Bertram-Huemmer and Kraehnert 2018) and thereby boosting the economy (Sawada and Takasaki 2017). Skidmore and Toya (2002) state that damages caused by natural disasters are positively correlated with household saving rates, which suggest that households have attempted to self-insure against some catastrophic events as insurance markets have not provided a sufficient level of protection against possible losses arising from natural catastrophes.

Furthermore, banks are often part of a larger financial conglomerate including an insurance branch. While banks provide insurance segment in its operation, it might incur substantial pay-out after a disaster, which subject banks to short-term liquidity; changes in weather patterns might lead to higher flood risk in the coming decade, and the increasing demand for insurance offers a lucrative market for banks.[8],[9]

2.2. Other determinants of bank risk-taking

Regarding banking characteristics, Boyd, Graham, and Hewitt (1993) and De Nicolo (2000) show that large banks' returns on assets and return volatilities increase in size, suggesting that large banks choose higher risk than their optimal level, and that risk-taking behaviour fully offsets the size-related scale economies and/or diversification benefits. On the contrary, the size of the bank and its natural diversification through widespread franchise to some extent can mitigate adverse shocks like natural disasters. Therefore, this study aims to fill the void of relationship between bank size and impact of climate risks on financial stability.

In addition, prior literature has shown that other factors related to macro-economy, such as GDP, interest rate, or even house price, should be considered to conduct the relationship between natural hazard and financial stability. For instance, both GDP growth and GDP per capita have a positive effect on the financial stability since the banks' investment opportunities may be correlated with business cycles, which in turn raises the banks' asset quality (Laeven and Majnoni 2003; Uhde and Heimeshoff 2009; Bushman and Williams 2012; Liang, Moreira, and Lee 2020). However, Fouejieu (2017) and IJtsma, Spierdijk, and Shaffer (2017) find the reverse effect of GDP growth on financial stability, which can be explained by the fact that increased risk taking and financial imbalances are often pro-cyclical (Vural-Yavaş 2020).

Interest rate as a central tenet of the recent global financial crisis has been studied in the relationship with bank's risk-taking behaviour. Recent empirical evidence lends support to the notion that low interest rates may help fuel increases in bank leverage and risk-taking (Maddaloni and Peydró 2011; Delis and Kouretas 2011; DellAriccia, Laeven, and Marquez 2014). This softening is amplified by securitization activity, weak supervision for bank capital, and low short-term interest rates for an extended period. In short, the negative relationship between interest rates and risk is more pronounced for banks with more liquid assets and highly capitalized banks (Ioannidou, Ongena, and Peydró 2015; Dell'Ariccia, Laeven, and Suarez 2017).

According to the so-called financial accelerator mechanism, real estate prices can have two contrasting effects on bank stability, which are the collateral value and the deviation hypotheses (Kiyotaki and Moore 1997; Niinimäki 2009). Almeida, Campello, and Liu (2006) provide both empirical evidence on international housing markets and underlying mechanism – contractual features of housing finance. The former suggests a positive relation because rising nominal house prices increases the value of collateral pledged, net wealth of borrowers, boost bank capital, and thus reduces the bank's probability of default (PD), enhancing the financial positions of bank (Niinimäki 2009; Killins 2020). The latter theory conjectures that persistent deviations from fundamentals may foster the adverse selection of increasingly excessive lending to risky real estate borrowers at unreasonably low rate seeking to expand their loan portfolios, which increases bank distress probabilities (Bernanke and Gertler 1995; Allen and Gale 2001).

Corporate governance has received an enormous attention in both academia and corporate. As the central theme of corporate governance is to align executive's interest to those of stakeholders and thereby increase corporate accountability, corporate governance plays a key role in mitigating conflict of interest (Luo 2005). Hence, corporate governance is usually linked with bank performance (Denis and McConnell 2003; Barth, Sun, and Zhang 2003; Adams, Hermalin and Weisbach 2010). The existence of female director has been empirically linked to higher bank performance (Low, Roberts, and Whiting 2015; Garcia-Meca, Garcia-Sanchez, and Martinez-Ferrero 2015). Board size also receives an unsettling impact on bank performance. Barth, Sun, and Zhang (2003) find a positive relationship between board size and bank performance, similar with Pathan and Faff (2013), Coles, Daniel, and Naveen (2008). In line with reputation hypothesis, Ferris, Jagannathan, and Pritchard (2003), and Trinh et al. (2020) document that a busy board will exhibit high bank performance and greater financial stability.[10] Hence, we investigate whether corporate governance assist banks to better recover in the aftermath of natural disasters.

3. Data

3.1. Sample

We exploit the Spatial Hazard Events and Losses Database for the United States (SHELDUS),[11] which is a rich database with several natural events at the county level over time. Recent empirical studies that use this database include Barrot and Sauvagnat (2016), Bernile, Bhagwat, and Rau (2017), Cortés and Strahan (2017) for all data on natural disasters. In particular, SHELDUS compiles data from different sources.[12] Advantages of the SHELDUS database include the annual availability of data, measurement at the county level, and a low threshold of inclusion that covers the impacts of comparably small events (Gall, Borden, and Cutter 2009). One limitation of SHELDUS is that assessments of flood damages are difficult to estimate (Gall, Borden, and Cutter 2009). We assume any variation in these estimates to be random over time and counties, which is plausible since the probability of extreme weather events occurrence is randomly drawn from a long-term distribution of weather pattern, i.e. climate.

By mainly combining SHELDUS data with financial banking information from S&P COMPUSTAT, we investigate how natural disaster affects the bank stability. Alongside that, we also combine with some other data sources such as DealScan and BoardEx to explore to what extent natural hazards may affect the banking activities. The full detail of the constructed sample can be obtained from Table A1.

3.2. Variables

3.2.1. Banking Z-score

Our main dependent variable of interest is Z-score. Representing the probability of insolvency within banking industry, Z-score receives a wide popularity with a role of measuring risk level in the banking and financial stability-related literature (Uhde and Heimeshoff 2009; Strobel 2011). The widespread use of z-score is due to its relative simplicity in computation using publicly available accounting data only. It thus can serve as either a complementary index to share market-based approaches or a main risk measure for investors where share prices are not available. In its general form, allowing for non-normal return distributions, it is generally attributed to Hannan and Hanweck (1988) and Boyd, Graham, and Hewitt (1993); Boyd and Graham (1986) had previously introduced Z-scores in the special context of normal return distributions. The basic principle of the Z-score measure is to relate a bank's capital level to variability of its returns. In doing so, one can identify the magnitude of the return variability absorbed by capital without the bank becoming insolvent. The main consequence of this measure is that a low-risk bank will have a high value of Z-score, which indicates that it requires a significant drop in standard deviations of a bank's asset return to become insolvent, and vice versa; a lower value of Z-score indicates higher risk of the bank.

In general, Z-score is built using the return on asset ratio (ROA) augmented by the equity-to-asset ratio (EA), all divided by a measure of variability in returns, often the standard deviation of ROA. In a cross-sectional setting, the standard approach to estimate the Z-score for an individual bank is as follows:

$$Z1_{i,T} = \frac{EA_{i,T} + ROA_{i,T}}{ROA_{i,T}} \tag{1}$$

or

$$Z2_{i,T} = \frac{EA_{i,T} + ROA_{i,T}}{ROA_{i,T}} \tag{2}$$

where $T = t - 3, .., t$. $\mu_{ROA} i, T$, $\sigma_{ROA} i, T$ and $\mu_{EA} i, T$ are calculated using moving mean and standard deviation estimates with window width of 3 quarters and for each period $t \in 1, \dots, T$.

Prior studies contend that Z-score is a noisy measure of financial stability as it can be skewed (Laeven and Levine 2009; Houston et al. 2010). Hence, motivated by these studies, we use the natural logarithm of Z-score to minimize the impact of skewness. We also employ other measure of bank stability, such as Loan loss provision, Change of equity, and Deposit volatility for robustness purpose. The data on the Z-score and other individual bank characteristics are obtained from the S&P COMPUSTAT Bank covering 2010–2020 period, available from WRDS database. For macroeconomic variables, we download and compile from two sources named as Bureau of Economic Analysis and US Census Bureau.

