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The shocks of natural disasters on NPLs: Global evidence

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ABSTRACT

The relationship between natural disasters and NPLs is of significant importance in the natural disaster economics field. Thus, this research investigates the effects of natural disasters on non-performing loans (NPLs) using panel data covering 101 countries from 1996 to 2017. We introduce interaction terms between natural disasters and different financial risks to represent the moderating effects of natural disasters through such risks. Several conclusions arise from the empirical results. (1) Natural disasters produce significant effects on NPLs both in current year and five-period lag terms. (2) Natural disasters increase NPLs through five kinds of financial risks, and the moderating effects are statistically significant. (3) The effects of natural disasters on NPLs present significant heterogeneity between OECD and non-OECD countries. From these results, we put forward several policy implications.

1. Introduction

Natural disasters have become more and more frequent during the past several decades (Chang and Berdiev, 2013; Leaning and Guha-Sapir, 2013). Due to the differences in natural environment, geographical location, social economy, and other factors in different countries or continents, the occurrence of natural disasters and the losses caused by them vary a lot. Fig. 1 presents the global occurrences from natural disasters from 1990 to 2020. From the figure we find that the two major countries with the most natural disasters are China and the United States, followed by India. Fig. 2 shows the total deaths from natural disasters during the period 1990–2020. The country with the most deaths due to natural disasters is Haiti, followed by Indonesia. Natural disasters bring about a severe destruction of both physical and human capital (Strobl, 2012; Wen and Chang, 2015; Yang et al., 2022; Wang et al., 2021; Yin et al., 2022b,a; Zheng et al., 2022; Wang et al., 2021, 2022a,b; Strobl, 2012; Wen and Chang, 2015), producing significantly negative shocks on economic development during the past several decades (Cohen and Werker, 2008). In addition, natural disasters also produce negative effects on financial stability and create a huge impact on the financial system (Schüwer et al., 2019). Since NPLs reflect the credit quality of banks, their amount is crucial for risk management functions and banking stability (Ozili, 2019), and the nexus between natural disasters and NPLs has great meaning on improving banking stability. Thus, the purpose of this study is to investigate how natural disasters affect NPLs.

The literature has documented those natural disasters produce severe impacts on economic growth and financial development. Amounts of researches have analyzed how natural disasters affect economic growth and concluded that natural disasters create

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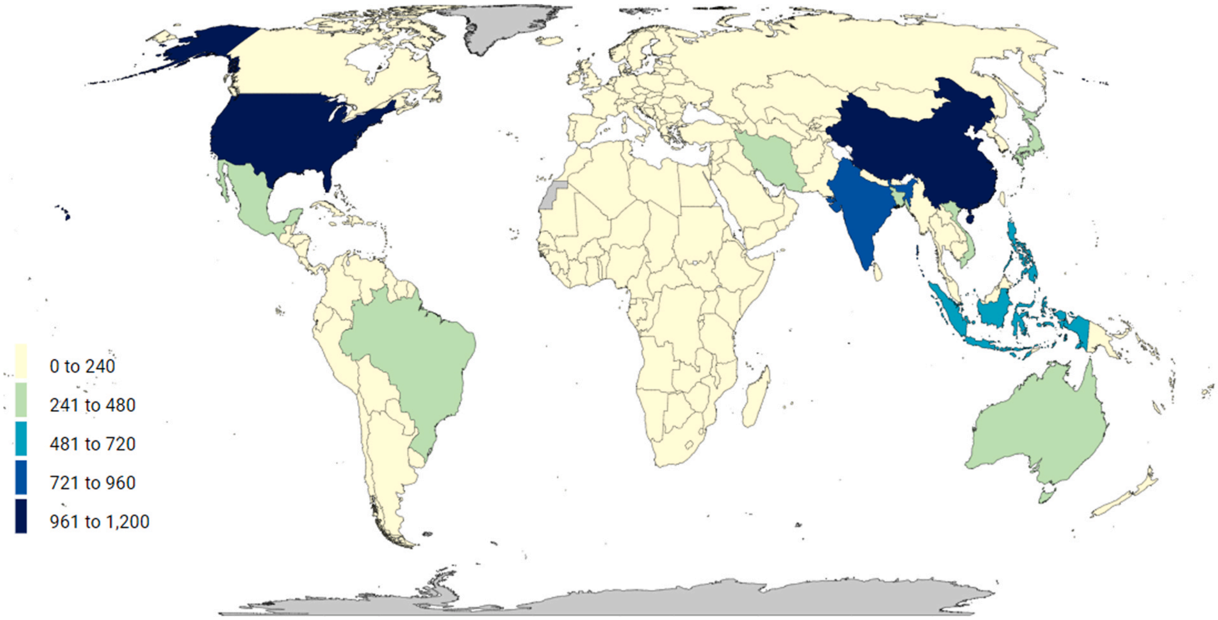

Fig. 1. Global occurrences from natural disasters, 1990–2020.

