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Does Disaster Risk Relate to Banks' Loan Loss Provision Estimates?

LORENZO DAL MASO, KIRIDARAN KANAGARETNAM, GERALD LOBO, FRANCESCO MAZZI

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DISEI, Università degli Studi di Firenze
Via delle Pandette 9, 50127 Firenze (Italia) www.disei.unifi.it

Does Disaster Risk Relate to Banks' Loan Loss Provision Estimates?

Lorenzo Dal Maso[1], Kiridaran Kanagaretnam[2], Gerald Lobo[3], Francesco Mazzi[4]

Abstract

We examine the relation between disaster risk and banks' loan loss provision (LLP) estimates. We propose a disaster risk measure based on the natural disasters declared as major disasters by the Federal Emergency Management Agency over the past fifteen years. We theoretically support and empirically validate our measure using three different approaches, including the UN Sendai Framework for disaster risk reduction, which relates disaster risk to natural hazard exposure, vulnerability and capacity, and hazard characteristics. Using more than 445,000 bank-quarter observations, we document that banks located in counties with higher disaster risk recognize larger LLP after controlling for other bank-level factors related to LLP estimates. We employ several techniques to ensure the robustness of our findings, including difference-in-differences estimation and matched samples. In additional analysis, we propose three alternative measures of disaster risk, explore the characteristics that better enable banks to recognize disaster risk in their LLP estimates, and investigate the consequences of managing disaster risk through LLP. Our results are important, especially because of the increasing concern about disaster risk and because they inform the growing debate on the economic consequences of disaster risk and the ability of the banking system to proactively manage the resulting credit risk through LLPs.

Keywords: Disaster Risk, Loan Loss Provisions, Future Charge-offs, Future Risk-Taking, Banks
Data Availability: All data are publicly available from sources identified in the manuscript.
JEL Classification: M40, M41, G20, G21, E50, E59

[1] University of Bologna
[2] Schulich School of Business, York University
[3] University of Houston – Bauer College of Business
[4] University of Florence

1. Introduction

Natural disasters have a tremendous economic and social impact, inflicting severe damage to property and infrastructure, devastating local economies, and potentially harming national economic output (UNISDR, 2015; UNDRR, 2019). These events are difficult to predict and, as highlighted by Jerome Powell, Chairman of the Board of Governors of the U.S. Federal Reserve System, can be classified as shocks to the financial system (Powell, 2019). Therefore, the Federal Reserve Board emphasizes the impact of natural disasters on financial stability, focusing in particular on the ability of financial institutions to identify, measure, and monitor disaster risk. Prior literature concentrates mainly on ex-post consequences of natural disasters (e.g., Cortés and Strahan, 2017; Dessaint and Matray, 2017). In this study, we investigate whether banks proactively manage credit risk by ex-ante reflecting disaster risk in their balance sheets through recognizing higher loan loss provisions (LLP).

The United Nations (UN) Sendai Framework for disaster risk reduction defines disaster risk as the consequence of the interaction between a natural hazard and the characteristics that make places and people exposed and vulnerable (UNISDR, 2015)[5]. If a natural hazard manifests in an area of no exposure, then there is no risk. Additionally, an exposed area can be more or less prepared for the occurrence of natural hazards. Consequently, disaster risk encompasses both natural hazard exposure and vulnerability.

A natural hazard is a potentially destructive event (e.g., hurricane, tornado, flood, and drought) that may cause loss of life, injury, property damage, and social and economic disruption. Many areas are exposed to multiple hazards that vary in terms of geographical scale (e.g., tornadoes are normally localized, while drought areas can cover thousands of square miles). Exposure refers to the attributes and value of assets that are important to the communities located in hazard-prone areas. People and assets become concentrated in areas exposed to hazards through population growth, migration, and

[5] The UN Sendai Framework for disaster risk reduction was adopted at the Third UN World Conference in Sendai, Japan, on March 18, 2015. The Sendai Framework replaced the Hyogo Framework for Action 2005-2015. Among others, the main objectives of the Sendai Framework are the improved understanding of disaster risk in all its dimensions, the strengthening of disaster risk governance, and the mobilization of risk-sensitive investment to avoid the creation of new risk.

urbanization (UNISDR, 2015). Vulnerability refers to the likelihood that assets will be damaged when exposed to hazard events and is related to physical, economic, social, and environmental factors. Given the characteristics of its components, disaster risk varies over time and across geographical areas.

From the financial risk management perspective, two important additional characteristics distinguish disaster risk from other types of risk. First, disaster risk impacts all sectors and asset classes, albeit with different intensities. Second, insurance services and public assistance programs provide insufficient coverage against disaster risk (Botzen et al., 2012; OECD, 2015; Dessaint and Matray, 2017; Noth and Schuwer, 2018). These characteristics imply that disaster risk cannot be avoided entirely but only mitigated (World Bank GFDRR, 2014; OECD, 2015). This is especially true for banks that are key actors in the financial system and provide significant amounts of capital to firms operating in multiple sectors. Disaster risk could concentrate on banks' lending portfolios and, if not properly managed, could create a systemic risk to financial stability (PriceWaterhouseCoopers, 2016).

Disaster risk faced by borrowers could transfer to banks' lending portfolios through the reduced ability of borrowers to repay loans due to disaster-related financial constraints. This translates into an increase in credit risk for banks, which could also lead to higher liquidity risk because of the reduction of cash inflows. Consequently, banks need to incorporate disaster risk into their risk management strategies to avoid creating a systemic risk to financial stability (e.g., OECD, 2015; Powell, 2019).

One approach for banks to manage disaster risk is the use of disaster risk financing tools, such as incorporating the risk in their lending decisions on a loan-by-loan basis. Since pricing disaster risk into corporate ratings and interest spreads can be challenging (Standard and Poor's, 2015b), the ability to mitigate disaster risk through the sole use of disaster risk financing tools is unclear. On the one hand, a recent report from Standard and Poor's (2015a) shows that only 60 negative rating actions (comprising downgrades and outlook revisions) were taken after natural disasters. Standard and Poor's (2015a) explains that the small number of negative rating actions is due to sufficient insurance protection and post-event recovery measures for their sample firms. However, both academic research and non-academic reports stress that, in general, there is insufficient use of disaster risk financing tools and, especially, insurance protection (Botzen et al., 2012; OECD, 2015; Dessaint and Matray, 2017; Noth and Schuwer, 2018). For example, a report from OECD (2015) highlights that disaster risk is often uninsurable even with public support for disaster insurance. In the U.S., only some state governments have established insurance pools for specific types of hazards (e.g., storms). However, these pools are often limited to residential and commercial customers, have low insurance limits (e.g., around $1.5 million), and include numerous conditions to gain access.

We argue that one of the effective ways that banks can handle an increase in disaster risk is by enhanced credit risk management through LLP, i.e., recognizing higher LLP in the current period to build reserves for possible future write-offs. By utilizing more effective credit risk models and incorporating longer time horizons when assessing potential credit losses influenced by disaster risk, managers can increase current LLP to accelerate the recognition of potential future bad debts that otherwise must be recognized in subsequent periods. This is especially so for banks facing higher disaster risk that will increase their lending risk.

Although disaster risk is not easy to predict, its impact on economic outcomes (e.g., Felbermayr and Groschl, 2014; Boustan et al., 2017; Hsiang et al., 2017) and on lending decisions (Berg and Schrader, 2012; Hosono et al., 2016; Cortés and Strahan, 2017; Nguyen and Wilson, 2020; Delis et al., 2019; Koetter et al., 2020) has been established in prior literature. Therefore, understanding the extent to which banks incorporate and absorb forward-looking information on disaster risk in their balance sheets through LLPs becomes critical.[6]

We predict that disaster risk positively relates to LLP estimates primarlily due to credit risk management reasons. Bank managers observe the components of disaster risk that impact their lending portfolios and estimate LLPs that are adequate to build reserves to absorb potential future

[6] We provide a more detailed discussion of the mechanism through which banks incorporate disaster risk in their LLP estimates in section 3.

losses. This argument is consistent with the growing body of literature showing the impact of natural disasters on the broader economy and lending decisions. A positive relation between disaster risk and LLP estimates is also consistent with the Federal Reserve's concerns about the ability of financial institutions to identify, measure, monitor, and control this particular type of risk (Powell, 2019). However, there is considerable heterogeneity in disaster risk perception, and disaster risk estimation techniques are in their infancy. These aspects could bias the relation between disaster risk and LLP estimates. Thus, whether disaster risk positively relates to LLP estimates is ultimately an empirical question.

Measuring disaster risk presents numerous challenges, mainly concerned with whether the resulting measure effectively captures the constructs of hazard, exposure, and vulnerability (UNISDR, 2015; UNDRR, 2019). Additionally, disaster risk measures should reflect both the spatial and temporal attributes of its components. We measure disaster risk by capturing the variation in the number of natural disasters declared as major disaseters by the Federal Emergency Management Agency (FEMA) over the past fifteen years for each county-quarter. The FEMA Disaster Declaration Process gives the authority to the President of the United States to provide federal assistance to the impacted areas. Thus, the FEMA dataset includes only relatively large natural disasters that materially affect local economies.

From a theoretical perspective, the use of past events indicates a level of hazard, exposure, and vulnerability (OECD, 2012). The number of past events reflects the materialization of the hazard component of disaster risk. The FEMA Disaster Declaration Process ensures that our measure incorporates the exposure and vulnerability components of disaster risk because only natural disasters that are contained in the FEMA dataset qualify for federal assistance. This ensures that the natural hazard materialized in an area where assets and people are exposed and sufficiently vulnerable to receive governmental support.

We empirically validate our disaster risk measure using three alternative approaches. First, we ensure that our disaster risk measure captures all the relevant dimensions suggested in the UN Sendai

Framework for disaster risk reduction (UNISDR, 2015). Second, we check whether our measure also captures the components of risk identified in the German Watch framework (Eckstein et al., 2021). Third, we test whether our measure is correlated with the National Risk Index recently released by FEMA. Our measure is also sufficiently granular to incorporate the spatial and temporal attributes of disaster risk and ensure an appropriate identification strategy.

After assigning our county-quarter disaster risk measure to bank headquarters, we examine the relation between disaster risk and LLP estimates for a sample of 445,924 bank-quarter observations (9,766 unique banks) over the period 2002-2019. We use quarterly data from the Federal Deposit Insurance Corporation's (FDIC) Statistics on Depository Institutions database.[7] We restrict our sample to non-interstate banks to ensure that the majority of a bank's loan portfolio is tied to clients whose operations are largely based in the same geographical area as the bank's headquarters. We focus on commercial banks because they specialize in lending activities and are more subject to estimates of LLPs.

We find that disaster risk positively relates to LLP estimates. In particular, we document that a one standard deviation change in disaster risk is associated with a change in LLPs ranging between +5.4% and +7.0%, which results in a reduction in earnings of 1.2% to 1.6%. Our findings hold when we use an alternative model and sample specifications. Our main results are robust to a battery of sensitivity tests. To strengthen identification and facilitate causal interpretation, we conduct an event study using Hurricane Katrina as a shock that induced banks to reprice disaster risk in LLP estimates (Dessaint and Matray, 2017). We find that Hurricane Katrina induced banks to reprice disaster risk in LLP estimates for banks located in counties previously affected by hurricane events but not directly impacted by Hurricane Katrina. Since we omit banks in counties that were directly impacted by Hurricane Katrina, the increase in LLP can be attributed to the repricing of disaster risk rather than to the direct effects of losses arising from hurricane damage.

[7] https://www7.fdic.gov/sdi/main.asp?formname=customddownload

We provide three types of additional analyses. First, with the aim of proposing alternative and more granualar measures of disaster risk, we generate three alternative measures of disaster risk that capture multicounty, frequent event and rare event disaster risk. Using yearly data on bank branches from the Summary of Deposits database, we calculate a multicounty measure of disaster risk at the county-year level. As a starting point, we assign the corresponding disaster risk to each bank branch. Then, we compute a weighted average measure of disaster risk using the number of branches in each county as weights. We also decompose disaster risk into frequent event disaster risk and rare event disaster risk. We define frequent (rare) natural disaster events as events that occurred with a frequency equal to or higher (lower) than the median frequency of the events in each county. We find that all three alternative measures of disaster risk are positively and significantly related to LLP estimates.

Second, we investigate whether certain types of banks are better able to incorporate disaster risk in LLP estimates. We focus on bank size, complexity, and loan concentration because these characteristics can enable banks to better impound disaster risk in LLP. The ability to incorporate disaster risk primarily originates from resources available to large banks to invest in disaster risk management. Banks with a complex set of activities may find it more challenging to estimate and incorporate disaster risk into LLP. We find that large, simple and concentrated banks are better able to proactively incorporate disaster risk in LLP estimates.

Lastly, we explore the consequences of managing disaster risk through LLP and investigate the relation between current LLPs and future loan charge-offs and the ability to take future risks. We reason that if disaster risk is appropriately incorporated in LLP estimates, then current LLPs should better anticipate future loan charge-offs when disaster risk materializes. Conversely, when disaster risk does not materialize in a natural disaster banks have more room to bear future risks. We find that disaster risk positively moderates the relation between current LLPs and future charge-offs (future risk) for banks experiencing (not experiencing) a disaster risk in the subsequent quarter.

Our study makes several contributions to the literature. Prior literature shows mostly ex-post economic consequences of natural disasters (e.g., Cortés and Strahan, 2017; Dessaint and Matray, 2017; Choi et al., 2020). We contribute to this line of research by examining whether banks proactively manage credit risk by making adequate LLP estimates to recognize disaster risk that impacts lending portfolios. Our study also introduces a new measure for disaster risk that can be a useful tool for quantifying this construct in the financial economics literature. Not only do we introduce this new disaster risk measure based on past natural disasters, but we also validate it using three alternative approaches. Additionally, our study informs the debate on the determinants of LLP estimates (e.g., Hribar et al., 2017; Nicoletti, 2018). We contribute to this line of research by identifying disaster risk as an important environmental determinant of the largest accrual in the banking industry. Our study also has important implications for the debate related to the supervision of the risk associated with natural disasters in the financial system. Our findings suggest that banks generally incorporate disaster risk in their LLP decisions and that these provisions are more related to future charge-offs.

The rest of this paper is organized as follows. We review the literature on natural disasters and their consequences on the broader economy and lending decisions in Section 2. We develop our hypothesis on the relation between disaster risk and LLP estimates in Section 3, present the research design and sample selection in Section 4, report the main results in Section 5, and present the results of additional tests in Section 6. We discuss the results and conclude the study in Section 7.

2. Prior Literature

Prior Literature on Economic Consequences of Natural Disasters

Using international data, Felbermayr and Groschl (2014) document that a massive disaster reduces GDP per capita by roughly 7%, while middle and small events induce a drop in GDP per capita of 0.33% and 0.01%, respectively. Hsiang et al. (2017) forecast similar consequences for economic damage from global warming in the U.S. For every 1 degree Celsius increase in the U.S. temperature, a loss of roughly 1.25% of GDP is expected annually. While some areas may benefit from such an increase in temperatures, others like Arizona and Texas will face losses higher than 10%.

