How do the intensity and damages of natural disasters affect economic vulnerability and the risk of financial crises across countries over time?

Maddalena Bruscagin, Ambroise Roesch

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"Do Natural Disasters Increase the Risk of Financial Crises?",
Daniel Fichmann (2023)

1 The paper

1.1 Context and motivation

Natural disasters are prominent in the global economic landscape, with significant implications for financial stability and economic vulnerability. These disasters often result in severe direct impacts, such as infrastructure damage, loss of property, and immediate economic disruptions, as well as long-term indirect consequences like reduced growth potential, increased unemployment, and systemic risks within the financial system. Understanding how disasters influence macroeconomic variables is crucial for policymakers, insurers, and financial institutions aiming to mitigate the adverse effects on both national and global economies. Disasters can lead to increases in government debt-to-GDP ratios due to reconstruction spending and insurance payouts. Shifts in unemployment rates, real wages, and exchange rates reflect the economic disorganization caused by such crises. In certain cases, as noted in historical instances like the San Francisco earthquake of 1906, natural disasters have even triggered systemic financial crises, underscoring their role in amplifying existing vulnerabilities within financial markets. The existing literature highlights the growing risks posed by "mega environmental risks" in the context of climate change. Scholars like Klomp and Valckx (2014) have demonstrated that climatic disasters disproportionately impact developing economies, amplifying their economic vulnerabilities. Meanwhile, insights from theoretical models, such as those proposed by Cavallo, Galiani, and Noy (2013), emphasize the importance of examining the long-term consequences of disasters on economic growth.

1.2 The model

The paper employs econometric models to analyze the impact of natural disasters on the likelihood of financial crises, with a focus on systemic crises. The primary model is a logistic regression (logit model), specified to estimate the probability of a crisis occurring in a given year. The dependent variable is a binary crisis indicator, and the key explanatory variable is the measure of disaster damages as a percentage of GDP, lagged across multiple periods $(t-1, t-2, \ldots)$ to capture delayed effects. The model includes country-fixed effects to control for unobserved, time-invariant heterogeneity and a set of control variables like credit growth and economic growth to address confounding factors.

The logit model is specified as follows:

$$\text{logit}(p_{i,t}) = \alpha_i + \sum_{j=0}^{4} \beta_j D_{i,t-j} + \phi X_{i,t} + e_{i,t}$$

Here, $p_{i,t}$ represents the probability of a crisis in country i at time t, $D_{i,t-j}$ denotes lagged disaster damages, and $X_{i,t}$ includes additional control variables. α_i accounts for country-fixed effects, while $e_{i,t}$ is the error term.

As a robustness check, the paper also uses a Linear Probability Model (LPM), which is specified as:

$$\text{Crisis}_{i,t} = \alpha_i + \gamma_t + \sum_{j=0}^{4} \beta_j D_{i,t-j} + \phi X_{i,t} + e_{i,t}$$

In this model, $\text{Crisis}_{i,t}$ is the binary indicator of a crisis, γ_t represents year-fixed effects to control for time-specific factors, and the remaining terms are as defined above. While the LPM allows for year-fixed effects, it assumes a linear relationship between the independent variables and crisis probability, which can be a limitation for binary outcomes.

The disaster damages variable, $D_{i,t}$, is created by summing the weighted damages of qualifying disasters in country i and year t, adjusting for inflation, and standardizing by real GDP. The formula is as follows:

$$D_{i,t} = \left(\frac{\sum_{d=1}^{n} \tilde{d}_{i,t}}{\text{CPI}_{i,t}} \right) \frac{1}{\text{rGDP}_{i,t}} \times 1000,$$

where $\tilde{d}_{i,t} = d_{i,t} \cdot \frac{12-\text{OM}}{12}$ is the weighted damage for each disaster d, OM is the onset month of the disaster, $d_{i,t}$ is the estimated damage (in current U.S. dollars), $\text{CPI}_{i,t}$ is the Consumer Price Index for inflation adjustment, and $\text{rGDP}_{i,t}$ is real GDP. The scaling factor of 1000 ensures that a one-unit change in $D_{i,t}$ corresponds to 0.1

Additionally, local projections are employed to analyze the dynamic effects of disasters on economic growth, credit expansion, and bank equity returns. Interaction terms between disaster damages and credit growth are also included to test whether periods of rapid credit expansion amplify the effects of disasters.