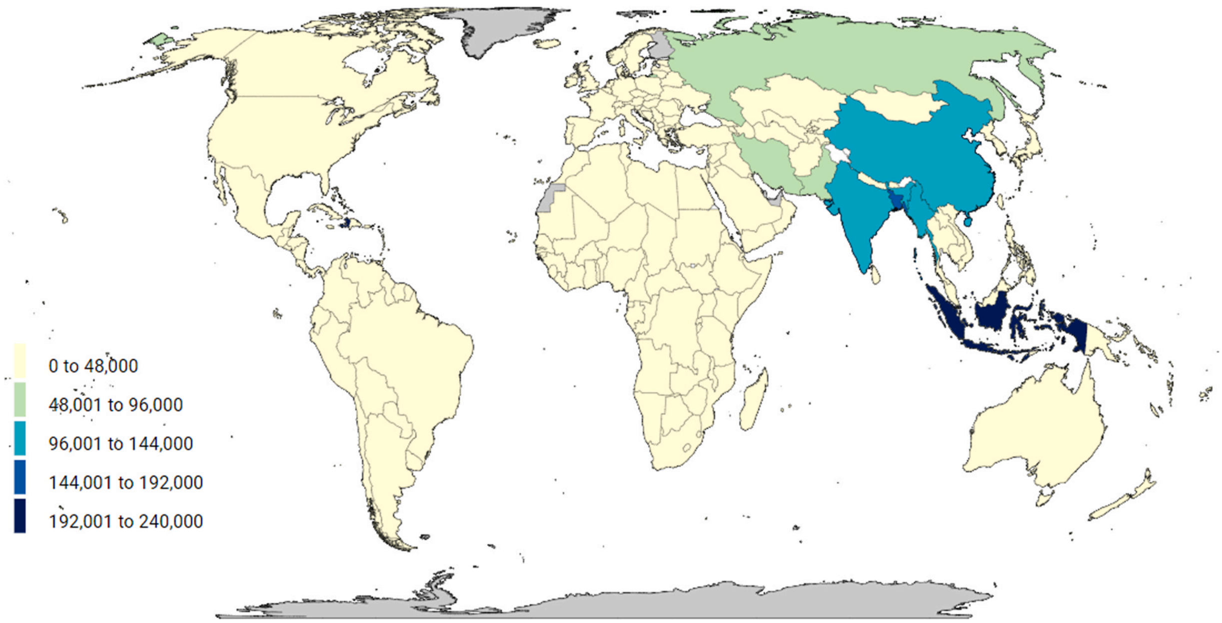

Fig. 2. Total deaths from natural disasters, 1990–2020.

significantly negative effects on economic development (Horwich, 2000; Kahn, 2005). Cavallo et al. (2013) employ synthetic controls to examine the average causal impact of natural disasters on economic growth and find that extremely large disasters produce negative effects on economic output in both short and long runs. Some researches employ light intensity to represent the economic development and conclude that light intensity data is a good measure to explore the physical damage caused by natural disasters (Kohiyama et al., 2004; Ebener et al., 2005). Bertinelli and Strobl (2013) reveal the relationship between natural disasters and economic development using luminosity data, the results prove that the light intensity reduce more than three percent when struck by hurricanes. Klomp (2016) analyze the influence of large-scale natural disasters on economic development using the data based on satellite images of night-time light intensity as an indicator to represent local economic development, and the results show that natural disasters reduce the number of lights visible significantly.

On the analysis of how natural disasters influence financial development, Klomp (2014) explore the impact of natural disasters on commercial banks using panel data for more than 160 countries and suggest that natural disasters may increase the probability of bank default. Keerthiratne and Tol (2017) investigate the impact of natural disasters on financial development by panel fixed effects model covering 147 countries and find that companies and households are more likely to get deeper into debt when struck by a natural disaster. Chen and Chang (2020) analyze the influence of natural disasters on financial systems using panel data and find that the effects of natural disasters exist heterogeneity between banking system, insurance system and stock markets. In addition to the effects of natural disasters on financial development, there are many researches examine the nexus between natural disasters and financial system from other perspectives. Berg and Schrader (2012) analyze the effects of natural disasters on loan demand using natural experiment and the results show that the credit demand increases due to natural disasters while access to credit is restricted. Schüwer et al. (2019) explore the react of banks to a natural disaster and find that independent banks trend to increase their risk-based capital ratios.

The existing literature mainly focuses on how natural disasters influence economic development and financial system, but few studies have analyzed the effects of natural disasters on NPLs. Moreover, no study has analyzed the moderating effects of natural disasters on NPLs through financial risks, thus prompting our research to fill this gap (Feng et al., 2021; Hu et al., 2022; Long et al., 2022; Wen et al., 2021; Zheng et al., 2021; Fu et al., 2020; X. Peng et al., 2022). Since richer countries have better infrastructure and more perfect financial systems, their banking sector will suffer less from natural disasters than poorer countries (Kahn, 2005; Kellenberg and Mobarak, 2008). Songwathana (2018) investigates the effects of natural disasters on economic development using global data, showing results that higher income can lower disaster losses, including numbers of deaths and those affected by natural disasters. Chang and Zhang (2020) also suggest that the effects of natural disasters produce vary among OECD and non-OECD countries. Therefore, except for the moderating effects through financial risks, we also aim to explore the heterogeneity between OECD and non-OECD countries of how natural disasters influence NPLs.

Our research contributes to the literature as follows. (1) We analyze the effects of natural disasters on the financial system from the perspective of NPLs. (2) In terms of how natural disasters influence NPLs, we not only care about the direct effects, but also take into consideration the moderating effects of natural disasters through different financial risks. By introducing interaction terms between natural disasters and financial risks, we can compare the direct and moderating effects of natural disasters on NPLs and draw a comprehensive evaluation of how NPLs are influenced by natural disasters. (3) We also take heterogeneity into analysis and compare the effects of natural disasters on NPLs between OECD and non-OECD countries.

The remainder of this paper runs as follows. Section 2 introduces the methodology employed in the empirical analysis, presents the data and explains the variables. Section 3 shows the empirical analysis, including the basic results and robustness test. Section 4 presents the further analysis for the sub-samples of OECD and non-OECD countries. Section 5 summarizes the empirical analysis and provides policy implications.

2. Methodology and data

2.1. Estimation method

The main goal of this article is to analyze the nexus between natural disasters and NPLs with panel data over the period 1996–2017. Panel data have many advantages over cross-sectional data. First, panel data offer a larger sample size and information, which reduce the possibility of collinearity between variables, increase the degree of freedom of test statistics, and enhance the validity of estimation results. Second, panel data not only have the cross-section dimension, but also the time dimension, so that the time variation trend of the effect can be investigated and dynamic analysis can be carried out. Third, panel data alleviate the endogeneity problem to a certain extent. Therefore, this paper uses the panel fixed effect model to estimate the impact of natural disasters on NPLs, which controls for not only country-level factors that do not vary with time, but also temporal factors that do not vary with country.

To test whether natural disasters affect NPLs, we first set up the baseline model as:

$$NPL_{it} = \alpha + \rho \times Death_{it} + \gamma_k \times Risk_{kit} + \sum_{l=1}^{m} \beta_l Z_{it,l} + \delta_i + \sigma_t + \varepsilon_{it} \tag{1}$$

Here, NPL_{it} denotes the dependent variable (i.e., NPLs); $Death_{it}$ is the number of deaths caused by natural disasters in country i at time t; ρ is the coefficient of *Death*, reflecting the effect of natural disasters on NPLs; $Risk_{kit}$ is the k^{th} financial risk; γ_k is the coefficient of the k^{th} financial risk; Z_{it} is a vector of control variables that may affect NPLs; δ_i is the fixed effect variable of the country; σ_t is the fixed effect variable of year; and ε_{it} is the residual of the model. Standard errors are clustered by country pair.