The reduction in economic growth propagates the impact of natural disasters through a domino effect. For example, Boustan et al. (2017) show that severe disasters increase local poverty rates, reduce home prices, and induce economic migration. These findings hold even in the presence of government assistance programs, as many people tend to take the money and move to different geographical areas.

Despite the negative economic outcomes of natural disasters, prior literature documents a significant heterogeneity in how they are perceived by the general population (Howe et al., 2015). This heterogeneity is reflected in economic transactions and in financial markets. For example, the impact of droughts on food stocks is not fully priced in the market. Food companies located in areas with a long-term trend of severe droughts are associated with relatively poor profit growth and stock returns. This result is consistent with the market underreacting to disaster risks (Hong et al., 2019). One reason is that climate *believers* and *deniers* behave differently when facing the risk of natural disasters. For example, when informed about the exposure of their homes to future inundation, *believers* tend to sell at a discount compared to *deniers* (Baldauf et al., 2020).

Contrary to the general population, institutional investors are aware that natural events lead to financial implications that are already materializing in their portfolios (Clark, 2019; Kruger et al., 2019). Because of temporarily reduced investor demand, yields of primary municipal bond issues increase after natural disasters. Municipalities react to the higher financing costs by issuing bonds with shorter maturities and less complex structures (Bennett and Wang, 2019).

Prior Literature on Natural Disasters and Lending Decisions

In addition to the negative impact on economic growth, natural disasters also create unpredictable credit shocks to the financial system (Cortés and Strahan, 2017; Powell, 2019). Consequently, the finance literature has mainly focussed on examining the reaction of credit demand, access to credit, and credit supply following natural disasters.

Berg and Schrader (2012) demonstrate an increase in credit demand and a restriction in access to credit after the Ecuadorian volcanic eruptions. They also find that these two negative impacts on the financial system are mitigated by bank-borrower relationships. In fact, after natural disasters, clients that have a closer relationship with a financial institution are more likely to receive loans. Nguyen and Wilson (2020) confirm that natural disasters, represented by the Indian Ocean Tsunami, have a negative effect on credit supply. However, this effect is mitigated by the presence of bank branches in affected regions. Using data from Japan's Great Hanshin-Awaji earthquake in 1995, Hosono et al. (2016) explore the consequences of natural disasters for banks' clients. They find that clients that rely on financial institutions located inside the earthquake area show significantly smaller investment than clients that rely on financial institutions located outside the earthquake area. This result is consistent with natural disasters inducing a shock to loan supply, which directly affects nonfinancial firms' investments. Brei et al. (2019) explain that the shock to loan supply is associated with banks facing deposit withdrawals and adverse funding shocks.

Cortés and Strahan (2017) find that after natural disasters, multi-market banks reallocate capital because of credit demand increases in affected areas. To reduce the impact of the demand shock on credit supply, banks also increase sales of more liquid loans and increase the rate on deposits. Similarly, Koetter et al. (2020) find that banks that reside in counties unaffected by natural disasters increase lending to firms inside affected counties by 3%. Among banks located in affected areas, fewer multi-market banks exhibit more credit risk and less equity capital. Schuwer et al. (2019) document that these effects are driven by independent banks based in the disaster areas. Thus, economic growth is higher for impacted areas with more independent banks than for areas with fewer independent banks.

However, natural disasters also represent a threat to the existence of a bank. Klomp (2014) suggests that geophysical and meteorological disasters enhance financial fragility and reduce distance-to-default. The impact of a natural disaster depends on its intensity, the strength of the financial regulation and supervision, and the level of financial and economic development. Noth and

Schuwer (2018) find similar consequences, showing that natural disasters significantly weaken bank stability. This is supported by an increase in nonperforming asset ratios, foreclosure ratios, and the probability of default, along with a decrease in return on assets, bank equity ratios, and z-scores.

3. Hypothesis

Disaster risk materializes in numerous negative consequences for the economic system and for bank customers. Beyond damages to assets and infrastructure, natural disasters could lead to secondary effects such as economic migration, disruption in the supply chain, and temporary scarcity of resources. Disaster risk impacts corporate customers through unexpected business interruptions, unbudgetable reconstruction costs, and asset impairments. Additionally, non-corporate customers, such as households, are exposed to disaster risk to the extent that their houses are not insured against natural disasters.

According to the Chairman of the Board of Governors of the Federal Reserve System, financial institutions should identify, measure, monitor, and control disaster risk (Powell, 2019). A potential method for controlling disaster risk is diversification. Because disaster risk will affect all sectors and asset classes, it cannot be avoided or fully diversified, but only managed (Ernst and Young, 2016). This is especially true for banks, because they are exposed to disaster risk in multiple sectors through their customers. Banks can deal with disaster risk on a loan-by-loan basis through disaster risk financing tools (OECD, 2012) or by enhancing scrutiny in their lending decisions. Even if banks implement mitigating mechanisms for disaster risk, they will still need to adjust and monitor disaster risk at the loan portfolio level because disaster risk varies over time and across different geographical areas.

We argue that an effective way for banks to deal with an increase in disaster risk is by strengthening credit risk management through LLP. Banks can employ more effective credit risk models and incorporate longer time horizons when assessing potential credit losses related to disaster risk. In other words, banks can build reserves for possible future write-offs by increasing current LLP to accelerate the recognition of potential future bad debts that otherwise must be recognized in subsequent periods. This is especially so for banks facing higher disaster risk that will increase their lending risks.[8]

Current U.S. accounting standards for LLP are based on the incurred loss model.[9] This model allows a loss to be accruable only if that loss is probable and can be reasonably estimated. Banks can incorporate disaster risk in their LLP estimates in four different ways. First, banks normally refer to historical loss rates and prior loss experiences to support their LLP estimates (Dugan, 2009; Gomaa et al., 2019). They can also take advantage of innovative lookback analysis developed to identify corporate updates where particular words relating to disaster risk factors have been used (Standard & Poor's, 2017).

Second, disaster risk consequences are observable in borrowers' operations. According to Standard and Poor's (2015b), when disaster risk manifests in natural disasters, losses can be related to direct property and production losses, supply chain disruption, and market impact. The direct impact is of particular concern for geographically concentrated companies as it refers to a firm's disruptions in its operations. The increasing integration of the economy makes supply chain disruption a key factor for estimating the impact of disaster risk for geographically dispersed firms. Market conditions can also deteriorate due to natural disasters. An increase in demand or a reduction in supply can induce raw material price movements and volatility. These consequences of disaster risk impose costs on borrowers, which directly affect earnings and cash flows. Prior literature on nonfinancial firms documents that disaster risk is associated with lower and more volatile earnings and cash flows, lower investment-to-assets ratios, and lower book-to-market ratios (Huang et al., 2018; Hugon and Law, 2019; Lanfear et al., 2019).

[8] In sensitity analysis, we show that managers explicitly estimate disaster risk into LLP and do not reflect the effects of a recent disaster in their estimations.

[9] In 2016 the FASB issued a new standard that replaces the incurred loss model with the expected loss model. The new standard for loan loss provisioning will become effective in 2020. Although we develop our hypothesis using arguments based on the incurred loss model (i.e., the current standard), we note that a similar line of reasoning is applicable under the expected loss model for loan loss provisioning (i.e., the new standard).

Third, banks can examine data on all components of disaster risk. These data are publicly available and rapidly growing in terms of coverage and accuracy (World Bank GFDRR, 2014). For example, data on natural disasters and related governmental assistance programs have been available since the early 1950s from FEMA.

Fourth, the incurred loss model also allows for some managerial judgment and the use of forward-looking factors (e.g., Dugan, 2009; Kanagaretnam et al., 2014). Bank managers could also make LLP estimates beyond provisions for normally expected losses based on their assessment of disaster risk.

Given these arguments, we state the following hypothesis:

H1: *Disaster risk positively relates to loan loss provision estimates.*

We note that a positive association between disaster risk and LLP estimates is not obvious. First, banks can diversify their loan portfolios and geographic exposures, thereby mitigating the effects of disaster risk and the need for higher LLPs. Second, disaster risk perception is heterogeneous and estimation techniques are in their infancy. Therefore, bank managers may be unable to reliably estimate LLPs associated with this type of risk. Third, borrowers operating in areas associated with high disaster risk tend to hold more cash to build organizational resilience (Huang et al., 2018). This could allow borrowers to repay their loans when disaster risk manifests in natural disasters. The above reasoning provides tension to our main hypothesis and justifies the empirical analysis.

4. Data and Research Design

Sample

We obtain data on natural disasters from FEMA to compute disaster risk,[10] accounting data from the Federal Deposit Insurance Corporation's (FDIC) Statistics on Depository Institutions database,[11] and data on branch locations from the FDIC's Summary of Deposits database[12] (see Appendix A for details of data sources and descriptions of the variables). The Statistics on Depository Institutions

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[10] https://www.fema.gov/openfema-data-page/disaster-declarations-summaries-v1
[11] https://www7.fdic.gov/sdi/main.asp?formname=customddownload
[12] https://www7.fdic.gov/sod/dynaDownload.asp?barItem=6

database contains information on commercial banks and bank holding companies. Data are collected by the FDIC every quarter, since all banks regulated by the Federal Reserve System, FDIC, and Comptroller of the Currency are required to file reports that include a balance sheet, income statement, risk-based capital measures, and off-balance sheet data.

We begin our sample selection with all non-interstate commercial banks operating in the U.S. that have data available in the Statistics on Depository Institutions database between 2002 and 2019. To reduce sample heterogeneity, we focus on commercial banks because they specialize in lending activities and, consequently, are more exposed to estimates of LLP. We restrict the sample to non-interstate banks (i.e., banks with headquarters and offices in a single U.S. state) to ensure that the majority of a bank's loan portfolio is tied to clients with operations largely based in the same geographical area as the bank's headquarters.[13] We use quarterly data filed under the Federal Financial Institutions Examination Council (FFIEC) 041 Call Report Form. Our sample starts in 2002 because the FFIEC-41 became effective during the second quarter of 2001, and we require data to calculate the change in nonperforming assets at quarter *t*-2. Our sample ends in 2019 in order to avoid the potential impact of the COVID19 pandemic on financial institutions and banks.

Following prior research, we define a bank's location as the location of its headquarters (e.g., Hilary and Hui, 2009). Although, in theory, this could introduce noise in our analysis, prior literature demonstrates that the number of firms that relocate is small (Pirinski and Wang, 2006). We use the county code (Statistics on Depository Institutions code BKMO) data to locate the headquarters of each bank. Although mainly concentrated close to the headquarters, bank operations may transcend county borders. In addition to restricting our sample to non-interstate banks, we also consider this aspect by controlling for branch diversification in our empirical model.

[13] Our main analysis is robust to the inclusion of interstate banks in the sample.

Lastly, we match accounting data from the Statistics on Depository Institutions database, branch locations from the Summary of Deposits database, and our measure of disaster risk using Federal Information Processing Standard (FIPS) county codes.

Our final sample contains 445,924 bank-quarter observations, covering 9,766 unique banks over the period from the first quarter of 2002 to the fourth quarter of 2019. We report the sample distribution by state and year in Online Appendix Table OA1. Texas has the largest number of bank-quarter observations (38,589), followed by Illinois (37,771), Minnesota (26,025), Iowa (23,355), Missouri (20,318), and Kansas (20,285).

Measure of Disaster Risk

According to the UN Sendai Framework for disaster risk reduction (UNISDR, 2015; UNDRR, 2019), disaster risk has both spatial and temporal attributes. First, disaster risk is dynamic as it can increase or decrease over time according to the ability to reduce the vulnerability component. Second, disaster risk occurs at different geographical levels. Although two contiguous areas may be affected by the same hazards (e.g., a hurricane), the pattern of disaster risk reflects exposure and vulnerability in different counties.

Although identifying, assessing, and understanding disaster risk is challenging (UNISDR, 2015; UNDRR, 2019), the analysis of past data on natural disasters serves as a common starting point (OECD, 2012). Past data are easier to interpret than future data because the latter would require estimating the probability of occurrence of a natural disaster at the county level. Although natural disasters partly depend on climatic conditions that are predictable on a seasonal time scale, the exact time and location of such future events are largely determined by weather patterns and other factors, which are only predictable a few days prior to the materialization of the hazard into a natural event (Dessaint and Matray, 2017). Additionally, estimating future natural disasters requires considering that each type of disaster has its own determinants (see Elsner and Jagger, 2006 about hurricane strikes and Arya, 2000, about earthquake risk prediction). Lastly, estimating future data would provide limited benefits in our case, as prior climatology literature establishes that the distribution of natural disasters tends to be stationary (e.g., Landsea, 2005; Pielke et al., 2005; Landsea et al., 2006; on the stationarity at the country and regional levels of hurricane strikes in the U.S.).

We derive our measure of disaster risk (DR_t) from the number of natural events declared as major disasters by FEMA over the past fifteen years for each county and quarter. We do not generate our disaster risk measure using all prior years of recorded disasters for which data are available because of a potential salience bias. Since the FEMA dataset starts in the 1950s, using all the recorded disasters could lead to a potential bias in our disaster risk measure. Selecting a 15-year window for measuring disaster risk allows us to select only salient disasters.

The FEMA Disaster Declaration Process is regulated by the Robert T. Stafford Disaster Relief and Emergency Assistance Act, 42 U.S.C. §§ 5121-5207. In order to assist in the recovery of the impacted area, the Governor of the affected state has to formally request a disaster declaration by the President. Under the Stafford Act, disaster declarations are classified into emergency declarations and major disaster declarations. Given the peculiarity of major disasters involving fire management, an internal FEMA regulation has also established a Fire Management Assistance Grant declaration. All three types of declarations empower the President to provide federal disaster assistance. Thus, the FEMA dataset includes only relatively large disasters that materially affect local economies.

From a theoretical perspective, the use of past events contained in the FEMA dataset indicates a level of hazard, exposure, and vulnerability (OECD, 2012). A measure based on past events captures the materialization of the hazard component of disaster risk. Additionally, the FEMA Disaster Declaration Process serves as a logical link between DR_t and the exposure and vulnerability components of disaster risk. Since they qualify for federal assistance, events contained in the FEMA dataset refer to natural hazards that occur in an area where assets and people are exposed and sufficiently vulnerable to receive governmental support.

For each disaster, the FEMA Disaster Declarations Summary provides information regarding the incident type, beginning date, ending date, and impacted area (identified by state, and county FIPS code). Additionally, for each disaster, FEMA reports the declaration date, closeout date, and the type(s) of assistance program declared.

In Online Appendix Table OA2, we report the distribution of disaster types contained in the FEMA dataset from the first quarter of 1987 to the fourth quarter of 2019. We include disasters from 1987 to 2001 because they are used to compute the disaster risk measure of the first quarter of 2002. Over the period from 1987 to 2019, the FEMA dataset contains 1,689 major disaster declarations. Severe Storm(s) is the most common type of disaster (887), followed by Flood (303), and Hurricane (172). A single event, on average, simultaneously affected 17 different counties. Hurricane and Severe Ice Storm are the types of disaster that, on average, affected the highest number of counties (25), followed by Snow (24), and Fire (20).