3.2.2. Banking fundamental characteristics

We look for a mechanism associated with (abnormal) profitability, risk, and growth. Our choice of signals within each category (profitability, prudence, and growth) is motivated by the guidance in the academic and practitioner literature (e.g. Calomiris and Nissim 2007; Koller et al. 2010).

3.2.2.1. Banking profitability. We emphasize the use of spread (Δ*Spread*) on a bank's loan portfolio as the ratio of net interest income (interest income – interest expense) to total loans, higher spread not just only reflects higher risk on the loan portfolio but also implies about the profit margin of the bank.

Loan-to-deposit ratio (Δ*Loans_Deposits*): This metric assesses a bank's capacity to effectively use its principal source of capital (deposits) to expand its primary generating asset (loans). If the ratio is very low, it signifies that the bank has a lot of idle cash, which indicates increasing inefficiency. It also indicates the risk of liquidity if a big number of depositors withdraw their funds at the same time.

Operating expense ratio (Δ*Expense_Ratio*): This determines how much of a bank's revenue is spent on operational and administrative costs.

Non-interest income (Δ*Noninterest_Income*): This metric is especially valuable for bigger universal banks whose non-lending/deposit operations account for a major share of their revenue. These revenues are frequently derived from higher-margin value-added services (such as investment banking and brokerage) that are either very lucrative or have no direct expenses (such as service fees).

3.2.2.2. Banking prudence. **Loan loss provision – LLP** (**Δ*LLP***): In terms of absolute quantity as well as influence on overall profitability and capital adequacy, this is the most critical accrual for banks.

Non-performing loan – NPL (Δ*NPL*): This is a credit risk statistic that measures the ratio of non-performing loans to total loans in the future. NPLs are noisy, yet they may be one of the most accurate predictors of future loan losses.

Allowance Adequacy (Δ*Allowance_Adequacy*): Banks having a higher loan loss allowance adequacy are typically better prepared to absorb the predicted credit losses without putting their capital at risk during difficult times.

3.2.2.3. Bank growth. **Revenue Growth (*SGR*)**: We measure SGR as the percentage annual change in total revenue, not distinguishing whether revenue growth arises from traditional banking activities or other non-banking activities.

Loan Growth (*LGR*): This is the percentage change in gross loans on the balance sheet over a year. Regulators and market participants routinely assess a bank's potential to extend its overall loan portfolio. On one side, increasing the loan base might result in more revenue. On the other hand, it might be a sign of a larger credit risk. During times of financial crisis, when banks are unwilling to issue loans due to concerns about the economy's credit risk, these concerns are amplified.

3.3. Descriptive analysis

The indicator of bank stability (*ln(Z-score)*) has a mean value of 4.779 and a wide difference between minimum (−4.753) and maximum value (10.427) in Table 1. Return-on-assets ratio, whose average value stands at 0.2%, also indicates a strong heterogeneity amongst observations within sample data. Turning to independent variable of interest, natural disasters, a mean of 54.9% shows that more than 55 percentage data points in the sample suffer from extreme weather events. The records of injuries and fatalities and total damages indicate the differences in severity and location-wise of distinct catastrophic types.

Both bank characteristic and governance variables again confirm the heterogeneity of observations. The mean value of bank age is 13 years.[13] The similarity is observed with bank size, whose value stands 7.5 million dollars (natural logarithm value). Turning to female ratio, the approximately percentage of female directors sitting on board is 13.3. Lastly, a value of 11 in board size shows that on average, there are 11 members in bank's board of directors, with the largest amount up to 33 members.

According to EM-DAT 2019, we reclassify 18 groups of natural disasters into 4 groups of natural hazards, including (i) hydrological disasters, (ii) meteorological disasters, (iii) geophysical disasters, and (iv) climatic disasters. In particular, hydrological disasters covers floods and wet mass movements; meteorological disasters usually relate to sudden and adverse changes in the weather or weather-forming processes, specifically storms and hurricanes; geophysical disasters entails earthquakes, tsunamis, and volcanic eruption, which rarely happen, but cause a massive losses upon occurrence; and climatic disasters are events caused by extreme temperatures, for example, heat wave, droughts, and wildfires. Table A8 shows the summary of 18 natural disasters in the US from 2000 to 2019. The bottom panel of Table A8 shows the distribution of four types of natural hazards, in which the meteorological disasters are the most common natural disasters (about 82%), while hydrological and climatic disasters take account of around 11% and 6%, respectively. Figures 2–5 in show the total number of different hazards events in the US from 2000 to 2019 across states. On average, the East of the US experiences higher frequency of hydrological and meteorological disasters than the West of the US. Texas and Iowa are states with the greatest number of climatic disasters, whereas California and New York are states with the highest number of geophysical disasters.

To further identify how corporate governance intervenes the level of bank stability in the event of natural disasters, we obtain and combine with BoardEx sample with regard to board characteristics. This allows us to understand how director and board characteristics affect the bank performance (i.e. bank stability) in the context of natural disaster.

4. Methodology

4.1. Baseline model

We build our model to estimate the relationship between natural disasters and distance-to-default of banks based on the Z-score. We use a dynamic model based on a panel dataset including approximately 907 banks in 50 states between 2010 and 2019. The estimates is given as follows:

$$\ln \mathrm{Z}_{i,t} = \alpha_{i,t} + \mu_t + \sum_{k=0}^{2} \gamma_k disaster_{c,t-k} + \sum_{j=1}^{2} \beta_j lnZ_{i,t-k} + \delta X_{i,t} + \varphi M_{c,t} + \epsilon_{i,t} \tag{3}$$

Table 1. Descriptive statistics.

Variable	Obs.	Mean	Std. Dev.	Min	Max
Bank stability					
ln_Z1	24,266	4.779	0.951	−4.753	10.427
ln_Z2	25,520	4.707	0.963	−4.753	10.833
EA	24,419	0.112	0.041	−0.129	0.910
ROA	24,712	0.002	0.004	−0.136	0.128
Provision of Loan Asset losses	24,788	0.824	1.194	−6.908	9.257
Volatility of total equity	24,012	3.536	1.889	−3.448	12.559
Volatility of total deposits	23,869	3.410	1.877	−7.254	12.162
Climate risks					
Natural disaster	27,504	0.549	0.498	0.000	1.000
CO_2 Emissions (1000 tons) (log)	27,210	8.112	1.031	0.693	10.171
Retail gas Consumption (Mcf) (log)	25,514	20.216	0.987	14.777	22.147
Records of hazards	27,494	1.189	1.342	0.000	8.000
Records of severe hazards	27,494	1.089	1.280	0.000	7.000
Total Damage (log)	4,300	10.974	3.088	0.000	23.026
Bank characteristics					
Bank age	27460	2.571	0.945	0.000	5.263
Bank size	26013	7.464	1.588	−1.155	15.014
Growth	24731	0.019	0.075	−5.078	7.607
Capital intensity	22491	1.055	1.123	−4.017	9.212
Tier 1 leverage	22597	0.015	0.030	−0.018	1.743
Change of cash	22750	0.002	0.140	−15.047	0.956
Dividend	22712	1.375	1.523	−1.245	9.449
Financial cash flow	22750	0.022	0.141	−0.530	18.985
Investment cash flow	22750	−0.026	0.229	−33.139	1.331
Operating cash flow	20384	2.698	1.880	−5.809	11.653
ΔSpread	31,693	−0.008	0.100	−3.733	1.229
ΔLoan_deposit	32,687	−0.007	0.021	−0.277	0.370
ΔLLP	32,630	0.014	0.138	−2.597	4.266
ΔExpense_ratio	32,882	0.001	0.204	−7.415	7.307
ΔNonInterest_income	32,887	−0.003	0.053	−0.483	0.481
ΔNPL	32,236	0.001	0.002	−0.042	0.036
ΔAllowance_adequacy	33,048	0.774	0.285	0.067	2.802
SGR	32,887	−0.002	0.109	−1.479	0.765
LGR	32,688	0.009	0.039	−0.198	0.936
Macroeconomic variables					
House price	20,059	0.008	0.021	−0.053	0.086
GDP growth	26,590	0.004	0.019	−0.137	0.105
Inflation	25,514	4.601	0.095	4.436	4.782
Unemployment	27,504	1.808	0.358	0.693	2.632
Interest rate	26,023	0.531	0.749	0.010	2.400
Governance variables					
Female ratio	15,897	0.133	0.102	0.000	0.562
STDEV.Age	15,898	7.612	2.344	0.000	17.800
Busyness	15,898	0.377	0.215	0.000	1.000
Boardsize	15,898	10.962	3.327	1.000	33.000
Network size (log)	15,898	6.456	0.904	2.691	8.887

Notes: This table reports summary statistics for all variables used. All variable descriptions are in Table A1.

where $lnZ_{i,t}$ is the logarithm of distance-to-default of the ith bank at county c at time t based on the Z-score, $disaster_{c,t}$ is a dummy variable whether there is any disaster events happening in county c at quarter t where the ith bank is located. We also include lagged dependent variables to control auto-regressive tendencies and lagged variables of natural disaster because we presume that the bank performance will be affected by some events happened in the past period. $X_{i,t}$ is a set of bank characteristics, $M_{c,t}$ is a set of macroeconomic variables at the county level, and μ_t is a time fixed effect.

