The Shocks of Climate Change on Bank Loans

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Abstract

Climate change poses new challenges to the banking sector. Thus, in this paper, we investigate the effect of climate change on bank loans using panel data covering 7,865 banks in Indonesia from 2011-2021. We define bank loans into three variables, i.e., outstanding credit, non-performing loans (NPLs), and interest rates. Our results suggest that, of the six climate-related disasters, the flood has a significant and consistent effect. An increase in the frequency of floods reduces credit and increases NPLs. Consistent results are found for disaster risk index scores. The empirical results show that there is a negative effect of climate change on bank loans so further policies from banks and regulators' side are needed.

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1. Introduction

Climate change has become a global issue that creates new challenges for the financial sector. The statement by the Governor of the Bank of England, Mark Carney, to the public regarding the possibility of a systemic financial crisis caused by climate change-related disasters has become one of the factors driving concern about the financial risks of climate change (Bolton et al., 2020). In general, Furukawa et al. (2020), Bolton et al. (2020), Bank of England (2018), Batten et al. (2016), and Carney (2015)explain that there are at least two types of climate change risks that affect financial stability, namely transition risks and physical risks.

Transition risks are seen as financial risks that arise as a result of a process of adjustment or transition towards a low-carbon economy driven by policy changes, technological breakthroughs, and shifts in social preferences and norms. (Bank of England, 2018; Bolton et al., 2020; Carney, 2015; Furukawa et al., 2020). Climate-related policies are the main drivers of transition risks, policies of the Paris Agreement. These policies make companies involved in fossil fuels and companies with high emission intensity face large changes in asset values or higher business costs, while companies in other sectors must adjust to these changes (Pinchot et al., 2021(Pinchot et al., 2021).

Several empirical studies support the effect of transition risks on the financial sector, particularly related to lending. Reghezza et al. (2021) found that after the Paris Agreement, European banks reallocated credit from polluting companies. The share of loans to more polluting companies decreased significantly – by about 3 percentage points – compared to less polluting companies. Fard et al. (2020) who conducted a study for 27 countries found that lenders charge higher interest rates, higher upfront costs, and shorter maturities to companies that face more stringent environmental regulations. Chava (2014)found that stock investors and lenders in the US, seem to take into account corporate environmental problems, leading to the issuing of higher costs of equity, debt capital, and interest rates to companies with environmental problems. Goss & Roberts (2011) found that companies with social responsibility issues in the US pay higher basis points, which is between 7 and 18 in borrowing costs compared to more responsible companies.

The second risk is the physical risks. In general, physical risks are assumed to affect the financial system through the macro and micro economic impacts created by climate-related disasters, including impacts on corporations, households, countries, or other financial institutions (European Central Bank, 2021). For example, a company affected by a climate-related disaster will incur adaptation costs and a reduction in economic conditions due to damage to physical capital as well as production and supply chain disruptions (IPCC, 2014).

Climate change-related disasters are proven to have an impact on the economy. Between 1980 and 2020, climate-related extreme weather caused economic losses estimated at EUR 487 billion, with 27 Member States of the European Union affected (European Environment Agency, 2022). The Italy and France floods in 2000 and the 2002 floods in Central Europe as the disasters with the biggest losses in the European Union since 1980, caused losses of EUR 13 billion and EUR 21 billion respectively (European Central Bank, 2021). WWF for Natur*e*-Australia estimates that forest fires in Australia in 2019-2020 caused economic losses, particularly in the agricultural sector, worth $4 - 5 billion or the equivalent of 6 - 8% of Australia's agricultural GDP (ABS, 2021; Bishop et al., 2021). Pacific Gas and Electric (PG&E), California's largest electric utility company, also filed for bankruptcy in 2018 after facing multibillion-dollar liability claims from disastrous wildfires (Gold et al., 2019).

The economic costs of climate change will continue to worsen if still ignored. Globally, the Swiss Re publication written by Guo et al. (2021) estimates that up to 18 percent of world GDP will be lost by 2050 if no action is taken on climate change. In this case, the economies of Southeast Asian countries (ASEAN), including Indonesia, will get the biggest economic hit with an estimated loss of GDP of up to 37 percent. In addition to facing the impact of the largest loss of GDP, countries in ASEAN are also very vulnerable to the adverse effects of climate change. Of the 48 countries (representing 90% of the world economy) ranked, Indonesia is the most vulnerable country and ranks last with an index of 39.2. In its release, Swiss Re also reveals that countries that are most vulnerable to negative impacts are often the countries with the fewest resources to adapt and reduce the impact of rising global temperatures.

Based on the report of the World Bank Group & Asian Development Bank (2021), Indonesia also ranks at the top, which is ranked 59th out of 191 countries, in terms of natural hazard risks according to the INFORM Risk Index. Indonesia has high flood exposure and is ranked 17th with the highest risk of flood. Indonesia is also very vulnerable to tropical cyclones, which is ranked 23rd. Moreover, related research on the influence of climate change, particularly physical risks, on bank credit in Indonesia is still extremely limited. Therefore, a more in-depth research is still needed regarding the effect of physical risks on credit from various perspectives, namely outstanding credit, non-performing loans (NPLs), and interest rates.

This study analyzes the effect of climate change on bank credit using panel data covering 7,865 banks per province in Indonesia for the 2011-2021 period. The empirical results show that, of the six climate change-related disasters studied, the flood has a significant and consistent effect. An increase in the number of floods was found to reduce the amount of credit and increase NPLs.

The rest of this paper is structured as follows. Section 2 explores relevant literature. Section 3 sets out the methodology and data. Then, Section 4 elaborates on the empirical results. The last section presents a conclusion and policy implications.

2. Literature review

In analyzing the effect of climate change, especially physical risks, on bank credit, various studies have generated various findings, such as the study conducted by Furukawa et al. (2020), Dafermos et al. (2018), and Batten et al. (2016). From the banking side, Furukawa et al. (2020) found that banks will limit their credit supply when a disaster occurs, the decline in bank credit supply occurs not only in areas where banks operate affected by natural disasters but also in areas that are not affected. Meanwhile, from the corporate side, Dafermos et al. (2018) found that climate change is likely to gradually worsen corporate liquidity due to loss of corporate capital and reduced profitability, leading to higher default rates to the detriment of the financial sector. Under these conditions, an economic imbalance occurs where there is an increase in demand for credit from companies and households for the post-disaster recovery process which cannot be matched by the supply of credit due to credit restrictions imposed (Furukawa et al., 2020). However, Batten et al. (2016) explained that financial instability and macroeconomic decline due to climate change-related disasters can only be triggered if they cause severe damage to the balance sheets of households, corporations, banks, and insurance companies.

Empirical evidence of the impact of natural disasters on bank loans is also reinforced by the findings obtained by Choudhary & Jain (2017), Cortés & Strahan (2017), Brei et al. (2019), Koetter et al. (2020), and Bos et al. (2022). Choudhary & Jain (2017) and Brei et al. (2019) found that banks experienced liquidity shock after experiencing a flood disaster in Pakistan (Choudhary & Jain, 2017) and hurricanes in the Eastern Caribbean (Brei et al., 2019) which was responded by reduction of credit and withdrawal of liquid assets. Meanwhile, Cortés & Strahan (2017), Koetter et al. (2020), and Bos et al. (2022) found that there was an increase in demand for credit by borrowers in response to shocks caused by exposure to natural disasters. The bank reallocated capital and sold or reduced holdings of government bonds to finance the credit surge caused by exposure from the natural disaster (Bos et al., 2022; Cortés & Strahan, 2017).

Furthermore, Klomp (2014), Choudhary & Jain (2017), Noth & Schüwer (2018), Calice & Miguel (2021), and Chen et al. (2022) analyzed the effect of natural disasters on the risk of default or non-performing loans (NPLs) and found unidirectional results. They found that loans in areas affected by natural disasters have a higher probability of default or an increase in non-performing loans (NPLs). Noth & Schüwer (2018)revealed that insurance payments and public assistance programs are not sufficient to protect bank borrowers from financial difficulties, causing the tendency of NPLs to increase. In contrast, McConnell et al. (2021) did not find a marked increase in bankruptcies, foreclosures, or arrears for disaster-affected bank borrowers because the disaster studied was forest fire which is considered not to have a detrimental impact like other natural disasters, such as hurricanes.

Studies related to the effect of natural disasters on interest rates or loan spreads have also been carried out by several researchers, namely Javadi & Masum (2021)and Nguyen et al. (2022). They found that banks charge higher interest rates for loans with greater climate risk. Lenders view climate change-related disasters as long-term risks so the adverse effects of disasters on interest rates will be more pronounced for long-term loans (Javadi & Masum, 2021; Nguyen et al., 2022). In contrast, Garbarino & Guin (2021)found that lenders did not see the impact of ex-post extreme weather as a risk for properties around the flood disaster area, so lenders did not make interest rate adjustments for mortgage and property loans in this area.

Rehbein (2018), Huynh et al. (2020), and Painter (2020)conducted studies related to the effect of natural disasters on company assets, capital costs, and others. Rehbein (2018) found that there was a spillover from natural disasters to the performance of companies in non-disaster areas that were transmitted through the banking system. Companies linked to disaster-exposed banks with capital below the median were found to reduce employment by 11% and fixed assets by 20% compared to firms within the same region without any links to disaster-exposed banks during the 2013 floods in Germany (Rehbein, (Rehbein, 2018). In addition, companies that are at risk of being affected by climate change (drought) are also found to have 92 basis points higher for their capital cost of equity (Huynh et al., 2020). Painters (2020) also found that regions that are more likely to be impacted by climate change pay more underwriting fees and initial yields to issue long-term municipal bonds.

3. Methodology and data

3.1. Estimation method

This research uses panel data that includes banks per province in Indonesia during the 2011-2021 period to analyze the effects of climate change on bank credit. According to Chen et al. (2022), panel data has many advantages over cross-section data. First, panel data provides a larger sample size and information, which reduces the possibility of collinearity between variables, increases the degree of freedom of the statistical test, and increases the validity of the estimation results. Second, panel data not only has a cross-sectional dimension but also a time dimension, so that time variation trends and dynamic analysis can be performed. Third, panel data minimizes the endogeneity problem.

The method used in this study is the fixed effect model (FEM) which is intended to minimize estimation bias by controlling for unobserved variables that are constant over time. The models used in this study are specified in the following equations:

$$LOAN_{it} = \beta_0 + \beta_1 F\_FLOOD_{it} + \beta_2 F\_ABRASION_{it} + \beta_3 F\_LANDSLIDE_{it} + \beta_4 F\_WHIRLWIND_{it} + \beta_5 F\_DROUGHT_{it} + \beta_6 F\_FIRE_{it} + \beta_7 TP_{it} + \beta_8 TIER1_{it} + \beta_9 RGDB_{it} + u_{it} \quad (1)$$

$$NPL_{it} = \beta_0 + \beta_1 F\_FLOOD_{it} + \beta_2 F\_ABRASION_{it} + \beta_3 F\_LANDSLIDE_{it} + \beta_4 F\_WHIRLWIND_{it} + \beta_5 F\_DROUGHT_{it} + \beta_6 F\_FIRE_{it} + \beta_7 TP_{it} + \beta_8 TIER1_{it} + \beta_9 RGDB_{it} + u_{it} \quad (2)$$

$$IR_{it} = \beta_0 + \beta_1 F\_FLOOD_{it} + \beta_2 F\_ABRASION_{it} + \beta_3 F\_LANDSLIDE_{it} + \beta_4 F\_WHIRLWIND_{it} + \beta_5 F\_DROUGHT_{it} + \beta_6 F\_FIRE_{it} + \beta_7 TP_{it} + \beta_8 TIER1_{it} + \beta_9 RGDB_{it} + u_{it} \quad (3)$$

Here, LOAN denotes the total credit, NPL is the non-performing loan, IR is the interest rate, F_FLOOD is the number of floods, F_ABRASION is the number of abrasion disasters, F_LANDSLIDE is the number of landslides, F_WHIRLWIND is the number of whirlwinds, F_DROUGHT is the number of drought events, F_FIRE is the number of land and forest fires, TP is third party funds, TIER1 is core capital, and RGDP is the gross regional domestic product at constant prices.

