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Review Article

Disaster Risk Management in Loan Disbursement: Analysis of Strategies and Techniques for Mitigating Financial Impact

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ABSTRACT: This study discusses the natural disaster risks and loan disbursal by banks in terms of Loan Loss Provision (LLP) policies. Over the last 15 years, the U.S. Federal Disaster Recovery Agency has noted some major natural disasters and emphasized a significant risk factor for financial institutions. We examine three approaches: the UN Sendai Framework for disaster risk reduction, to analyze the effects of natural hazards, vulnerability, capacity, and other factors on loan distribution and risk management. We present both theoretical underpinnings and empirical evidence to support these approaches. Based on more than 445,000 bank-quarter data, we find that banks in counties with higher disaster risks tend to allocate larger LLPs after controlling for other bank-level characteristics. We then examine how banks discover and manage disaster risks using LLP policies and evaluate the effectiveness of such practices in mitigating financial exposure from natural disasters. With growing concerns about catastrophic events and the associated financial costs of disasters, our results are critical to illuminating how the insurance sector and financial institutions use LLPs to mitigate the monetary risk associated with natural disasters.

KEYWORDS: Disaster Risk Management, Loan Disbursement, Natural Hazards, Loan Loss Provision, Financial Impact, Risk Mitigation.

INTRODUCTION

Disasters damage property, economy, and productivity (UNDRR, 2019; UNISDR, 2015). These occurrences are irregular and classified as industry shocks by Jerome Powell, chairman of the U.S. Federal Reserve Sector the government of directors (Powell, 2019). In considering this, the Federal Reserve Board emphasizes how natural disasters impact liquidity, specifically the ability of lenders to evaluate and control disaster risk. The main emphasis of earlier studies has been on the consequences of natural disasters after they have occurred [1]. Banks may control credit risk by raising loan loss safeguards to reflect catastrophic risk.

Many areas face a range of hazards that vary in their geographic extent. Exposure refers to the characteristics along with the worth of resources that are important to the populations living in environmentally hazardous areas. Due to urbanization, migration, and population expansion, resources and people are concentrated in risky locations (UNISDR, 2015). Vulnerability, which is influenced by environmental, social, economic, and physical variables, is the probability that assets may sustain harm when exposed to hazard occurrences. Disaster risk fluctuates throughout time and between regions due to the properties of its constituent parts. Two significant extra features set catastrophe risk apart from other risk categories from the standpoint of financial risk management. First, albeit to varying degrees, catastrophe risk affects all industries and asset types. Second, there is inadequate protection against catastrophe risk offered by insurance services and public assistance programs [2-5]. These traits suggest that catastrophe risk can only be reduced rather than completely avoided. According to [6], disaster risk may be focused on banks' loan portfolios and, if improperly handled, might pose a systemic risk to financial stability. Borrowers' decreased capacity to repay loans as a result of financial limitations brought on by disasters might shift catastrophe risk to banks' lending portfolios. This results in a rise in banks' credit risk, which may also raise their liquidity risk due to a decrease in cash inflows. Therefore, in order to prevent posing a systemic risk to financial stability, banks must include catastrophe risk in their risk management plans (e.g. OECD, 2015; Powell, 2019). Using disaster risk finance techniques, such as factoring the risk into loan-by-loan decisions, is one way banks may manage catastrophe risk. It is uncertain whether disaster risk can be reduced just by using disaster risk financing mechanisms since it might be difficult to price disaster risk into business ratings and interest spreads [7]. However, according to a recent [8], just 60 negative rating actions—which include outlook revisions and downgrades—were implemented after natural catastrophes.

According to [8], the sample businesses' adequate insurance protection and post-event recovery strategies account for the few negative rating actions. Nonetheless, both scholarly and non-scholarly assessments emphasize that, generally speaking, insurance protection and catastrophe risk finance methods are not used enough [9-11].For instance, despite widespread support for disaster insurance, an OECD analysis from 2015 emphasizes that catastrophe risk is often uninsurable. Only a few state governments in the US have set up insurance pools for certain kinds of risks, including hurricanes. Nevertheless, these pools sometimes have modest insurance limits (such as around $1.5 million), are restricted to residential and business clients, and have a number of requirements to be eligible. In part 2, we examine the research on natural catastrophes and how they affect loan choices and the overall economy. In part 3, we formulate our hypothesis on the relationship between LLP and catastrophe risk. In part 4, we describe the primary findings. In part 5, we show the findings of supplementary tests. In part 7, we address the findings and draw conclusions.