The alternative way of writing the previous equation is as follows:

$$\ln \mathrm{Z}_{i,t} - \ln \mathrm{Z}_{i,t-1} = \alpha_{i,t} + \mu_t = \sum_{k=0}^{2} \gamma_k disaster_{c,t-k} + (\beta_1 - 1)\, ln\, \mathrm{Z}_{i,t-1} + \beta_2\, ln\, \mathrm{Z}_{i,t-2} + \delta X_{i,t} + \varphi M_{c,t} + \epsilon_{i,t} \quad (4)$$

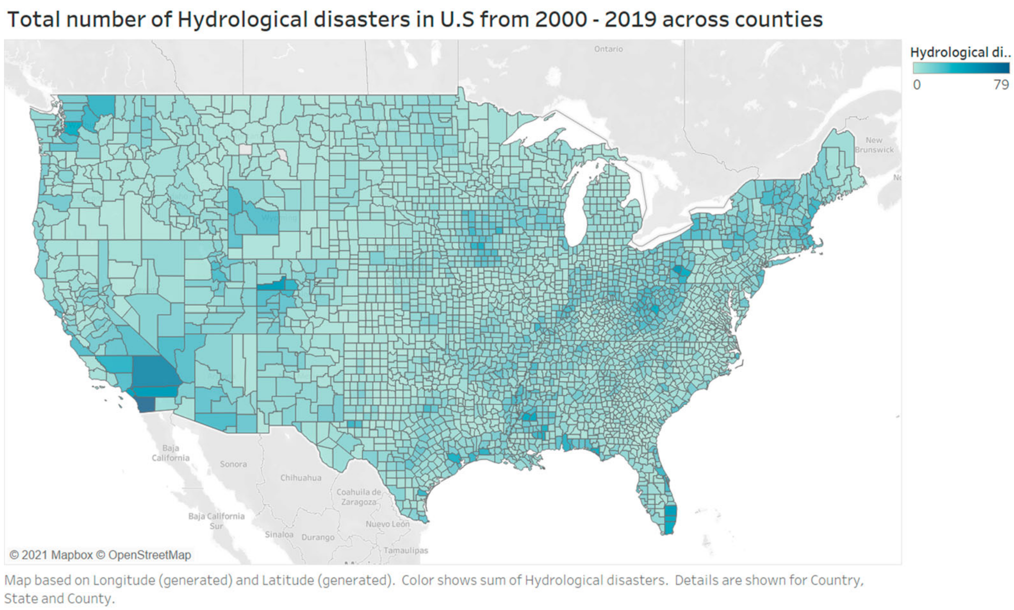

Figure 2. Hydrological disasters in the US from 2000 to 2019.

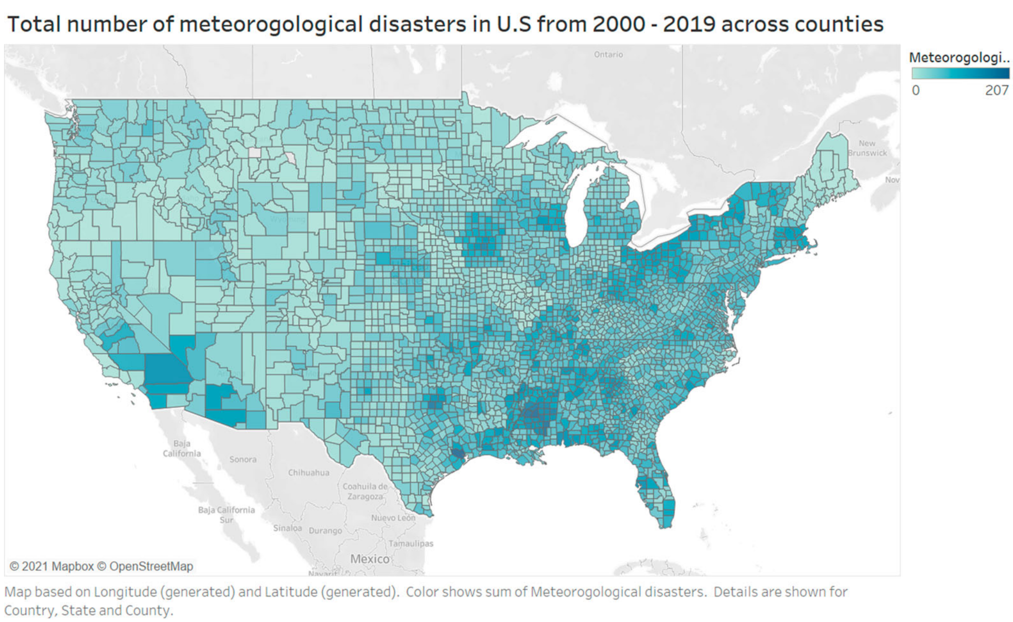

Figure 3. Meteorological disasters in the US from 2000 to 2019.

or

$$\Delta lnZ_{i,t} = \alpha_{i,t} + \mu_t + \sum_{k=0}^{2} \gamma_k disaster_{c,t-k} + (\beta_1 - 1)lnZ_{i,t-1} + \beta_2 lnZ_{i,t-2} + \delta X_{i,t} + \varphi M_{c,t} + \epsilon_{i,t} \quad (5)$$

In this specification, the dependent variable is the log-change of the Z-score. Further, to exploit the exogeneity of the timing and intensity of natural disasters and control for economic developments over time, we include

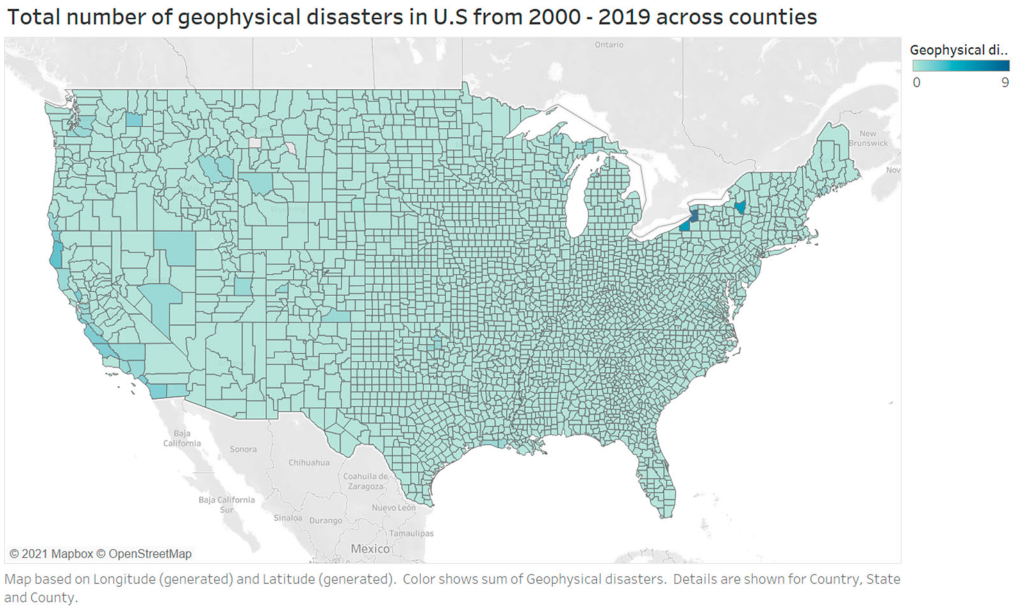

Figure 4. Geophysical disasters in the US from 2000 to 2019.