3.2. Data and variables

This study combines banking data obtained from the Financial Services Authority (Otoritas Jasa Keuangan, OJK), natural disaster data obtained from the National Agency for Disaster Management (Badan Nasional Penanggulangan Bencana, BNPB), and macroeconomic data obtained from the Statistics Indonesia (Badan Pusat Statistik, BPS). The dependent variable used in this study is credit proxied to three variables, namely the amount of outstanding loans, non-performing loans (NPLs), and average loan interest rates. We also divide loans by type, namely corporate, retail, micro, mortgages, and non-mortgages, for the robustness test.

Meanwhile, the independent variable used is the number of incidents/frequency of disasters. The natural disasters related to climate change selected in this study are floods, droughts, landslides, abrasion, whirlwinds, as well as land and forest fires. Those six natural disasters were selected based on adjustments to the classification made by the EM-DAT (n.d.) and Thomas et al. (2013) also the availability of data owned by BNPB. For the robustness test, we also use the Disaster Risk Index of Indonesia (Indeks Risiko Bencana Indonesia, IRBI) score variable. IRBI is an index compiled by BNPB to show the potential negative impacts that may arise because of a potential disaster that strikes. IRBI is calculated based on the following formula:

$$Risk = Hazard\ x \frac{Vulnerability}{Capacity}$$

Hazard is calculated based on the spatial probability, frequency, and strength (magnitude) of a natural phenomenon such as earthquakes, floods, and others. Vulnerability is calculated based on socio-cultural, economic, physical, and environmental parameters. Capacity is assessed using the regional resilience level approach.

To reduce estimation bias, this study uses control variables, namely third-party funds, core capital, and Gross Regional Domestic Product (GRDP). After cleaning and combining data from these various sources, a sample of 7,865 observations was obtained for 2011-2021, or 715 observations for each year. Below are the descriptive statistics of the data used in this study (see Table 1).

Table 1
Descriptive statistics

Variable	Observation	Average	Min	Max
Total Credit	7,865	5,360,000,000,000	0	420,000,000,000,000
Corporate Credit	7,865	2,580,000,000,000	0	307,000,000,000,000
Retail Credit	7,865	1,520,000,000,000	0	85,300,000,000,000
Micro Credit	7,865	256,000,000,000	0	56,700,000,000,000
Mortgage Credit	7,865	514,000,000,000	0	77,200,000,000,000
Non-Mortgage Credit	7,865	1,000,000,000,000	0	69,300,000,000,000
Total NPLs	7,865	136,000,000,000	0	11,400,000,000,000
Corporate NPL	7,865	65,400,000,000	0	9,370,000,000,000
Retail NPLs	7,865	23,500,000,000	0	1,650,000,000,000
Micro NPLs	7,865	4,990,000,000	0	1,210,000,000,000
Mortgage NPLs	7,865	12,100,000,000	0	1,530,000,000,000
Non-Mortgage NPLs	7,865	11,300,000,000	0	1,220,000,000,000

Total Interest Rate	7,865	12.03779	0	59.28625
Corporate Interest Rates	7,865	8.70211	0	52.40032
Retail Interest Rates	7,865	12.24299	0	61.14860
Micro Interest Rate	7,865	9.63362	0	71.23
Mortgage Interest Rates	7,865	9.53335	0	61.1486
Non-Mortgage Interest Rates	7,865	12.24770	0	58.77719
DPK	7,865	6,240,000,000,000	0	504,000,000,000,000
TIER1	7,865	25,500,000,000,000	102,000,000,000	225,000,000,000,000
GRDP	7,865	543,000,000,000,000	16,000,000,000,000	1,860,000,000,000,000
Flood Frequency	7,865	34.34291	0	254
Landslide Frequency	7,865	31.86078	0	489
Abrasion Frequency	7,865	0.87031	0	12
Whirlwind Frequency	7,865	39.23102	0	452
Drought Frequency	7,865	3.67769	0	63
Fire frequency	7,865	8.63611	0	181
Flood Index Score	6,188	21.25413	2.022668	34.26667
Abrasion Index Score	6,650	14.82294	2.323276	35.76
Landslide Index Score	6,650	16.09306	5.77957	26.4
Drought Index Score	6,650	20.31290	6.466046	35.73333
Fire Index Score	6,650	26.08967	3.117558	36

Source: OJK, BNPB, and BPS (processed by Stata 14)

4. Empirical results

4.1. Banking credit mapping based on disaster risk level classification.

We group the IRBI scores for each disaster in each province in 2021 into three risk class groups, namely low, medium, and high. In this classification, we use five types of disasters, namely floods, abrasion, landslides, droughts, as well as land and forest fires. After grouping by disaster risk class, the average disaster score is compared to the average number of credits and is mapped based on the classification of the level of disaster risk. Mapping is performed for 2015-2021. The mapping results can be seen in Appendix 1.

The results of disaster mapping based on the classification of disaster risk levels show that most provinces in Indonesia are classified as high risk for all disasters, ranging from floods, abrasion, landslides, drought, to land and forest fires. The high IRBI score in Indonesia is triggered by the low-capacity factor, which is calculated based on two things, namely the Regional Resilience Index (Indeks Ketahanan Daerah, IKD) and the Community Preparedness Index (Indeks Kesiapsiagaan Masyarakat, IKM). Regions also face obstacles in calculating the role of the community because these calculations use an evidence-based approach where many activities that have been conducted by the community cannot be proven due to a lack of documentation. These factors then pushed the IRBI score in most parts of Indonesia to be quite high. The high IRBI scores for most regions in Indonesia can be used as a tool to anticipate the potential of disasters' negative impacts.

Furthermore, when the IRBI score is paired with data on the average credit distribution, it is found that the average credit distribution tends to increase, especially in the high-risk classification. Even though the increase in the number of credits is in line with the decreasing disaster score, banks must still be careful because a high disaster risk score is one of the factors that illustrate the region’s low capacity in dealing with disasters. The low regional capacity in dealing with such disasters is likely to gradually worsen liquidity due to the severe damage that will be caused when a major disaster occurs in the region. Thus, banks need to be careful and anticipate a higher risk of failure in areas with a high level of disaster risk.

4.2. The effect of the number of disasters on bank credit

Before the empirical analysis is conducted, a model selection test is carried out first and it is found that the fixed-effect model is selected as the best model to estimate Model 2 and Model 3, while Model 1 would be estimated using the random effect model. The results of the panel regression model selection test are shown in Appendix 2.

Table 2

The result of estimating the effect of the number of disasters on the amount of credit

VARIABLE	LOANS (1)	LOANS (2)	LOANS (3)	LOANS (4)	LOANS (5)	LOANS (6)	LOANS (7)	LOANS (8)
F_FLOOD	-4.41132e+09 ***						**-1.05584e+10 *****	**-1.00344e+10 *****
	(-2.61)						(-4.03)	(-3.59)
F_ABRASION		1.70428e+10					3.99472e+10	5.01106e+10
		(0.60)					(1.36)	(1.47)
F_LANDSLIDE			-113933936.5				**3.65664e+09 ***	2.45012e+09
			(-0.13)				(1.90)	(1.11)
F_WHIRLWIND				-152399865.6			257009156.7	1.11777e+09
				(-0.17)			(0.14)	(0.49)
F_DROUGHT					2.36430e+09		483569051.7	-1.04333e+09
					(0.49)		(0.09)	(-0.18)
F_FIRE						-1.54147e+09	-2.87044e+09	-3.80429e+09
						(-0.83)	(-1.28)	(-1.62)
TP	0.695 ***	0.696 ***	0.696 ***	0.696 ***	0.696 ***	0.696 ***	0.695 ***	0.695 ***
	(148.95)	(149.21)	(149.01)	(148.81)	(149.15)	(148.72)	(148.30)	(147.80)
TIER1	0.0184 ***	0.0180 ***	0.0180 ***	0.0181 ***	0.0181 ***	0.0182 ***	0.0188 ***	0.0188 ***
	(9.76)	(9.60)	(9.60)	(9.60)	(9.61)	(9.64)	(9.87)	(9.80)
RGDP	0.00232 ***	0.00209 ***	0.00211 ***	0.00211 ***	0.00212 ***	0.00216 ***	0.00239 ***	0.00239 ***
	(8.25)	(7.79)	(7.59)	(7.47)	(7.80)	(7.76)	(8.08)	(7.91)
Control the number of casualties and damage	NO	NO	NO	NO	NO	NO	NO	YES
_cons	-5.57916e+11 **	-5.96073e+11 **	-5.86867e+11 **	-5.87941e+11 **	-6.06663e+11 **	-6.07197e+11 **	-5.33134e+11 *	-5.65047e+11 **
	(-2.12)	(-2.26)	(-2.22)	(-2.23)	(-2.27)	(-2.29)	(-1.96)	(-2.02)
N	7865	7865	7865	7865	7865	7865	7865	7865
Within R2	0.761	0.761	0.761	0.761	0.761	0.761	0.761	0.761
Between R2	0.904	0.904	0.904	0.904	0.904	0.904	0.904	0.904
Overall R2	0.889	0.889	0.889	0.889	0.889	0.889	0.889	0.889

Note: t statistics are in ( ) and stars illustrate statistical significance *p < 0.1; **p < 0.05; ***p < 0.01

Source: OJK, BNPB, and BPS (processed by Stata 14)

First, we analyze the effect of the number of disasters on the number of credits estimated using eight different treatments (see Table 2). Columns 1-6 in Table 2 show the estimates for each disaster variable controlled by the variables TP, TIER1, and RGDP. The estimation results show that of the six disasters studied, only flood is found to have a negative and significant effect on the amount of credit. In column 7, the six disasters are estimated together by controlling for the variables TP, TIER1, and RGDP, and it is found that flood consistently has a negative and significant effect on the amount of credit. Meanwhile, landslides are found to have a positive and significant effect on the amount of credit. Furthermore, in column 8, the number of victims and damage variables for each disaster is added as a control variable and it is found that only flood has a negative and significant effect on the amount of credit. The negative effect of floods on the amount of credit indicates that an increase in the number of floods will reduce the amount of bank credit, whereas the positive effect of landslides indicates that an increase in the number of landslides will increase the amount of bank credit.