RESEARCH METHODS AND METHODOLOGIES

Illustration of the model

We use FEMA-provided natural disaster information to calculate risk for catastrophes, FDIC-provided accounting data, and FDIC-provided branch information on location (refer to the appendices for sources of information and variables). The Statistics on Deposit Entities database includes data on commercial financial institutions and bank holding corporations. The FDIC gathers data every quarter since all financial institutions subject to FDIC, Secretary of the currencies, and the Federal Reserve Banks regulation must submit statements that contain financial information, balance sheets, risk-based capital metrics, and off-balance-sheet data.

Because financial institutions specialize on lending activities and, as a result, have higher quantities of LLP, we concentrate on these in order to decrease sampling variability. In accordance with other studies, we define a bank's site as the site of its corporate office [12]. The headquarters of each bank are located using the county code. Bank activities may extend outside county lines, although they are mostly centered on the headquarters. Finally, we compare our measure of catastrophe danger via the FIPS counties designations with financial information taken from the Statistics on Financial Banks data and the locations of branches from the Overview of Deposits dataset. Our dataset includes 445,924 bank-quarter observations from 2002 to 2019, encompassing 9766 individual banks. In Additional Table of Contents OA1, we provide a sample dispersion by year and region.

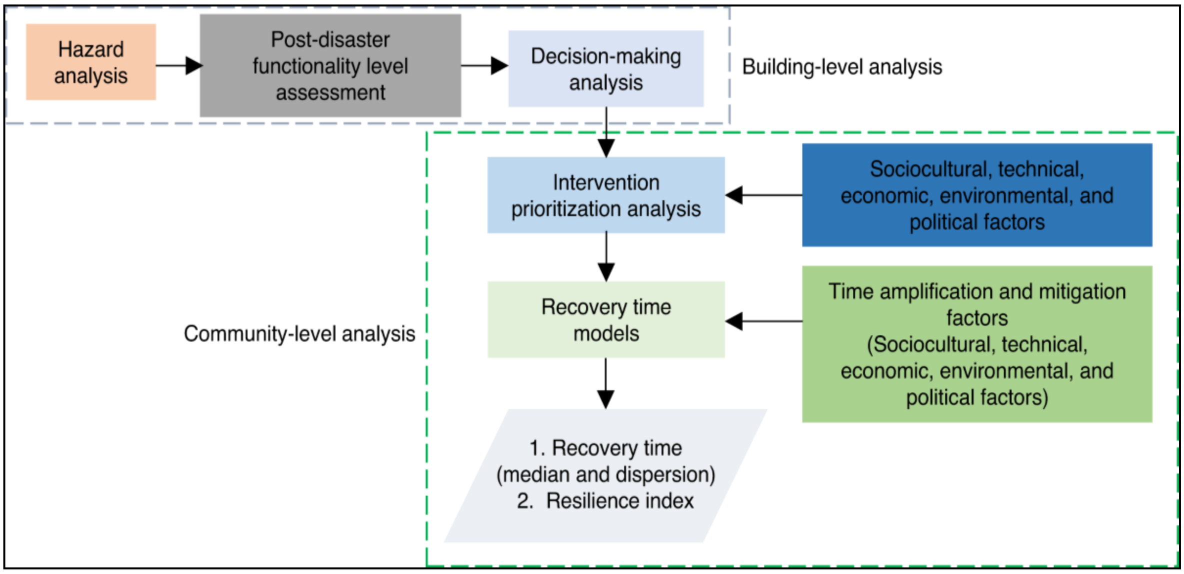

Figure 1: Policy flow of risk management

Disaster Risk Indicator

Disaster risk involves both temporal and geographical characteristics, catastrophe risk is dynamic, meaning that it may change over time based on the capacity to lessen the vulnerability component as the flow in figure 1. Second, there are many geographic levels at which catastrophe risk exists. Analyzing historical data on natural disasters is a frequent place to start, even if defining, evaluating, and comprehending disaster risk is difficult (OECD, 2012). Because future data would entail calculating the likelihood of a natural catastrophe occurring at the county level, past data is simpler to analyses.