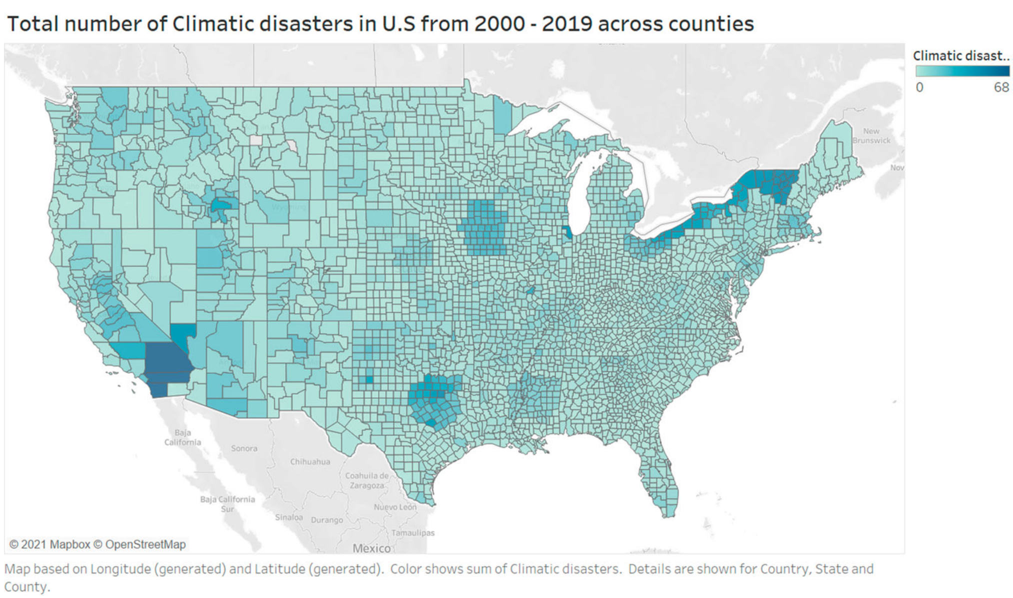

Figure 5. Climatic disasters in the US from 2000 to 2019.

time fixed effects in all regressions, which allows us to control for unobservable time-invariant variables, such as generic disaster risks, disaster management structures, and economic structures in the banks' business regions.[14]

4.2. CO_2 emission as instrumental variable in IV-GMM

We tackle the endogenous problem resulting from potential influence of unobserved heterogeneity and past realizations of climate risks as well as CO_2 emission on the banking stability by employing IV-GMM technique.

We test for the endogeneity of climate risk in the IV-GMM model. We argue that the IV-GMM model presented in this paper is appropriate for estimating the relationship between climate risks and banking stability due to the presence of both unobserved heterogeneity and the influence of past 'natural' and 'anthropogenic' (human-induced) factors.

Carbon dioxide (CO_2) emissions due to fossil fuels account for more than half of greenhouse gas (GHG) emissions, where it is believed that greenhouse gas emissions or CO_2 emissions are largely to blame for the several trends in weather extremes in the form of heatwaves, floods, storms, droughts, and rising sea levels. As such, the risk from natural disaster should not be analysed or treated in isolated, but instead should be integrated into the effects of climate change (Van Aalst 2006; and Phalkey and Louis 2016 for details). For example, the rise in temperature on land surfaces leads to the alteration of the hydrologic cycle (i.e. making it faster), which in turn intensifies cycles of droughts and floods. The rise in temperature at the higher humidity also increases the incidence of tropical storms (Phalkey and Louis 2016). Therefore, it is necessary to consider effects of consumption-based carbon emission together with the impact of natural disaster on financial stability in the causal settings.

Financial institutions' decisions to fund activities with high CO_2 emissions can, albeit indirectly, contribute to an increase in climate-related physical risks; on the other hand, their financing of technologies that help reduce CO_2 emissions can contribute to a reduction in climate-related physical risks (Batten, Sowerbutts, and Tanaka 2016). Numerous efforts have been discussed to identify among which methods to properly apply for controlling GHG emissions. While carbon tax or trade-and-cap framework offers potential positive outcome, the uncertainty in pricing carbon has raised problems in implementation (Davis, Thurber, and Wolak 2020). The current literature has also documented connection between financial sectors and carbon emission (Omri et al. 2015 Cornille, Rycx, and Tojerow 2019). Hence, we use carbon emission as instrument for our model. Also, to strengthen our results by reducing selection bias, we re-analyse our data using propensity score matching technique, as reported in Appendix. This is to ensure that our control and treatment groups are as similar as possible before the event, and that our results are not driven by confounding variables.

5. Empirical results

5.1. Baseline results

In this section, we start by presenting how occurrence of natural disasters impacts banking Z-score. Results obtained by estimating Equation (3) are reported in Table 2. It is worth noting that we have estimated Equation (3) four times using different combinations of controls. Specifically, we simply run an univariate regression in model 1, presenting our naïve model, model 2 includes year fixed-effects. In models 3 and 4, we include controls for different individual bank characteristics and time fixed effects, subsequently while model 5 controls for cross-sectional macroeconomic condition. We find that negative coefficients of the first lagged variable of natural hazards are significant across the models. This means that the occurrence of natural disasters in the previous quarter has a negative impact on the bank Z-score. The coefficient of -0.072 in column (5) means that the occurrence of natural disasters in the previous quarter, on average, other things being unchanged, reduces the Z-score (i.e. bank stability) by approximately 7%. This result is in line with what we expect. The negative relationship between natural hazard and banking Z-scores persists when adding banking characteristics and macroeconomic condition controls as in columns (3)–(5). Hence, our findings are robust at the either 1% or 0.1% statistical significance level, irrespective of the model specification.

An additional point worth mentioning is the positively significant coefficients of lagged two quarters of variable of interest (*L2.Natural hazard*) in all columns (1)–(5). We believe that these coefficients capture the medium-term bank's recovery ability. Put differently, the coefficients of previous two-quarter period signify the extent to how fast banks can recover after the occurrence of natural disasters. While *L.Natural hazard* captures the short-term effect of extreme weather events, the positive coefficient of previous two-quarter (*L2.Natural hazard*) implies that banks which are previously hit by natural disasters have recovered to adapt and stabilize in the aftermath, consistent with Klomp and De Haan (2012). In other words, banks generally manage to overcome adverse effects on their stability and performance within few quarters after a weather-related natural

Table 2. How do natural disasters affect banking financial stability? (baseline result).

	Dependent variable: Ln_Z1				
	(1)	(2)	(3)	(4)	(5)
L.ln_Z1	0.495***	0.492***	0.493***	0.505***	0.505***
	(0.014)	(0.014)	(0.015)	(0.015)	(0.016)
L2.ln_Z1	0.370***	0.371***	0.372***	0.362***	0.365***
	(0.017)	(0.017)	(0.016)	(0.019)	(0.020)
Natural hazard	0.000	−0.007	−0.002	−0.003	−0.013
	(0.013)	(0.014)	(0.014)	(0.013)	(0.014)
L.Natural hazard	−0.081**	−0.079**	−0.073**	−0.058**	−0.072***
	(0.027)	(0.026)	(0.023)	(0.018)	(0.018)
L2.Natural hazard	0.069**	0.072**	0.074**	0.051*	0.061*
	(0.023)	(0.023)	(0.022)	(0.020)	(0.024)
Bank age			−0.013*	−0.020*	−0.018*
			(0.006)	(0.008)	(0.008)
Size			0.033***	0.121***	0.119***
			(0.007)	(0.023)	(0.020)
Growth			−0.287**	−0.138	−0.331+
			(0.099)	(0.141)	(0.178)
Capital intensity			−0.052***	−0.027**	−0.023*
			(0.012)	(0.010)	(0.009)
Tier1 leverage				0.102	0.331
				(0.401)	(0.386)
Change of Cash				0.831	1.356+
				(0.830)	(0.733)
Dividend				0.018+	0.028**
				(0.010)	(0.010)
Financial cash flow				−0.959	−0.989
				(0.918)	(0.844)
Investment cash flow				−0.893	−1.355+
				(0.871)	(0.802)
Operating cash flow				−0.103***	−0.105***
				(0.016)	(0.016)
House price					1.123
					(0.747)
GDP growth					−2.742**
					(0.819)
Inflation					0.005
					(0.067)
Unemployment					−0.060+
					(0.034)
Interest rate					−0.247***
					(0.058)
Constant	0.651***	0.395***	0.227*	−0.148	0.023
	(0.055)	(0.067)	(0.093)	(0.180)	(0.335)
Year Fixed Effects	N	Y	Y	Y	Y
Err. clustered by state	Y	Y	Y	Y	Y
Observations	22,364	22,364	19,582	16,854	12,657
R-squared	0.672	0.675	0.681	0.686	0.701

Notes: This table reports the baseline OLS results of how natural disasters affect banking financial stability. L.ln_Z1 and L2.ln_Z1 are lag 1 and lag 2 of ln_Z1, respectively. The same notion goes for natural hazard. All variable descriptions are in Table A1. The corresponding robust standard errors are reported in parentheses. $+$, $*$, $**$ and $***$ and correspond to the 10%, 5%, 1% and 0.1%, respectively

disaster occurred, consistent with findings in previous studies (Brei, Mohan, and Strobl 2019; Chen and Chang 2021).