2.2. Data and variables

The dependent variable (*NPL*), measured as the ratio of bank NPLs to gross loans, is employed to measure bank NPLs in the countries. Moreover, we utilize bank Z-score (*Z*) as another financial indicator for a robustness test. All the dependent data are obtained from GFDD.

Certain kinds of natural disasters may bring about damages to society, and the damages vary with different severities (Doytch, 2020). Following Wen and Chang (2015) and Chen et al. (2021), we utilize the total number of persons confirmed as dead caused by a natural disaster as the independent variable (proxied by *Death*).[1] There are eight kinds of serious natural disasters included in our analysis: droughts, earthquakes, epidemics, extreme temperatures, storms, landslides, floods, and volcanic eruptions. All the data of natural disasters are obtained from EM-DAT. The values of *Death* reflect the influence of natural disasters, whereby the larger the value is, the higher is the natural disaster's severity.

Financial development is not only affected by natural disasters directly, but also influenced through financial risk. Therefore, financial risk can be treated as a moderating variable when analyzing how natural disasters impact the financial system (Chen and Chang, 2020). According to the International Country Risk Guide (ICRG) classification (Chiu and Lee, 2019; Chang and Zhang, 2020), financial risks can be categorized into the five following factors.

(1) Total foreign debt (*Risk1*). The variable *Risk1* is measured by the ratio of foreign debt to GDP, in which all terms are converted into US dollars at the average exchange rate for that year. A country faces less serious financial risks when its total foreign debt increases.
(2) Debt service (*Risk2*). The variable *Risk2* is calculated by the ratio of debt service to total exports of goods and services, where all terms are converted into US dollars at the average exchange rate for that year. A country faces less serious financial risks when its debt service increases.
(3) Current account (*Risk3*). The variable *Risk3* is assessed by the current account as the percent of the total exports of goods and services, where all terms are converted into US dollars at the average exchange rate for that year. A country faces less serious financial risks when its current account increases.
(4) International liquidity (*Risk4*). The variable *Risk4* is measured by official gold holdings as a percentage of the monthly cost of merchandise imports, where all terms are converted into US dollars at the average exchange rate for that year. Financial risks decrease with the increasing value of international liquidity.
(5) Exchange rate stability (*Risk5*). The variable *Risk5* is represented by the value of the appreciation or depreciation of the currency against the US dollar over a period of 12 months. Its implication is the same as international liquidity - that is, the financial risks decrease with the increasing value of the exchange rate stability. All the financial risk data are from the International Country Risk Guide.

In addition to natural disasters and financial risks, we collect various of control variables that can reflect the economic development. (1) GDP per capital (*Pgdp*). Countries with high income levels are equipped with more mature financial system, which may reduce damages from natural disasters and financial risks (Robinson et al., 2017). Here, we use GDP per capital to measure the national income level, which is converted into US dollars. (2) Trade level (*Trade*). Trade liberalization can help improve the development of financial markets and produce influence on bank performance (Svaleryd and Vlachos, 2002). Referring to Chang and Zhang (2020), we employ the ratio of imports and exports of goods and services to the GDP to represent the trade levels. (3) Inflation rate (*Infla*). Since inflation rate produces significant effect on financial system (Aliyu, 2012), following Phan et al. (2020), we employ consumer price index to represent the inflation rate and take it into analysis. (4) Exchange rate (*Exch*). Referring to Reboredo et al. (2016), we introduce the exchange rate into our model to reflect the national currency. (5) Bank deposit to GDP (*Deposit*). Since bank deposit is one of factors that can affect financial stability, we utilize the ratio of bank deposits to GDP as an indicator of deposit (Phan et al., 2020). (6) EI Nino years (*Nino*). If EI Nino occurs, climate changes dramatically, the frequency and intensity of natural disasters may increase (Chen et al., 2021). Thus, we utilize EI Nino years as dummy variable.

The Definition, data source, and summary statistics of the variables are listed in Table 1.

3. Empirical results

3.1. Unit root test

Since our sample covers a long-time span, a panel unit root test is carried out before our empirical analysis. We utilize the IPS test to check whether there exists a panel unit root, because the cross-sectional dimension of our sample is large (Im et al., 2003). The results appear in Table 2. From the table we find that CD tests are all statistically significant at the 1% level, rejecting the null hypothesis of no cross-sectional correlation and revealing cross-sectional dependence (Chen and Chang, 2020). To guarantee robustness, we next analyze the stability of variables checked by IPS test. IPS tests of all variables, except for *Nino*, show that the null hypothesis of panel unit root is rejected at 1% significance level, confirming that there is no unit root.

3.2. Baseline results

We employ panel data model to analyze how natural disasters and kinds of financial risks affect nonperformance loans. Before our empirical analysis, Hausman test is conducted and the value is statistically significant at 1% significance level, indicating that fixed effect model is more appropriate during our analysis. The empirical results of fixed effect panel data model are shown in Table 3.

We first consider the result without lagged variables in columns 1–5. The coefficients of *Death* on *NPL* are positive and statistically

[1] Since there is a large number of zeros in the dataset of natural disasters, we have standardized it according to Noy (2009), but do not adopt a logarithm when processing the dataset of natural disasters.

Table 1
Definition, data source, and summary statistics of the variables.