The negative effect of disasters on credit distribution is in line with the findings of Choudhary & Jain (2017) and Brei et al. (2019) who found that banks tend to reduce lending in response to liquidity shocks caused by exposure to disaster. Meanwhile, the positive effect of disasters on credit distribution is in line with the findings of Cortés & Strahan (2017) and Bos et al. (2022) who found that firms and households increase demand for credit in response to shocks caused by exposure to disasters. Banks respond to the surge in demand for credit by increasing their lending in areas directly affected by the disaster through reallocating capital and reducing or selling government bond holdings. (Bos et al., 2022; Cortés & Strahan, 2017).

Table 3
The result of estimating the effect of the number of disasters on NPL

VARIABLE	NPLs (9)	NPLs (10)	NPLs (11)	NPLs (12)	NPLs (13)	NPLs (14)	NPLs (15)	NPLs (16)
F_FLOOD	**281539396.1** **						**421100190.2** **	281331842.4
	(1.99)						(2.12)	(1.24)
F_ABRASION		281548054.3					-1.00432e+09	449203771.9
		(0.24)					(-0.83)	(0.29)
F_LANDSLIDE			74640561.3				-184610878.0	-172472026.2
			(0.90)				(-1.46)	(-1.24)
F_WHIRLWIND				103757142.5			118628343.8	64131563.7
				(1.17)			(0.93)	(0.46)
F_DROUGHT					-216646844.2		-225562597.3	196958828.7
					(-0.79)		(-0.74)	(0.64)
F_FIRE						146664693.1	119532669.0	248980195.3
						(1.15)	(0.72)	(1.63)
TP	0.0292 ***	0.0291 ***	0.0291 ***	0.0292 ***	0.0291 ***	0.0292 ***	0.0292 ***	0.0293 ***
	(11.65)	(11.63)	(11.64)	(11.65)	(11.64)	(11.64)	(11.65)	(11.68)
TIER1	-0.0000143	0.00000423	0.000000565	-0.00000505	4.30e-08	-0.00000892	-0.0000395	-0.0000532
	(-0.05)	(0.02)	(0.00)	(-0.02)	(0.00)	(-0.03)	(-0.15)	(-0.20)
RGDP	0.000000734	0.0000159	0.00000799	0.00000184	0.0000121	0.00000717	-0.0000141	-0.0000272
	(0.02)	(0.34)	(0.17)	(0.04)	(0.25)	(0.14)	(-0.26)	(-0.48)
Control the number of casualties and damage	NO	NO	NO	NO	NO	NO	NO	YES
_cons	-5.57133e+10 **	-5.48340e+10 **	-5.26801e+10 **	-5.10302e+10 **	-5.16709e+10 **	-5.09748e+10 **	-5.02557e+10 *	-4.23483e+10
	(-2.32)	(-2.28)	(-2.20)	(-2.12)	(-2.04)	(-2.04)	(-1.83)	(-1.45)
N	7865	7865	7865	7865	7865	7865	7865	7865
Within R2	0.592	0.592	0.592	0.592	0.592	0.592	0.593	0.594
Between R2	0.864	0.864	0.864	0.864	0.864	0.864	0.863	0.862
Overall R2	0.755	0.754	0.755	0.755	0.754	0.754	0.754	0.754

Note: estimates use *robust standard error,* t statistics in ( ), and stars illustrate statistical significance *p < 0.1; **p < 0.05; ***p < 0.01
Source: OJK, BNPB, and BPS (processed by Stata 14)

Second, we analyze the effect of the number of disasters on NPL (see Table 3). Columns 9-14 in Table 3 show the estimates for each of the disaster variables controlled by TP, TIER1, and RGDP. The estimation results show that of the six disasters studied, only flood has a positive and significant effect on NPL. In column 15, the six disasters are estimated with controlling TP, TIER1, and RGDP, and it is found that flood consistently has a positive and significant effect on NPL. Meanwhile, column 16 is found no significant effect between the six disasters and NPL.

The positive effect of flood indicates that an increase in the number of floods will increase the NPLs or risk of default of the borrower. These results are in line with the findings of Klomp (2014), Choudhary & Jain (2017), Noth & Schüwer (2018), Calice & Miguel (2021), and Chen et al. (2022). Chen et al. (2022) revealed that there are at least two reasons that support these findings. First, from a macro perspective, the occurrence of natural disasters increases macroeconomic uncertainty. Uncertainty shocks can trigger a downgrade of a country's sovereign rating, which in turn causes a downgrade of local bank ratings, increasing problem loans (Boumparis et al., 2019). Second, from a micro perspective, natural disasters will directly affect the production processes of firms and households, which will harm capital accumulation and productivity, which in turn will result in a decline in asset values. Both of these impacts are transmitted to financial institutions as loan contracts between entrepreneurs and banks that lead to an increase in NPLs (Lamperti et al., 2019). Noth & Schüwer (2018) also found that insurance payments and public assistance programs were not sufficient to protect bank borrowers from financial difficulties.

Table 4
The results of the estimation of the effect of the number of disasters on interest rates

VARIABLE	INTEREST RATE (17)	INTEREST RATE (18)	INTEREST RATE (19)	INTEREST RATE (20)	INTEREST RATE (21)	INTEREST RATE (22)	INTEREST RATE (23)	INTEREST RATE (24)
F_FLOOD	-0.00617 ***						-0.0151 ***	-0.0113 ***
	(-4.13)						(-8.82)	(-5.93)
F_ABRASION		-0.0584 ***					-0.0172	-0.0147
		(-3.63)					(-1.08)	(-0.72)
F_LANDSLIDE			-0.0000514				**0.00546** ***	0.00118
			(-0.05)				(4.81)	(0.72)
F_WHIRLWIND				-0.000870			-0.000704	0.00202
				(-0.93)			(-0.72)	(1.32)
F_DROUGHT					-0.0172 ***		-0.0210 ***	-0.0230 ***
					(-4.08)		(-4.00)	(-4.07)
F_FIRE						-0.00155	0.0000486	-0.00218
						(-1.19)	(0.03)	(-1.37)
TP	5.50e-15	6.07e-15	6.19e-15	5.83e-15	7.14e-15	5.82e-15	6.88e-15	5.86e-15
	(1.13)	(1.23)	(1.27)	(1.20)	(1.46)	(1.18)	(1.41)	(1.22)
TIER1	-1.97e-14 ***	-2.01e-14 ***	-2.01e-14 ***	-2.01e-14 ***	-2.05e-14 ***	-2.00e-14 ***	-1.98e-14 ***	-1.87e-14 ***
	(-13.66)	(-13.88)	(-13.91)	(-13.86)	(-14.09)	(-13.93)	(-13.69)	(-12.91)
RGDP	-3.38e-15 ***	-3.69e-15 ***	-3.71e-15 ***	-3.59e-15 ***	-4.03e-15 ***	-3.62e-15 ***	-3.76e-15 ***	-3.63e-15 ***
	(-6.73)	(-7.00)	(-7.39)	(-7.03)	(-7.74)	(-6.66)	(-6.95)	(-6.71)
Control the number of casualties and damage	NO	NO	NO	NO	NO	NO	NO	YES
_cons	14.55 ***	14.56 ***	14.53 ***	14.50 ***	14.77 ***	14.49 ***	15.01 ***	14.84 ***
	(53.49)	(53.53)	(55.09)	(54.72)	(55.31)	(52.29)	(52.46)	(51.51)
N	7865	7865	7865	7865	7865	7865	7865	7865
Within R2	0.0816	0.0792	0.0781	0.0783	0.0814	0.0782	0.0912	0.104
Between R2	0.0470	0.0515	0.0527	0.0519	0.0477	0.0533	0.0401	0.0428
Overall R2	0.0477	0.0503	0.0508	0.0505	0.0465	0.0516	0.0422	0.0482

Note: estimates use *robust standard error,* t statistics in ( ), and stars illustrate statistical significance *p < 0.1; **p < 0.05; ***p < 0.01
Source: OJK, BNPB, and BPS (processed by Stata 14)

Finally, we analyze the effect of the number of disasters on interest rates (see Table 4). Columns 17-22 in Table 4 show the estimates for each disaster variable controlled by the variables TP, TIER1, and RGDP. The estimation results show that of the six disasters studied, flood, abrasion, and drought are found to have a negative and significant effect on interest rates. In column 23, the six disasters are estimated together by controlling TP, TIER1, and RGDP, and it is found that flood and drought are found to have a negative and significant effect on interest rates, whereas landslide is found to have a positive and significant effect on interest rates. Then, in column 24, it is found that flood and drought are consistently found to have a negative and significant effect on interest rates.

Estimation of the effect of disasters on interest rates has an inconsistent result, which is a flood, where the disaster increased NPLs and decreased the amount of credit, it also was found to lower interest rates. This is because interest rates are more influenced by other factors, such as the benchmark interest rate, short/long loan positions, cash ratio, and risk premium.

4.3. Robustness tests

To ensure reliable empirical results, we perform robustness tests in three ways. First, we analyze the effect of the number of disaster events on credit by type, namely corporate credit, retail credit, micro-credit, mortgage loans, and non-mortgage loans. Second, we replace the variable number of disaster events with a disaster risk index score and analyze its effect on credit. Third, we analyze the effect of the disaster risk index score on credit by type, namely corporate credit, retail credit, micro-credit, mortgage loans, and non-mortgage loans. The model used in the robustness tests is shown in Appendix 3.

4.3.1. The effect of the number of disasters on credit by type

We analyzed the effect of the number of disaster events on credit by type, namely corporate credit, retail credit, micro-credit, mortgage loans, and non-mortgage loans, and obtained the following results (see Tables 5, 6, and 7). The estimation results in Table 5 show that an increase in the number of floods will significantly reduce the number of corporate loans, micro loans, and non-mortgage loans. An increase in the number of landslides will significantly increase the number of corporate loans. The increase in the number of whirlwinds will significantly reduce the number of corporate loans but increase the number of retail loans and mortgage loans. Increasing the number of occurrences of drought will significantly increase the number of corporate loans, but decreased the number of retail loans, mortgage loans, and non-mortgage loans. Land and forest fires were found to significantly reduce the amount of corporate credit. Meanwhile, no significant effect was found between the abrasion disaster and the amount of corporate credit, retail credit, micro-credit, mortgage loans, and non-mortgage loans.