We note that the FEMA Disaster Declarations Summary contains disaster declarations for peculiar types of events. For example, over the period from 1987 to 2019, the FEMA dataset contains disasters related to Human Cause, Terrorist attacks, and Fishing Losses. Additionally, some events are classified as "Other", making it difficult to attribute these events to natural disasters. We exclude all these events in computing DR_t.

Figure 1 shows the average disaster risk at the county level from 2002 to 2019. Walsh County (ND) has the highest disaster risk with an average of 6.13 natural disasters declared by FEMA over the past fifteen years, followed by San Bernardino County (CA) (5.97), Riverside County (CA) (5.97), Los Angeles County (CA) (5.86), and Pike County (KY) (5.81).

[Insert Figure 1 About Here]

To explore the characteristics of our disaster risk measure, in Section 6 we also compute three additional measures. $DR\_MULTICOUNTY_t$ incorporates the ability of banks to mitigate disaster risk across branches outside the headquarters' county. $DR\_FREQUENT_t$ (DR_RARE_t) is the component of disaster risk originating from frequent (rare) events defined as events that occurred with a frequency higher (lower) than the median of the frequency of the events in each county.

Validation of Disaster Risk Measure

We validate DR_t using three alternative approaches. First, we ensure that our disaster risk measure captures all the relevant dimensions suggested in the UN Sendai Framework for disaster risk reduction (UNISDR, 2015). Second, we check whether DR_t also captures the components of risk identified in the German Watch framework (Eckstein et al., 2021). Third, we test whether our disaster risk measure is correlated with the National Risk Index recently released by the FEMA. We report the validation of DR_t under the UN Sendai Framework for disaster risk reduction in this section and include the tests based on the German Watch framework and the FEMA National Risk Index in Online Appendix OA1.

According to the UN Sendai Framework for disaster risk reduction, disaster risk is the consequence of the interaction between the natural hazards and the characteristics that make places and people exposed and vulnerable. Thus, disaster risk can be expressed as follows:

$$DR_t = f(HAZARD_t, EXPOSURE_t, VULNERABILITY_t) \quad (1a)$$

Hazard is the probability of experiencing a particular event (e.g., hurricane, flood, etc.) at a specific location. Exposure captures the situation of people and infrastructures located in hazard-prone areas. Vulnerability is determined by social and environmental factors that increase susceptibility to the impact of hazards.

We employ the following model to validate our disaster risk measure under the UN Sendai Framework for disaster risk reduction:

$$DR_t = \theta_0 + \theta_1\, NHI_t + \theta_2\, POP_t + \theta_3 EMPL\%_t + \theta_4\, SoVI_t + \theta_5 PTY\_DAMAGE_t + \Sigma\theta_i Fixed\ Effects + \varepsilon_t \quad (1b)$$

All variables are defined in Appendix A and Online Appendix OA2 and are measured at the county-level. We estimate Equation (1b) at the county-quarter level, including all counties and quarters with available data from 2002 to 2019. The final sample for which disaster risk and disaster risk determinants are available consists of 218,952 county-quarter observations.

In Equation (1b), we measure the hazard component of disaster risk using the natural hazard index (NHI_t) designed by the National Center for Disaster Preparedness (NCDP) at Columbia University. NHI_t is a multiple hazard index that captures historical and projected data for numerous natural hazards at the county level. We proxy the exposure component of disaster risk with population density (POP_t) and total employment ($EMPL\%_t$). Although exposure to natural disasters is a complex construct, the use of population and labor data is widespread (UNDRR, 2019). Lastly, we measure the vulnerability component using the social vulnerability index ($SoVI_t$) developed by the Hazard & Vulnerability Research Institute (HVRI) at University of South Carolina. Synthesizing more than 25 socioeconomic variables, $SoVI_t$ specifically measures the social vulnerability of U.S. counties to environmental hazards. Since vulnerability also relates to damage and losses (World Bank GFDRR, 2014), we also include property losses per capita (PTY_DAMAGE_t) from the Spatial Hazard Events and Losses Database (SHELDUS) measured at the county-quarter level.

Under the UN Sendai Framework for disaster risk reduction, we expect all control variables to positively correlate with DR_t. To absorb potential time and geographical trends in disaster risk, we step-by-step include year-quarter and state fixed effects.

Panel A of Table 1 reports summary statistics for disaster risk and disaster risk determinants. The table shows that the average county is associated with a disaster risk of 4.65, indicating that on average FEMA declared 4.65 major disasters in each county-quarter over the past fifteen years. The standard deviation of DR_t is 2.84, which indicates substantial variation in our measure.[14]

[Insert Table 1 About Here]

Panel B of Table 1 presents the estimation results of Equation (1b). Consistent with the UN Sendai Framework for disaster risk reduction, we find that all variables are significantly positively associated with disaster risk. These results validate our measure of disaster risk, as they indicate that it captures the components of hazard, exposure, and vulnerability. Additionally, our measure varies

[14] The full dataset containing disaster risk and disaster risk determinants at the county level is available upon request from the authors.

systematically by county-quarter, indicating that it captures the spatial and temporal attributes of disaster risk (UNISDR, 2015; UNDRR, 2019).

Online Appendix OA1 reports the results of validating our disaster risk measure using the German Watch framework and the FEMA National Risk Index. The analysis shows that DR_t captures all the relevant components of disaster risk under both frameworks. Through these validations, we confirm that our measure based on the number of major disasters declared by the FEMA over the past fifteen years serves as a good proxy for disaster risk.

Empirical Model

We employ the following model, commonly used in the banking literature (e.g., Kanagaretnam et al., 2014; Hribar et al., 2017; Nicoletti, 2018), to test the association between disaster risk and LLP estimates:

$$\begin{aligned} LLP_t = {} & \beta_0 + \beta_1\, DR_t + \beta_2\, \Delta NPA_{t+1} + \beta_3\, \Delta NPA_t + \beta_4\, \Delta NPA_{t-1} + \beta_5\, \Delta NPA_{t-2} + \beta_6\, \Delta LOANS_t \\ & + \beta_7\, EBTLLP_t + \beta_8\, CO_{t-1} + \beta_9\, TIER1_{t-1} + \beta_{10}\, ALLOWANCE_{t-1} + \beta_{11}\, SIZE_{t-1} \\ & + \beta_{12}\, BRANCHDIV_t + \Sigma\, \beta_i\, LoanTypes_t + \Sigma\, \beta_j\, Fixed\ Effects + \varepsilon_t \end{aligned} \quad (2)$$

All variables are defined in Appendix A. To facilitate interpretation of the regression coefficients, we multiply LLP_t by 100. Except for DR_t, $TIER1_{t-1}$, $SIZE_{t-1}$, and $BRANCHDIV_t$, all variables are scaled by beginning-of-quarter total loans and leases.

Our main variable of interest is DR_t. We expect that disaster risk relates positively to LLP. Therefore, we expect the coefficient β_1 to be greater than zero. We calculate our measure of disaster risk using data on natural disasters at the county-quarter level to allow sufficient variation in our main variable of interest. This feature is critical as it allows us to measure the association between disaster risk and LLP, while including numerous fixed effects to control for heterogeneity in LLP. Thus, our measure is sufficiently granular to ensure an appropriate identification strategy.

In Equation (2), we control for the quality and size of the underlying loan portfolio, incentives to smooth earnings and manage regulatory capital, and other bank-level factors related to LLP estimates. We include leading and current changes in nonperforming assets (ΔNPA_{t+1}, ΔNPA_t) to reflect current and forward-looking information on nonperforming loans (Beatty and Liao, 2014). Similarly, we include one-quarter and two-quarters lagged changes in nonperforming assets (ΔNPA_{t-1}, ΔNPA_{t-2}) to control for changes in loan portfolio performance in the estimation of LLP (Tomy, 2019). We include the change in loans ($\Delta LOANS_t$) to control for the change in the size of the loan portfolio (Nicoletti, 2018). We include earnings before taxes and LLPs ($EBTLLP_t$) and Tier 1 risk-based capital ratio ($TIER1_{t-1}$) to control for potential incentives to manage earnings (Kanagaretnam et al., 2010; Beatty and Liao, 2014). Prior research also suggests the inclusion of lagged loan loss allowance ($ALLOWANCE_{t-1}$) to account for accumulated allowance (Kanagaretnam et al., 2010). As LLP, loan loss allowance, and charge-offs are closely related we follow prior research and include the past four quarters' rolling average of net charge-offs (CO_{t-1}) (Beatty et al., 1995; Collins et al., 1995). We control for bank size ($SIZE_{t-1}$) because larger banks are better able to mitigate risk, which may affect estimates of LLP. Additionally, larger banks are subject to potential differences in regulatory scrutiny. We control for branch diversification at the year level by including the proportion of bank branches outside the county where the bank is headquartered ($BRANCHDIV_t$). Lastly, to account for diversification in the loan portfolio ($LoanTypes_t$), we include the ratio of residential, commercial, consumer, and agricultural loans to total loans at the end of each quarter (Liu and Ryan, 2006; Costello et al., 2019).

We include year-quarter fixed effects in Equation (2) to eliminate common shocks, such as general macroeconomic trends, to the LLP estimates. To account for trends in LLP timeliness, we use an alternative specification that augments the regression model by including year-quarter fixed effects interacted with ΔNPA_t. Banks located in similar geographic regions are subject to local time-invariant factors in the estimates of LLP. To absorb this variation, we estimate Equation (2) by including state-county fixed effects. We also employ a more rigorous specification that includes bank fixed effects, thus controlling for time-invariant bank-level characteristics. By introducing these sets of progressively more detailed fixed effects, we remove differences in the aggregate level of LLP and focus on within state-county or bank-level differences. We winsorize all continuous variables at the

1st and 99th percentiles to mitigate the influence of extreme values and estimate standard errors clustered by bank because of the nature of LLP.

5. Empirical Results

Main analysis

Table 2 presents the descriptive statistics for the dependent and independent variables over the sample period. The table shows that the mean disaster risk is 4.97, indicating that on average FEMA declared 4.97 natural disasters in each county-quarter over the past fifteen years. The standard deviation of *DR* is 2.85, which indicates substantial variation in our main independent variable. Like other studies (e.g., Kanagaretnam et al., 2010; Nicoletti, 2018), we find that banks' LLP estimates are on average 0.1% of lagged total loans (LLP_t).

Online Appendix Table OA5 presents Pearson correlation coefficients between the variables used in our analysis. Univariate correlation reveals that disaster risk negatively relates to LLP estimates (-0.001, p>0.10). As shown by the positive and significant coefficients on ΔNPA, LLPs reflect past, current, and forward-looking information on loan quality.

[Insert Table 2 here]

Table 3 presents the estimation results for the three different specifications of Equation (2). Column (1) reports the baseline OLS model, which includes the independent variable of interest, bank-specific control variables, and state-county and year-quarter fixed effects. Column (2) augments the model with year-quarter fixed effects interacted with ΔNPA_t to account for trends in LLP timeliness, and column (3) includes bank and year-quarter fixed effects.

We find that disaster risk positively and significantly relates to LLP estimates in all three specifications (coefficients of *DR* vary from 0.0027 in columns (1) and (2) to 0.0021 in column (3), with p<0.01) even after controlling for previously identified determinants of LLP. These results are also economically significant. A one standard deviation change in disaster risk is associated with an increase in LLP ranging from 5.43% (= 0.0021 × 2.8456 / 0.0011, the coefficient in column (3) multiplied by the standard deviation of *DR* and divided by the mean of *LLP*) to 6.98% (= 0.0027 × 2.8456 / 0.0011, coefficient in columns (1) and (2) multiplied by the standard deviation of *DR* and divided by the mean of *LLP*). The increase in LLP induces a reduction in earnings ranging between -1.22% (= -0.0011 × 5.43% / 0.0049, mean of *LLP* multiplied by the increase in *LLP* and divided by the mean of earnings before taxes and LLPs) and -1.57% (= -0.0011 × 6.98% / 0.0049, mean of *LLP* multiplied by the increase in *LLP* and divided by the mean of earnings before taxes and LLPs). The coefficients of the bank-level control variables are similar to those reported in prior literature both in terms of magnitude and sign. The positive association between LLP_t and ΔNPA shows that for every dollar change in nonperforming assets, the bank records 3 to 5 cents of LLP (i.e., we multiply LLP_t by 100 to facilitate interpretation of regression coefficients).

These results indicate that disaster risk is strongly positively associated with LLP estimates. Based on these findings, which support H1, we conclude that bank managers incorporate disaster risk considerations in their estimates of LLP.

[Insert Table 3 here]

To further address sample heterogeneity arising from a bank's ability to incorporate disaster risk in LLP estimates, in online Appendix OA3 we examine whether the positive relation between disaster risk and LLP estimates is robust to matched samples using coarsened exact matching and entropy matching. Using these techniques, we confirm a positive and significant relation between disaster risk and LLP estimates.

Difference-in-Differences Estimation

Our main regression exploits the time-series and cross-county variations in disaster risk, which are largely exogenous to firm decisions. Moreover, we use bank fixed effects to control for potential unobservable omitted variables. Nonetheless, to strengthen identification and facilitate causal interpretation, we conduct an event study using Hurricane Katrina as a shock that induced banks to reprice disaster risk in LLP estimates (Dessaint and Matray, 2017). The use of hurricanes is supported by prior literature because of the substantial damages they inflict, the likelihood of no or under-insurance coverage, and the variety of indirect losses that may occur (Dessaint and Matray, 2017). During the third quarter of 2005, Hurricane Katrina generated around 170 billion dollars of estimated costs, causing 1,833 deaths (NOAA, 2005). Hurricane Katrina remains the disaster that generated the heaviest losses in the United States.

Figure 2 shows a map of counties affected by Hurricane Katrina. Counties coloured light grey were directly affected by Hurricane Katrina during the third quarter of 2005. We exclude banks headquartered in these counties because of the direct effects of Hurricane Katrina on their operations. In Figure 2, counties coloured dark grey were not affected by Hurricane Katrina. However, these counties experienced at least one hurricane event in the FEMA dataset during the 10 years prior to Hurricane Katrina. Although not directly affected by Hurricane Katrina, disaster risk becomes more salient for banks located in these areas as they were recently subject to the materialization of the hurricane hazard. Thus, we classify these bank-quarter observations in the treated group. Lastly, in Figure 2, counties coloured black were not affected by Hurricane Katrina and never registered hurricane events in the FEMA dataset during the 10 years prior to Hurricane Katrina. We assign banks located in these areas to the control group because they did not recently experience disaster risk from hurricane hazard.