Variable	Description	Source	Obs.	Mean	Std. Dev	Min	Max
Non-performing loans (NPL)	Bank NPLs to gross loans	GFDD	2222	8.16	7.62	0.10	74.1
Z-score (Z)	Country-level Z-score	GFDD	2156	13.25	9.15	0.02	96.68
Disaster death (Death)	Total number of deaths	EM-DAT	2222	343.05	4258.16	0	166752
Disaster loss (Loss)	Total disaster loss	EM-DAT	2222	417422.4	4925236	0	2.13e + 8
Total Foreign Debt (Risk1)	Total foreign debt as a percent of GDP	ICRG	2222	6.00	2.49	0	10
Debt Service (Risk2)	Debt service as a percent of the exports of goods and services	ICRG	2222	8.59	1.60	0	10
Current Account (Risk3)	Current account as a percent of the exports of goods and services	ICRG	2222	11.15	2.31	0	15
International Liquidity (Risk4)	International liquidity as months of import cover	ICRG	2222	2.15	1.41	0	7
Exchange Rate (Risk5)	Exchange rate stability as a percentage change	ICRG	2222	8.97	1.55	0	10
GDP per capita (Pgdp)	GDP per capita of a country	WDI	2222	13344.86	18528.84	102.59	118823.60
Inflation rate (Infla)	Change in the consumer price index	WDI	2222	8.97	61.74	-27.63	2630.12
Trade (Trade)	Ratio of imports and exports to GDP	WDI	2222	81.36	49.35	0.02	442.62
Exchange rate (Exch)	Exchange rate of a country	GFDD	2222	504.68	1950.03	0.001	33226.3
Deposit (Deposit)	Bank deposits to GDP	GFDD	2222	55.52	60.06	0.93	972.18
EI Nino (Nino)	El Niño and La Niña Years	Oceanic Niño Index	2222	0.18	0.38	0	1

Notes: GFDD represents the World Bank Global Financial Development Database. EM-DAT represents the international disasters database. ICRG represents the International Country Risk Guide. WDI represents the World Bank Development Indicators.

Table 2
Cross-section correlation test and panel unit root test.

Variable	Cross-section correlation		Panel unit root	
	CD-test	p-value	IPS-test	p-value
NPL	18.85	0.000	-3.28	0.000
Z	17.66	0.000	-12.33	0.000
Death	8.61	0.000	-15.43	0.000
Loss	126.02	0.000	-21.57	0.000
Affect	18.60	0.000	-24.65	0.000
Risk1	4.82	0.000	-6.93	0.000
Risk2	112.83	0.000	-9.19	0.000
Risk3	12.35	0.000	-8.30	0.000
Risk4	31.96	0.000	-6.82	0.000
Risk5	142.09	0.000	-19.74	0.000
Pgdp	285.91	0.000	-2.19	0.014
Infla	46.24	0.000	-22.70	0.000
Trade	68.40	0.000	-6.15	0.000
Exch	52.79	0.000	-7.25	0.000
Deposit	188.06	0.000	-4.87	0.000
Nino	333.32	0.000	–	–

Table 3
The effect of natural disasters on NPLs.

Variable	(1)	(2)	(3)	(4)	(5)
Death	0.0741 *	0.0702 **	0.0710 ***	0.0760 *	0.0731 ***
	(1.69)	(1.98)	(2.60)	(1.93)	(2.61)
Risk1	-0.118				
	(−0.73)				
Risk2		-0.149			
		(−0.90)			
Risk3			-0.916***		
			(−5.01)		
Risk4				-0.713***	
				(−3.58)	
Risk5					-0.116
					(−0.83)
Pgdp	-0.0898 *	-0.135 *	-0.0501 **	-0.0871 **	-0.189 *
	(−1.72)	(−1.77)	(−2.20)	(−2.32)	(−1.71)
Trade	0.0286	0.140	0.274	0.0392	0.146
	(0.09)	(0.41)	(0.81)	(0.12)	(0.43)
Infla	-0.226 *	-0.230 *	-0.194 *	-0.240 *	-0.243 *
	(−1.84)	(−1.86)	(−1.68)	(−1.95)	(−1.95)
Exch	-0.0012	0.004	-0.024	0.048	-0.0141
	(−0.01)	(0.02)	(−0.11)	(0.23)	(−0.07)
Deposit	0.0083	0.129	0.0406	0.168	0.150
	(0.03)	(0.47)	(0.15)	(0.62)	(0.55)
Nino	0.0221 **	0.0304 **	0.0764 **	0.0119 **	0.0412 *
	(2.07)	(2.10)	(2.25)	(2.04)	(1.73)
cons	8.919***	9.301***	8.601***	7.431**	9.766***
	(4.73)	(3.84)	(4.00)	(3.26)	(4.36)
Country	Yes	Yes	Yes	Yes	Yes
N	2222	2222	2222	2222	2222
R-squared	0.0150	0.0186	0.0142	0.0085	0.0028
F test	21.23	21.27	21.72	21.41	21.28

Notes: *t* statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

significant at 10% significance level, proving that when natural disaster occurs in a country, the NPLs will increase. The possible reasons are as follows. From a macro-level perspective, the occurrence of natural disasters increases macroeconomic uncertainty. Uncertainty shocks can trigger a country's sovereign rating downgrade, which in turn leads to a downgrade of local banks' ratings, resulting in an increase in their non-performing loans (Boumparis et al., 2019). From a micro-level perspective, natural disasters directly affect the production and operation of real enterprises, which have a negative impact on their capital accumulation and productivity, resulting in asset impairment losses. The above two effects are further transmitted to bank financial institutions as the loan contract between entrepreneurs and banks, which can lead to a significant increase of NPLs (Lamperti et al., 2019). When analyzing how financial risks affect NPLs, it is worth noting that the coefficients of *Risk3* and *Risk4* are significantly negative, whose values are − 0.916 and − 0.713, respectively. The results indicate that the effects of current account and international liquidity on NPLs are significantly negative. If current account and international liquidity are high in a country, the country is faced with less financial risk in currency, along with less NPLs. Though the coefficients of *Risk1*, *Risk2* and *Risk5* are negative, they are not significant, which reveals that total foreign debt, debt service and exchange rate stability do not produce significantly influence on NPLs directly.

Then we turn to analyzing control variables, the coefficients of *Pgdp* on NPLs are significantly negative, which means *Pgdp* produces negative effect on *NPL*, indicating that if the economic development level is high in a country, it may be faced with low risk in NPLs. This result is consistent with Haniifah (2015), in which the economic development level is represented by the growth of gross domestic product. Similar with *Pgdp*, the effects of *Infla* are also significantly negative, revealing that stable inflation is conductive to lower the NPLs. It is notable that the coefficients of *Nino* are significantly positive in all models, proving that EI Nino years will cause severe climate change, influenced by climate change and natural disasters, managers cannot repay the loans, which lead to the increase of NPLs (Chen et al., 2021).