The precise time and location of such future events are largely determined by weather patterns and other factors, which are only predictable a few days before the hazard materializes into a natural event, even though natural disasters are partially dependent on seasonal climate conditions [13]. Furthermore, each kind of catastrophe has unique variables that must be taken into account when projecting future natural disasters. Last but not least, there would be little advantage to projecting future data in our situation because previous climatology literature has shown that natural disaster distribution is typically stationary [14]. We base our risk of disasters (DRT) measure on FEMA's 15-year list of notable catastrophic events for each region and quarter. We may choose just noteworthy catastrophes by determining the disaster risk over a 15-year period.

The Stafford Act distinguishes between two types of catastrophe announcements: emergencies and major disaster announcements. Given the special characteristics of catastrophic events, particularly fire control, the request for a Fire Control Support Grant has also been made in accordance with an inner FEMA regulation. Each of the three proclamation types allows the president to award government catastrophe assistance. The hazard aspect of catastrophic risk manifests itself via a measure derived from past events. DR and hazards of exposure & vulnerability are linked by the FEMA Disaster Notification Program. The FEMA disaster Declarations. Overview lists the kind of event, commencement and conclusion dates, and impacted area for each disaster. The announcement date, closing date, and kind or types of aid initiatives announced for every catastrophe are also included by FEMA.