Untabulated descriptive statistics show that during the third quarter of 2005, 179 counties (21,655 bank-quarter observations) were affected by Hurricane Katrina, 689 counties (68,855 bank-quarter observations) were not affected by Hurricane Katrina and registered at least one hurricane event in the FEMA dataset during the 10 years prior to Hurricane Katrina (treated group), and 2,367 counties (355,414 bank-quarter observations) were not affected by Hurricane Katrina and never registered a hurricane event in the FEMA dataset during the 10 years prior to Hurricane Katrina (control group).

[Insert Figure 2 here]

Although they are not prone to disaster risk from hurricane hazard, banks assigned to the control group are subject to other types of natural hazards. This implies that for both groups DR_t varies over time and across different geographical areas.

We employ the following model, to test whether Hurricane Katrina induced banks located in hurricane areas to reprice disaster risk in their LLP estimates:

$$\begin{aligned} LLP_t = {} & \beta_0 + \beta_1 \, DR_t + \beta_2 \, POST_t + \beta_3 \, HURRICANE_t + \beta_4 \, DR_t \text{ x } POST_t + \beta_5 \, DR_t \text{ x } HURRICANE_t \\ & + \beta_6 \, POST_t \text{ x } HURRICANE_t + \beta_7 \, DR_t \text{ x } POST_t \text{ x } HURRICANE_t + \beta_8 \, \Delta NPA_{t+1} \\ & + \beta_9 \, \Delta NPA_t + \beta_{10} \, \Delta NPA_{t-1} + \beta_{11} \, \Delta NPA_{t-2} + \beta_{12} \, \Delta LOANS_t + \beta_{13} \, EBTLLP_t \\ & + \beta_{14} \, CO_{t-1} + \beta_{15} \, TIER1_{t-1} + \beta_{16} \, ALLOWANCE_{t-1} + \beta_{17} \, SIZE_{t-1} + \beta_{18} \, BRANCHDIV_t \\ & + \Sigma \, \beta_i \, LoanTypes_t + \Sigma \, \beta_j \, Fixed \; Effects + \varepsilon_t \qquad (3) \end{aligned}$$

All variables are defined in Appendix A. The variable $HURRICANE_t$ indicates if a bank is headquartered in a county that is prone to hurricane hazard. $HURRICANE1_t$ equals 1 if a bank registered at least one hurricane event during the 10 years prior to Hurricane Katrina, 0 otherwise. Similarly, $HURRICANE2_t$ equals 1 if a bank registered frequent hurricane events during the 10 years prior to Hurricane Katrina (i.e., top quartile of the distribution), 0 otherwise. $POST_t$ is an indicator variable that equals 1 from the third quarter of 2005 onwards, 0 otherwise. To test whether Hurricane Katrina induced banks located in hurricane areas to reprice disaster risk in LLP estimates, we examine the coefficient β_7 of the interaction term DR_t x $POST_t$ x $HURRICANE_t$. If Hurricane Katrina induces banks to reprice disaster risk in LLP estimates, the coefficient β_7 in Equation (3) should be positive.

Table 4 presents the estimation results of the difference-in-differences analysis in Equation (3). In Column (1) we use $HURRICANE1_t$ to attribute bank-quarter observations to the treated and control groups, and in Column (2), we distinguish bank-quarter observations between the treated and control group based on $HURRICANE2_t$. We find that Hurricane Katrina induced banks to reprice disaster risk in LLP estimates for banks located in counties previously affected by hurricane events (coefficients β_7 in columns (1) and (2) are 0.0033 and 0.0180, respectively, with $p<0.01$)[15]. Together, these results facilitate a causal interpretation of the relation between disaster risk and LLP estimates.

[15] We assess the reliability of the causal interpretation of our results by testing for the parallel trends assumption. We first assume a linear pre-treatment trend and then test this assumption using a local approach. Untabulated results show that treated and untreated firms exhibit the same pre-treatment linear trend and that no time-to-time difference arises between treated and untreated units during the pre-treatment period.

[Insert Table 4 here]

***Sensitivity Analyses*[16]**

We check the robustness of our main findings by performing a battery of sensitivity analyses. First, we provide a subsample analysis to further address sample heterogeneity arising from a bank's ability to incorporate disaster risk in LLP estimates. Thus, we replicate our main analysis (1) excluding bank-quarter observations from the financial crisis period, (2) excluding observations of banks headquartered in counties with high disaster risk (i.e., more than 20 disasters overall), (3) including only observations without M&A activity, defined as a change in total assets between -10% and +10%, and (4) including only single-county banks with no branches outside the headquarters' county. We repeat our analysis on a subsample that excludes the financial crisis period because of the unusually large LLP estimates during this period and the consequent reduced ability to incorporate disaster risk. We exclude observations headquartered in counties with high disaster risk to ensure that extreme levels of DR_t are not driving our results. We exclude banks with M&A activity because these banks face higher regulatory scrutiny and may also be more able to mitigate disaster risk. We also replicate our analysis on a subsample of single-county banks because these banks are inherently unable to mitigate disaster risk through branch networks across different counties and states. Untabulated results support a positive relation between disaster risk and LLP estimates.

To mitigate the concern that our disaster risk measure reflects the effects of a recent disaster rather than managers explicitly taking disaster risk into account, we exclude disasters that occurred in the previous five years from our measure and repeat our main analysis using a measure of DR_t calculated using the disasters from year t_{-6} to t_{-15}. Untabulated results show that the coefficient of disaster risk is similar in magnitude to that of our main analysis and is significant.

Third, when estimating Equation (2) in our main analysis, we follow prior literature and cluster standard errors at the bank level because of the nature of LLP (Nicoletti, 2018). However, our main

[16] Full results are available upon request from the authors.

variable of interest is a county-quarter measure of disaster risk. We find consistent results when we cluster standard errors at the county-quarter level.

Fourth, despite including multiple levels of fixed effects, we estimate Equation (2) in our main analysis without excluding singleton groups (i.e., groups with only one observation). Prior literature demonstrates that including these observations in linear regressions with multiple levels of fixed effects can inflate statistical significance and lead to incorrect inferences. We repeat our analysis after dropping singleton observations and obtain consistent results.

Fifth, we include numerous fixed effects in Equation (2) in the main analysis to control for local time-invariant effects on the coefficient estimates. We check the robustness of our results to the inclusion of additional year-variant county characteristics related to the economic environment by augmenting Equation (2) with year-variant county controls for population, total employment, unemployment insurance compensation per capita, and income per capita (retrieved from the Bureau of Economic Analysis).[17] We find consistent results after including these additional controls.

Sixth, we include year-quarter fixed effects in Equation (2) in the main analysis to eliminate common shocks, such as general macroeconomic trends, to the LLP estimates. To account for trends in quarters, we also estimate the model after replacing year-quarter fixed effects with year fixed effects and controlling for trends in quarters by introducing quarter-level changes in macroeconomic data that prior literature demonstrates affect LLP estimates (Hribar et al., 2017). Therefore, we augment Equation (2) with the change in the unemployment rate, the change in Gross Domestic Product, and CFO Sentiment.18 We find consistent results after including these additional controls.

6. Additional Analyses

Additional Measures of Disaster Risk

We explore potential attributes of disaster risk to create alternative measures of DR_t. Thus, we

[17] https://apps.bea.gov/regional/downloadzip.cfm

[18] The data in the Duke CFO Magazine Global Business Outlook survey, which is available at https://www.cfosurvey.org, starts from 2004. Therefore, our sample size is reduced to 308,125 bank-quarter observations for this test.

check the sensitivity of our results to multicounty, frequent event and rare event disaster risk. First, we compute an alternative measure of disaster risk (*$DR\_MULTICOUNTY_t$*) to consider the potential disaster risk mitigation generated through branch diversification outside the headquartered county but within the same state. Using yearly data on bank branches from the Summary of Deposits database, we calculate a multicounty measure of disaster risk at the county-year level. As a starting point, we assign the corresponding disaster risk to each bank branch. Then, we compute a weighted average measure of disaster risk using the number of branches in each county as weights. The weighted average allows consideration of the effective pervasiveness of a bank in each county, which may also vary over our sample period (i.e., a bank may progressively increase or decrease the number of branches in a county). Untabulated descriptive statistics show that the mean of $DR\_MULTICOUNTY_t$ is similar to that of DR_t (4.95) but less volatile than the headquarters disaster risk measure (standard deviation for $DR\_MULTICOUNTY_t$ is 2.70; standard deviation for DR_t is 2.84).

Second, depending on the geographical area, some climate events are more frequent than others. For example, hurricanes are frequent in Florida, fire events in Texas, and floods in Iowa. Our disaster risk measure includes both frequent and rare natural disasters declared by FEMA over the past fifteen years in each county and quarter. To explore the attributes of our original DR_t measure, we decompose disaster risk into frequent event disaster risk ($DR\_FREQUENT_t$) and rare event disaster risk (DR_RARE_t). We define a frequent (rare) natural event as an event that occurred with a frequency equal to or higher (lower) than the median of the event's frequency in each county. Untabulated descriptive statistics show that the mean of $DR\_FREQUENT_t$ (DR_RARE_t) is 3.37 (1.60).

Table 5 presents the estimation results using the three alternative measures of disaster risk described above. In columns (1), (2) and (3), we replace DR_t with $DR\_MULTICOUNTY_t$, $DR\_FREQUENT_t$, and DR_RARE_t, respectively, as the main independent variable. Lastly, in column (4) we include both $DR\_FREQUENT_t$, and DR_RARE_t. We find that all three alternative measures of disaster risk are positively and significantly related to LLP estimates. The coefficients for $DR\_FREQUENT_t$, and DR_RARE_t are not significantly different.

[Insert Table 5 here]

Which Banks are Better Able to Incorporate Disaster Risk?

In this section, we investigate whether certain types of banks are better able to incorporate disaster risk in LLP estimates. We focus on bank size, complexity, and loan concentration as the main characteristics that can enable banks to better incorporate disaster risk in LLP.

First, we reason that relatively larger banks have more resources to invest in disaster risk management. For this reason, larger banks may be better able to incorporate disaster risk into LLP estimates. We define small (large) banks as banks with total assets below (above) the 25th (75th) percentile of the distribution. Second, banks with a complex set of activities (i.e., that engage in activities other than traditional lending) may find it more challenging to incorporate disaster risk into LLP. We define simple (complex) banks as banks with non-interest income over total income below (above) the 25th (75th) percentile of the distribution. Third, banks that concentrate their loan portfolio on specific loan categories are probably better able to assess the magnitude and characteristics of the disaster risk in their loan portfolio. We define unconcentrated (concentrated) banks as banks with a standard deviation of loan categories below (above) the 25th (75th) percentile of the distribution. We investigate whether these bank characteristics facilitate better recognition of disaster risk through LLP.

We estimate Equation (2) separately for each subsample based on the aforementioned bank characteristics and compare β_1 across the subsamples and present the estimation results in Table 6. Columns (1) and (2) report the results for small and large banks, respectively, columns (3) and (4) for simple and complex banks, respectively, and columns (5) and (6) for unconcentrated and concentrated banks, respectively. Table 6 also reports the difference in the coefficients of DR_t across subsamples.

We find that disaster risk is positively and significantly related to LLP estimates only for relatively large banks and not for small banks (coefficient of DR_t is -0.0001, $p>0.10$ in column (1) and 0.0027, $p<0.01$ in column (2)), and the coefficient of large banks is greater than the coefficient for small banks (the difference between the coefficients of DR_t in columns (2) and (1) is 0.0028,

$p<0.01$). By contrast, disaster risk is significantly positively related to LLP for both simple and complex banks (coefficient of DR_t is 0.0056, $p<0.01$ in column (3) and 0.0015, $p<0.05$ in column (4)), and the coefficient for complex banks is less than the coefficient for simple banks (the difference between the coefficients of DR_t in columns (4) and (3) is -0.0041, $p<0.05$). The results also show that disaster risk is significantly positively related to LLP for concentrated banks but not for unconcentrated banks (coefficient of DR_t is 0.0005, $p>0.10$ in column (5) and 0.0053, $p<0.01$ in column (6)), and the coefficient for concentrated banks is greater than the coefficient for unconcentrated banks (the difference between the coefficients of DR_t in columns (6) and (5) is 0.0048; $p<0.01$). These results indicate that bank characteristics like size, complexity, and loan concentration are related to the ability of banks to proactively recognize disaster risk in their LLP estimates.

[Insert Table 6 here]

What are the Consequences of Managing Disaster Risk through LLP?

If disaster risk is appropriately managed and incorporated in LLP estimates, banks should experience positive future outcomes. For instance, when DR_t is better incorporated in LLP estimates, current LLPs should better anticipate future loan charge-offs when the natural event materializes. Conversely, if the natural event does not materialize in the future, banks should be able to bear more risk due to the fact that LLP already impounds disaster risk. We employ the following model that is commonly used in the prior literature (Hribar et al., 2017) to test whether disaster risk moderates the relation between current LLPs, future charge-offs, and future risk:

$$CO_{t+1,t+4} \mid RISK_{t+1,t+4} = \beta_0 + \beta_1\, LLP_t + \beta_2\, DR_t + \beta_3\, LLP_t \times DR_t + \Sigma\, \beta_k\, BankControls_t$$
$$+ \Sigma\, \beta_i\, LoanTypes_t + \Sigma\, \beta_j\, Fixed\ Effects + \varepsilon_t \quad (4)$$

All variables are defined in Appendix A. We calculate future charge offs ($CO_{t+1,t+4}$) as the average of net charge-offs from quarter $t+1$ to quarter $t+4$, divided by net loans and leases in quarter t. Similarly, we compute future risk ($RISK_{t+1,t+4}$) as the average of z-score from quarter $t+1$ to quarter $t+4$. We multiply the score by -1 so that higher values of z-score imply higher risk-taking.

Table 7 presents the estimation results of Equation (4). The dependent variable is future charge offs ($CO_{t+1,t+4}$) in columns (1) and (2) and future risk ($RISK_{t+1,t+4}$) in columns (3) and (4). We estimate Equation (4) for subsamples of bank-quarter observations that experience a disaster in quarter t+1 (columns (2) and (4)) and bank-quarter observations that do not experience a disaster in quarter t+1 (columns (1) and (3)).

We find that disaster risk positively moderates the relation between future charge-offs and current LLPs only for the subsample of bank-quarter observations that experience a disaster in quarter *t+1* (coefficient for the interaction term LLP_t x DR_t is insignificant in column (1), while it is positive and significant in column (2), with $p<0.05$). Conversely, we show that disaster risk positively moderates the relation between future risk and current LLPs only for the subsample of bank-quarter observations that do not experience a disaster in quarter *t+1* (coefficient of the interaction term LLP_t x DR_t is positive and significant in column (3), $p<0.01$, and is insignificant in column (4)).

We interpret these results as evidence that LLP better anticipates future charge-offs following the incorporation of disaster risk in LLP estimates when future risk materializes in natural events. Conversely, when disaster risk does not materialize, the incorporation of disaster risk in LLP estimates allows banks to bear more future risk.