This multi-model approach ensures robustness and allows the paper to provide nuanced insights into how disasters affect financial stability.

1.3 Why implement a simulation

We conducted some simulations in order to critically analyze the key hypotheses and design of the paper, addressing potential doubts and limitations. By replicating the relationships between disaster damages, credit growth, and fiscal capacity under controlled conditions, we aimed to validate the paper's findings and explore scenarios not fully represented in historical data. Simulations are a powerful tool because they allow us to test for potential issues, such as omitted variable bias, where excluding critical variables like disaster damages or fiscal capacity could lead to inflated or biased coefficients. They also enable us to assess the robustness of the paper's conclusions by introducing realistic random errors and varying model assumptions. Through these simulations, we were able to examine the interplay between variables, detect biases, and understand the conditions under which the results of the paper hold true. This process highlights the importance of simulations as a complementary tool for validating theoretical models and addressing limitations in empirical research design.

2 Replication

2.1 The main regression results

To better understand the paper and for better data manipulation, we replicated the main results, i.e. the table of the main regressions (in the paper called Table 2). The first set of regression models evaluates the relationship between strong natural disasters, measured as standardized damages as a percentage of GDP, and the probability of a financial crisis. The models are estimated using logistic regression and ordinary least squares (OLS) with clustered standard errors to address heteroskedasticity. Key findings from this table reveal that contemporary damages from strong disasters (Damages_t) do not exhibit a statistically significant direct effect on crisis risk across all models. However, lagged effects of disaster damages appear to gain significance in some specifications. For instance, Damages_{t-2} shows a positive and marginally significant relationship with crisis risk in models that include country fixed effects. The results suggest that the impact of natural disasters on crises may materialize with a delay rather than immediately. The restricted sample from 1950–2020 enhances the significance of the second and third lags of disaster damages, indicating potential structural changes in the global economy or data quality improvements over time. Interestingly, the inclusion of fixed effects changes the estimates substantially. Country fixed effects control for unobserved heterogeneity across nations. These additions improve the explanatory power of the models, as seen in the adjusted R^2 and log-likelihood values. Compared to the original table, the following one includes an additional column (number 6) which isolates the period from 2000 to 2020, which we have added. The reason for this addition is to want to observe the effects in our contemporary years, in order to address today's policy makers. A significant effect can be seen in Damages$_{t-3}$, which also carries a significant meaning.

Table 1: Effect of a strong natural disaster on crisis risk (1900 - 2020)

	Dependent Variable: Crisis in *year* = *t*					
		logistic		*OLS*		*logistic*
	(1)	(2)	(3)	(4)	(5)	(6)
$Damages(pcGDP)_t$	−0.171	−0.148	−0.111	−0.001	−0.0002	−0.558
	(0.185)	(0.176)	(0.202)	(0.001)	(0.0004)	(0.828)
$Damages(pcGDP)_{t-1}$	0.009	0.012	0.098*	−0.00002	0.00004	0.072
	(0.030)	(0.033)	(0.059)	(0.001)	(0.001)	(0.129)
$Damages(pcGDP)_{t-2}$	0.058***	0.060***	0.165***	0.005***	0.006***	0.082
	(0.006)	(0.006)	(0.054)	(0.002)	(0.002)	(0.106)
$Damages(pcGDP)_{t-3}$	0.060*	0.062	0.166*	0.005	0.002	0.346***
	(0.036)	(0.040)	(0.095)	(0.006)	(0.002)	(0.129)
Country fixed effects	*No*	*Yes*	*Yes*	*No*	*Yes*	*Yes*
Year fixed effects	*No*	*No*	*No*	*No*	*Yes*	*No*
Restricted sample	*No*	*No*	*Yes*	*No*	*No*	*Yes*
Observations	2,084	2,084	1,278	2,084	2,084	378
Adjusted R^2				0.005	0.204	
Log Likelihood	-268.928	-262.137	-113.029			-44.488
Residual Std. Error				0.167	0.149	
F Statistic				3.542***	4.898***	
Note:	*p<0.1; **p<0.05; ***p<0.01 Cluster-robust standard errors are shown in parentheses.					