Table 5

The results of the estimation of the effect of the number of disasters on the amount of credit by type of credit

VARIABLE	CORPORATE LOANS (25)	RETAIL LOANS (26)	MICRO LOANS (27)	MORTGAGES (28)	NONMORTGAGE (29)
F_FLOOD	-5.74527e+09 ***	-1.30845e+09	-1.83843e+09 *	267334922.5	-1.57965e+09 **
	(-2.64)	(-1.24)	(-1.85)	(0.36)	(-2.12)
F_ABRASION	2.30696e+10	8.37291e+09	2.03096e+09	-2.79297e+09	1.11846e+10
	(1.64)	(0.71)	(0.34)	(-0.34)	(1.34)
F_LANDSLIDE	2.58900e+09 **	566113557.3	322385177.0	-104525393.2	668524313.5
	(2.28)	(0.74)	(0.56)	(-0.19)	(1.22)
F_WHIRLWIND	-3.52093e+09 ***	1.87842e+09 ***	570904910.5	1.17786e+09 **	702367271.9
	(-3.47)	(2.64)	(0.95)	(2.33)	(1.39)
F_DROUGHT	1.81805e+10 ***	-6.65863e+09 ***	-3.85177e+09	-2.68724e+09 *	-3.96089e+09 ***
	(3.28)	(-3.11)	(-1.48)	(-1.78)	(-2.60)
F_FIRE	-4.36154e+09 **	842005444.9	-45965709.1	78478387.3	764963919.3
	(-1.99)	(0.94)	(-0.06)	(0.12)	(1.21)
TP	0.472 ***	0.116 ***	0.0159	0.0331 ***	0.0828 ***
	(5.34)	(59.89)	(1.52)	(24.42)	(59.94)
TIER1	-0.0140 ***	0.00769 ***	0.0127 ***	0.00112 **	0.00661 ***
	(-2.90)	(9.98)	(4.17)	(2.07)	(12.06)
RGDP	0.00267 **	0.000525 ***	-0.000148	0.000450 ***	0.0000590
	(2.07)	(4.12)	(-0.80)	(5.11)	(0.64)
_cons	-1.25280e+12 **	2.73887e+11 **	-4.43165e+10	-6.27859e+09	2.89536e+11 ***
	(-2.30)	(2.13)	(-0.37)	(-0.07)	(3.09)
N	7865	7865	7865	7865	7865
Within R2	0.615	0.377	0.138	0.100	0.372
Between R2	0.780	0.629	0.120	0.230	0.627
Overall R2	0.759	0.599	0.123	0.209	0.597

Note: retail credit, mortgage loans, and non-mortgage loans are estimated using the *random effect method,* while corporate loans and micro loans are estimated using the *fixed effect* and *robust standard error methods.* t statistics in ( ) and stars illustrate statistical significance *p < 0.1; **p < 0.05; ***p < 0.01.

Source: OJK, BNPB, and BPS (processed by Stata 14)

The estimation results in Table 6 show that flood has a positive and significant effect on corporate credit NPLs, but a negative and significant effect on micro-credit NPLs. Abrasion has a negative and significant effect on mortgage loan NPL. Landslide has a negative and significant effect on mortgage loan NPLs. A whirlwind has a positive and significant effect on retail credit NPLs. Meanwhile, drought as well as land and forest fires are found to have no significant effect on NPLs for corporate loans, retail loans, micro loans, mortgage loans, and non-mortgage loans.

Table 6
The results of the estimation of the effect of the number of disasters on NPL are based on the type of credit.

VARIABLE	CORPORATE NPL (30)	NPL RETAILS (31)	MICRO NPL (32)	NPL MORTGAGES (33)	NONMORTGAGE NPL (34)
F_FLOOD	**317036024.8** **	26654538.1	**-39421007.4** *	18339061.1	6738453.3
	(2.27)	(1.03)	(-1.82)	(1.47)	(0.36)
F_ABRASION	251378644.7	-326455470.0	-56383081.9	**-242164261.7** **	-79729601.1
	(0.16)	(-1.12)	(-0.67)	(-2.12)	(-0.37)
F_LANDSLIDE	-128071579.3	-19405028.8	16053284.9	**-12821598.4** *	-8097167.4
	(-1.24)	(-1.02)	(0.94)	(-1.71)	(-0.59)
F _WHIRLWIND	40554400.5	**39651626.1** **	-5552019.8	25735628.4	9485095.0
	(0.42)	(2.23)	(-0.45)	(1.13)	(0.73)
F_DROUGHT	-178163741.4	-50764961.0	-56527381.1	-25239225.5	5966212.5
	(-0.63)	(-0.97)	(-1.27)	(-0.69)	(0.16)
F_FIRE	129304680.7	-2691697.4	-13497290.6	-7788010.2	-8187581.0
	(1.06)	(-0.12)	(-0.91)	(-0.41)	(-0.50)
TP	0.0149 ***	0.00255 ***	0.000165	0.000932 ***	0.00164 ***
	(68.83)	(56.70)	(1.20)	(5.59)	(56.42)
TIER1	-0.000218 **	0.0000374 **	0.000193 ***	0.0000490 **	-0.0000219 *
	(-2.27)	(2.01)	(3.78)	(2.39)	(-1.70)
RGDP	-0.00000738	0.00000971 ***	0.00000284	0.0000197 ***	-0.000000848
	(-0.62)	(3.55)	(0.55)	(2.76)	(-0.52)
_cons	-2.69314e+10 ***	-69630487.4	-1.06431e+09	-6.47001e+09	1.85701e+09
	(-2.82)	(-0.03)	(-0.33)	(-1.61)	(1.43)
N	7865	7865	7865	7865	7865
Within R2	0.410	0.328	0.0637	0.181	0.245
Between R2	0.661	0.543	0.140	0.150	0.682
Overall R2	0.555	0.496	0.113	0.152	0.563

Note: corporate loans, retail loans, and non-KPR loans are estimated using the *random effect* method, while micro loans and mortgage loans are estimated using *the fixed effect* and *robust standard error methods.* t statistics in ( ) and stars illustrate statistical significance *p < 0.1; **p < 0.05; ***p < 0.01.
Source: OJK, BNPB, and BPS (processed by Stata 14)

Furthermore, the estimation results in Table 7 show that flood has a negative and significant effect on interest rates for corporate loans, retail loans, micro loans, mortgage loans, and non-mortgage loans. Landslide has a positive and significant effect on interest rates for corporate loans, micro loans, and mortgage loans. Drought has a negative and significant effect on interest rates on corporate loans, retail loans, mortgage loans, and non-mortgage loans. Meanwhile, abrasion, whirlwind, as well as land and forest fires are found to have no significant effect on interest rates on corporate loans, retail loans, micro loans, mortgage loans, and non-mortgage loans.

Table 7
The results of the estimation of the effect of the number of disasters on interest rates by type of credit

VARIABLE	CORPORATE IR (35)	RETAIL IR (36)	MICRO IR (37)	MORTGAGES IR (38)	NONMORTGAGE IR (39)
F_FLOOD	**-0.0136** ***	**-0.0108** ***	**-0.0141** ***	**-0.00935** ***	**-0.00996** ***
	(-4.85)	(-4.06)	(-2.77)	(-3.76)	(-3.04)
F_ABRASION	-0.00333	-0.0111	-0.0442	-0.00179	-0.0184
	(-0.09)	(-0.51)	(-0.87)	(-0.07)	(-0.67)
F_LANDSLIDE	**0.00496** **	0.00207	**0.00593** *	**0.00496** **	0.000531
	(2.16)	(1.02)	(1.92)	(2.55)	(0.23)
F_WHIRLWIND	-0.00104	-0.00150	-0.00360	-0.00142	0.000415
	(-0.52)	(-0.97)	(-1.14)	(-0.90)	(0.21)
F_DROUGHT	**-0.0300** ***	**-0.0309** ***	-0.00913	**-0.0211** ***	**-0.0324** ***
	(-4.56)	(-3.96)	(-0.64)	(-3.33)	(-3.34)
F_FIRE	0.000762	-0.000475	-0.00446	-0.00102	0.000141
	(0.26)	(-0.20)	(-0.93)	(-0.41)	(0.05)
TP	-1.63e-14 ***	6.86e-15	1.80e-14 **	3.78e-15	-8.16e-15
	(-3.32)	(0.59)	(2.53)	(1.03)	(-0.36)
TIER1	8.49e-15 **	-8.42e-15 ***	-4.03e-14 ***	-1.12e-14 ***	-9.20e-15 ***
	(2.10)	(-4.52)	(-12.10)	(-8.06)	(-3.47)

RGDP	-1.23e-15 *	-3.43e-15 ***	-6.90e-15 ***	-1.96e-15 ***	-2.85e-15 ***
	(-1.89)	(-4.05)	(-5.97)	(-3.51)	(-2.76)
_cons	9,712 ***	14.77 ***	14.84 ***	11.17 ***	14.52 ***
	(28.05)	(33.97)	(23.68)	(36.64)	(27.67)
N	7865	7865	7865	7865	7865
Within R2	0.00944	0.0359	0.0497	0.0187	0.0197
Between R2	0.0138	0.00405	0.000000900	0.0000275	0.00970
Overall R2	0.00261	0.000555	0.00208	0.000897	0.00282

Note: estimates use *robust standard error,* t statistics in ( ), and stars illustrate statistical significance *p < 0.1; **p < 0.05; ***p < 0.01

Source: OJK, BNPB, and BPS (processed by Stata 14)

4.3.2. The effect of disaster risk index scores on credit

Next, we replace the variable number of disaster events with a disaster risk index score. The results obtained using the disaster risk index score are quite consistent as using the variable number of disaster events. The empirical results are in Tables 8, 9, and 10.

The estimation results in Table 8 show that as disasters are estimated individually (columns 40-44), it is found that an increase in the index score for abrasion, landslide, as well as land and forest fire significantly increases the amount of credit. Meanwhile, as all disaster risk index scores are estimated simultaneously (column 45), it is found that an increase in the flood index score significantly reduces the number of credits, while an increase in the land and forest fire disaster index score significantly increases the number of credits. No significant effect is found between the drought disaster risk index score and the number of credits.

Table 8

Estimation results of the effect of the disaster risk index on the amount of credit

VARIABLE	LOANS (40)	LOANS (41)	LOANS (42)	LOANS (43)	LOANS (44)	LOANS (45)
FLOOD SCORE	-3.70544e+10					**-2.32909e+11 ****
	(-1.07)					(-2.32)
ABRASION SCORE		**5.55417e+10 ****				1.10644e+11
		(1.98)				(1.51)
LANDSLIDE SCORE			**5.58776e+10 ***			-1.03555e+11
			(1.74)			(-1.08)
DROUGHTS SCORE				8.71731e+09		-1.29658e+11
				(0.35)		(-1.56)
FIRE SCORE					**4.23093e+10 ***	**2.47395e+11 ****
					(1.73)	(2.58)
TP	0.499 ***	0.499 ***	0.498 ***	0.499 ***	0.497 ***	0.495 ***
	(7.47)	(7.45)	(7.46)	(7.48)	(7.47)	(7.41)
TIER1	0.0267 ***	0.0276 ***	0.0276 ***	0.0262 ***	0.0282 ***	0.0317 ***
	(3.92)	(4.07)	(4.12)	(4.06)	(4.25)	(4.25)
RGDP	0.00166	0.00392 ***	0.00392 ***	0.00313 **	0.00400 **	-0.00155
	(1.03)	(2.76)	(2.61)	(2.13)	(2.55)	(-0.92)
_cons	1.30881e+12	-1.65502e+12	-1.72836e+12	-5.27663e+11	-1.98679e+12	3.45633e+12 **
	(0.79)	(-1.32)	(-1.21)	(-0.39)	(-1.26)	(2.12)
N	6188	6650	6650	6650	6650	6188
Within R2	0.583	0.583	0.583	0.583	0.584	0.588
Between R2	0.902	0.889	0.890	0.895	0.888	0.845
Overall R2	0887	0.875	0.876	0.880	0.874	0.831

Note: estimates use *robust standard error,* t statistics in ( ), and stars illustrate statistical significance *p < 0.1; **p < 0.05; ***p < 0.01

Source: OJK, BNPB, and BPS (processed by Stata 14)