Table 2 also indicates that the bank size positively associates with bank Z-score, implying that the bigger the local bank, the more solvent it is. One explanation can be that bigger bank might have more expertise in assessing risks upon loan approval and higher efficiency in terms of operation. Also, larger bank tends to have more branches so that it can reallocate its loss and profit faster than others (Collier, Katchova, and Skees 2011). Among macroeconomic controls, GDP growth and interest rate significantly affect banking Z-score as well. Our findings, nevertheless, depart from the traditional expectation of the existing literature supporting the positive effect of GDP growth on financial stability (Laeven and Majnoni 2003; Uhde and Heimeshoff 2009; Liang, Moreira, and Lee 2020). We conjecture that GDP growth might increase risk-taking behaviours of banks, thereby decreasing the finance stability, which is consistent with Fouejieu (2017), IJtsma, Spierdijk, and Shaffer (2017). Our results also suggest a negative relationship between interest rate and Z-score. This implies that the higher the interest rate, the lower the Z-score, which is contradictory with some previous studies, such as Maddaloni and Peydró (2011), Delis and Kouretas (2011), DellAriccia, Laeven, and Marquez (2014). We argue that when interest rate suddenly increases, banks cannot immediately adjust their portfolio accordingly to the new rate, thus reducing the profit margin. As Z-score is estimated based on bank's ROA, an unexpected thinner margin of profitability results in reduction of bank's stability.

5.2. IV-GMM results

Human activities are largely to blame for the alarming increase in GHG emissions in the environment in recent decades (Kurz et al. 2018), causing dramatic changes in the Earth's temperature (Ritchie and Roser 2020). These drastic changes in temperature divulge in shifts of weather patterns, such as floods, storms, droughts, and rising sea levels (Zhang, Wang, and Wang 2018). In particular, carbon dioxide (CO_2) emission from fossil fuels accounting for more than half of GHG emissions has been the research subject for numerous studies nowadays.

To incorporate the effects of CO_2 emission, we use consumption-based carbon emission reported by each state quarterly as an instrumental variable. As clarified in the literature review, we postulate that the greenhouse gas emission owns a relationship with natural hazard. Therefore, we redesign a model in which CO_2 emission and retail natural gas consumption are instrumental variables for natural hazard and report the results in Table 3. We acknowledge that CO_2 might not serve as the best instrument for climate change. One of the reasons is that banks are the major lender of 'dirty' industries, which, in turn, increase the level of CO_2 emission, accelerating the materialization of climate change which takes the form of natural hazards. Additionally, we also include another instrument, which is the total damage (both crop and property damages, measured in US dollar) caused by natural disasters recorded by SHELDUS.

As Batten, Sowerbutts, and Tanaka (2016) show that though banks can also finance technology outbreaks increasing/reducing CO_2 emission, banks do not necessarily or directly suffer the losses and gains from that in near future. The reporting results (Table 3)[15] in the first stage show that CO_2 emission is positively related with natural disasters. The endogeneity test statistic is significant at least at 1% level ($p = 0.0157$ (model 1), $p = 0.01$ (model 2), $p = 0.0083$ (model 3)) while Hansen test values are between the range 0.05 and 0.7 (models 2 and 3), which means natural hazard must be treated as endogenous and instrumental variables are partly acceptable, proving that our models are valid.

We find that controlling for endogeneity, the results in the second stage also support our baseline conclusions, which show that natural disasters may affect the banking stability (if that bank is not financially healthy) and this effect, in fact, raises banks' awareness about new risks and develops adaptation plans to that shortly afterward. High capital intensity also means that bank may over-invest, thus lessen the buffer for loss provision and become riskier. Additionally, we conjecture that banks which have a large proportion of fixed assets will bear more damages caused by natural disasters relative to those with high intangible assets. Hence, our result confirms that capital intensity imposes negative relationship on bank stability.

5.3. Which channels climate risk affects banking stability

We argue that climate risks affect banking stability through its impact on several channels, i.e. profitability, prudence, and growth. To validate mechanisms, we examine the interactions between natural hazard and signals of bank financial health towards Z-score. For profitability, we employ loan spread,[16] operating expense ratio, non-interest income, and loans to deposits. For signals related to prudence, we use loan loss provision, non-performing loans, and allowance adequacy. We include revenue growth and loan growth to measure the bank's

Table 3. How do natural disasters affect banking financial stability? (IV-GMM results).

Dependent variable: Ln_Z1			
	Model 1	Model 2	Model 3
Natural hazard	1.200***	1.020	1.166*
	(0.000)	(0.212)	(0.012)
L.Natural hazard	−1.483+	−2.744	−1.127
	(0.056)	(0.752)	(0.103)
L.ln_Z1	0.393***	0.409*	0.482***
	(0.000)	(0.034)	(0.000)
L2.ln_Z1	0.465***	0.490	0.381***
	(0.000)	(0.152)	(0.000)
Bank age		−0.073	−0.017
		(0.744)	(0.421)
Bank size		0.067	0.100**
		(0.334)	(0.003)
Growth		−0.518	−0.418*
		(0.708)	(0.037)
Capital intensity		0.061	−0.012
		(0.856)	(0.698)
Tier 1 leverage		1.474	0.613
		(0.755)	(0.361)
Change of cash		3.492	2.254*
		(0.661)	(0.042)
Dividend		0.045	0.036*
		(0.363)	(0.012)
Financial cash flow		−4.058	−2.066+
		(0.646)	(0.088)
Investment cash flow		−3.825	−2.238+
		(0.665)	(0.051)
Operating cash flow		−0.065	−0.100***
		(0.512)	(0.000)
House			−5.912*
			(0.028)
GDP growth			−2.331
			(0.218)
Inflation			−0.002
			(0.981)
Unemployment			−0.066
			(0.458)
Interest rate			0.185
			(0.385)
Constant.	0.864	1.368	0.079
	(0.120)	(0.798)	(0.889)
Year Fixed Effects	Y	Y	Y
Err. clustered by state	Y	Y	Y
Observations	21,578	16,402	12,471
R-squared	0.9644	0.9235	0.9706
Hansen test	0.0295	0.8141	0.0677
Endogeneity test	0.0157	0.0100	0.0083

Notes: This table reports the main stage of 2SLS-GMM regression results of the interaction between CO_2 Emissions and natural disasters affect bank stability (The first stage result is reported in Appendix Table A6, see also the IV-GMM version without lag of natural hazard in Table A7). L.ln_Z1 and L2.ln_Z1 are lag 1 and lag 2 of ln_Z1, respectively. The same notion goes for natural hazard. All variable descriptions are in Table A1. The corresponding robust standard errors are re- ported in parentheses. +, ∗, ∗∗ and ∗∗∗ and correspond to the 10%, 5%, 1% and 0.1%, respectively

growth in its core traditional business and other activities. The choice and measures of mechanism channels follow the previous research (Calomiris and Nissim 2007; Koller et al. 2010; Mohanram, Saiy, and Vyas 2018).