3.3. Time lag effect

The long-term economic consequences of natural disasters cannot be ignored. Some researchers indicate that the occurrence of natural disasters not only influences an economic system in the short term, but that the significant impact will still exist in the long term and may even be greater (Skidmore and Toya, 2002; Akao and Sakamoto, 2018; Chang and Zhang, 2020; Zhao et al., 2022). The reason for this phenomenon is that after natural disasters, it may take some time for economic systems to recover. For example, Miao and Popp (2014) point out that the effects of natural disasters on economies are spread over the long term. Furthermore, Zhao et al. (2022) conclude that the negative impact of natural disasters on energy innovation not only exist in the current year, but also exist 4 years after the occurrence by examine the impact lagging 1–5 years. Thus, it is more appropriate to take the dynamic effects of natural disasters into consideration. Following Doytch (2020) and Zhao et al. (2022), we add the lagged 5 terms of natural disasters and construct a new model:

$$NPL_{it} = \alpha + \rho_j \times Death_{it,j} + \gamma_k \times Risk_{kit} + \sum_{l=1}^{m} \beta_l Z_{it,l} + \delta_i + \sigma_t + \varepsilon_{it} \tag{2}$$

Here, j represents the lagged rank of natural disasters, ρ_0 represents the effect of natural disaster on current NPLs, and ρ_1, ρ_2, ρ_3, ρ_4, and ρ_5 are the coefficients of natural disaster in the previous one to five years, respectively. The other symbols are the same as those in Eq. (1). The empirical results are listed in Table 4.[2] It is seen that when taking the lagged terms of natural disasters into consideration, the significant impact of natural disasters on NPLs still exists. This finding reminds researchers and policy maker not only to consider the immediate impact of natural disasters on the economy, but also the long-term impact, and to plan for economic recovery and reconstruction after natural disasters from the perspective of long-term sustainable development.

3.4. Moderating effects of financial risk

With the significant increase in the frequency of natural disaster events, their impact has gradually spread to the real economy, leading to sluggish consumption, investment, and economic recession (Dell et al., 2014). The connection between the real economy and the financial system has become increasingly closer, and the impact of natural disasters on the real economy will inevitably be transmitted to the financial system and institutions, affecting financial stability and generating a series of financial risks. Since financial performance may create moderating effects on economic development (Wahba, 2008), Chen and Chang (2020) also prove that natural disasters create moderating effects on financial development through financial risk. Therefore, we next take moderating effects (i.e., the interaction term of natural disasters and financial risks) into consideration to test whether natural disasters will affect NPLs through financial risks. The overall aim of the financial risk rating is to provide a means of assessing a country's ability to pay its way. In essence, this requires a system of measuring a country's ability to finance its official, commercial, and trade debt obligations.[3] Following Chen and Chang (2020), we add an interaction term between natural disasters and financial risks in Eq. (3).

$$NPL_{it} = \alpha + \rho_j \times Death_{it,j} + \eta_{kj} \times Death_{it,j}{*}Risk_{kit} + \gamma_k \times Risk_{kit} + \sum_{l=1}^{m} \beta_l Z_{it,l} + \delta_i + \sigma_t + \varepsilon_{it} \tag{3}$$

Here, η_{kj} presents the coefficient for the moderating effect between natural disasters and the k^{th} financial risk. The other symbols are the same as those in Eq. (1). The empirical results with moderating effects are shown in Table 5.

[2] We only report the results with a lag of 1, 3, and 5 years due to the limited length of the paper.

[3] This is done by assigning risk points to a pre-set group of factors, termed financial risk components. The minimum number of points that can be assigned to each component is zero, while the maximum number of points depends on the fixed weight that a component is given in the overall financial risk assessment. In every case the lower the risk point total is, the higher is the risk, where conversely the higher the risk point total is, the lower is the risk. To ensure comparability between countries the components are based on accepted ratios between measured data within the national economic/financial structure. It is the ratios that are compared and not the data themselves. The risk points assigned to each component (ratio) are taken from a fixed scale.

Table 4
The time lag effect of natural disasters on NPLs (1–5 years).

Variable	(1)	(2)	(3)	(4)	(5)
Death$_{-1}$	0.0198*	0.0203*	0.0201*	0.0203*	0.0203*
	(1.86)	(1.92)	(1.90)	(1.92)	(1.91)
Death$_{-3}$	0.0421*	0.0427*	0.0431*	0.0432*	0.0431*
	(1.86)	(1.88)	(1.91)	(1.91)	(1.90)
Death$_{-5}$	0.0040*	0.0040*	0.0041*	0.0041*	0.0040*
	(1.71)	(1.71)	(1.76)	(1.76)	(1.74)
Risk1	0.1377*				
	(1.85)				
Risk2		-0.1177			
		(−1.00)			
Risk3			-0.2795***		
			(−3.14)		
Risk4				-0.4749***	
				(−2.96)	
Risk5					0.1140
					(0.92)
Pgdp	-4.8226***	-4.5639***	-4.7224***	-4.2145***	-4.6789***
	(−7.33)	(−6.94)	(−7.26)	(−6.32)	(−7.17)
Trade	-0.0084	-0.0119	-0.0107	-0.0116	-0.0101
	(−0.95)	(−1.35)	(−1.23)	(−1.33)	(−1.16)
Infla	-0.0254	-0.0256	-0.0258	-0.0276	-0.0216
	(−1.42)	(−1.43)	(−1.44)	(−1.54)	(−1.16)
Exch	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002
	(−1.46)	(−1.32)	(−1.53)	(−1.34)	(−1.31)
Deposit	-0.0015	-0.0034	-0.0039	-0.0024	-0.0029
	(−0.34)	(−0.77)	(−0.89)	(−0.56)	(−0.66)
Nino	5.1552***	5.1474***	5.1372***	4.8215***	5.0350***
	(5.43)	(5.39)	(5.44)	(5.09)	(5.32)
cons	45.8469***	45.8815***	49.2556***	43.0580***	44.6626***
	(8.43)	(8.42)	(8.87)	(7.85)	(8.09)
Country	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
N	1717	1717	1717	1717	1717
R-squared	0.0543	0.0529	0.0581	0.0575	0.0528
F test	3.3813	3.2862	3.6324	3.5902	3.2796