[Insert Table 7 here]

7. Conclusions

Natural disasters have been increasing in frequency and intensity since the early 1950s. These phenomena impose a strain on the financial system. Therefore, there is considerable concern about whether and how financial institutions identify, measure, and monitor disaster risk. In fact, disaster risk could concentrate on lending portfolios and create a systemic risk to financial stability. In this study, we investigate whether disaster risk relates to banks' LLP estimates.

We propose a measure of disaster risk based on the number of natural disasters declared by FEMA over the preceding fifteen years for each county and quarter. We validate our measure using three approaches, including the UN Sendai Framework for disaster risk reduction and show that it captures the constructs of natural hazard, exposure, and vulnerability. Using a sample of 445,924 bank-quarter observations, we find evidence that banks operating in high disaster-risk counties estimate higher LLPs. In particular, disaster risk is positively related to LLPs even after controlling for previously identified determinants of normal LLPs such as loan charge-offs and current, past, and future changes in nonperforming assets. This finding is robust to several techniques to alleviate sample heterogeneity and endogeneity concerns. To strengthen a causal interpretation of the relation between disaster risk and LLP estimates, we conduct a difference-in-differences analysis using Hurricane Katrina as a shock that induced banks to reprice disaster risk in LLP estimates. Our results are also robust to other sensitivity tests, including the use of alternative measures of disaster risk that captures multicounty, frequent events and rare events disaster risk.

Our findings have implications for the debate related to supervision of the risk associated with natural disasters in the financial system. While our findings show that bank managers incorporate disaster risk in their estimation of LLPs, they also highlight that large banks, which have more resources to invest, are better able to manage credit risk from disasters through LLPs. Our study is important for regulators and policy-makers. Our results indicate that giving managers discretion to incorporate future disaster risk in current LLP estimates allows them to better absorb future long-term loan losses. In this regard, the proposed expected credit loss accounting rules for LLP are timely and will further enable managers to build reserves to mitigate disaster-related risk exposures.

Our study is subject to certain limitations. First, our measure of disaster risk is new in the literature and could be further refined. Future studies could identify firm-level measures of disaster risk and loan portfolio disaster risk. Second, we note that our measure is based on major disasters declared by FEMA and could be further enriched by including additional data on natural disasters from other sources. Lastly, we restrict our sample to U.S. banks and, as a result, our findings may have implications for these banks only.

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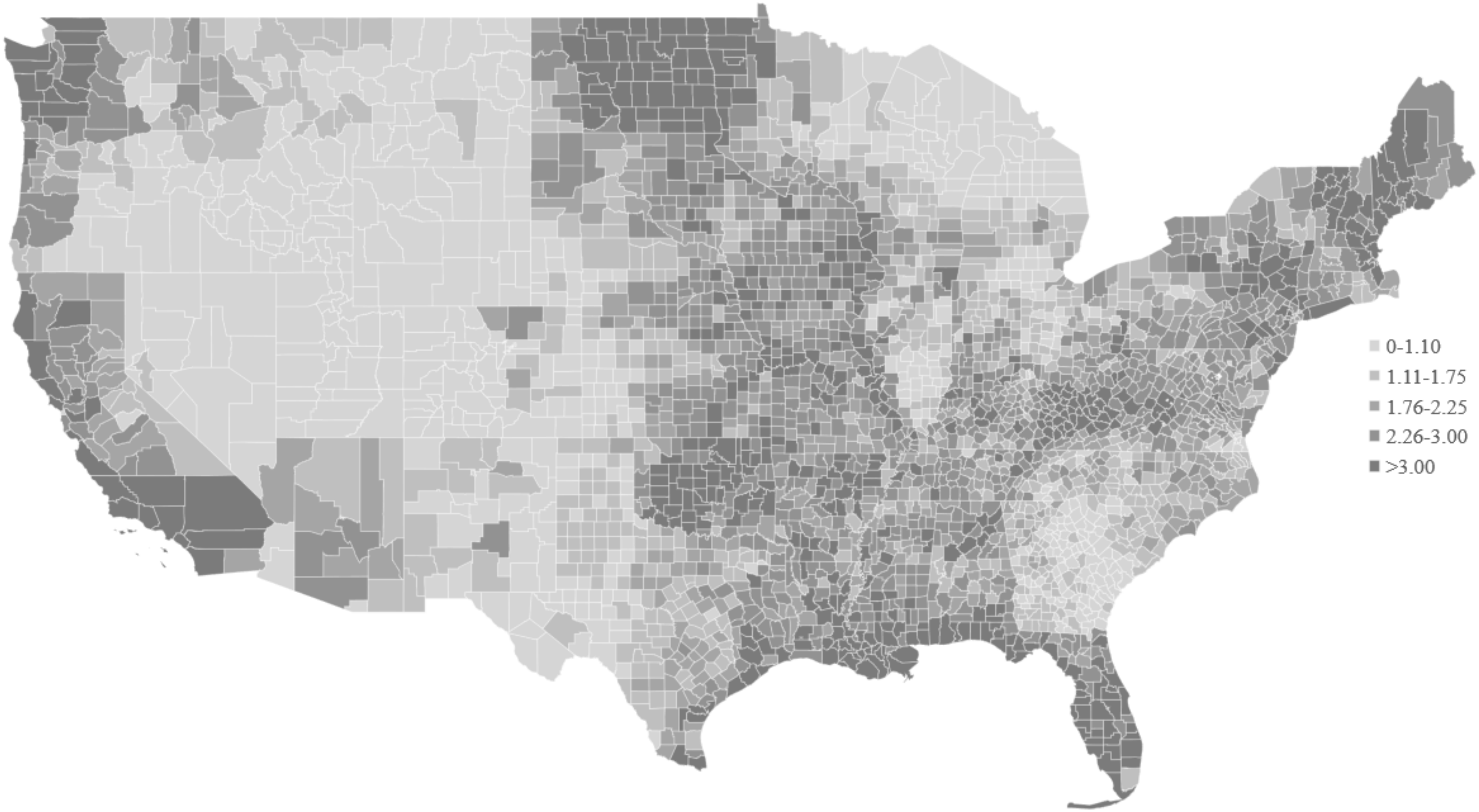
Appendix A: Variable definitions

Name	**Description**	**Source**
Loan Loss Provisions (LLP_t)	Provision for credit losses in quarter *t* divided by net loans and leases in quarter *t*-1.	FDIC: ELNATQ, LNLSNET.
Future net charge-offs on loan ($CO_{t+1,\ t+4}$)	Average of net charge-offs from quarter *t+1* to quarter t+4, divided by net loans and leases in quarter *t*.	FDIC: NTLNLSQ, LNLSNET.
Future risk-taking ($RISK_{t+1,\ t+4}$)	Average z-score from quarter *t+1* to quarter *t+4*. We measure z-score as the natural logarithm of [(ROA + CAP_REG) / SD_ROA], where ROA is income before extraordinary items and provision for credit losses divided by total assets, CAP_REG is total regulatory capital ratio (Tier-1), SD_ROA is the standard deviation of ROA on four quarters rolling window. We multiply the score by -1 so that higher z-score implies higher risk-taking.	FDIC: IBEFXTRQ, ELNATQ, RBCT1J, ASSET.
Disaster Risk (DR_t)	Number of natural disasters declared as major disasters over the past fifteen years by the Federal Emergency Management Agency in each county-quarter.	Federal Emergency Management Agency
Multicounty Disaster Risk ($DR\_MULTICOUNTY_t$)	Weighted average measure of disaster risk using the number of branches in each county as weights.	Federal Emergency Management Agency; Bank Regulatory: Federal Deposit Insurance Corporation, Summary of Deposits.
Frequent Event Disaster Risk ($DR\_FREQUENT_t$)	The number of natural disasters related to frequent events declared as major disasters over the past fifteen years by the Federal Emergency Management Agency in each county-quarter. We define frequent natural events as events that occurred with a frequency equal or higher than the median of the events frequency in each county.	Federal Emergency Management Agency
Rare Event Disaster Risk (DR_RARE_t)	The number of natural disasters related to rare events declared as major disasters over the past fifteen years by the Federal Emergency Management Agency in each county-quarter. We define rare natural events as events that occurred with a frequency lower than the median of the events frequency in each county.	Federal Emergency Management Agency
Post Hurricane Katrina ($POST_t$)	Indicator variable that takes the value of 1 after Hurricane Katrina strike (i.e., third quarter of 2005), 0 otherwise.	Federal Emergency Management Agency

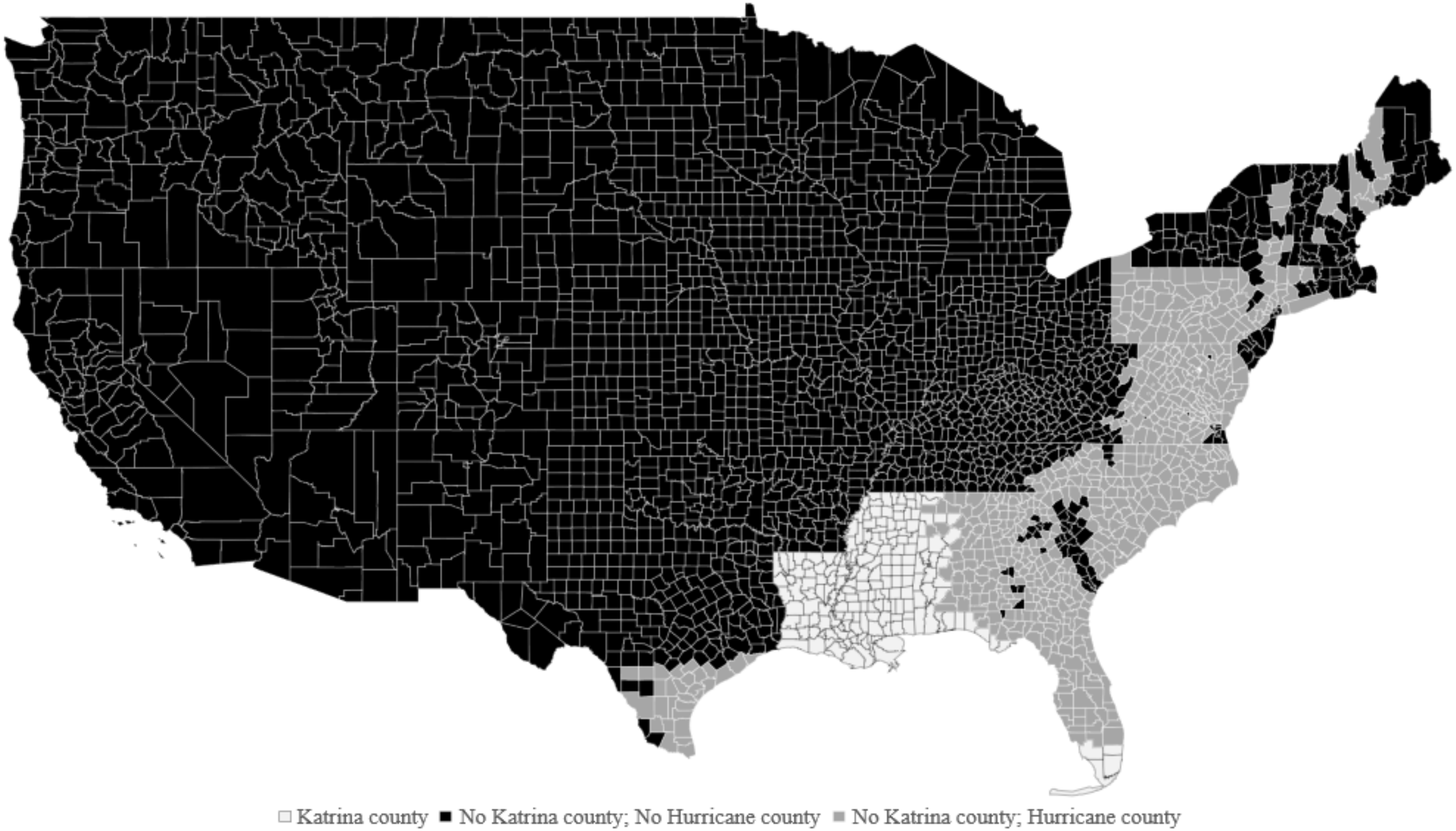
Hurricane hazard area ($HURRICANE1_t$)	Indicator variable that takes the value of 1 if a bank is headquartered in a county that registered at least one hurricane event in the FEMA dataset in the ten years before Hurricane Katrina (i.e., third quarter of 2005), 0 otherwise.	Federal Emergency Management Agency
Hurricane hazard area ($HURRICANE2_t$)	Indicator variable that takes the value of 1 if a bank is headquartered in a county that registered frequent hurricane strikes in the FEMA dataset in the ten years before Hurricane Katrina (i.e., third quarter of 2005), 0 otherwise. We define frequent hurricane strikes counties as counties in the top quartile of the distribution of the number of hurricane event.	Federal Emergency Management Agency
Change in nonperforming assets (ΔNPA_{t-2}; ΔNPA_{t-1}; ΔNPA_t; ΔNPA_{t+1})	Change in assets in nonaccrual status from quarter *t-1* to quarter *t,* divided by net loans and leases in quarter *t*-1.	FDIC: NAASSET, LNLSNET.
Change in total loans and leases ($\Delta LOANS_t$)	Change in net loans and leases from quarter *t-1* to quarter *t,* divided by net loans and leases in quarter *t*-1.	FDIC: LNLSNET.
Earnings before taxes and loan and leases losses ($EBTLLP_t$)	Sum of income before extraordinary items and provision for credit losses, both in quarter *t*, divided by net loans and leases in quarter *t*-1.	FDIC: IBEFXTRQ, ELNATQ, LNLSNET.
Net charge-offs on loan (CO_{t-1})	Past four quarters rolling average of net charge-offs in quarter *t* divided by net loans and leases in previous quarter.	FDIC: NTLNLSQ, LNLSNET.
Tier1 capital ratio ($TIER1_{t-1}$)	Tier one (core) capital in quarter *t*-1 divided by total assets in quarter *t*-2.	FDIC: RBCT1J, ASSET.
Allowance for loan and leases losses ($ALLOWANCE_{t-1}$)	Loan and leases loss allowance in quarter *t*-1 divided by net loans and leases in quarter *t*-2.	FDIC: LNATRES, LNLSNET.
Size ($SIZE_{t-1}$)	Natural logarithm of total assets in quarter *t*-1.	FDIC: ASSET.
Branch diversification ($BRANCHDIV_t$)	Number of bank branches outside the county where the bank is headquartered divided by the total number of bank branches in year *t*.	FDIC: STCNTYBR, STCNTY.
Loan portfolio composition ($LoanTypes_t$)	Residential, commercial, consumer and agricultural loans in quarter *t* divided by net loans and leases in quarter *t*.	FDIC: LNRE, LNCI, LNCON, LNAG, LNLSNET.

Figure 1: Disaster risk (*DR*) across counties in continental USA



Figures 1 presents a map chart of average disaster risk (*DR*) across counties in continental USA.