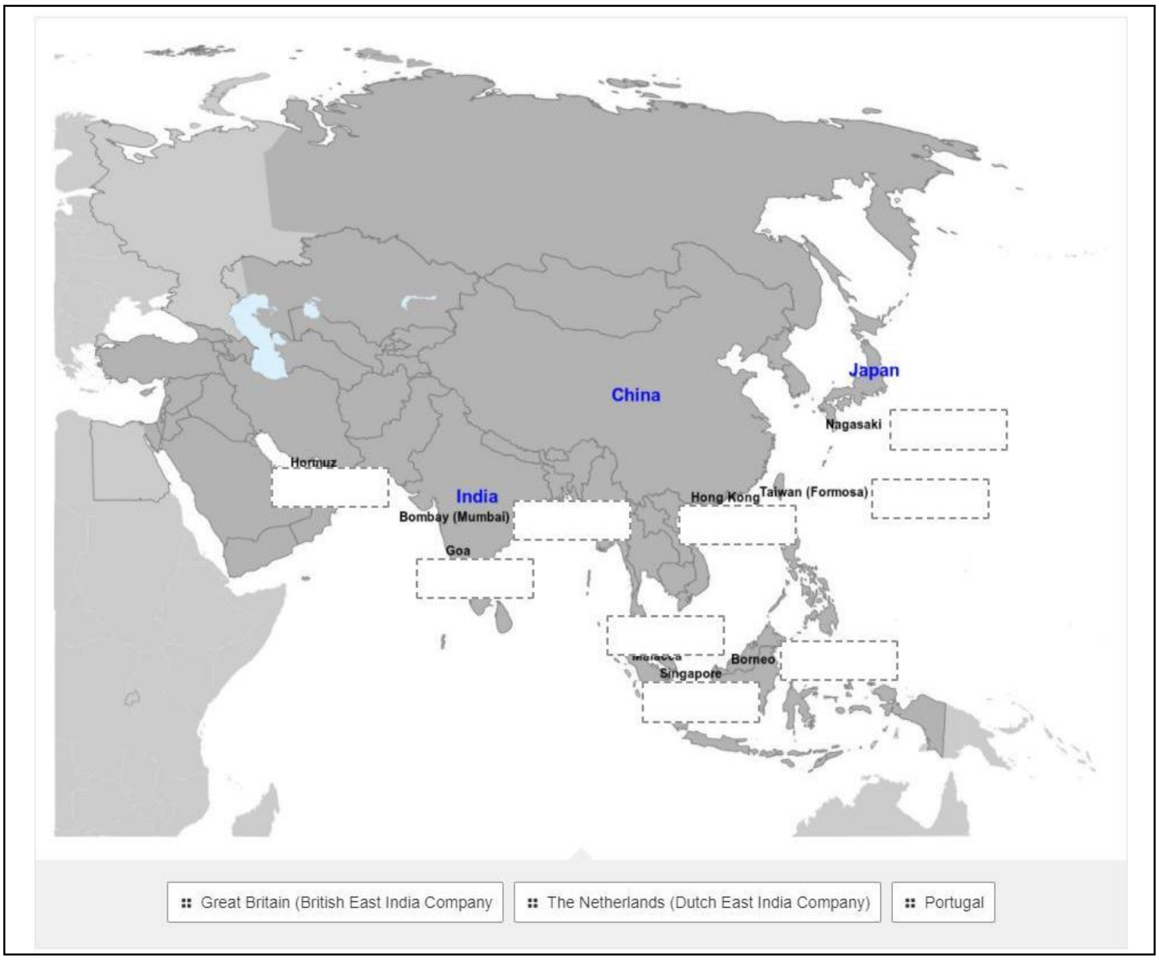

Figure 2: DR in the continental United States by county

Since the disaster risk metric for the first quarter of 2002 is calculated using disasters from 1987 to 2001, we include them. The FEMA dataset includes 1689 significant disaster designations over the years 1987–2019. The most frequent catastrophe category is severe storms (887), which are followed by floods (303) and hurricanes (172). On average, 17 distinct counties were impacted by a single incident at the same time. For instance, the FEMA dataset includes catastrophes associated with human causes, terrorist attacks, and fishing losses from 1987 to 2019. Furthermore, certain occurrences are categorised as "Other," which makes it difficult to link them to natural catastrophes. When calculating DRt, we do not include any of these occurrences. From 2002 to 2019, Figure 2 displays the median county-level catastrophic risk. Walsh Country (ND) has the highest probability of disaster from nature, with a mean of 6.13 events occurring during the fifteen-year period recorded by FEMA. The next highest scores are 5.97 for the county of San Bernardino (CA), 5.97 for the county of Riverside (CA), 5.86 for Angeles County (CA), and 5.81 for Pike Country (KY). In DR_MULTICOUNTYt, banks' ability to lower catastrophe risk across branch beyond of the main county is taken into account. The part of disaster danger resulting from regular (rare) incidents, or events which occurred more (less) than an average of every county's event the rate, is DR_FREQUENTt.

Disaster Risk Measure Validation

We use three different methods to verify DRT. First, we make sure that every relevant factor recommended in (UNISDR, 2015) is included in our disaster risk measure. Second, we examine if the risk factors mentioned in the German Watch framework are likewise captured by DRt[15]. Third, we examine the potential correlation between our catastrophe risk measure and the risk indicators included in the FEMA National Risk Index. Utilizing the UN the Sendai Structure for reducing the risk of catastrophe risk is expressed as follows:

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

Hazard is the likelihood of encountering a certain occurrence (such as a storm or flood) at a given place. Exposure depicts the state of infrastructure and people in locations that are prone to hazards.

$$DR_T = \theta_0 + \theta_1 NHI_t + \theta_2 POP_t + \theta_3 EMPL\%_t + \theta_4 SOVI_t + \theta_5 PTY\_DAMAGE_t + \sum_i \theta \; Fixed\ Effect_i + e_t \quad \ldots (1b)$$

The exposition component of disaster risk is proxied by the density of people (POPt) and overall employment (EMPL%t). Despite the complexity of the concept of exposure to natural disasters, labor and demographic statistics are often used (UNDRR, 2019).

And last, the University of South Carolina's Hazard & Vulnerability Studies Institute (HVRI)'s social vulnerabilities index (SoVIt) measures susceptibility. SoVIt combined over 25 economic variables to evaluate U.S. states' vulnerability to natural threats. Since sensitivity is also associated with destruction and expenses, we also utilise losses to property per person (PTY_DAMAGEt) derived from the Spatial Hazard Event and Loss Dataset (SHELDUS), that is computed at the county-quarter stage (World Bank GFDRR, 2014). UN The Sendai System for the Prevention of Disasters recommends a positive association between DRT and all factors affecting control. Year-quarter and state fixed effects are progressively included to account for any regional and seasonal variations in the probability of a disaster. The top row of Table 1 displays brief data regarding the risk of catastrophe and catastrophe risk components. The typical county has an earthquake risk of 4.65, which indicates that, on a median, FEMA recorded 4.65 devastating catastrophes for each county quarterly throughout the course of 15 years. As the DRt a variance of 2.84.10 indicates, our metric is quite variable. Panel B of Table 1 displays the estimated outcomes of Equation (1b).