Columns (1)–(4) in Table 4 focus on how natural disasters affect the banking profitability. Starting with the spread on a bank's loan portfolio, which is defined as the ratio of net interest income (difference between interest income and interest expense) to total loans, larger spread not only reflects the higher risk on loan portfolio, but also implies information regarding the bank's profit margin. It is obvious that banks will increase the loan spread when being exposed to natural disasters (Huang et al. 2020; Correa et al. 2020).[17] However, to which extent an increase in spread affects Z-score remains a question. Column (1) shows that the sign of interaction term is negative, and its absolute coefficient (0.076) is higher than that of natural hazard (0.049), implying that increasing the spread when bearing the climate risk is not the ultimate solution because Z-score still declines. The suggestive explanation is that since bank has to keep its spread comparable with its peers, it can only increase the spread up to a threshold but not indefinitely. The consequence is either bank may lose its customers and shrink its loan portfolio or the increasing spread cannot compensate all the natural disaster risks.

Supporting the above conjecture are results about interactions (of natural hazard) with each of operating expense ratio, loans to deposits, and non-interest income. The positive and significant coefficient in Column (4) indicates that if operating and administrative expenses are well-managed, it can help mitigate the climate risk. Meanwhile, there are no significant results for interactions (of natural hazard) with either loan to deposits or non-interest income. The insignificance of coefficients indicates that natural disasters do not have a material effect on these two variables. Put differently, non-interest income or lending efficiency cannot compensate for a bank's stability upon extreme weather hazards.

Towards the prudence channel, we present the results of loan loss provision (LLP), non-performing loan ratio (NPL), and allowance adequacy (AA) in columns (5)–(7) subsequently. The positive interaction coefficients between natural hazard with either LLP or AA, which are both significant at 0.1% and 1%, respectively, strongly emphasize how appropriate the provision/allowance level helps mitigate climate risks without impairing capital during periods of distress. It also implies that if bank is well-diversified and has pertinent expertise to correctly provision for the loss of lending portfolio, Z-score will be enhanced better. On the other hand, banks holding more non-performing loans will be riskier when natural disasters strike. The results are confirmed with the sub-sample analyses in Columns (3) and (4) of Table 5. The coefficient of interaction term with NPL reported in column (6) is −1.010 and significantly at 5% level.

We use both revenue growth (SGR)[18] and loan growth (LGR)[19] to investigate the growth channel on banking stability. The interaction term between natural hazard and growth of bank loan portfolio (LGR) in column (9) is positive at 5% significance level, illustrating that bank can cope with extreme weather conditions by expanding and diversifying its loan portfolio. Nevertheless, negative result in column (8) representing the interaction term between natural hazard and total revenue growth still holds that revenue growth does not compensate bank's stability in the unpredictable climate environment.

6. Additional tests

6.1. Sub-sample analyses

Table 5 reports sub-sample results. First, we classify states into either less- or more-exposed group based on the frequency of natural hazard occurrence.[20] We then categorize bank by its geographical locations in the above two groups and discover that the effect of extreme weather events is more pronounced in the less-exposed group. Consistent with the literature,[21] banks that are not familiar with handling the aftermath of natural disasters are less prepared to cope with climate risk; while the more-exposed group is more likely to have good prediction and preparation. For instance, banks operating in wildfire-prone areas, such as California or Texas, will accumulate more experience in assessing the likelihood of destruction caused by potential fire, and require additional measure to mitigate before providing mortgage to households. Hence, these banks will have more expertise in preparing or handling the occurrence of natural disaster, compared to others.

Another way to split the sample is to base on its non-performing loan using the sample's median as threshold (see columns (3)–(4)). We find that banks which hold higher portion of bad debts will suffer more severely, worsening natural disaster's impacts. Intuitively, banks with high portion of bad debts in their portfolio are less

Table 4. How natural disasters affect banking *Z*-score through various channels?.

	Dependent variable: Ln_Z1								
	Profitability channel				Prudence channel			Growth channel	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
L1.ln_Z1	0.479***	0.503***	0.505***	0.507***	0.505***	0.498***	0.503***	0.506***	0.503***
	(0.021)	(0.016)	(0.016)	(0.015)	(0.015)	(0.016)	(0.016)	(0.015)	(0.016)
L2.ln_Z1	0.392***	0.365***	0.365***	0.364***	0.365***	0.370***	0.364***	0.364***	0.365***
	(0.022)	(0.020)	(0.020)	(0.019)	(0.019)	(0.020)	(0.020)	(0.020)	(0.020)
L1. Natural hazard	−0.049*	−0.061***	−0.061***	−0.061***	−0.063***	−0.061***	−0.093***	−0.060***	−0.067***
	(0.022)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.020)	(0.017)	(0.017)
L1. Natural hazard #Spread	−0.076+								
	(0.040)								
L1. Natural hazard #Loans_Deposits		0.234							
		(0.208)							
L1. Natural hazard #Noninterest_Income			−0.052						
			(0.053)						
L1. Natural hazard #Expense_Ratio				0.161***					
				(0.028)					
L1. Natural hazard #LLP					0.199***				
					(0.034)				
L1. Natural hazard #N P L						−1.010*			
						(0.483)			
L1. Natural hazard #Allowance_Adequacy							0.047**		
							(0.015)		
L1. Natural hazard #SGR								−0.088*	
								(0.042)	
L1. Natural hazard#LGR									0.331*
									(0.127)
Constant	0.293	0.028	0.037	0.039	0.045	−0.066	0.081	0.050	0.036
	(0.315)	(0.343)	(0.343)	(0.343)	(0.342)	(0.345)	(0.360)	(0.343)	(0.341)
Control variables	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Err. Clustered by state	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	8,148	12,589	12,651	12,651	12,515	12,212	12,500	12,644	12,589
R-squared	0.710	0.700	0.700	0.703	0.702	0.699	0.699	0.701	0.700

Notes: This table illustrates the results for channels of which natural disaster affect bank risk. L.ln_Z1 and L2.ln_Z1 are lag 1 and lag 2 of ln_Z1, respectively. The same notion goes for natural hazard. For the definitions of all the control variables and the details of their construction, see Appendix. The corresponding robust standard errors are reported in parentheses. Significance levels are indicated by +, ∗, ∗∗ and ∗∗∗ and correspond to the 10%, 5%, 1% and 0.1% significance levels, respectively.

Table 5. Sub-sample analyses.

	Dependent variable: Ln_Z1					
	Frequently exposed to natural hazard		Nonperforming loan		ROE	
	Less exposed (1)	More exposed (2)	Less (3)	More (4)	Lower (5)	Higher (6)
L1.ln_Z1	0.518***	0.488***	0.536***	0.481***	0.529***	0.471***
	(0.027)	(0.020)	(0.021)	(0.021)	(0.017)	(0.026)
L2.ln_Z1	0.380***	0.352***	0.333***	0.382***	0.341***	0.385***
	(0.026)	(0.028)	(0.034)	(0.024)	(0.027)	(0.029)
L1. Natural hazard	−0.101***	−0.032	−0.026	−0.084***	−0.031+	−0.099***
	(0.011)	(0.027)	(0.016)	(0.019)	(0.016)	(0.020)
Constant	−0.474	0.309	0.180	0.220	0.003	0.277
	(0.516)	(0.409)	(0.368)	(0.452)	(0.348)	(0.516)
Control variables	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Err. Clustered by state	Y	Y	Y	Y	Y	Y
Observations	6,180	6,477	5,333	7,324	7,219	5,438
R-squared	0.748	0.655	0.708	0.689	0.697	0.688

Notes: This table reports the sub-sample results. L.ln_Z1 and L2.ln_Z1 are lag 1 and lag 2 of ln_Z1, respectively. The same notion goes for natural hazard. All variable descriptions are in Table A1. +, ∗, ∗∗ and ∗∗∗ and correspond to the 10%, 5%, 1% and 0.1%, respectively

sound and, consequently, subject to fragility when extreme climatic events occur (aforementioned in previous part).

Upon splitting sample by using ROE median value as threshold, banks with higher ROE need to take better care of climate risk comparing to those in a lower-ROE group. In this case, the higher magnitude (and stronger regarding significance level) of negative relationship between natural disaster and bank stability across two sub-samples (see columns (5)–(6), $0.099 > 0.031$) illustrates our finding. Higher ROE may be attributable to many causes, among which are lower provision or riskier asset allocation leading thinner protection. Researchers and practitioners show that ROE actually encourages greater risk-taking by banks. These beliefs affect banks' choices in terms of asset allocation and financial policy, distorting their strategic planning (Moussu and Petit-Romec 2014).