Notes: *t* statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Similar with the analysis without moderating effects, we first consider the static results in columns 1–5 in Table 5. The coefficients of *Death* on *NPL* are significantly positive in all models, further proving that natural disaster will create an increase in NPLs. The coefficients of *Risk3* and *Risk4* are significantly negative, while the coefficients of *Risk1*, *Risk2* and *Risk5* are not significant, indicating that *Risk3* and *Risk4* will produce significant influence on NPLs while *Risk1, Risk2* and *Risk5* do not, which is consistent with the results without moderating effects. The coefficients of *Deathrisk1*, *Deathrisk2*, *Deathrisk3*, *Deathrisk4* and *Deathrisk5* are 0.132, 0.0451, 3.146, 0.732 and 2.097, respectively, with t-test values of 1.86, 2.05, 2.51, 2.75 and 2.33. This result shows that natural disasters not only increase NPLs directly, but also affect NPLs through the type of financial risk. It is worth noting that *Risk1*, *Risk2*, and *Risk5* do not affect NPLs directly, but if there exist these financial risks in a country, then when natural disaster occurs, NPLs rise not only from damages caused by natural disasters directly, but also from the moderating effects through these financial risks.

During our analysis, all control variables are also taken into consideration, and the effects are similar with the results that do not introduce moderating effects. Here, *Pgdp* and *Infla* produce significantly negative effects on *NPL*, while the effects of *Nino* on *NPL* are significantly positive. When taking moderating effects into analysis, a high level of economic development and stable consumer price index can help lower NPLs in a country, but EI Nino years lead to an increase of NPLs.

3.5. Robustness tests

We next conduct robustness tests from three aspects to ensure that the empirical results are reliable. First, we use a new financial indictor to measure bank performance. Second, we replace the index for natural disasters. As property loss is another important thing impacted by natural disasters, we employ total loss caused by natural disasters as an indicator of them. Third, we carry out an empirical analysis using different time periods.

3.5.1. A new financial index

We now use the country-level Z-score (*Z*) to measure the development level of a banking system and explore the influence of natural disasters and their moderating effects. The empirical results are in Table 6.

Table 5
The moderating effect of natural disasters on NPLs.

Variable	(1)	(2)	(3)	(4)	(5)
Death	0.0096 **	0.115 **	3.061**	0.577**	2.000 **
	(2.06)	(2.12)	(2.45)	(2.17)	(2.28)
Deathrisk1	0.132 *				
	(1.86)				
Deathrisk2		0.0451 **			
		(2.05)			
Deathrisk3			3.146*		
			(2.51)		
Deathrisk4				0.732**	
				(2.75)	
Deathrisk5					2.079 **
					(2.33)
Risk1	-0.0955				
	(−0.58)				
Risk2		-0.148			
		(−0.90)			
Risk3			-0.976***		
			(−5.30)		
Risk4				-0.726***	
				(−3.64)	
Risk5					-0.139
					(−1.00)
cons	10.20***	9.304***	8.548***	7.526***	9.844***
	(4.74)	(3.84)	(3.98)	(3.31)	(4.39)
Country	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
N	2222	2222	2222	2222	2222
R-squared	0.1093	0.1872	0.1719	0.1229	0.1881
F test	21.21	21.25	21.74	21.37	21.28

Notes: *t* statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 6
Robust tests of the new financial index.

Variable	(1)	(2)	(3)	(4)	(5)
Death	0.0261 **	1.433 *	1.286 **	0.053 * *	0.0510 **
	(2.21)	(1.83)	(2.01)	(2.24)	(2.04)
$Risk_1$	-0.300*				
	(−2.24)				
$Risk_2$		-0.700***			
		(−5.38)			
$Risk_3$			-0.305*		
			(−2.05)		
$Risk_4$				-0.380*	
				(−2.35)	
$Risk_5$					-0.172 *
					(−1.69)
cons	5.005**	9.202***	4.983*	2.798	3.506
	(2.58)	(4.36)	(2.56)	(1.38)	(1.75)
Control variables	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
N	2156	2156	2156	2156	2156
R-squared	0.1851	0.3052	0.1813	0.1855	0.1709
F test	64.92	65.28	65.24	64.93	64.28

Notes: *t* statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Comparing the empirical results in Table 6 and Table 4, we find that the coefficients of *Death* are positive and statistically significant at the 10% level in all models, indicating that natural disasters increase the value of country-level Z-score and raise the risk of bank bankruptcy. The moderating effects of natural disasters on the Z-score through financial risks are significantly positive, denoting that natural disasters raise the chance of bank bankruptcy through financial risks. Different from Table 4, the coefficients of *Risk1*, *Risk2*, *Risk3*, *Risk4*, and *Risk5* are significantly negative, indicating that all financial risks enhance the risk of bank bankruptcy. However, the main results, including the effects of control variables, are similar with those in Table 4, which confirms the credibility of our analysis.

Table 7
Robust tests of the new natural disaster index: *Pdeath*.

Variable	(1)	(2)	(3)	(4)	(5)
Pdeath	0.0145**	0.0142**	0.0132**	0.0157**	0.0142**
	(2.18)	(2.08)	(2.19)	(2.47)	(2.16)
$Risk_1$	0.0294				
	(0.19)				
$Risk_2$		-0.2581			
		(−1.00)			
$Risk_3$			-0.3545*		
			(−1.84)		
$Risk_4$				-0.7312**	
				(−2.34)	
$Risk_5$					-0.0868
					(−0.82)
cons	8.9084***	11.0525***	12.8565***	10.4709***	9.7040***
	(4.80)	(4.10)	(5.02)	(7.08)	(5.79)
Control variables	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
N	2156	2156	2156	2156	2156
R-squared	0.0258	0.0287	0.0352	0.0390	0.0261
F test	1.7492	1.7570	1.9031	1.8687	1.7556

Notes: *t* statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

3.5.2. A new indicator of natural disasters

Except for using the number of deaths (*Death*) due to the total of different types of natural disasters to measure natural disasters, we also use the number of deaths divided by total population (proxied by *Pdeath*) to measure natural disasters by following the research of Keerthiratne and Tol (2018) and Lee et al. (2021). The results are listed in Table 7. Following Ward and Shively (2017), to carry out the robustness tests we next adopt the total economic damages (*Loss*) caused by natural disasters and persons affected (*Affected*) as indicators to represent the influence of natural disasters, respectively. *Affected* includes the total number of persons affected from a natural disaster. *Loss* is defined as all estimated economic damages (in US$) caused by a natural disaster. The empirical results are shown in Tables 8 to 9. From the tables we find that the empirical results are almost the same as the basic results, in which the number of deaths from natural disasters is used to reflect the impact of natural disasters. The results further prove that the independent variables are valid, and our empirical results are reliable.