Table 9
Estimation results of the effect of the disaster risk index on NPL

VARIABLE	NPLs (46)	NPLs (47)	NPLs (48)	NPLs (49)	NPLs (50)	NPLs (51)
FLOOD SCORE	-1.41913e+09					**8.92990e+09** *
	(-0.59)					(1.69)
ABRASION SCORE		-413222409.9				**1.13224e+10** **
		(-0.24)				(2.23)
LANDSLIDE SCORE			-5.13050e+09 **			-4.04769e+09
			(-2.22)			(-0.62)
DROUGHTS SCORE				-4.22652e+09 **		-4.04595e+09
				(-2.10)		(-0.69)
FIRE SCORE					-3.92376e+09 **	-1.07847e+10 *
					(-2.38)	(-1.77)
TP	0.0264 ***	0.0264 ***	0.0265 ***	0.0265 ***	0.0266 ***	0.0268 ***
	(6.88)	(6.87)	(6.89)	(6.89)	(6.92)	(6.97)
TIER1	0.000121	0.000118	-0.0000230	0.00000537	-0.0000745	-0.0000969
	(0.31)	(0.31)	(-0.06)	(0.01)	(-0.20)	(-0.24)
RGDP	-0.000148	-0.000107	-0.000192 *	-0.000203 *	-0.000200 *	-0.0000460
	(-1.20)	(-1.11)	(-1.81)	(-1.84)	(-1.82)	(-0.38)
_cons	9.96498e+10	4.83254e+10	1.75706e+11 *	1.84350e+11 *	2.01060e+11 **	8.87708e+10
	(0.85)	(0.66)	(1.95)	(1.94)	(2.03)	(0.72)
N	6188	6650	6650	6650	6650	6188
Within R2	0.390	0.388	0.389	0.389	0.390	0.394
Between R2	0.861	0.871	0.853	0.847	0.852	0.863
Overall R2	0.783	0.791	0.776	0.771	0.775	0.783

Note: estimates use *robust standard error,* t statistics in ( ), and stars illustrate statistical significance *p < 0.1; **p < 0.05; ***p < 0.01
Source: OJK, BNPB, and BPS (processed by Stata 14)

The estimation results in Table 9 show that as disasters are estimated individually (columns 46-50), it is found that landslides, drought, as well as land and forest fire, have a negative and significant effect on NPLs. Meanwhile, as all disaster risk index scores are estimated simultaneously (column 51), it is found that flood and abrasion have a positive and significant effect on NPLs. On the contrary, land and forest fires have a negative and significant effect on NPLs.

The estimation results in Table 10 show that as disasters are estimated individually (columns 52-56), it is found that flood, abrasion, landslide, drought, as well as land and forest fires, have a positive and significant effect on interest rates. Meanwhile, as all disaster risk index scores are estimated simultaneously (column 57), it is found that flood has a negative and significant effect on interest rates, while landslide consistently has a positive and significant effect on interest rates.

Table 10
Estimation results of the effect of the disaster risk index on interest rates

VARIABLE	INTEREST RATE (52)	INTEREST RATE (53)	INTEREST RATE (54)	INTEREST RATE (55)	INTEREST RATE (56)	INTEREST RATE (57)
FLOOD SCORE	**0.153** ***					-0.247 ***
	(6.97)					(-3.68)
ABRASION SCORE		**0.274** ***				0.0538
		(10.97)				(0.89)
LANDSLIDE SCORE			**0.372** ***			**0.348** ***
			(12.74)			(3.16)
DROUGHTS SCORE				**0.241** ***		0.0830
				(10.83)		(0.90)
FIRE SCORE					**0.193** ***	0.0797
					(9.09)	(0.82)
TP	8.35e-15	7.95e-15	3.82e-15	4.87e-15	1.50e-15	2.20e-15
	(1.34)	(1.30)	(0.62)	(0.78)	(0.23)	(0.32)
TIER1	-2.46e-14 ***	-1.99e-14 ***	-1.69e-14 ***	-2.09e-14 ***	-1.79e-14 ***	-1.59e-14 ***
	(-11.25)	(-9.85)	(-9.04)	(-10.84)	(-9.78)	(-8.10)
RGDP	-6.20e-15 ***	-6.36e-15 ***	-4.64e-15 ***	-5.44e-15 ***	-6.36e-15 ***	-8.24e-15 ***
	(-4.01)	(-4.35)	(-2.91)	(-3.38)	(-3.74)	(-7.03)

_cons	13.71 ***	12.64 ***	9,704 ***	11.33 ***	11.66 ***	13.09 ***
	(11.42)	(12.43)	(7.88)	(9.25)	(8.25)	(12.75)
N	6188	6650	6650	6650	6650	6188
Within R2	0.140	0.157	0.167	0.155	0.163	0.170
Between R2	0.0123	0.00571	0.0101	0.00864	0.00956	0.00689
Overall R2	0.0171	0.00913	0.0157	0.0133	0.0137	0.00935

Note: estimates use *robust standard error,* t statistics in ( ), and stars illustrate statistical significance *p < 0.1; **p < 0.05; ***p < 0.01

Source: OJK, BNPB, and BPS (processed by Stata 14)

4.3.3. The effect of disaster risk index scores on credit by type

Finally, we analyze the effect of the disaster risk index score on credit by type, namely corporate credit, retail credit, micro-credit, mortgage loans, and non-mortgage loans (see Tables 11, 12, and 13). The estimation results in Table 11 show that flood has a negative and significant effect on the number of corporate loans. Abrasion has a positive and significant effect on the amount of non-mortgage loans. Landslide has a negative and significant effect on the number of corporate loans but has a positive and significant effect on the number of mortgage loans. Land and forest fire has a positive and significant effect on the amount of corporate credit but has a negative and significant effect on the amount of retail credit.

The estimation results in Table 12 show that flood has a positive and significant effect on corporate credit NPLs but has a negative and significant effect on retail credit NPLs. Abrasion has a positive and significant effect on corporate credit NPLs. Land and forest fire has a negative and significant effect on the NPL of non-mortgage loans. Meanwhile, no significant effect is found between landslides and drought with all types of NPL. Finally, the estimation results from Table 13 show that only flood has a negative and significant effect on corporate credit interest rates, retail credit interest rates, and micro credit interest rates. No significant effect is found between abrasion, landslide, drought, as well as land and forest fire with all types of credit interest rates.

Table 11

Estimation results of the effect of the disaster risk index on the amount of credit based on the type of credit.

VARIABLE	CORPORATE LOANS (58)	RETAIL LOANS (59)	MICRO LOANS (60)	MORTGAGES (61)	NONMORTGAGE (62)
FLOOD SCORE	-2.28616e+11 ***	5.36771e+09	1.78442e+09	3.93820e+10	-2.59072e+10
	(-3.18)	(0.55)	(0.07)	(1.25)	(-0.92)
ABRASION SCORE	7.05750e+09	2.12473e+10	3.75314e+10	-2.15748e+10	**5.32126e+10** **
	(0.13)	(1.62)	(1.59)	(-1.10)	(2.11)
LANDSLIDE SCORE	-1.89257e+11 ***	8.44895e+09	2.13005e+10	**6.05107e+10** **	-5.28496e+10
	(-2.74)	(0.38)	(1.07)	(1.98)	(-1.44)
DROUGHTS SCORE	-4.92640e+10	-1.15369e+10	-9.62743e+09	-4.88572e+10	2.35817e+09
	(-0.83)	(-0.64)	(-0.21)	(-1.51)	(0.09)
FIRE SCORE	**3.19822e+11** ***	-2.71426e+10 **	-2.39916e+10	-3.06974e+10	1.21417e+10
	(3.87)	(-2.32)	(-0.80)	(-1.61)	(0.41)
TP	0.356 ***	0.0828 ***	0.0109	0.0316 ***	0.0330 *
	(3.84)	(39.38)	(1.43)	(3.51)	(1.90)
TIER1	-0.0111 ***	0.00907 ***	0.0177 ***	0.000201	0.00921 ***
	(-2.65)	(8.34)	(3.84)	(0.17)	(5.01)
RGDP	-0.00248	0.000731 ***	0.000348	0.000846	0.0000962
	(-1.63)	(4.27)	(1.17)	(1.29)	(0.22)
_cons	2.54656e+12 *	6.93678e+11 ***	-5.57513e+11	6.41385e+10	7.64661e+11 *
	(1.81)	(2.68)	(-1.59)	(0.16)	(1.86)
N	6188	6188	6188	6188	6188
Within R2	0.431	0.207	0.126	0.107	0.142
Between R2	0.669	0.581	0.113	0.140	0.486
Overall R2	0.655	0.562	0.113	0.137	0.467

Note: retail credit is estimated using the *random effect method,* while corporate credit, micro-credit, mortgage loans, and non-mortgage loans are estimated using the *fixed effect* and *robust standard error methods.* t statistics in ( ) and stars illustrate statistical significance *p < 0.1; **p < 0.05; ***p < 0.01.

Source: OJK, BNPB, and BPS (processed by Stata 14)

Table 12

Estimation results of the effect of the disaster risk index on NPL by type of credit

VARIABLE	CORPORATE NPL (63)	NPL RETAILS (64)	MICRO NPL (65)	NPL MORTGAGES (66)	NONMORTGAGE NPL (67)
FLOOD SCORE	**7.51302e+09 ***	**-348853170.9 ***	183522068.1	-294830887.9	-39226088.0
	(1.79)	(-1.84)	(0.34)	(-0.47)	(-0.39)
ABRASION SCORE	**9.09862e+09 *****	-17643.9	286144754.3	228749028.6	108762245.3
	(2.30)	(-0.00)	(0.53)	(0.55)	(0.84)
LANDSLIDE SCORE	-5.41893e+09	-77125378.8	-435766904.1	769308992.0	10003985.9
	(-0.98)	(-0.18)	(-0.97)	(1.28)	(0.04)
DROUGHTS SCORE	-3.31306e+09	17944154.2	-403283039.6	83644895.8	-1843637.0
	(-0.71)	(0.05)	(-0.49)	(0.13)	(-0.01)
FIRE SCORE	-8.01337e+09	-92752933.8	242143101.7	-650845442.9	**-217633610.3 ***
	(-1.49)	(-0.38)	(0.46)	(-1.16)	(-1.65)
TP	0.0166 ***	0.00222 ***	0.000106	0.000881 ***	0.00145 ***
	(4.91)	(45.82)	(0.73)	(5.66)	(52.20)
TIER1	-0.000681 **	0.0000767 ***	0.000306 ***	0.0000579 *	0.00000692
	(-2.16)	(3.01)	(3.27)	(1.87)	(0.47)
RGDP	-0.0000893	0.00000966 ***	0.00000171	0.0000132	0.00000103
	(-0.82)	(2.99)	(0.15)	(0.96)	(0.61)
_cons	1.15535e+11	1.30726e+10 **	-3.48020e+09	3.69206e+09	6.40821e+09 **
	(1.04)	(2.40)	(-0.33)	(0.34)	(2.04)
N	6188	6188	6188	6188	6188
Within R2	0.245	0.234	0.0499	0.120	0.180
Between R2	0.663	0.577	0.125	0.169	0.720
Overall R2	0.579	0.544	0.105	0.164	0.659

Note: retail credit and non-mortgage loans are estimated using the *random effect* method, while corporate loans, micro-loans, and mortgage loans are estimated using *the fixed effect* and *robust standard error methods*. t statistics in ( ) and stars illustrate statistical significance *p < 0.1; **p < 0.05; ***p < 0.01.