Table 1: Efforts for catastrophic mitigation are validated using the UN Sendai model for reducing risks associated with disasters.

Panel A

Variables	N	Avergae	SD	Q1	Median	Q3
DRt	218,952	4.953	2.867	3	4	6
NHIt		12.034	2.243	10	12	14
POPt		10.267	1.487	9.315	10.150	11.094
EMPL%t		0.029	0.087	0.003	0.007	0.018
SOVIt		50.98	28.671	25.4	49.9	74.7
PTY_DAMAGEt		5.343	2.345	4.192	5.453	6.676

Panel B

Column	(1)	(2)	(3)

Variable	DRt	DRt	DRt
Constant	−2.52412***	0.3912***	−1.1098***
Result	[−43.48]	[6.70]	[−19.66]
NHIt	0.0360***	0.0856***	0.0915***
Result	[12.50]	[35.014]	[34.65]
POPt	0.3125***	0.21124**	0.27788***
Result	[64.80]	[42.124]	[56.48]
EMPL%t	0.32587***	0.84252***	0.9785***
Result	[3.68]	[9.32]	[10.70]
SOVIt	0.0022***	0.0126***	0.0048***
Result	[6.158]	[3.60]	[4.60]
PTY_DAMAGEt	0.58257***	0.16521***	0.3358***
Result	[175.32	[64.56]	[120.45]
Fixed Effects	Year-Quarter	Year-Quarter	Year-Quarter & State
Observations	218,258	219,145	218,358
R^2	0.1157	0.42547	0.51257

We find that all the parameters have an important beneficial connection with the chance of a disaster. According to these results, our assessment of catastrophic risk includes the components of exposure, threat, and susceptibility. See Online Supplement OA1. Our measure, which counts the quantity of significant accidents that FEMA declared over a 15-year period, is a trustworthy indication of disaster risk, and these endorsements enable us to confirm this.

The Model of Empiricism

We investigate the connection among catastrophe risk and LLP using the following model:

$$\begin{aligned} LLP_T = \beta_O + \beta_1\Delta DR_T + \beta_2\Delta NPA_{T+1} + \beta_3\Delta NPA_T + \beta_4\Delta NPA_{T\_1} + \beta_5\Delta NPA_{T-2} \\ + \beta_6\Delta L0ANS_{T-1} + \beta_7\Delta EBTLLP_T + \beta_8\Delta CO_{T-1} + \beta_9\Delta TIER_{T-1} \\ + \beta_{10}\Delta ALLOWANCE_{T-1} + \beta_{11}\Delta SIZE_{T-1} + \beta_{12}\Delta BRANCHDIV_{T+\beta 1} \\ + \beta_I FIXED\ EFFECT + \beta_I \Delta lOAN\ TYPEST + \varepsilon_I \quad \ldots\ (2) \end{aligned}$$

Appendix A has definitions for every variable. We multiply LLPt by 100 to make it easier to comprehend the regression results. All variables are scaled by the total loans and leases at the start of the quarter, with the exception of DRt, TIER1t−1, SIZEt−1, and BRANCHDIVt.DRt is our primary variable of interest. We anticipate a favorable relationship between LLP and catastrophe risk. Consequently, we anticipate that the coefficient β1 will be higher than zero. This characteristic is crucial because it enables us to quantify the relationship between LLP and catastrophe risk while accounting for variation in LLP by including several fixed effects. As a result, our measure is fine enough to guarantee a suitable identification approach.