Figure 2: Counties affected by hurricanes and hurricane Katrina during the third quarter of 2005



Figures 2 presents a map chart of counties affected by hurricane Katrina (coloured in light grey, 179 counties, 21,655 bank-quarter observations), counties not affected by hurricane Katrina without hurricane events in the FEMA dataset during the 10 years prior to Hurricane Katrina (coloured in black, 2,367 counties, 355,414 bank-quarter observations), and counties not affected by hurricane Katrina with at least 1 hurricane event in the FEMA dataset during the 10 years prior to Hurricane Katrina (coloured in dark grey, 689 counties, 68,855 bank-quarter observations).

Table 1: Validation of disaster risk measure through the UN Sendai framework for disaster risk reduction

Panel A: Descriptive statistics

Variable	***N***	**Mean**	**Std. Dev.**	**Q1**	**Median**	**Q3**
DR_t	218,952	4.653	2.838	3	4	6
NHI_t	218,952	12.033	2.220	10	12	14
POP_t	218,952	10.263	1.460	9.315	10.150	11.094
$EMPL\%_t$	218,952	0.028	0.076	0.003	0.007	0.018
$SOVI_t$	218,952	49.999	28.571	25.4	49.9	74.7
PTY_DAMAGE_t	218,952	5.314	2.161	4.192	5.453	6.676

Panel B: Validation of disaster risk measure

	Column (1) DR_t	Column (2) DR_t	Column (3) DR_t
Constant	-2.6512***	0.3912***	-1.1091***
	[-43.28]	[6.69]	[-19.66]
NHI_t	0.0359***	0.0976***	0.0921***
	[12.49]	[35.04]	[34.61]
POP_t	0.3610***	0.2117***	0.2728***
	[64.78]	[42.16]	[56.38]
$EMPL\%_t$	0.3286***	0.8422***	0.9625***
	[3.65]	[9.30]	[10.80]
$SOVI_t$	0.0012***	0.0006***	0.0007***
	[6.15]	[3.60]	[4.60]
PTY_DAMAGE_t	0.5826***	0.1621***	0.3371***
	[175.48]	[64.53]	[120.48]
Fixed Effects	Year-Quarter	State	Year-Quarter & State
Observations	218,952	218,952	218,952
R^2	0.1612	0.4667	0.5225

This table reports the results for the validation approach our disaster risk measure (DR_t) through the UN Sendai framework for disaster risk reduction. Panel A reports summary statistics for disaster risk and disaster risk determinants. *N* is the number of county-quarter observations for which disaster risk and disaster risk determinants are available. Panel B reports estimation results for the following model validating our disaster risk measure (*DR*) through the UN Sendai framework for disaster risk reduction:

$$DR_t = f(HAZARD_t, EXPOSURE_t, VULNERABILITY_t)$$

Natural Hazard Index (NHI_t) is the natural hazard index is a multiple hazard measure that varies from 0 to 33. The higher the NHI_t, the higher the natural hazard in a county (National Center for Disaster Preparedness, NCDP, at Columbia University); Population (POP_t) is the natural logarithm of 1 plus the yearly number of individuals (both civilian and military) who reside in a given county (Bureau of Economic Analysis); Total employment ($EMPL\%_t$) is the natural logarithm of 1 plus yearly total job at county level divided by the total job at country level (Bureau of Economic Analysis); Social Vulnerability Index ($SoVI_t$) is the social vulnerability index is a measure of social vulnerability to environmental hazards that varies from 0 to 100. The higher the $SoVI_t$, the more vulnerable a county (Hazard & Vulnerability Research Institute, HVRI, at University of South Carolina); Property damage (PTY_DAMAGE_t) is the natural logarithm of 1 plus property losses per capita from natural disasters over the past 15 years in each county-quarter (Spatial Hazard Events and Losses Database, SHELDUS). *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels (two-tailed), respectively. t-statistics are presented in parentheses and are based on robust standard errors.

Table 2: Descriptive statistics

Variable	Obs.	Mean	Std. Dev.	Q1	Median	Q3
LLP_t	445,924	0.0011	0.0024	0.0000	0.0004	0.0011
DR_t	445,924	4.9660	2.8456	3.0000	5.0000	7.0000
ΔNPA_{t+1}	445,924	0.0001	0.0068	-0.0012	0.0000	0.0008
ΔNPA_t	445,924	0.0001	0.0067	-0.0012	0.0000	0.0008
ΔNPA_{t-1}	445,924	0.0001	0.0067	-0.0011	0.0000	0.0008
ΔNPA_{t-2}	445,924	0.0001	0.0066	-0.0011	0.0000	0.0008
$\Delta LOANS_t$	445,924	0.0164	0.0532	-0.0122	0.0115	0.0384
$EBTLLP_t$	445,924	0.0049	0.0041	0.0028	0.0045	0.0065
CO_{t-1}	445,924	0.0009	0.0018	0.0000	0.0003	0.0010
$TIER1_{t-1}$	445,924	0.1075	0.0346	0.0854	0.0988	0.1192
$ALLOWANCE_{t-1}$	445,924	0.0156	0.0082	0.0108	0.0136	0.0180
$SIZE_{t-1}$	445,924	11.8729	1.1632	11.0903	11.7947	12.5564
$BRANCHDIV_t$	445,924	23.2934	27.9751	0.0000	0.0000	50.0000
$LoanTypes_t$ *(residential)*	445,924	0.7064	0.1975	0.5916	0.7411	0.8533
$LoanTypes_t$ *(commercial)*	445,924	0.1381	0.0968	0.0708	0.1198	0.1845
$LoanTypes_t$ *(consumer)*	445,924	0.0736	0.0826	0.0188	0.0476	0.0969
$LoanTypes_t$ *(agricultural)*	445,924	0.0771	0.1270	0.0000	0.0110	0.1003

Variable definitions are in Appendix A. All bank-specific continuous variables have been winsorized at the 1st and 99th percentiles (except $SIZE_{t-1}$ which is expressed as natural logarithm, while $BRANCHDIV_t$ is expressed in percentage).

Table 3: Relation between disaster risk and loan loss provisions

	Column (1) LLP_t	Column (2) LLP_t	Column (3) LLP_t
Constant	0.0019	0.0016	-0.4701***
	[0.07]	[0.06]	[-9.42]
DR_t	**0.0027*** **	**0.0027*** **	**0.0021*** **
	[9.78]	**[9.81]**	**[6.56]**
ΔNPA_{t+1}	1.7317***	1.7224***	1.2800***
	[19.13]	[19.10]	[14.48]
ΔNPA_t	3.5484***	3.4997***	3.1288***
	[34.19]	[4.69]	[30.73]
ΔNPA_{t-1}	4.5013***	4.4932***	4.0273***
	[48.17]	[48.24]	[44.11]
ΔNPA_{t-2}	3.7364***	3.7295***	3.3793***
	[43.70]	[43.68]	[39.90]
$\Delta LOANS_t$	-0.0113	-0.0074	-0.1158***
	[-0.88]	[-0.57]	[-9.61]
$EBTLLP_t$	5.3512***	5.3855***	6.9741***
	[19.02]	[19.14]	[21.42]
CO_{t-1}	49.9029***	49.7603***	40.5223***
	[69.77]	[69.54]	[64.39]
$TIER1_{t-1}$	0.0810***	0.0834***	0.3451***
	[3.59]	[3.69]	[9.15]
$ALLOWANCE_{t-1}$	1.4151***	1.3730***	0.5259***
	[10.03]	[9.71]	[3.07]
$SIZE_{t-1}$	0.0005	0.0003	0.0216***
	[0.45]	[0.33]	[6.53]
$BRANCHDIV_t$	0.0002***	0.0002***	0.0002***
	[7.61]	[7.63]	[3.60]
Loan Types Controls	Yes	Yes	Yes
Time Fixed Effects	Year-Quarter	Year-Quarter × ΔNPA_t	Year-Quarter
State-County Fixed Effects	Yes	Yes	No
Bank Fixed Effects	No	No	Yes
Observations	445,924	445,924	445,924
R^2	0.317	0.319	0.358

This table reports estimation results for the following model relating loan loss provision (LLP_t) to disaster risk (DR_t)

$$LLP_t = \beta_0 + \beta_1\, DR_t + \Sigma\beta_j\, Controls + \Sigma\beta_i\, Fixed\ Effects + \varepsilon_t$$

Variable definitions are in Appendix A. All bank-specific continuous variables are winsorized at the 1st and 99th percentiles (except $SIZE_{t-1}$ which is expressed as natural logarithm, while $BRANCHDIV_t$ is expressed in percentage). *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels (two-tailed), respectively. t-statistics are presented in parentheses and are based on standard errors clustered at the bank level.

Table 4: Relation between disaster risk and loan loss provisions: Diff-in-Diff approach

	Column (1)		Column (2)	
	LLP_t		LLP_t	
Constant	-0.4534***	[-8.77]	-0.4505***	[-8.83]
DR_t	0.0015***	[3.11]	0.0013***	[2.82]
DR_t x $POST_t$	-0.0000	[-0.01]	0.0000	[0.03]
$HURRICANE1_t$	0.0080	[0.41]		
DR_t x $HURRICANE1_t$	-0.0000	[-0.03]		
$POST_t$ x $HURRICANE1_t$	-0.0055	[-0.77]		
DR_t x $POST_t$ x $HURRICANE1_t$	**0.0033*** **	**[2.59]**		
$HURRICANE2_t$			-0.0088	[-0.15]
DR_t x $HURRICANE2_t$			0.0087***	[2.97]
$POST_t$ x $HURRICANE2_t$			-0.1340***	[-4.57]
DR_t x $POST_t$ x $HURRICANE2_t$			**0.0180*** **	**[5.38]**
ΔNPA_{t+1}	1.2825***	[14.08]	1.2757***	[14.01]
ΔNPA_t	3.1272***	[29.89]	3.1188***	[29.84]
ΔNPA_{t-1}	4.0313***	[43.13]	4.0227***	[43.04]
ΔNPA_{t-2}	3.3954***	[39.28]	3.3876***	[39.19]
$\Delta LOANS_t$	-0.1105***	[-8.97]	-0.1102***	[-8.95]
$EBTLLP_t$	6.9914***	[20.72]	6.9711***	[20.68]
CO_{t-1}	40.2954***	[62.48]	40.1822***	[62.31]
$TIER1_{t-1}$	0.3347***	[8.60]	0.3325***	[8.56]
$ALLOWANCE_{t-1}$	0.5476***	[3.05]	0.5359***	[2.99]
$SIZE_{t-1}$	0.0215***	[6.33]	0.0215***	[6.34]
$BRANCHDIV_t$	0.0002***	[3.31]	0.0002***	[3.35]
Loan Types Controls	Yes		Yes	
Time Fixed Effects	Year-Quarter		Year-Quarter	
Bank Fixed Effects	Yes		Yes	
Observations	424,269		424,269	
R^2	0.360		0.360	

This table reports estimation results for the following difference-in-differences model:

$$LLP_t = \beta_0 + \beta_1 DR_t + \beta_2 POST_t + \beta_3 HURRICANE_t + \beta_4 DR_t \text{ x } POST_t + \beta_5 DR_t \text{ x } HURRICANE_t + \beta_6 POST_t \text{ x } HURRICANE_t + \beta_7 DR_t \text{ x } POST_t \text{ x } HURRICANE_t + \Sigma\beta_j\, Controls + \Sigma\beta_i\, Fixed\ Effects + \varepsilon_t$$

Variable definitions are in Appendix A. All bank-specific continuous variables are winsorized at the 1st and 99th percentiles (except $SIZE_{t-1}$ which is expressed as natural logarithm, while $BRANCHDIV_t$ is expressed in percentage). The main effect of POST is absorbed by the fixed effects. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels (two-tailed), respectively. t-statistics are presented in parentheses and are based on standard errors clustered at the bank level.

Table 5: Relation between additional measures of disaster risk and loan loss provisions

	Column (1) LLP_t	Column (2) LLP_t	Column (3) LLP_t	Column (4) LLP_t
Constant	-0.4746***	-0.4661***	-0.4611***	-0.4701***
	[-9.52]	[-9.33]	[-9.21]	[-9.42]
DR_MULTICOUNTY$_t$	**0.0028*** **			
	[7.95]			
DR_FREQUENT$_t$		**0.0017*** **		**0.0020*** **
		[5.30]		**[5.98]**
DR_RARE$_t$			**0.0017*** **	**0.0023*** **
			[3.01]	**[4.08]**
Bank & Loan Types Controls	Yes	Yes	Yes	Yes
Time Fixed Effects	Year-Quarter	Year-Quarter	Year-Quarter	Year-Quarter
Bank Fixed Effects	Yes	Yes	Yes	Yes
Observations	445,924	445,924	445,924	445,924
R^2	0.358	0.358	0.358	0.358

This table reports estimation results for the following model relating loan loss provision (LLP_t) to additional measures of disaster risk, namely multicounty disaster risk ($DR\_MULTICOUNTY_t$), frequent event disaster risk ($DR\_FREQUENT_t$), and rare event disaster risk (DR_RARE_t):

$$LLP_t = \beta_0 + \beta_1 \,(DR\_MULTICOUNTY_t \mid DR\_FREQUENT_t \mid DR\_RARE_t) + \Sigma\beta_j \, Controls + \Sigma\beta_i \, Fixed\ Effects + \varepsilon_t$$

Variable definitions are in Appendix A. DR is measured using the disaster risk at branch level (column 1), frequent events (column 2), and rare events (column 3). All bank-specific continuous variables are winsorized at the 1st and 99th percentiles (except $SIZE_{t-1}$ which is expressed as natural logarithm, while $BRANCHDIV_t$ is expressed in percentage). *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels (two-tailed), respectively. t-statistics are presented in parentheses and are based on standard errors clustered at the bank level.

Table 6: Relation between disaster risk and loan loss provisions: Cross-sectional tests based on banks' characterisctis

	Column (1)	Column (2)	Column (3)	Column (4)	Column (5)	Column (6)
	LLP_t	LLP_t	LLP_t	LLP_t	LLP_t	LLP_t
Constant	-0.8092***	-0.3364***	-0.5595***	-0.3215***	-0.2936**	-3.3285***
	[-7.92]	[-2.64]	[-6.19]	[-2.87]	[-2.31]	[-13.25]
DR_t	**-0.0001**	**0.0027*****	**0.0056*****	**0.0015****	**0.0005**	**0.0053*****
	[-0.10]	**[4.19]**	**[7.39]**	**[2.16]**	**[0.64]**	**[6.48]**
Cross-sectional sample	Small	Large	Simple	Complex	Unconcentrated	Concentrated
Difference in DR_t	*0.0028****		*-0.0041***		*0.0048****	
Bank & Loan Types Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Year-Quarter	Year-Quarter	Year-Quarter	Year-Quarter	Year-Quarter	Year-Quarter
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	111,484	111,482	111,481	111,489	111,481	111,481
R^2	0.215	0.519	0.374	0.432	0.396	0.418

This table reports estimation results for the following model relating loan loss provision (LLP_t) to disaster risk (DR_t) for three subsamples based on asset size, bank complexity, and loan portfolio concentration:

$$LLP_t = \beta_0 + \beta_1 DR_t + \Sigma\beta_j \, Controls + \Sigma\beta_i \, Fixed \, Effects + \varepsilon_t$$

We define small (large) banks if the total asset is lower (higher) than the 25th (75th) percentile of the distribution. We define simple (complex) banks if the non-interest income over total income is lower (higher) than the 25th (75th) percentile of the distribution. We define unconcentrated (concentrated) banks if the standard deviation of loan categories is lower (higher) than the 25th (75th) percentile of the distribution. Variable definitions are in Appendix A. All bank-specific continuous variables are winsorized at the 1st and 99th percentiles (except $SIZE_{t-1}$ which is expressed as natural logarithm, while $BRANCHDIV_t$ is expressed in percentage). *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels (two-tailed), respectively. t-statistics are presented in parentheses and are based on standard errors clustered at the bank level.