3.5.3. Endogeneity concerns

The regression analysis of the impact of natural disasters on NPLs may have endogeneity problems. The omitted variables and reverse causality are the main reasons for endogeneity in the model (Zhao et al., 2020; Wen et al., 2021; Zhao et al., 2022). It is worth

Table 8
Robust tests of the new natural disaster index: *Loss*.

Variable	(1)	(2)	(3)	(4)	(5)
Loss	0.817 **	0.820 *	1.567 ***	0.389 * *	0.989 **
	(2.00)	(1.79)	(2.61)	(2.49)	(2.51)
$Risk_1$	-0.0264				
	(−0.16)				
$Risk_2$		-0.155			
		(−0.97)			
$Risk_3$			-0.774***		
			(−4.31)		
$Risk_4$				-0.782***	
				(−4.00)	
$Risk_5$					-0.0099
					(−0.01)
cons	10.09***	8.931***	8.299***	6.749**	9.935***
	(4.27)	(3.46)	(3.51)	(2.74)	(4.07)
Control variables	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
N	2156	2156	2156	2156	2156
R-squared	0.1378	0.1748	0.1412	0.1175	0.1361
F test	22.76	22.80	23.13	23.04	22.79

Notes: *t* statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 9
Robust tests of the new natural disaster index: *Affected*.

	(1)	(2)	(3)	(4)	(5)
Affected	2.700***	0.785 *	4.241***	2.138**	0.327 **
	(2.62)	(1.71)	(2.79)	(2.49)	(2.33)
Risk₁	-0.133				
	(−0.80)				
Risk₂		-0.140			
		(−0.85)			
Risk₃			-0.927***		
			(−5.07)		
Risk₄				-0.747***	
				(−3.73)	
Risk₅					-0.110
					(−0.79)
cons	10.38***	9.512***	8.456***	7.476***	10.06***
	(4.82)	(3.92)	(3.92)	(3.27)	(4.48)
Control variables	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
N	2156	2156	2156	2156	2156
R-squared	0.0084	0.0131	0.0165	0.0115	0.0131
F test	21.28	21.23	21.80	21.47	21.21

Notes: *t* statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

noting that the panel fixed effect model used in the basic regression can control the influence of unobservable individual effects (and year effects) that do not change with time to a certain extent and can effectively deal with the endogeneity problem caused by missing variables. Control variables that are shown to have a significant impact on NPLs, including *Pgdp*, *Infla*, etc., have also been considered. Therefore, endogeneity issues arising from omitted variables are less troubling to empirical results. However, endogeneity caused by reverse causality is difficult to control. To this end, following Chen et al. (2021), this study further adopts the system GMM method to deal with the endogeneity problem mainly caused by reverse causality.[4] The results are listed in Table 10. Here, we see that the Hansen test does not reject the null hypothesis that the instrumental variables are valid, and the AR (2) test does not reject the null hypothesis that there is no second-order serial correlation in the random error term of the first-order difference equation. The result of the coefficient of lagged *NPLs* is significantly positive at the 1% level, which implies that non-performing loans are persistent and dynamic. Moreover, the effects of natural disasters on NPLs are positive and statistically significant at 10% level, further revealing the fact that natural disasters lead to an increase of NPLs. Therefore, we conclude after considering the possible endogeneity problems that the nexus between natural disasters and NPLs is still robustly significant.

3.5.4. A different time period

The 2008 financial crisis had a severe impact on economic development all over the world, and there exist international linkages between financial development and potential influence of a crisis (Rose and Spiegel, 2010). Therefore, referring to Ramcharan (2007), we take the year 2008 as a breakpoint and conduct empirical analysis over the time periods of 1996–2008 and 2008–2017, respectively. The results appear in Table 11. The coefficients of *Death* are nearly the same with the basic results, indicating that the effects of natural disasters are consistent before and after the 2008 financial crisis. Overall, the results stay similar with the analysis above, thus again confirming that our analyses are reliable.

4. Further analysis

Countries with a high level of economic development are equipped with better infrastructure, and so when a natural disaster occurs, banking systems in these countries encounter less damage than do low-income countries (Keerthiratne and Tol, 2017). Therefore, we examine whether the effects of natural disasters on NPLs exhibit heterogeneity. Zheng et al. (2019) point out that OECD countries reflect substantial heterogeneity compared to non-OECD countries. Therefore, we conduct analysis for the sub-samples of OECD and non-OECD countries and present the empirical results in Table 12.

Table 12 shows that the effects of natural disasters on NPLs present several differences between the sub-samples. The coefficients of *Death* are not statistically significant in the sub-sample of OECD countries, while they are significantly positive in non-OECD

[4] The GMM method has the following two advantages in estimating dynamic panel methods. First, it is still valid in the presence of a unit root. Second, and more importantly, it solves the endogeneity problem between dependent variables and independent variables by using instrumental variables appropriately. Moreover, GMM estimation methods include differential GMM and system GMM, but differential GMM cannot estimate the coefficients of variables that do not change with time and is prone to weak instrumental variables. In contrast, system GMM can overcome the limitation of the differential GMM estimation and improve the estimation efficiency. Thus, the study here chooses the system GMM estimation method.

Table 10
Robustness tests: The GMM estimator results.