Equation (2) accounts for incentives to maintain regulatory capital and smooth profits, the size and quality of the underlying loan portfolio, and other LLP-related bank-level characteristics. Similarly, in order to account for variations in loan portfolio performance while estimating LLP, we use delayed changes (one and two quarters) in nonperforming assets (ΔNPAt−1, ΔNPAt−2)[16,17]. In order to compensate for cumulative, the allowance, we additionally incorporate delayed loss of loan allowances (ALLOWANCEt−1). Since LLP, mortgage loss allowances and discharges are strongly correlated, we follow other research and employ the yearly mean of net charges (COt−1) for the preceding four quarters [18–24]. Bigger banks reduce risk, potentially affecting their LLP, thus we consider their size (SIZEt−1). Various levels of governmental oversight may also apply to bigger companies. We consider branch diversifying at the yearly stage by considering the proportion of branch locations established beyond the county in which the bank is headquartered (BRANCHDIVt). Lastly, we add the percentage of business, customers, or loans for agriculture to total loans at the conclusion of every month to diversify the loan pool.

Equation (2) incorporates year-quarter fixed effects to exclude typical shocks to LLP, such as broad macroeconomic changes. We include state-county fixed effects in our estimation of Equation (2) to account for this variance. To account for time-invariant bank-level features, we additionally use a stricter specification that incorporates bank fixed effects. Showing these collections of more detailed fixed impacts allows us to focus on changes within states, counties, or institutions while excluding variances at the larger LLP scale. By estimating average errors aggregated by bank and winsorizing every constant variable at the first and 99th percentages, we lessen the influence of extremes because of the fact that of LLP.

EMPIRICAL FINDINGS

Key Findings

Characterization data for the variables that are both independent and dependent both the entire study period is shown in Table 2. The data shows that throughout a span of fifteen years, FEMA reported a median of 4.97 natural catastrophes every county-quarter. In line with other studies [25–28], we find that LLPs usually account for 0.1% of postponed total loans (LLPt). Online Appendices the Pearson correlation values for the factors we examined are shown in Table OA5. LLP and disaster risk are negatively correlated, according to a multivariate interaction (−0.001, $p > 0.10$). LLP provides information on credit quality from the past, around, and future, as seen by the substantial and favourable coefficient on ΔNPA. The estimation results for Formula (2)'s four variables are in Table 3.

Table 2: Distinctive data

Variable	Obs.	Average	SD	Q1	Median	Q3
LLPt	445,924	0.0011	0.0024	0.0000	0.0004	0.0011
DRt		4.9660	2.8456	3.0000	5.0000	7.0000
ΔNPAt+1		0.0001	0.0068	−0.0012	0.0000	0.0008
ΔNPAt		0.0001	0.0067	−0.0012	0.0000	0.0008
ΔNPAt−1		0.0001	0.0067	−0.0011	0.0000	0.0008
ΔNPAt−2		0.0001	0.0066	−0.0011	0.0000	0.0008
ΔLOANSt		0.0164	0.0532	−0.0122	0.0115	0.0384
EBTLLPt		0.0049	0.0041	0.0028	0.0045	0.0065
COt−1		0.0009	0.0018	0.0000	0.0003	0.0010
TIER1t−1		0.1075	0.0346	0.0854	0.0988	0.1192
ALLOWANCEt−1		0.0156	0.0082	0.0108	0.0136	0.0180
SIZEt−1		11.8729	1.1632	11.0903	11.7947	12.5564
BRANCHDIVt		23.2934	27.9751	0.0000	0.0000	50.0000
LoanTypest (residential)		0.7064	0.1975	0.5916	0.7411	0.8533
LoanTypest	445,924	0.1381	0.0968	0.0708	0.1198	0.1845
LoanTypest	445,924	0.0736	0.0826	0.0188	0.0476	0.0969

LoanTypest	445,924	0.0771	0.1270	0.0000	0.0110	0.1003

To account for changes in LLP timeliness, year-quarter fixed impacts that interact with ΔNPAt [29] are included to the mathematical framework in column (2), while bank and year-quarter fixed effects are featured in column (3).

Table 3: Hazard risk and loan loss provisions are related.