Table 7: Relation between disaster risk, current loan loss provisions and risk management

	Column (1) $CO_{t+1,\ t+4}$	Column (2) $CO_{t+1,\ t+4}$	Column (3) $RISK_{t+1,\ t+4}$	Column (4) $RISK_{t+1,\ t+4}$
Constant	-0.0059***	-0.0056***	-2.9145***	-2.8977***
	[-14.51]	[-7.24]	[-14.28]	[-7.70]
LLP_t	0.0018***	0.0015***	0.4571***	0.4990***
	[34.90]	[8.17]	[22.90]	[9.69]
DR_t	0.0000***	0.0000	-0.0029	0.0009
	[2.94]	[0.37]	[-1.33]	[0.25]
LLP_t x DR_t	**0.0000**	**0.0001****	**0.0116*****	**0.0007**
	[0.52]	**[1.98]**	**[3.31]**	**[0.09]**
Events in t+1	No	Yes	No	Yes
Bank & Loan Types Controls	Yes	Yes	Yes	Yes
Time Fixed Effects	Year-Quarter	Year-Quarter	Year-Quarter	Year-Quarter
Bank Fixed Effects	Yes	Yes	Yes	Yes
Observations	396,838	35,505	396,465	35,462
R^2	0.554	0.632	0.550	0.643

This table reports estimation results for the following models of the moderating effect of disaster risk (DR_t) on the relation between loan loss provisions (LLP_t), future charge-offs ($CO_{t+1,\ t+4}$) and future risk-taking ($RISK_{t+1}$):

$$CO_{t+1,\ t+4} = \beta_0 + \beta_1\ LLP_t + \beta_2\ DR_t + \beta_3\ LLP_t \times DR_t + \Sigma\beta_j\ Controls_j + \Sigma\beta_i\ Fixed\ Effects_i + \varepsilon_t$$

$$RISK_{t+1} = \beta_0 + \beta_1\ LLP_t + \beta_2\ DR_t + \beta_3\ LLP_t \times DR_t + \Sigma\beta_j\ Controls_j + \Sigma\beta_i\ Fixed\ Effects_i + \varepsilon_t$$

Variable definitions are in Appendix A. All bank-specific continuous variables are winsorized at the 1st and 99th percentiles (except $SIZE_{t-1}$ which is expressed as natural logarithm, while $BRANCHDIV_t$ is expressed in percentage). *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels (two-tailed), respectively. t-statistics are presented in parentheses and are based on standard errors clustered at the bank level.

Online Appendix

Does Disaster Risk Relate to Banks' Loan Loss Provision Estimates?

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Appendix OA1. Validation of Disaster Risk Measure using the German Watch Framework and the National Risk Index from the FEMA

Disaster risk is complicated to define and capture, a fact that is witnessed by the numerous frameworks trying to describe, measure, and validate it (e.g., UNDRR, 2019; UNISDR, 2015; World Bank, 2014). In the paper, we use the UN Sendai Framework for disaster risk reduction as a tool for validating our disaster risk measure. We show that our measure of DR_t captures the components of hazard, exposure, and vulnerability and the spatial and temporal attributes of disaster risk (UNISDR, 2015; UNDRR, 2019). However, the UN Sendai Framework for disaster risk reduction is not the only framework trying to identify the drivers of disaster risk. In this Online Appendix, we also validate DR_t using the German Watch framework (Eckstein et al., 2021) and the FEMA National Risk Index.[19]

The German Watch framework (Eckstein et al., 2021) is used to compile and publish the Global Climate Risk Index (CRI), which captures at the country level the extent of losses from extreme weather events. CRI has been used in prior business and accounting literature (e.g., Huang et al., 2018; Ding et al., 2021). More specifically, German Watch identifies past loss figures for death toll, deaths per 100,000 inhabitants, absolute losses in Purchasing Power Parities, and losses per GDP unit as main determinants of CRI. We employ the following model to validate our disaster risk measure under the German Watch Framework:

$$DR_t = \theta_0 + \theta_1\, PTY\_DAMAGE_t + \theta_2\, CRP\_DAMAGE_t + \theta_3\, INJURIES_t + \theta_4\, FATALITIES_t + \Sigma\theta_i\, Fixed\ Effects + \varepsilon_t \qquad \text{(OA1)}$$

[19] https://hazards.fema.gov/nri/

All variables are defined in Appendix A and Online Appendix OA2. We estimate Equation (OA1) at the county-quarter level, including all counties and quarters with available data from 2002 to 2019. The final sample for which disaster risk and disaster risk determinants are available consists of 232,920 county-quarter observations. Under the German Watch Framework, we expect all control variables to be positively associated with DR_t. To account for potential time and geographical trends in disaster risk, we include year-quarter and county fixed effects.

Panel A of Table OA3 reports summary statistics for disaster risk and its determinants. Panel B of Table OA3 presents the estimation results of Equation (OA1). Consistent with the German Watch Framework, we find that all explanatory variables are significantly positively associated with disaster risk.

[Insert Table OA3 About Here]

Additionally, we validate our disaster risk measure using the FEMA National Risk Index (*NRI*). In this measure, risk is defined as the potential for negative impacts as a result of a natural hazard. Therefore, *NRI* should be highly associated with our DR_t measure. Accordingly, we first employ the following model to establish whether our disaster risk measure is positively associated with *NRI*:

$$DR\_YEAR_t = \theta_0 + \theta_1 \, NRI_t + \varepsilon_t \qquad \text{(OA2a)}$$

Since NRI_t is estimated at the year level, we also compute a yearly measure of disaster risk (DR_YEAR_t) by averaging the quarterly disaster risk.

According to FEMA, *NRI* includes three components: a natural hazards risk component measured via expected annual losses (EAL_SCORE_t), a consequence enhancing component proxied by the Social Vulnerability Index ($SoVI\_SCORE_t$), and a consequence reduction component based on community resilience ($RESL\_SCORE_t$). We employ the following model to understand whether our disaster risk measure captures all the relevant characteristics included in NRI:

$$DR\_YEAR_t = \theta_0 + \theta_1\ EAL\_SCORE_t + \theta_2\ SOVI\_SCORE_t + \theta_3\ RESL\_SCORE_t + \varepsilon_t \qquad \text{(OA2b)}$$

All variables included in Equation (OA2a) and Equation (OA2b) are defined in Appendix A and Online Appendix OA2. We estimate Equation (OA2a) and Equation (OA2b) at the county level, including data for 2020 only because FEMA started publishing *NRI* only from 2020. The final sample for which disaster risk, *NRI*, and the determinants of *NRI* are available consists of 3,140 county observations.

Panel A of Table OA4 reports summary statistics for disaster risk, *NRI*, and *NRI* determinants. Panel B of Table OA4 presents the estimation results of Equation (OA2a) and Equation (OA2b), columns (1) and (2) respectively. Consistent with our expectations, we find that the *NRI* correlates positively and significantly with our disaster risk measure (coefficient for NRI_t is 0.0705, $p<0.01$). Additionally, we find that all the components of *NRI* are significantly positively associated with disaster risk (see coefficient estimates in Column (2)).

[Insert Table OA4 About Here]

Together with the results reported in Section 3.3 of the paper, these results further validate our measure of disaster risk, as they indicate that it captures the main components of disaster risk indicated by three different frameworks, namely the UN Sendai framework for disaster risk reduction, the German Watch Framework, and the National Risk Index from FEMA.

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Appendix OA2. Definition of variables used in validating disaster risk

Name	Description	Source
Natural Hazard Index (NHI_t)	The natural hazard index is a multiple hazard measure that varies from 0 to 33. NHI_t represents the aggregate of hazard from eleven individual disasters. Each type of hazard receives a score (None/Low/Medium/High) and is then aggregated in the multiple hazard index. The higher the NHI_t, the higher the natural hazard in a county.	National Center for Disaster Preparedness (NCDP) at Columbia University
Population (POP_t)	Population is the natural logarithm of 1 plus the yearly number of individuals (both civilian and military) who reside in a given county.	Bureau of Economic Analysis
Total employment ($EMPL\%_t$)	Total employment is the natural logarithm of 1 plus yearly total job at county level divided by the total job at country level.	Bureau of Economic Analysis
Social Vulnerability Index ($SoVI_t$)	The social vulnerability index is a measure of social vulnerability to environmental hazards that varies from 0 to 100. Data from various sources are standardized and placed into a principal component analysis. The higher the $SoVI_t$, the more vulnerable a county.	Hazard & Vulnerability Research Institute (HVRI) at University of South Carolina
Property damage (PTY_DAMAGE_t)	Property damage is the natural logarithm of 1 plus property losses per capita from natural disasters over the past fifteen years in each county-quarter.	Spatial Hazard Events and Losses Database (SHELDUS)
Crop damage (CRP_DAMAGE_t)	Natural logarithm of 1 plus direct damage to crop in U.S. dollars losses over the past fifteen years in each county-quarter.	Spatial Hazard Events and Losses Database (SHELDUS)
Injuries ($INJURIES_t$)	Natural logarithm of 1 plus the number of people injured directly by the event over the past fifteen years in each county-quarter.	Spatial Hazard Events and Losses Database (SHELDUS)
Fatalities ($FATALITIES_t$)	Natural logarithm of 1 plus the number of people directly killed by the event over the past fifteen years in each county-quarter.	Spatial Hazard Events and Losses Database (SHELDUS)

Disaster Risk at year level (DR_YEAR_t)	Annual measure of disaster risk calculated by averaging the quarterly disaster risk.	Federal Emergency Management Agency
National Risk Index (NRI_t)	Risk score based on three components: a natural hazards risk component (EAL_SCORE_t), a consequence enhancing component ($SOVI\_SCORE_t$), and a consequence reduction component ($RESL\_SCORE_t$).	Federal Emergency Management Agency
Expected Annual Loss Score (EAL_SCORE_t)	Natural hazards risk score based on average economic loss in dollars resulting from natural hazards each year. The expected annual loss is calculated using data for exposure, annualize frequency of natural disasters, and historic loss ratio.	Federal Emergency Management Agency
Social Vulnerability Index Score ($SOVI\_SCORE_t$)	Consequence enhancing score based on the Social Vulnerability Index from the Hazard & Vulnerability Research Institute (HVRI) at University of South Carolina.	Federal Emergency Management Agency
Community Resilience Score ($RESL\_SCORE_t$)	Consequence reduction score based on the Baseline Resilience Indicators for Communities Index from the Hazard & Vulnerability Research Institute (HVRI) at University of South Carolina.	Federal Emergency Management Agency

Appendix OA3. Sample heterogeneity: Coarsened Exact Matching and Entropy Matching Analysis

The ability to incorporate disaster risk in LLP estimates may vary across banks. In Table 3 of the paper, we confirm that our results are robust to using a measure that captures the ability of banks to mitigate disaster risk through branches located outside the headquarters' county. To further address sample heterogeneity arising from a bank's ability to incorporate disaster risk in LLP estimates, we provide a subsample analysis, which we discuss in Section 5.3.

Banks headquartered in counties with high disaster risk may be fundamentally different from those headquartered in counties with low disaster risk. To further reduce potential sample heterogeneity, we replicate our main analysis using two matched samples. The treated group includes banks located in high disaster risk counties (i.e., above the 75th percentile of the sample distribution), while the control group includes banks located in low disaster risk counties (i.e., below the 25th percentile of the sample distribution). We match banks based on size ($SIZE_{t-1}$), Tier 1 risk-based capital ratio ($TIER1_{t-1}$), net charge-offs (CO_t), and changes in nonperforming assets (ΔNPA_t).

First, we eliminate differences between treated and control banks using coarsened exact matched (CEM) samples (DeFond et al., 2016). After implementing this matching procedure, we obtain a multivariate distance L1 of 0.999 and a matched sample of 157,093 bank-quarter observations.

Second, we use entropy matching (EM) to identify an alternative matched sample. Entropy balancing provides the advantage of identifying weights for the control sample to equalize the distribution of determinants across treatment and control samples (McMullin & Schonberger, 2020). We obtain a matched sample of 168,396 bank-quarter observations for this analysis.

Lastly, we re-estimate Equation (2) in the paper on the CEM-matched and EM-matched samples. Table OA6 shows that our main results are robust to using these alternative matching techniques. We find evidence that disaster risk is significantly positively related to LLP estimates (coefficient on DR_t is 0.0025; $p<0.01$ in column (1) and 0.032; $p<0.01$ in column (2)).