6.2. How board governance help mitigate climate risk?

To capture how the governance responses with the natural disaster, we also consider the below estimate:

$$\mathrm{lnZ}_{i,t} = \mu_t + \gamma_1 disaster_{c,t-1} + \lambda_1 board_{i,t} + \delta_1 disaster_{c,t-1} * board_{i,t} + \sum_{j=1}^{2} \beta_j lnZ_{i,t-k} + \delta X_{i,t} + \epsilon_{i,t} \quad (6)$$

In addition, by combining with BoardEx dataset, we try to identify which kind of board characteristics better mitigate climate risks. Table 6 illustrates the association of the board characteristics and bank stability in the context of natural disaster. We find that the coefficient of interaction term between natural disaster and female ratio is statistically significant in column (1). This means that given the natural disaster happens, a 1% increase in proportion of female directors on the board the Z-score increases by around 27%. This result is in line with previous studies (e.g. Abbott, Parker, and Presley 2012; Green and Homroy 2018) and once again confirms that one of primary female characteristics is risk-averse. Column (2) reports a positive coefficient (though not significant) of the interaction term regarding the variance in ages of the board, but a negative coefficient of itself.

Regarding the busyness of the board, we find the significance of its coefficient but no significance of the interaction term (shown in column (3)). This means that the bank stability is generally deteriorated with the busy board regardless of natural disasters (Core, Holthausen, and Larcker 1999; Kress 2018). According to reputation hypothesis, board networks also contribute to a better governance. In the last column, we account for average network size of the board and find the negative coefficient for itself and positive coefficient for the interaction term. However, these effects almost cancel out to leave the net effect of network size relatively marginal. Last but

Table 6. Which kind of board mitigate better climate risks?

	Dependent variable: Ln_Z1				
	(1)	(2)	(3)	(4)	(5)
L.Natural disaster	−0.089**	−0.089**	−0.073*	−0.139**	−0.233**
	(0.028)	(0.032)	(0.032)	(0.047)	(0.066)
Female ratio in board	−0.112				
	(0.067)				
L.Natural disaster # Female_ratio	0.270*				
	(0.113)				
STDEV.Age		−0.006*			
		(0.002)			
L.Natural disaster # STDEV.Age		0.005			
		(0.004)			
Busyness			−0.064		
			(0.038)		
L.Natural disaster # Busyness			0.055		
			(0.060)		
Boardsize				0.002	
				(0.002)	
L.Natural disaster # Boardsize				0.008*	
				(0.003)	
Network size					−0.035***
					(0.008)
L.Natural disaster # Network size					0.028**
					(0.010)
Constant	0.321***	0.345***	0.309**	0.340***	0.489***
	(0.086)	(0.093)	(0.091)	(0.087)	(0.116)
Control variables	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y
Err. clustered by state	Y	Y	Y	Y	Y
Observations	14,039	14,040	14,040	14,040	14,040
R-squared	0.698	0.697	0.697	0.698	0.698

Notes: This table reports the regression results about which kind of board mitigate better climate risks. L.Natural hazard is the lag 1 of natural hazard occurrence. All variable descriptions are in Table A1. $+$, $*$, $**$ and $***$ and correspond to the 10%, 5%, 1% and 0.1%, respectively.

not least, the number of directors on the board is another factor contributing to banks' corporate governance. The significantly positive coefficient in column (4) means that when there are more directors on boards, the banking financial health may be more stable in the event of natural disaster. This may be plausible when there is more bank management among the board members to get the bank over the natural disasters.

6.3. Testing on non-linear relationship

6.3.1. Does total damages effect follow a non-linear nexus?

This section provides additional test on non-linear relationship between natural disasters and banking stability, which have not been addressed well in previous studies. Rather using dummy variable to proxy for climate risk, we use total damage caused by natural disasters,[22] and report the results of which are shown in Panel A of Table 7. The results suggest a U-shaped relationship between hazard damage and bank Z-score. The non-linearity relation implies that the Z-score initially reduces as natural hazards cause increasing damage, but starts improving when the total damage exceeds threshold. This sounds sensible because there is some indemnity has been paid out for the designated peril loss due to hazard events under the Federal crop insurance programmes administered by the Risk Management Agency (RMA).

Alternatively, we divide the total damage into different bins to capture the non-linear effect of natural hazards on the banking stability. Panel B of Table 7 shows how different bins of total damage affect the Z-score. We find the negative statistical significance of bin 3 and bin 4 relative to bin 1, but the absolute coefficient value of bin 3 greater than that of bin 4 implies a U-shaped relationship, which is consistent with the findings in Panel A.

Table 7. Non-linear effect of natural disaster on banking stability.

Panel A: Using polynomial form for total damages of natural hazard			
	Dependent variable: ln_Z1		
	(1)	(2)	(3)
L.ln_Z1	0.4912***	0.5037***	0.5042***
	(0.0150)	(0.0144)	(0.0156)
L2.ln_Z1	0.3737***	0.3630***	0.3645***
	(0.0163)	(0.0191)	(0.0196)
L.Total damages	−0.0096**	−0.0091**	−0.0150***
	(0.0035)	(0.0030)	(0.0036)
L.Total damages # L.Total damages	0.0005*	0.0005**	0.0009***
	(0.0002)	(0.0002)	(0.0002)
Bank characteristics	N	Y	Y
Macro economics	N	N	Y
Year Fixed Effects	Y	Y	Y
Err. clustered by state	Y	Y	Y
Observations	19,582	16,854	12,657
R-squared	0.6795	0.6856	0.7005

Panel B: Using bin of total damages			
	Dependent variable: ln_Z		
	(1)	(2)	(3)
L.ln_Z1	0.4913***	0.5038***	0.5046***
	(0.0150)	(0.0144)	(0.0156)
L2.ln_Z1	0.3735***	0.3627***	0.3649***
	(0.0163)	(0.0190)	(0.0195)
Bin 2	−0.0198	−0.0077	−0.0143
	(0.0256)	(0.0229)	(0.0298)
Bin 3	−0.0561*	−0.0490**	−0.0745***
	(0.0221)	(0.0175)	(0.0192
Bin 4	−0.0353+	−0.0305+	−0.0405*
	(0.0204)	(0.0166)	(0.0177)
Bank characteristics	N	Y	Y
Macro economics	N	N	Y
Year Fixed Effects	Y	Y	Y
Err. clustered by state	Y	Y	Y
Observations	19,582	16,854	12,657
R-squared	0.6796	0.6856	0.7005

Notes: This table reports the OLS regression results on non-linear relation- ship between natural disasters and banking stability. L.ln_Z1 and L2.ln_Z1 are lag 1 and lag 2 of ln_Z1, respectively. The same notion goes for natural hazard and total damages. Panel A displays the model with the square term of total damage caused by natural disasters. Panel B shows the model with 4 different bins of total damage caused by natural disasters. $Bin = 1$ if L.ln_totaldmg $= 0$. $Bin = 2$ if L.ln_totaldmg > 0 & L.ln_totaldmg $< p(50)$. $Bin = 3$ if L.ln_totaldmg $> = p(50)$ & L.ln_totaldmg $< p(75)$. $Bin = 4$ if L.ln_totaldmg $> = p(75)$. All variable descriptions are in Table A1. The corresponding robust standard errors are reported in parentheses. $+$, $*$, $**$ and $***$ and correspond to the 10%, 5%, 1% and 0.1%, respectively.

6.3.2. Different levels of destruction: the role of indemnity

Furthermore, we also perform another test to see the effect of indemnity paid out due to natural hazards, which is illustrated in Table 8. First, we divide our sample into the high- and low-damaged ones using median value as threshold. Panel A of Table 8 depicts the differences in Z-score between these two groups. Panel B of Table 8 presents the regression results of the two groups. As we expect, indemnity does not help to recover Z-score in the low-damaged group, whereas we find significant result of indemnity on Z-score in the high-damaged group. The results suggest an inverse-U shaped relationship between indemnity and Z-score. This means that the Z-score improves as the paid-out indemnity keeps increasing. However, up to a certain level, the Z-score

Table 8. Non-linear effect of indemnity on banking stability.