Source: OJK, BNPB, and BPS (processed by Stata 14)

Table 13

Estimation results of the effect of the disaster risk index on interest rates by type of credit

VARIABLE	CORPORATE IR (68)	RETAIL IR (69)	MICRO IR (70)	MORTGAGES IR (71)	NONMORTGAGE IR (72)
FLOOD SCORE	**-0.307 *****	**-0.168 ***	**-0.272 ****	-0.0416	-0.104
	(-2.76)	(-1.66)	(-2.01)	(-0.56)	(-0.93)
ABRASION SCORE	0.161	-0.0903	-0.0107	-0.00670	-0.150
	(1.55)	(-1.02)	(-0.08)	(-0.12)	(-1.40)
LANDSLIDE SCORE	0.138	0.164	0.377	0.0109	0.274
	(0.74)	(0.96)	(1.53)	(0.11)	(1.38)
DROUGHTS SCORE	0.225	-0.0220	0.170	-0.0371	-0.0557
	(1.43)	(-0.13)	(0.77)	(-0.31)	(-0.31)
FIRE SCORE	0.0365	0.166	0.149	0.112	0.0985
	(0.32)	(1.26)	(1.01)	(1.59)	(0.69)
TP	-1.17e-14 *	-5.85e-15	1.01e-14	4.61e-15	-1.81e-14
	(-1.66)	(-0.37)	(1.09)	(1.32)	(-0.73)
TIER1	1.73e-14 ***	-1.54e-14 ***	-2.66e-14 ***	-2.80e-14 ***	-1.26e-14 ***
	(2.61)	(-5.51)	(-6.19)	(-12.19)	(-3.70)
RGDP	-8.62e-15 ***	-5.89e-15 **	-3.69e-15	-5.02e-15 ***	-4.01e-15
	(-4.11)	(-2.51)	(-1.36)	(-3.91)	(-1.46)
_cons	9,649 ***	13.97 ***	5,263 **	11.16 ***	13.05 ***
	(5.22)	(6.65)	(2.03)	(9.50)	(5.28)
N	6188	6188	6188	6188	6188
Within R2	0.0384	0.0238	0.0453	0.0608	0.0120
Between R2	0.0295	0.0180	0.000513	0.00628	0.0192
Overall R2	0.0121	0.00892	0.00156	0.00240	0.0102

Note: estimates use *robust standard error,* t statistics in ( ), and stars illustrate statistical significance *p < 0.1; **p < 0.05; ***p < 0.01

Source: OJK, BNPB, and BPS (processed by Stata 14)

5. Conclusion and policy implications

This study analyzes the effect of climate change on bank credit using panel data covering 7,865 banks per province in Indonesia for the 2011-2021 period. The empirical results show that, of the six climate change-related disasters studied, the flood has a significant and consistent effect. An increase in the number of the flood is found to reduce the amount of credit and increase NPLs. Consistent results are also found as the variable number of disasters is replaced by a disaster risk index score.

Based on these findings, this study compiles several policy recommendations for banks and regulators. From the bank's point of view, first, banks need to consider adjusting disaster risk/physical risks in determining the risk premium, especially for flood disasters because the flood has been proven to affect credit risk. Second, banks need to consider credit risk transfer mechanisms, especially for customers located in disaster-prone areas. The most common mechanism is to have insurance against default risk.

From the regulatory side, first, the regulator needs to consider adjusting/drafting regulations related to dispensations for customers affected by the disaster, for example by providing interest/collateral subsidies for capital loans aimed at post-disaster business recovery. Second, regulators need to consider setting disincentives for granting credit to businesses that have a high carbon footprint and vice versa credit incentives for businesses that contribute to reducing greenhouse gas emissions.

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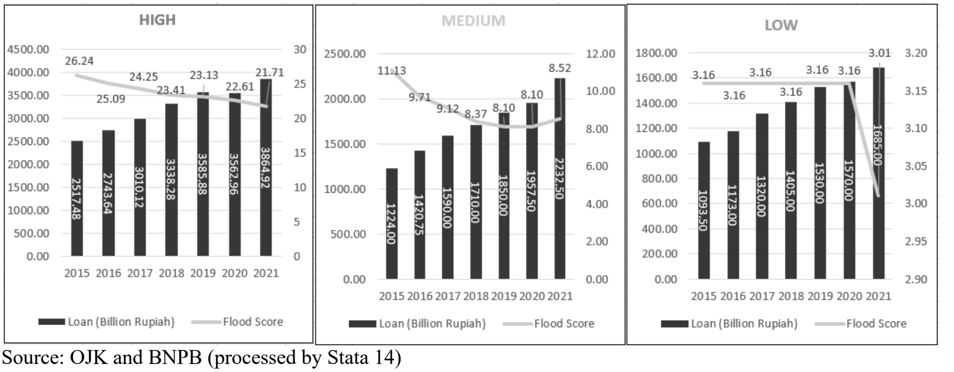
Appendix 1. Banking credit mapping based on disaster risk level classification.

Disaster risk class group for flood in 2021

HIGH		MEDIUM		LOW	
Province	Score: >12	Province	Score: 5.33-12	Province	Score: <5.33
East Kalimantan	30.98	Southeast Sulawesi	10.64	Gorontalo	4
South Kalimantan	30.5	West Nusa Tenggara	10.23	North Sulawesi	2.02
Bangka Belitung	28.74	Central Sulawesi	6.61		
West Kalimantan	28.71	South Sulawesi	6.6		
Riau	28.09				
Lampung	27.59				
South Sumatra	26.53				
Central Kalimantan	26.49				
Jambi	25.23				
West Papua	25.11				
Papua	24.98				
Aceh	24.23				
North Maluku	23.26				
North Sumatra	22.06				
Bengkulu	21.19				
East Java	19.57				
Banten	17.9				
West Java	17.05				
Maluku	14.88				
West Sumatra	14.87				
Central Java	14.1				
DKI Jakarta	13.37				
West Sulawesi	12.55				
East Nusa Tenggara	12.42				
Special Region of Yogyakarta	12.26				

Source: BNPB (processed by Stata 14)

Classification of flood risk level toward credit



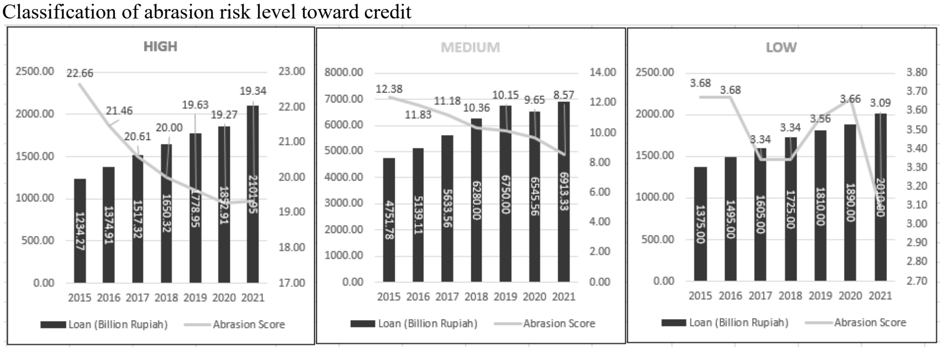
Source: OJK and BNPB (processed by Stata 14)

Disaster risk class group for abrasion in 2021

HIGH		MEDIUM		LOW	
Province	Score: >12	Province	Score: 5.33-12	Province	Score: < 5.33
Southeast Sulawesi	30.22	North Sumatra	11.29	Jambi	3.78
Maluku	29.80	South Kalimantan	10.51	South Sumatra	2.39
Riau islands	27.50	East Java	8.77		
Central Sulawesi	27.09	West Java	8.44		
Bangka Belitung	23.73	Special Region of Yogyakarta	8.36		
West Sulawesi	22.93	West Sumatra	8.11		
West Papua	22.83	Central Java	7.58		
West Nusa Tenggara	22.82	DKI Jakarta	7.26		
North Sulawesi	20.78	Papua	6.82		
North Maluku	19.87				
Gorontalo	18.87				
Aceh	17.93				
South Sulawesi	17.73				
East Kalimantan	16.07				
Bengkulu	16.02				
Bali	14.03				
East Nusa Tenggara	13.88				
West Kalimantan	13.73				
Lampung	12.83				
Banten	12.35				
Central Kalimantan	12.24				
Riau	12.15				

Source: BNPB (processed by Stata 14)

Classification of abrasion risk level toward credit



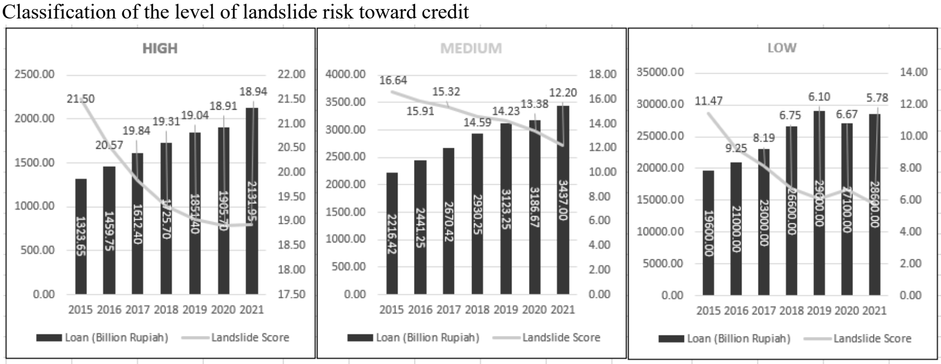
Source: OJK and BNPB (processed by Stata 14)

Disaster risk class group for landslide in 2021

HIGH		MEDIUM		LOW	
Province	Score: >15	Province	Score: 6.67-15	Province	Score: <6.67
Central Sulawesi	23.52	Maluku	14.92	DKI Jakarta	5.78
West Sulawesi	23.17	Riau islands	14.38		
West Papua	23.11	West Kalimantan	13.88		
East Nusa Tenggara	22.90	Jambi	13.67		
Aceh	21.09	Central Kalimantan	13.45		
Bengkulu	20.64	Bali	12.53		
North Sumatra	19.91	Riau	12.37		
South Sulawesi	19.65	West Java	12.34		
Papua	19.59	Central Java	10.77		
North Sulawesi	18.51	East Java	10.01		
Southeast Sulawesi	18.36	Special Region of Yogyakarta	9.73		
West Sumatra	17.95	Banten	8.32		
North Maluku	17.10				
South Sumatra	16.90				
Lampung	16.73				
West Nusa Tenggara	16.69				
Gorontalo	16.61				
South Kalimantan	15.58				
East Kalimantan	15.50				
Bangka Belitung	15.29				

Source: BNPB (processed by Stata 14)

Classification of the level of landslide risk toward credit



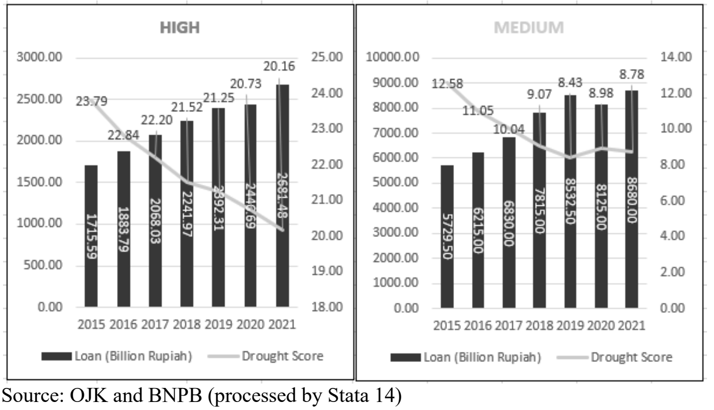
Source: OJK and BNPB (processed by Stata 14)