Variable	Column (1)	Column (2)	Column (3)
Constant	0.0019 [0.07]	0.0016 [0.06]	−0.4701*** [−9.42]
DRt (Disaster Risk)	0.0027*** [9.78]	0.0027*** [9.81]	0.0021*** [6.56]
ΔNPAt+1 (Change in NPA at t+1)	1.7317*** [19.13]	1.7224*** [19.10]	1.2800*** [14.48]
ΔNPAt (Change in NPA at t)	3.5484*** [34.19]	3.4997*** [4.69]	3.1288*** [30.73]
ΔNPAt−1 (Change in NPA at t−1)	4.5013*** [48.17]	4.4932*** [48.24]	4.0273*** [44.11]
ΔNPAt−2 (Change in NPA at t−2)	3.7364*** [43.70]	3.7295*** [43.68]	3.3793*** [39.90]
ΔLOANSt (Change in Loans)	−0.0113 [−0.88]	−0.0074 [−0.57]	−0.1158*** [−9.61]
EBTLLPt (Earnings Before Tax of LLP)	5.3512*** [19.02]	5.3855*** [19.14]	6.9741*** [21.42]
Cot−1 (Cost of Operations at t−1)	49.9029*** [69.77]	49.7603*** [69.54]	40.5223*** [64.39]
TIER1t−1 (Tier 1 Capital at t−1)	0.0810*** [3.59]	0.0834*** [3.69]	0.3451*** [9.15]
ALLOWANCEt−1 (Allowance at t−1)	1.4151*** [10.03]	1.3730*** [9.71]	0.5259*** [3.07]
SIZEt−1 (Size at t−1)	0.0005 [0.45]	0.0003 [0.33]	0.0216*** [6.53]
BRANCHDIVt (Branch Diversification)	0.0002*** [7.61]	0.0002*** [7.63]	0.0002*** [3.60]
Loan Types	Yes		
Time Fixed	Year-Quarter	Year-Quarter × ΔNPAt	Year-Quarter
State-County Fixed Effects	Y	Y	N
Bank Fixed Effects	N	N	Y
Observations	445,895		
R^2	0.317	0.319	0.358

We show that catastrophe risk has a substantial and positive relationship with LLP in every one of the dimensions, despite controlling for previously known determinants of LLP (DR values range from 0.0027 in column (1) and (2) to 0.0021 in columns (3), with $p < 0.01$). These results also have major monetary implications. For each deviation (SD) change in dangers LLP boosts by 5.43% (=0.0021 × 2.8456 / 0.0011, the amount of in columns (3) raised by the median deviations of DR and assigned by the median value of LLP) to 6.98%. Earnings decrease by −1.22% (= −0.0011 × 5.43% / 0.0049) and −1.57% (= −0.0011 × 6.98% / 0.0049) when LLP increases. The size and sign of the bank-level controlling variable coefficients are comparable to those found in earlier research. The bank registers 3–5 cents of LLP for every dollar of change in ineffective resources, as shown by the strong relationship between LLPt and ΔNPA.

These findings suggest a substantial positive correlation between LLP and catastrophe risk. These results, which lend credence to H1, lead us to the conclusion that bank management take catastrophe risk into account when creating their LLP [30-35]. To address sample variability from banks’ capacity to integrate disaster risk into LLP, we test the robustness of the positive correlation among disaster risk and LLP 39utilizing coarsened exact and stochastic match in Internet Supplement OA3. By using these methods, we validate the significant positive relationship between LLP and catastrophe risk.

CONCLUSION

The financial system is strained by these occurrences. Consequently, the question of whether and how financial institutions detect, quantify, and track catastrophe risk is of great interest. Actually, there may be a systemic danger to financial stability if catastrophe risk concentrates in lending portfolios. Using an examination of 445,924 bank-quarter information, it is shown that institutions operating in disaster-prone places report higher LLP. Even after correcting for expected LLP indicators like loan charges and poorly performing property changes, disaster risk has a beneficial impact with LLP. The result here is robust to many tests, easing worries surrounding endogenous variables and sampling variability. We do a difference-in-differences study that supports a causal explanation of the link among catastrophe danger and LLP, employing Katrina's destruction for a shock that led banks to recalculate calamity risk in LLP. Our data show that financial company supervisors involve catastrophe risk when using LLP, but they also show that large banks are better suited to employ LLP to oversee the risk of credit from disasters since they have more financial capabilities. Policymakers and regulators should take note of our work. According to our findings, managers can more effectively account for potential long-term loan losses when they have the freedom to include future catastrophe risk in their present LLP. In this sense, the anticipated credit loss accounting standards for LLP that have been suggested are appropriate and will help management increase their reserves to lessen their exposure to risk from disasters.

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