Panel A: Difference in Z-score between two groups (high damage vs. low damage)

	Low damage	High damage	Difference
ln_Z1	4.797	4.761	0.036***

Panel B: OLS regression (sub-sample: high damage vs. low damage)

	Dependent variable: ln_Z1	
	High damage (1)	Low damage (2)
L.ln_Z1	0.6421***	0.4473***
	(0.0500)	(0.0433)
L2.ln_Z1	0.2762***	0.3834***
	(0.0556)	(0.0370)
L.Indemnity	0.0726+	0.0486
	(0.0373)	(0.0312)
L.Indemnity # L.Indemnity	−0.0034+	−0.0020
	(0.0017)	(0.0013)
Bank characteristics	Y	Y
Macro economics	Y	Y
Year Fixed Effects	Y	Y
Err. clustered by state	Y	Y
Observations	3,878	2,682
R-squared	0.7539	0.6597

Notes: This table reports the OLS regression results on non-linear relationship between indemnity and banking stability in two sub-samples. L.ln_Z1 and L2.ln_Z1 are lag 1 and lag 2 of ln_Z1, respectively. The same notion goes for natural hazard and indemnity. All variable descriptions are in Table A1. The corresponding robust standard errors are reported in parentheses. +, *, ** and *** and correspond to the 10%, 5%, 1% and 0.1%, respectively

deteriorates as the indemnity paid-out keeps increasing. This refers to the situation when natural hazards hit us hard, and the indemnity cannot recover the loss caused by hazards. This result is similar to the findings of Linnerooth-Bayer and Mechler (2006) which suggests that insurance would be an assisting adaptation to climate change in developing countries.

7. Conclusion

In this study, we provide results showing that the growing trend in the frequency and intensity of severe natural events due to climate change has potentiality to stress and threaten banks to the point of impaired viability or even insolvency. To date, the empirical evidence on the mentioned relationship is mixed due to the fact that realized disaster-related damages are affected by local economic structure and disaster management under local economic conditions. To do so, we use Spatial Hazard Events and Losses Database for the United States (SHELDUS) and banking financial data from S&P COMPUSTAT alongside several macroeconomic, market structure, and bank-related variables from Bureau of Economic Analysis (BEA) for the period 2010–2019.

Controlling for bank characteristics, macroeconomic factors, and time fixed effects, we show that natural disasters negatively influence the financial stability. Alternatively, we insist that the relationship between natural hazards and financial stability in fact should be considered under the association with CO_2 (in the first stage of IV-GMM) to provide a revealing relationship. Addressing potential endogeneity issue with 2SLS, we show that our findings have significant economic interpretations. Specifically, the occurrence of natural disasters in the previous quarter, on average, ceteris paribus, reduces the Z-score (proxied for financial stability) by around 7%. This result holds true, especially for local medium-sized banks but not for big banks.

Through examining the mechanism by which natural disasters increase bank risk, we demonstrate that increasing the interest rate spread does not adequately compensate for the risk of natural disasters, but rather results in future declines in lending activity. Sub-sample analyses demonstrate that inexperienced banks in dealing with natural disasters are less able to cope with climate risk.

Further, we find suggestive evidence that strong corporate governance helps stabilize banks in the aftermath of disasters. Particularly, our results find that banks with more female directors and having large networks tend to recover better than their counterparts. Hence, board characteristics do play a role in determining the level of bank risk.

Last but not least, we find a non-linear relationship between weather extreme damage and bank stability, which may be resulted in the joint effect of government aid programmes. However, no matter how much indemnity is paid out, the loss of natural hazard barely recovers when natural hazards severely hit a region up to a certain limit.

Our results call for more attention from banks' management team to increase efforts in preparing and adapting strategies, given the fact that global warming is occurring, potentially leading to growing numbers and intensity of extreme weather events. While natural hazards adversely affect the bank stability, banks can better adapt to increasing climate risk by adjusting operational activities to influence the level of loss provision or allowance adequacy. Additionally, strong corporate governance assists banks to recovery better than their cohort. Hence, our results also speak to policymakers to have prompt regulations, such as compulsory diversified board members, or capital adequacy in regions that are suffered from natural disasters at high frequency, with the ultimate aim of increasing bank's health, ensuring normal function of financial institution when adverse climatic events strike.

8. Limitation and remark

Despite our efforts of trying to provide a comprehensive picture of how natural hazards affect bank stability, we derive our results by focusing on only bank's headquarters, neglecting the effect of natural hazards on branches of the concerned banks in different regions. Recent findings by Correa et al. (2020) prove a spillover effect of natural disasters on banking sectors. Hence, a closer investigation on network of bank establishments (i.e. branches, partnerships, or even competitors) or spatial effect (of natural hazard) might reveal a stronger outcome.

Second, the materialization of climate change might reveal beyond natural hazards and probably have second-order effect on banking sectors. According to Graff Zivin and Neidell (2014), excessive temperatures reduce employee working hours, thus affecting firm's – banks' customers – bottom line. Third, banks might adopt certain mechanisms to better adapt to the increasing risk from climate change. Such adaptive strategies might provide certain banks competitive advantage relative to others, highlighting heterogeneity effect of future hazards events. Next, regulatory risk might become tightened in the future, which expose either banks or their customers, i.e. oil and gas companies, to higher costs of doing business. Lastly, insurance programme may be designed better to cope with severe risks like natural catastrophes. All together might lead to increasing bank stability.

Notes

1. https://www.bankofengland.co.uk/speech/2015/breaking-the-tragedy-of-the-horizon-climate-change-and-financial-stability
2. See Statista, Countries with the most natural disasters in 2020, https://www.statista.com/statistics/269652/countries-with-the-most-natural-disasters/
3. The SHELDUS database is provided by Center for Emergency Management and Homeland Security at the Arizona State University Carolina https://cemhs.asu.edu/sheldus). Figure 1 summarizes various types of natural disasters in the US from 2000 to 2019.
4. Together with the 2SLS analysis, the propensity score match constitutes one of the sharpest tests to isolate the effect of natural disasters on bank risk as it compares banks that are very similar to each other taking into account their propensity to be exposed with natural disasters. In Appendix, we provide the results of propensity score matching using a variety of factors such as bank characteristics, macroeconomic circumstances, CO_2 emissions, and governance.
5. Extra findings (in Appendix) suggest that the negative influence of climate risks on financial stability is strongest for local medium-sized banks. On the other hand, we also provide solid evidence showing that local economic condition does invert the impact of natural hazard on financial stability, which also holds true in case of big banks due to their widespread franchise and better diversification.
6. https://nca2018.globalchange.gov/chapter/2/
7. As a result, two quarters after a hurricane, bank lending has been contracted. Similar findings have been found in studies on the impact of natural disasters, indicating that researchers should consider one- and/or two-period lag terms. As a result, when

a natural hazard occurs, the effects on the financial system should include both the current and time-period lag terms Cortés (2014) and Chen and Chang (2021).
8. https://www.reuters.com/article/us-usa-fema-floodinsurance-idUSKBN2BO6SB
9. We do not address this problem of private sector insurance in this study as only federal insurance data is available.
10. By leveraging expertise and network of outside directors to make better decision, utilize more efficiently resources and monitor more effectively
11. The SHELDUS database is provided by Center for Emergency Management and Homeland Security at the Arizona State University Carolina https://cemhs.asu.edu/sheldus)
12. The National Climatic Data Center, the National Geophysical Data Center, and the Storm Prediction Center on fatalities and direct losses in the form of property damages associated with 18 types of natural hazards (e.g. hurricanes, floods, severe storms, tornados, and wildfires, etc.).
13. $13 = e^{5.3}$
14. Also, we are able to estimate the parameter γ by a propensity score matching methodology, where banks in county c affected by natural disasters are the "treated", otherwise they are the "controls" (see the results Table A5).
15. We also report another version of IV-GMM without lag of natural disasters in Table A6.
16. This measure is different with Spread_DealScan variable, reported in Table **A2**.
17. The results from alternative measures of banking stability confirm on this, see Table A2, with Spread_DealScan.
18. Both traditional banking activities and other non-banking activities are included for the revenue calculation.
19. The percentage annual change in gross loans reported on the balance sheet.
20. https://worldpopulationreview.com/state-rankings/states-with-the-least-natural-disasters
21. See, e.g. Chavaz (2016), Noth and Schüwer (2018), Skidmore and Toya (2002).
22. Total damage is the sum of property damage and crop damage, reported in US dollars.

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