Disaster risk class group for drought in 2021

HIGH		MEDIUM	
Province	**Score: >12**	**Province**	**Score: 5.33-12**
Bangka Belitung	32.17	Central Sulawesi	11.88
West Sulawesi	30.20	North Sulawesi	8.74
South Sulawesi	29.53	DKI Jakarta	7.53
West Kalimantan	29.00	West Nusa Tenggara	6.98
Riau islands	24.85		
East Kalimantan	23.52		
Bali	10.70		
South Sumatra	22.12		
West Sumatra	21.82		
Lampung	21.57		
Papua	21.54		
Riau	9.39		
Jambi	20.76		
Bengkulu	20.14		
Southeast Sulawesi	20.05		
South Kalimantan	19.55		
Central Kalimantan	19.13		
West Java	17.64		
North Sumatra	17.36		
Maluku	16.56		
West Papua	16.33		
Central Java	16.06		
North Maluku	15.85		
East Nusa Tenggara	15.85		
Aceh	15.02		
Banten	13.93		
East Java	13.80		
Special Region of Yogyakarta	13.21		
Gorontalo	13.03		

Source: BNPB (processed by Stata 14)

Classification of the level of drought risk toward credit



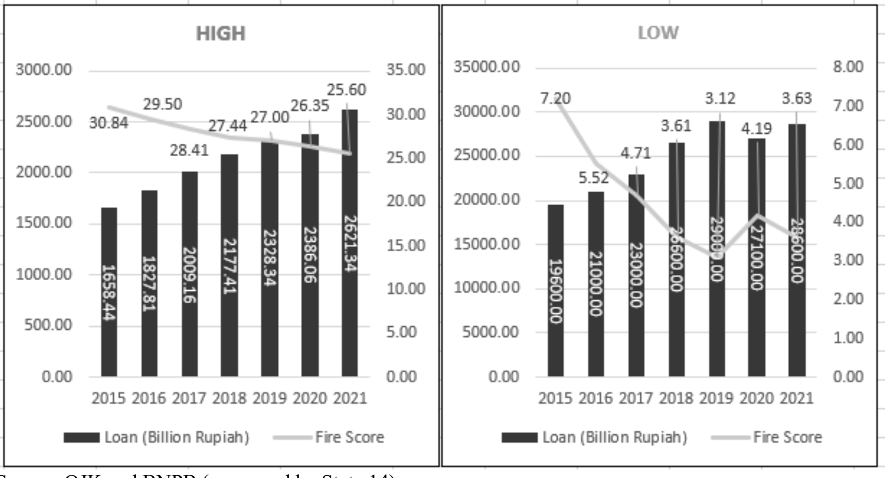
Source: OJK and BNPB (processed by Stata 14)

Disaster risk class group for land and forest fires in 2021

HIGH		LOW	
Province	**Score: >12**	**Province**	**Score: < 5.33**
Bangka Belitung	35.60	DKI Jakarta	3.63
South Sumatra	32.61		
Riau	32.09		
East Kalimantan	32.09		
Southeast Sulawesi	31.91		
Central Kalimantan	31.79		
South Kalimantan	31.53		
Jambi	31.25		
West Sumatra	31.18		
Maluku	29.32		
West Kalimantan	29.13		
West Sulawesi	28.55		
East Nusa Tenggara	27.15		
Central Sulawesi	26.29		
North Sumatra	25.99		
South Sulawesi	25.37		
North Maluku	24.03		
Gorontalo	23.47		
West Papua	23.21		
West Nusa Tenggara	22.82		
Lampung	22.53		
West Java	21.65		
Bali	21.14		
East Java	20.88		
Riau islands	20.84		
Banten	20.75		
North Sulawesi	20.34		
Bengkulu	19.98		
Special Region of Yogyakarta	19.81		
Aceh	19.61		
Central Java	19.24		
Papua	17.03		

Source: BNPB (processed by Stata 14)

Risk level classification land and forest fires toward credit



Source: OJK and BNPB (processed by Stata 14)

Appendix 2. The results of the panel regression model selection test.

Test	Prob.	Selected Models
Disaster Frequency		
Model 1: Credit		
Chow Test	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.2357**	**RE**
Model 2: NPLs		
Chow Test _	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.0041**	**FE**
Model 3: Interest Rates		
Chow Test _	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.0000**	**FE**
Loans		
Model 4		
Chow Test	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.0000**	**FE**
Model 5		
Chow Test _	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.1603**	**RE**
Model 6		
Chow Test	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.0016**	**FE**
Model 7		
Chow Test	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.3249**	**RE**
Model 8		
Chow Test	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.4781**	**RE**
Non-Performing Loans		
Model 9		
Chow Test	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.9230**	**RE**
Model 10		
Chow Test	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.1926**	**RE**
Model 11		
Chow Test	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.0079**	**FE**
Model 12		
Chow Test	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.0001**	**FE**
Model 13		
Chow Test	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.1548**	**RE**

Interest Rates		
Model 14		
Chow Test	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.0000**	**FE**
Model 15		
Chow Test	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.0000**	**FE**
Model 16		
Chow Test	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.0000**	**FE**
Model 17		
Chow Test	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.0003**	**FE**
Model 18		
Chow Test	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.0000**	**FE**
Disaster Risk Index Score		
Model 19: Credit		
Chow Test	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.0000**	**FE**
Model 20: NPLs		
Chow Test	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.0000**	**FE**
Model 21: Interest Rates		
Chow Test	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.0000**	**FE**
Loans		
Model 22		
Chow Test	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.0000**	**FE**
Model 23		
Chow Test	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.2515**	**RE**
Model 24		
Chow Test	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.0002**	**FE**
Model 25		
Chow Test	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.0005**	**FE**
Model 26		
Chow Test	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.0005**	**FE**

Non-Performing Loans		
Model 27		
Chow Test	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.0000**	**FE**
Model 28		
Chow Test	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.3138**	**RE**
Model 29		
Chow Test	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.2873**	**RE**
Model 30		
Chow Test	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.0317**	**FE**
Model 31		
Chow Test	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.2300**	**RE**
Interest Rates		
Model 32		
Chow Test	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.0000**	**FE**
Model 33		
Chow Test	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.0000**	**FE**
Model 34		
Chow Test	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.0015**	**FE**
Model 35		
Chow Test	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.0000**	**FE**
Model 36		
Chow Test	0.0000	FE
LM Test	0.0000	RE
Hausman Test	**0.0035**	**FE**

Appendix 3. The model used in the *robustness test.*

$$CORPORATE\ LOAN_{it} = \beta_0 + \beta_1 F\_FLOOD_{it} + \beta_2 F\_ABRASION_{it} + \beta_3 F\_LANDSLIDE_{it} + \beta_4 F\_WHIRLWIND_{it} + \beta_5 F\_DROUGHT_{it} + \beta_6 F\_FIRE_{it} + \beta_7 TP_{it} + \beta_8 TIER1_{it} + \beta_9 RGDB_{it} + u_{it} \quad (4)$$

$$RETAIL\ LOAN_{it} = \beta_0 + \beta_1 F\_FLOOD_{it} + \beta_2 F\_ABRASION_{it} + \beta_3 F\_LANDSLIDE_{it} + \beta_4 F\_WHIRLWIND_{it} + \beta_5 F\_DROUGHT_{it} + \beta_6 F\_FIRE_{it} + \beta_7 TP_{it} + \beta_8 TIER1_{it} + \beta_9 RGDB_{it} + u_{it} \quad (5)$$

$$MICRO\ LOAN_{it} = \beta_0 + \beta_1 F\_FLOOD_{it} + \beta_2 F\_ABRASION_{it} + \beta_3 F\_LANDSLIDE_{it} + \beta_4 F\_WHIRLWIND_{it} + \beta_5 F\_DROUGHT_{it} + \beta_6 F\_FIRE_{it} + \beta_7 TP_{it} + \beta_8 TIER1_{it} + \beta_9 RGDB_{it} + u_{it} \quad (6)$$

$$MORTGAGE_{it} = \beta_0 + \beta_1 F\_FLOOD_{it} + \beta_2 F\_ABRASION_{it} + \beta_3 F\_LANDSLIDE_{it} + \beta_4 F\_WHIRLWIND_{it} + \beta_5 F\_DROUGHT_{it} + \beta_6 F\_FIRE_{it} + \beta_7 TP_{it} + \beta_8 TIER1_{it} + \beta_9 RGDB_{it} + u_{it} \quad (7)$$

$$NONMORTGAGE_{it} = \beta_0 + \beta_1 F\_FLOOD_{it} + \beta_2 F\_ABRASION_{it} + \beta_3 F\_LANDSLIDE_{it} + \beta_4 F\_WHIRLWIND_{it} + \beta_5 F\_DROUGHT_{it} + \beta_6 F\_FIRE_{it} + \beta_7 TP_{it} + \beta_8 TIER1_{it} + \beta_9 RGDB_{it} + u_{it} \quad (8)$$

$$CORPORATE\ NPL_{it} = \beta_0 + \beta_1 F\_FLOOD_{it} + \beta_2 F\_ABRASION_{it} + \beta_3 F\_LANDSLIDE_{it} + \beta_4 F\_WHIRLWIND_{it} + \beta_5 F\_DROUGHT_{it} + \beta_6 F\_FIRE_{it} + \beta_7 TP_{it} + \beta_8 TIER1_{it} + \beta_9 RGDB_{it} + u_{it} \quad (9)$$

$$RETAIL\ NPL_{it} = \beta_0 + \beta_1 F\_FLOOD_{it} + \beta_2 F\_ABRASION_{it} + \beta_3 F\_LANDSLIDE_{it} + \beta_4 F\_WHIRLWIND_{it} + \beta_5 F\_DROUGHT_{it} + \beta_6 F\_FIRE_{it} + \beta_7 TP_{it} + \beta_8 TIER1_{it} + \beta_9 RGDB_{it} + u_{it} \quad (10)$$

$$MICRO\ NPL_{it} = \beta_0 + \beta_1 F\_FLOOD_{it} + \beta_2 F\_ABRASION_{it} + \beta_3 F\_LANDSLIDE_{it} + \beta_4 F\_WHIRLWIND_{it} + \beta_5 F\_DROUGHT_{it} + \beta_6 F\_FIRE_{it} + \beta_7 TP_{it} + \beta_8 TIER1_{it} + \beta_9 RGDB_{it} + u_{it} \quad (11)$$

$$MORTGAGE\ NPL_{it} = \beta_0 + \beta_1 F\_FLOOD_{it} + \beta_2 F\_ABRASION_{it} + \beta_3 F\_LANDSLIDE_{it} + \beta_4 F\_WHIRLWIND_{it} + \beta_5 F\_DROUGHT_{it} + \beta_6 F\_FIRE_{it} + \beta_7 TP_{it} + \beta_8 TIER1_{it} + \beta_9 RGDB_{it} + u_{it} \quad (12)$$