[Insert Table OA6 About Here]

References

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Table OA8. Sample distribution by state and year

State	**Code**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	***Total***
Alaska	AK	21	26	24	24	24	22	24	24	20	20	24	23	20	20	20	20	20	20	*396*
Alabama	AL	415	550	542	526	525	520	515	523	532	520	529	491	479	465	451	420	402	385	*8,790*
Arkansas	AR	500	636	617	580	555	538	522	492	497	487	492	438	388	368	351	332	319	300	*8,412*
Arizona	AZ	93	119	136	152	148	149	168	166	146	126	113	88	79	67	60	55	52	45	*1,962*
California	CA	715	920	861	846	848	883	937	960	942	893	888	765	715	642	568	534	478	450	*13,845*
Colorado	CO	452	602	585	583	560	529	503	501	463	392	399	351	339	317	303	283	261	250	*7,673*
Connecticut	CT	147	193	175	167	163	151	154	155	168	163	183	154	142	132	124	122	113	105	*2,711*
Delaware	DE	55	73	67	62	58	52	53	63	59	53	65	55	49	52	52	52	49	47	*1,016*
Florida	FL	684	907	873	863	873	881	898	902	839	775	782	694	635	570	517	456	404	365	*12,918*
Georgia	GA	875	1,163	1,175	1,184	1,161	1,165	1,131	1,061	986	905	893	821	771	719	676	640	605	561	*16,492*
Hawaii	HI	12	14	11	8	8	13	16	16	16	16	24	24	23	20	20	20	20	20	*301*
Iowa	IA	1,194	1,550	1,534	1,503	1,472	1,439	1,396	1,370	1,374	1,333	1,330	1,235	1,191	1,155	1,118	1,097	1,060	1,004	*23,355*
Idaho	ID	38	51	50	47	43	43	48	56	64	65	60	47	41	40	40	40	34	28	*835*
Illinois	IL	2,111	2,763	2,649	2,476	2,370	2,309	2,270	2,212	2,220	2,127	2,177	1,993	1,916	1,795	1,704	1,628	1,558	1,493	*37,771*
Indiana	IN	428	554	524	490	459	427	408	395	414	410	505	444	424	405	376	357	341	328	*7,689*
Kansas	KS	1,035	1,372	1,356	1,335	1,291	1,242	1,212	1,218	1,253	1,216	1,183	1,058	1,031	993	955	894	841	800	*20,285*
Kentucky	KY	635	836	814	777	752	726	692	691	715	713	750	690	669	627	597	564	539	503	*12,290*
Louisiana	LA	415	541	525	511	512	518	512	510	533	515	561	514	497	467	456	433	400	380	*8,800*
Massachusetts	MA	535	707	663	621	612	579	553	550	571	555	591	525	503	472	443	411	386	356	*9,633*
Maryland	MD	191	249	220	208	205	177	171	179	200	194	296	237	220	193	166	148	133	112	*3,499*
Maine	ME	84	112	115	112	108	100	89	88	88	88	112	104	102	94	92	86	84	83	*1,741*
Michigan	MI	460	618	604	598	585	572	552	509	494	484	509	483	453	426	398	371	351	333	*8,800*
Minnesota	MN	1,355	1,785	1,755	1,704	1,648	1,626	1,589	1,549	1,521	1,479	1,496	1,391	1,314	1,255	1,208	1,170	1,115	1,065	*26,025*
Missouri	MO	995	1,309	1,291	1,260	1,228	1,219	1,186	1,184	1,235	1,213	1,243	1,108	1,087	1,061	996	943	894	866	*20,318*
Mississippi	MS	271	357	347	338	334	335	321	320	338	329	331	286	275	260	256	253	243	237	*5,431*
Montana	MT	232	299	297	298	295	281	279	275	280	273	254	241	227	208	195	184	175	164	*4,457*
North Carolina	NC	234	301	292	289	279	284	282	301	333	320	338	260	222	205	187	168	144	136	*4,575*
North Dakota	ND	294	381	369	356	344	331	328	330	360	356	342	279	263	246	240	233	226	221	*5,499*
Nebraska	NE	766	995	968	942	916	883	860	848	860	836	836	752	712	680	645	615	590	570	*14,274*
New Hampshire	NH	66	87	87	81	69	59	56	63	68	67	81	64	62	55	52	54	51	48	*1,170*
New Jersey	NJ	270	350	337	320	294	291	294	309	343	337	423	374	340	308	282	265	235	208	*5,580*
New Mexico	NM	144	190	184	179	176	175	172	175	182	175	180	155	140	129	128	126	118	104	*2,832*
Nevada	NV	86	117	121	118	110	108	114	115	97	87	81	60	52	50	48	48	46	45	*1,503*
New York	NY	360	456	439	424	405	399	396	416	440	434	542	463	451	435	428	417	405	390	*7,700*

Ohio	OH	589	768	737	705	698	673	636	629	655	653	888	806	757	722	685	653	623	594	*12,471*
Oklahoma	OK	797	1,049	1,031	1,020	993	957	932	933	964	940	916	826	781	750	738	730	699	676	*15,732*
Oregon	OR	80	98	99	105	109	108	105	111	126	125	123	93	89	76	72	66	56	52	*1,693*
Pennsylvania	PA	607	782	760	729	706	688	658	668	725	699	762	669	643	598	543	507	472	436	*11,652*
Rhode Island	RI	12	23	26	24	26	25	24	25	28	31	44	32	31	28	28	28	26	24	*485*
South Carolina	SC	219	288	284	273	261	254	255	254	252	237	276	250	233	217	202	185	167	155	*4,262*
South Dakota	SD	265	342	330	327	316	311	306	300	310	302	299	264	246	235	221	209	192	180	*4,955*
Tennessee	TN	532	684	670	655	652	655	655	667	699	691	709	636	613	588	557	531	500	482	*11,176*
Texas	TX	2,019	2,619	2,548	2,481	2,414	2,352	2,327	2,346	2,357	2,306	2,249	2,066	1,949	1,844	1,771	1,717	1,649	1,575	*38,589*
Utah	UT	138	185	182	190	199	201	194	189	190	185	206	182	176	171	162	152	134	124	*3,160*
Virginia	VA	312	407	407	412	361	318	300	325	398	392	389	308	285	263	239	218	200	181	*5,715*
Vermont	VT	41	52	56	54	47	38	32	38	52	52	51	34	32	33	32	32	32	32	*740*
Washington	WA	230	305	306	294	287	279	286	291	286	261	266	201	188	170	156	149	137	128	*4,220*
Wisconsin	WI	832	1,089	1,066	1,043	1,032	1,005	977	982	1,005	990	1,036	947	908	869	798	756	733	683	*16,751*
West Virginia	WV	170	224	218	209	200	186	182	193	238	231	229	179	172	169	162	155	145	136	*3,398*
Wyoming	WY	129	161	156	154	149	144	139	125	136	134	135	119	116	115	113	111	107	104	*2,347*
Total		*23,140*	*30,259*	*29,483*	*28,657*	*27,880*	*27,220*	*26,709*	*26,602*	*27,072*	*26,185*	*27,191*	*24,279*	*23,051*	*21,779*	*20,631*	*19,638*	*18,564*	*17,584*	*445,924*

Table OA1 reports the sample distribution by state and year. The sample consists of bank-quarter observations from the first quarter of 2002 to the fourth quarter of 2019.

Table OA2. Disaster type distribution

Disaster Type	Single events	Percent	Average Counties Affected	Included in DR_t measure
Coastal Storm	16	0.95%	7	Yes
Dam/Levee Break	1	0.06%	1	Yes
Drought	2	0.12%	14	Yes
Earthquake	21	1.24%	6	Yes
Fire	45	2.66%	20	Yes
Fishing Losses	3	0.18%	6	No
Flood	303	17.94%	17	Yes
Freezing	10	0.59%	18	Yes
Human Cause	2	0.12%	1	No
Hurricane	172	10.18%	25	Yes
Mud/Landslide	5	0.30%	6	Yes
Other	1	0.06%	1	No
Severe Ice Storm	47	2.78%	25	Yes
Severe Storm(s)	887	52.52%	17	Yes
Snow	63	3.73%	24	Yes
Terrorist	1	0.06%	1	No
Tornado	64	3.79%	11	Yes
Tsunami	3	0.18%	3	Yes
Typhoon	41	2.43%	2	Yes
Volcano	2	0.12%	1	Yes
Total	*1,689*	*100.00%*	*17*	

Table OA2 reports the distribution of major disaster declarations by disaster type contained in the FEMA dataset from the first quarter of 1987 to the fourth quarter of 2019. Data from 1987 to 2002 are reported as they are used to compute the disaster risk measure of 2002 first quarter. Single events represent the number of disasters for each disaster type, while the average number of counties affected is the average number of counties affected by a single disaster. Not all disaster types are used to compute the disaster risk measure.

Table OA3: Validation of disaster risk measure through the German Watch framework

Panel A: Descriptive statistics

Variable	***N***	**Mean**	**Std. Dev.**	**Q1**	**Median**	**Q3**
DR_t	232,920	4.551	2.843	2	4	6
PTY_DAMAGE_t	232,920	14.551	4.646	14.237	15.569	16.834
CRP_DAMAGE_t	232,920	10.352	6.868	0	13.075	16.061
$INJURIES_t$	232,920	1.097	1.194	0	0.720	1.792
$FATALITIES_t$	232,920	0.529	0.715	0	0.140	0.820

Panel B: Validation of disaster risk measure

	Column (1)	
	DR_t	t-stat
Constant	2.6560***	[76.67]
PTY_DAMAGE_t	0.1188***	[48.27]
CRP_DAMAGE_t	0.0021***	[2.98]
$INJURIES_t$	0.1098***	[20.83]
$FATALITIES_t$	0.0444***	[4.85]
Time Fixed Effects	Year-Quarter	
State-County Fixed Effects	Yes	
Observations	232,920	
R^2	0.793	

This table reports the results for the validation approach our disaster risk measure (DR_t) through the German Watch Framework. Panel A reports summary statistics for disaster risk and disaster risk determinants. *N* is the number of county-quarter observations for which disaster risk and disaster risk determinants are available. Panel B reports estimation results for the following model validating our disaster risk measure (DR_t) through the German Watch framework:

$$DR_t = f(PTY\_DAMAGE_t, CRP\_DAMAGE_t, INJURIES_t, FATALITIES_t)$$

Variable definitions are in Online Appendix OA2. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels (two-tailed), respectively. t-statistics are presented in parentheses and are based on robust standard errors.

Table OA4: Validation of disaster risk measure through the National Risk Index

Panel A: Descriptive statistics

Variable	***N***	**Mean**	**Std. Dev.**	**Q1**	**Median**	**Q3**
DR_YEAR_t	3,140	4.770	3.001	2.5	4.5	6.75
NRI_t	3,140	10.602	6.769	6.689	9.089	12.529
EAL_SCORE_t	3,140	13.339	7.737	8.802	11.524	15.521
$SOVI\_SCORE_t$	3,140	38.317	11.062	31.868	38.333	44.462
$RESL\_SCORE_t$	3,140	54.596	2.938	52.651	54.662	56.747

Panel B: Validation of disaster risk measure

	Column (1) DR_YEAR_t	Column (2) DR_YEAR_t
Constant	4.0232***	-2.1195*
	[42.89]	[-1.93]
NRI	0.0705***	
	[9.91]	
EAL_SCORE_t		0.0589***
		[9.86]
$SOVI\_SCORE_t$		0.0188***
		[3.76]
$RESL\_SCORE_t$		0.0986***
		[5.24]
Observations	3,140	3,140
R^2	0.0249	0.033

This table reports the results for the validation approach our disaster risk measure at annual level (DR_YEAR_t) through the FEMA National Risk Index. Panel A reports summary statistics for disaster risk and disaster risk determinants. *N* is the number of county-quarter observations for which disaster risk and disaster risk determinants are available. Panel B reports estimation results for the following model validating our disaster risk measure (DR_YEAR_t) through the FEMA National Risk Index:

$$DR\_YEAR_t = f(EAL\_SCORE_t, SOVI\_SCORE_t, RESL\_SCORE_t)$$

Variable definitions are in Online Appendix OA2. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels (two-tailed), respectively. t-statistics are presented in parentheses and are based on robust standard errors.

Table OA5. Pearson's correlation coefficients

		1	2	3	4	5	6	7
LLP_t	1	1						
DR_t	2	-0.001	1					
ΔNPA_{t+1}	3	0.032***	0.003**	1				
ΔNPA_t	4	0.083***	0.004**	-0.043***	1			
ΔNPA_{t-1}	5	0.111***	0.004***	-0.014***	-0.046***	1		
ΔNPA_{t-2}	6	0.108***	0.005***	-0.011***	-0.017***	-0.049***	1	
$\Delta LOANS_t$	7	-0.058***	0.007***	0.034***	0.057***	-0.013***	-0.023***	1
$EBTLLP_t$	8	0.052***	-0.053***	0.020***	-0.003**	0.004***	0	0.052***
CO_{t-1}	9	0.440***	-0.010***	-0.073***	-0.057***	-0.069***	-0.020***	-0.174***
$TIER1_{t-1}$	10	-0.023***	0.015***	0.004***	-0.001	-0.002	-0.016***	0.074***
$ALLOWANCE_{t-1}$	11	0.218***	-0.010***	-0.078***	-0.064***	-0.003**	-0.010***	-0.103***
$SIZE_{t-1}$	12	0.081***	0.056***	0.008***	0.009***	0.012***	0.013***	0.013***
$BRANCHDIV_t$	13	0.025***	0.020***	0.001	0.003**	0.005***	0.006***	0.005***

Continues…

		8	9	10	11	12	13
$EBTLLP_t$	8	1					
CO_{t-1}	9	-0.044***	1				
$TIER1_{t-1}$	10	0.132***	-0.078***	1			
$ALLOWANCE_{t-1}$	11	0.038***	0.420***	0.103***	1		
$SIZE_{t-1}$	12	0.070***	0.079***	-0.188***	-0.052***	1	
$BRANCHDIV_t$	13	-0.027***	0.030***	-0.187***	-0.038***	0.423***	1

Variable definitions are in Appendix A. All bank-specific continuous variables have been winsorized at the 1st and 99th percentiles (except $SIZE_{t-1}$ which is expressed as natural logarithm, while $BRANCHDIV_t$ is expressed in percentage). *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels respectively

Table OA6: Relation between disaster risk and loan loss provisions: Matched sample selection

	Column (1) LLP_t *Coarsened exact matching*	Column (2) LLP_t *Entropy matching*
Constant	-0.3510***	-0.4085***
	(-2.93)	(-3.72)
DR_t	**0.0025*****	**0.0032*****
	(3.95)	**(5.08)**
ΔNPA_{t+1}	1.0857***	1.2143***
	(6.27)	(8.30)
ΔNPA_t	3.3522***	3.5096***
	(14.92)	(19.46)
ΔNPA_{t-1}	3.6585***	4.0349***
	(21.41)	(26.65)
ΔNPA_{t-2}	3.2363***	3.4234***
	(20.78)	(23.00)
$\Delta LOANS_t$	-0.0565***	-0.0848***
	(-2.94)	(-3.92)
$EBTLLP_t$	6.7061***	7.2703***
	(12.39)	(12.58)
CO_{t-1}	41.9633***	39.5108***
	(33.06)	(34.38)
$TIER1_{t-1}$	0.3464***	0.3118***
	(5.48)	(4.49)
$ALLOWANCE_{t-1}$	0.0539	0.9211***
	(0.18)	(2.75)
$SIZE_{t-1}$	0.0098*	0.0174**
	(1.68)	(2.56)
$BRANCHDIV_t$	0.0002*	0.0002**
	(1.77)	(1.98)
Loan Types Controls	Yes	Yes
Time Fixed Effects	Year-Quarter	Year-Quarter
Bank Fixed Effects	Yes	Yes
Observations	157,093	168,396
R^2	0.333	0.375
Treated (on support)	76,287	81,024

This table reports estimation results for the following model relating loan loss provision (LLP_t) to disaster risk (DR_t) for coarsened exact matched and entropy matched samples:

$$LLP_t = \beta_0 + \beta_1 DR_t + \Sigma\beta_j \, Controls + \Sigma\beta_i \, Fixed\ Effects + \varepsilon_t$$

Variable definitions are in Appendix A. All bank-specific continuous variables are winsorized at the 1st and 99th percentiles (except $SIZE_{t-1}$ which is expressed as natural logarithm). *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels (two-tailed), respectively. t-statistics are presented in parentheses and are based on standard errors clustered at the bank level.