Variable	(1)	(2)	(3)	(4)	(5)
L.NPLs	0.8277***	0.8263***	0.7774***	0.8013***	0.8197***
	(25.80)	(25.94)	(23.18)	(24.14)	(25.19)
Death	0.0225*	0.0232*	0.0161	0.0227*	0.0229*
	(1.68)	(1.76)	(1.11)	(1.69)	(1.76)
$Risk_1$	0.0062				
	(0.15)				
$Risk_2$		-0.0515			
		(−0.71)			
$Risk_3$			-0.0659		
			(−0.94)		
$Risk_4$				-0.1495	
				(−0.86)	
$Risk_5$					0.0536
					(0.80)
cons	0.2984	0.1007	0.0271	-1.4576	-0.5655
	(0.17)	(0.05)	(0.02)	(−0.42)	(−0.18)
Control variables	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
AR (1)-P	0.003	0.003	0.002	0.002	0.003
AR (2)-P	0.205	0.206	0.201	0.204	0.203
Hansen-P	0.600	0.631	0.561	0.522	0.489
N	2121	2121	2121	2121	2121
F test	75.3327	76.3492	83.0391	73.7657	81.8320

Notes: *t* statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

countries. The reason may be that OECD countries own perfect financial systems that can provide support for those enterprises suffering severe losses from natural disasters, which is consistent with the opinion of Toya and Skidmore (2007).

5. Conclusions and policy implications

5.1. Conclusions

This paper analyzes the effects of natural disasters on NPLs from a global perspective. Panel data covering 101 countries from 1996 to 2017 are employed, and moderating effects of natural disasters through financial risks are introduced during our analysis. Moreover, empirical analysis is carried out to investigate whether there exists heterogeneity between the sub-samples of OECD and non-OECD countries.

Several conclusions can be drawn from the empirical results. (1) Natural disasters produce significant effects on NPLs both in current and one-period lag terms. (2) Financial risks have differentiated effects on NPLs. current account and international liquidity do produce a significantly negative influence on NPLs, while total foreign debt, debt service, and exchange rate stability do not. (3) Natural disasters increase NPLs through five kinds of financial risks, and the moderating effects are statistically significant. (4) The direct effects of natural disasters on NPLs are not significant in OECD countries, and the moderating effects of natural disasters through financial risks exhibit heterogeneity between OECD and non-OECD countries.

5.2. Policy implications

According to the empirical results above, several suggestions and policy implications are proposed as follows.

(1) The dynamic and moderating effects when assessing the influence of natural disasters. Since the effects of natural disasters on NPLs are significant in one-period lag terms and there exist significant moderating effects through financial risks, policy makers should take these effects into consideration when analyzing the impact of natural disasters on NPLs.
(2) Protect the environment to prevent natural disasters. Climate change is an important factor that causes natural disasters (Chen and Chang, 2021). Governments all around the world should develop clean energy technologies and improve pollution treatment to reduce the emissions of greenhouse gases. At the same time, strict environmental laws should be established, and residents' awareness of environmental protection should be strengthened so as to reduce the occurrence of natural disasters.
(3) Lower financial risks and perfect the economic system. Higher financial risks do bring about an increase of NPLs, and when a natural disaster occurs, the existence of financial risks further aggravates the influence of natural disasters on NPLs. Additionally, NPLs in countries with a higher level of economic development are less influenced by natural disasters than those in low-income countries. Thus, governments should construct a perfect economic system and establish measures to lower financial risks, such as improving production technology to increase revenue and raising the issuance of currency suitably.

Table 11
Robust tests of different time periods.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Full sample: 1996–2008					Full sample: 2008–2017				
Death	0.103 ***	0.433 **	3.520**	1.273**	2.192 *	1.660 *	0.396 **	3.135 **	1.752 *	4.901 ***
	(2.65)	(2.43)	(2.54)	(2.48)	(−1.68)	(1.93)	(2.21)	(2.23)	(1.68)	(2.87)
Risk1	-0.415					-0.219				
	(−1.77)					(−0.66)				
Risk2		-0.227					-0.122			
		(−1.05)					(−0.61)			
Risk3			-0.648**					-0.263		
			(−2.75)					(−1.10)		
Risk4				-0.196					-1.038***	
				(−0.88)					(−3.41)	
Risk5					-0.180					-0.266
					(−1.17)					(−1.49)
cons	15.08***	13.76***	12.94***	14.51***	13.89***	21.47*	20.83*	20.40*	14.80	16.92
	(5.02)	(4.22)	(4.20)	(4.79)	(4.27)	(2.44)	(2.37)	(2.35)	(1.69)	(1.88)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1313	1313	1313	1313	1313	1010	1010	1010	1010	1010
R-squared	0.1319	0.1143	0.2056	0.1553	0.1275	0.1981	0.1801	0.2043	0.3356	0.2036
F test	19.12	19.06	19.67	19.49	19.41	24.76	24.82	24.85	25.07	25.03

Notes: *t* statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 12
Heterogeneity analysis: OECD and non-OECD countries.

Variable	(1) OECD	(2)	(3)	(4)	(5)	(6) Non-OECD	(7)	(8)	(9)	(10)
Death	0.269	0.756	0.020	1.055	2.109	0.0282 **	0.557 **	3.098**	0.629**	2.109 **
	(0.28)	(0.18)	(0.00)	(0.51)	(0.15)	(2.19)	(2.30)	(2.56)	(2.38)	(2.40)
Risk1	-1.106**					0.258				
	(−2.66)					(1.40)				
Risk2		-0.301					-0.169			
		(−0.69)					(−0.96)			
Risk3			-3.234***					-0.808***		
			(−3.65)					(−4.46)		
Risk4				-2.282***					-0.222	
				(−4.75)					(−1.01)	
Risk5					-0.359					-0.0856
					(−0.80)					(−0.60)
cons	-15.28	-25.67*	-24.27**	-21.66*	-24.36*	12.72***	10.98***	10.42***	11.20***	11.84***
	(−1.58)	(−2.55)	(−2.64)	(−2.37)	(−2.58)	(6.14)	(4.78)	(5.12)	(5.01)	(5.58)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	616	616	616	616	616	1606	1606	1606	1606	1606
R-squared	0.3946	0.2821	0.3776	0.6402	0.1155	0.1337	0.1224	0.2234	0.1362	0.1285
F test	23.00	22.46	26.25	34.03	22.44	19.43	19.34	19.74	19.40	19.46

Notes: *t* statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

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