$$NONMORTGAGE\ NPL_{it} = \beta_0 + \beta_1 F\_FLOOD_{it} + \beta_2 F\_ABRASION_{it} + \beta_3 F\_LANDSLIDE_{it} + \beta_4 F\_WHIRLWIND_{it} + \beta_5 F\_DROUGHT_{it} + \beta_6 F\_FIRE_{it} + \beta_7 TP_{it} + \beta_8 TIER1_{it} + \beta_9 RGDB_{it} + u_{it} \quad (13)$$

$$CORPORATE\ IR_{it} = \beta_0 + \beta_1 F\_FLOOD_{it} + \beta_2 F\_ABRASION_{it} + \beta_3 F\_LANDSLIDE_{it} + \beta_4 F\_WHIRLWIND_{it} + \beta_5 F\_DROUGHT_{it} + \beta_6 F\_FIRE_{it} + \beta_7 TP_{it} + \beta_8 TIER1_{it} + \beta_9 RGDB_{it} + u_{it} \quad (14)$$

$$RETAIL\ IR_{it} = \beta_0 + \beta_1 F\_FLOOD_{it} + \beta_2 F\_ABRASION_{it} + \beta_3 F\_LANDSLIDE_{it} + \beta_4 F\_WHIRLWIND_{it} + \beta_5 F\_DROUGHT_{it} + \beta_6 F\_FIRE_{it} + \beta_7 TP_{it} + \beta_8 TIER1_{it} + \beta_9 RGDB_{it} + u_{it} \quad (15)$$

$$MICRO\ IR_{it} = \beta_0 + \beta_1 F\_FLOOD_{it} + \beta_2 F\_ABRASION_{it} + \beta_3 F\_LANDSLIDE_{it} + \beta_4 F\_WHIRLWIND_{it} + \beta_5 F\_DROUGHT_{it} + \beta_6 F\_FIRE_{it} + \beta_7 TP_{it} + \beta_8 TIER1_{it} + \beta_9 RGDB_{it} + u_{it} \quad (16)$$

$$MORTGAGE\ IR_{it} = \beta_0 + \beta_1 F\_FLOOD_{it} + \beta_2 F\_ABRASION_{it} + \beta_3 F\_LANDSLIDE_{it} + \beta_4 F\_WHIRLWIND_{it} + \beta_5 F\_DROUGHT_{it} + \beta_6 F\_FIRE_{it} + \beta_7 TP_{it} + \beta_8 TIER1_{it} + \beta_9 RGDB_{it} + u_{it} \quad (17)$$

$$NONMORTGAGE\ IR_{it} = \beta_0 + \beta_1 F\_FLOOD_{it} + \beta_2 F\_ABRASION_{it} + \beta_3 F\_LANDSLIDE_{it} + \beta_4 F\_WHIRLWIND_{it} + \beta_5 F\_DROUGHT_{it} + \beta_6 F\_FIRE_{it} + \beta_7 TP_{it} + \beta_8 TIER1_{it} + \beta_9 RGDB_{it} + u_{it} \quad (18)$$

$$LOAN_{it} = \beta_0 + \beta_1 FLOOD\ SCORE_{it} + \beta_2 ABRASION\ SCORE_{it} + \beta_3 LANDSLIDE\ SCORE_{it} + \beta_4 DROUGHT\ SCORE_{it} + \beta_5 FIRE\ SCORE_{it} + \beta_6 TP_{it} + \beta_7 TIER1_{it} + \beta_8 RGDP_{it} + u_{it} \quad (19)$$

$$NPL_{it} = \beta_0 + \beta_1 FLOOD\ SCORE_{it} + \beta_2 ABRASION\ SCORE_{it} + \beta_3 LANDSLIDE\ SCORE_{it} + \beta_4 DROUGHT\ SCORE_{it} + \beta_5 FIRE\ SCORE_{it} + \beta_6 TP_{it} + \beta_7 TIER1_{it} + \beta_8 RGDP_{it} + u_{it} \quad (20)$$

$$IR_{it} = \beta_0 + \beta_1 FLOOD\ SCORE_{it} + \beta_2 ABRASION\ SCORE_{it} + \beta_3 LANDSLIDE\ SCORE_{it} + \beta_4 DROUGHT\ SCORE_{it} + \beta_5 FIRE\ SCORE_{it} + \beta_6 TP_{it} + \beta_7 TIER1_{it} + \beta_8 RGDP_{it} + u_{it} \quad (21)$$

$$CORPORATE\ LOAN_{it} = \beta_0 + \beta_1 FLOOD\ SCORE_{it} + \beta_2 ABRASION\ SCORE_{it} + \beta_3 LANDSLIDE\ SCORE_{it} + \beta_4 DROUGHT\ SCORE_{it} + \beta_5 FIRE\ SCORE_{it} + \beta_6 TP_{it} + \beta_7 TIER1_{it} + \beta_8 RGDP_{it} + u_{it} \quad (22)$$

$$RETAIL\ LOAN_{it} = \beta_0 + \beta_1 FLOOD\ SCORE_{it} + \beta_2 ABRASION\ SCORE_{it} + \beta_3 LANDSLIDE\ SCORE_{it} + \beta_4 DROUGHT\ SCORE_{it} + \beta_5 FIRE\ SCORE_{it} + \beta_6 TP_{it} + \beta_7 TIER1_{it} + \beta_8 RGDP_{it} + u_{it} \quad (23)$$

$$MICRO\ LOAN_{it} = \beta_0 + \beta_1 FLOOD\ SCORE_{it} + \beta_2 ABRASION\ SCORE_{it} + \beta_3 LANDSLIDE\ SCORE_{it} + \beta_4 DROUGHT\ SCORE_{it} + \beta_5 FIRE\ SCORE_{it} + \beta_6 TP_{it} + \beta_7 TIER1_{it} + \beta_8 RGDP_{it} + u_{it} \quad (24)$$

$$MORTGAGE_{it} = \beta_0 + \beta_1 FLOOD\ SCORE_{it} + \beta_2 ABRASION\ SCORE_{it} + \beta_3 LANDSLIDE\ SCORE_{it} + \beta_4 DROUGHT\ SCORE_{it} + \beta_5 FIRE\ SCORE_{it} + \beta_6 TP_{it} + \beta_7 TIER1_{it} + \beta_8 RGDP_{it} + u_{it} \quad (25)$$

$$NONMORTGAGE_{it} = \beta_0 + \beta_1 FLOOD\ SCORE_{it} + \beta_2 ABRASION\ SCORE_{it} + \beta_3 LANDSLIDE\ SCORE_{it} + \beta_4 DROUGHT\ SCORE_{it} + \beta_5 FIRE\ SCORE_{it} + \beta_6 TP_{it} + \beta_7 TIER1_{it} + \beta_8 RGDP_{it} + u_{it} \quad (26)$$

$$CORPORATE\ NPL_{it} = \beta_0 + \beta_1 FLOOD\ SCORE_{it} + \beta_2 ABRASION\ SCORE_{it} + \beta_3 LANDSLIDE\ SCORE_{it} + \beta_4 DROUGHT\ SCORE_{it} + \beta_5 FIRE\ SCORE_{it} + \beta_6 TP_{it} + \beta_7 TIER1_{it} + \beta_8 RGDP_{it} + u_{it} \quad (27)$$

$$RETAIL\ NPL_{it} = \beta_0 + \beta_1 FLOOD\ SCORE_{it} + \beta_2 ABRASION\ SCORE_{it} + \beta_3 LANDSLIDE\ SCORE_{it} + \beta_4 DROUGHT\ SCORE_{it} + \beta_5 FIRE\ SCORE_{it} + \beta_6 TP_{it} + \beta_7 TIER1_{it} + \beta_8 RGDP_{it} + u_{it} \quad (28)$$

$$MICRO\ NPL_{it} = \beta_0 + \beta_1 FLOOD\ SCORE_{it} + \beta_2 ABRASION\ SCORE_{it} + \beta_3 LANDSLIDE\ SCORE_{it} + \beta_4 DROUGHT\ SCORE_{it} + \beta_5 FIRE\ SCORE_{it} + \beta_6 TP_{it} + \beta_7 TIER1_{it} + \beta_8 RGDP_{it} + u_{it} \quad (29)$$

$$MORTGAGE\ NPL_{it} = \beta_0 + \beta_1 FLOOD\ SCORE_{it} + \beta_2 ABRASION\ SCORE_{it} + \beta_3 LANDSLIDE\ SCORE_{it} + \beta_4 DROUGHT\ SCORE_{it} + \beta_5 FIRE\ SCORE_{it} + \beta_6 TP_{it} + \beta_7 TIER1_{it} + \beta_8 RGDP_{it} + u_{it} \quad (30)$$

$$NONMORTGAGE\ NPL_{it} = \beta_0 + \beta_1 FLOOD\ SCORE_{it} + \beta_2 ABRASION\ SCORE_{it} + \beta_3 LANDSLIDE\ SCORE_{it} + \beta_4 DROUGHT\ SCORE_{it} + \beta_5 FIRE\ SCORE_{it} + \beta_6 TP_{it} + \beta_7 TIER1_{it} + \beta_8 RGDP_{it} + u_{it} \quad (31)$$

$$CORPORATE\ IR_{it} = \beta_0 + \beta_1 FLOOD\ SCORE_{it} + \beta_2 ABRASION\ SCORE_{it} + \beta_3 LANDSLIDE\ SCORE_{it} + \beta_4 DROUGHT\ SCORE_{it} + \beta_5 FIRE\ SCORE_{it} + \beta_6 TP_{it} + \beta_7 TIER1_{it} + \beta_8 RGDP_{it} + u_{it} \quad (32)$$

$$RETAIL\ IR_{it} = \beta_0 + \beta_1 FLOOD\ SCORE_{it} + \beta_2 ABRASION\ SCORE_{it} + \beta_3 LANDSLIDE\ SCORE_{it} + \beta_4 DROUGHT\ SCORE_{it} + \beta_5 FIRE\ SCORE_{it} + \beta_6 TP_{it} + \beta_7 TIER1_{it} + \beta_8 RGDP_{it} + u_{it} \quad (33)$$

$$MICRO\ IR_{it} = \beta_0 + \beta_1 FLOOD\ SCORE_{it} + \beta_2 ABRASION\ SCORE_{it} + \beta_3 LANDSLIDE\ SCORE_{it} + \beta_4 DROUGHT\ SCORE_{it} + \beta_5 FIRE\ SCORE_{it} + \beta_6 TP_{it} + \beta_7 TIER1_{it} + \beta_8 RGDP_{it} + u_{it} \quad (34)$$

$$MORTGAGE\ IR_{it} = \beta_0 + \beta_1 FLOOD\ SCORE_{it} + \beta_2 ABRASION\ SCORE_{it} + \beta_3 LANDSLIDE\ SCORE_{it} + \beta_4 DROUGHT\ SCORE_{it} + \beta_5 FIRE\ SCORE_{it} + \beta_6 TP_{it} + \beta_7 TIER1_{it} + \beta_8 RGDP_{it} + u_{it} \quad (35)$$

$$NONMORTGAGE\ IR_{it} = \beta_0 + \beta_1 FLOOD\ SCORE_{it} + \beta_2 ABRASION\ SCORE_{it} + \beta_3 LANDSLIDE\ SCORE_{it} + \beta_4 DROUGHT\ SCORE_{it} + \beta_5 FIRE\ SCORE_{it} + \beta_6 TP_{it} + \beta_7 TIER1_{it} + \beta_8 RGDP_{it} + u_{it} \quad (36)$$