2.2 The Role of Credit Model

We also replicated the results presented in Table 3, which tests the hypothesis that natural disasters are particularly risky when they occur during periods of credit expansion. The model is based on the following equation:

$$\text{logit}(p_{i,t}) = \alpha_i + \beta\overline{D_{M5}} + \delta\overline{C_{M5}} + \lambda(\overline{D_{M5}} \times \overline{C_{M5}}) + \phi X_{i,t} + e_{i,t},$$

where $\overline{D_{M5}}$ represents the 5-year moving average of disaster damages, $\overline{C_{M5}}$ is the 5-year moving average of the log change in real total debt, and $X_{i,t}$ is a vector of control variables. Table 3 presents results from both logistic and OLS regressions, with the dependent variable being the probability of a financial crisis in year t. Key explanatory variables include lagged disaster damages and credit growth, as well as their interaction term to assess the combined effect. The results demonstrate that credit growth, particularly lagged values, plays a significant role in amplifying crisis risk, as evidenced by its consistently significant coefficients. These findings are essential for our simulations, where credit growth is a central variable, allowing us to further test the robustness of these relationships and explore omitted variable bias and interaction effects under controlled conditions.

Table 2: Interaction credit expansions and natural disasters (1900 - 2020)

	Dependent Variable: Crisis in $year = t$					
	logistic				*OLS*	
	(1)	(2)	(3)	(4)	(5)	(6)
$Damages(pctGDP)_t$	−0.125	−0.124				
	(0.155)	(0.154)				
$Damages(pctGDP)_{t-1}$	0.033	0.033				
	(0.030)	(0.030)				
$Damages(pctGDP)_{t-2}$	0.074	0.078				
	(0.009)	(0.013)				
$Damages(pctGDP)_{t-3}$	0.078	0.078				
	(0.043)	(0.044)				
$\Delta Credit_{t-1}$	−0.333	−0.319				
	(1.451)	(1.472)				
$\Delta Credit_{t-2}$	8.137	8.155				
	(2.050)	(2.066)				
$\Delta Credit_{t-3}$	−0.537	−0.526				
	(1.198)	(1.214)				
$\Delta Credit_{t-4}$	1.931	1.929				
	(0.894)	(0.894)				
Damages 5yr ma			0.184	−0.080	0.008	0.003
			(0.057)	(0.089)	(0.001)	(0.002)
Credit 5yr ma			9.554	8.293	0.199	0.179
			(2.459)	(2.211)	(0.046)	(0.050)
$Damages_{t-2} \times \Delta Credit_{t-2}$		−0.245				
		(0.701)				
Damages ma $\times \Delta Credit$ ma				9.948		0.299
				(2.053)		(0.182)
Constant	−5.321	−5.319	−5.320	−5.688	−0.033	−0.037
	(0.219)	(0.217)	(0.184)	(0.176)	(0.005)	(0.006)
Country fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year fixed effects	*No*	*No*	*No*	*No*	*Yes*	*Yes*
Observations	1,964	1,964	1,966	1,966	1,966	1,966
Adjusted R^2					0.222	0.224
Log Likelihood	-233.230	-233.208	-240.674	-235.443		
Residual Std. Error					0.148	0.148
F Statistic					5.165	5.180

Note: p<0.1; p<0.05; p<0.01
Cluster-robust standard errors are shown in parantheses.

3 The simulations

The simulations we conducted progressively increased in complexity to test various aspects of the model discussed in the paper, ensuring alignment with its assumptions and findings.

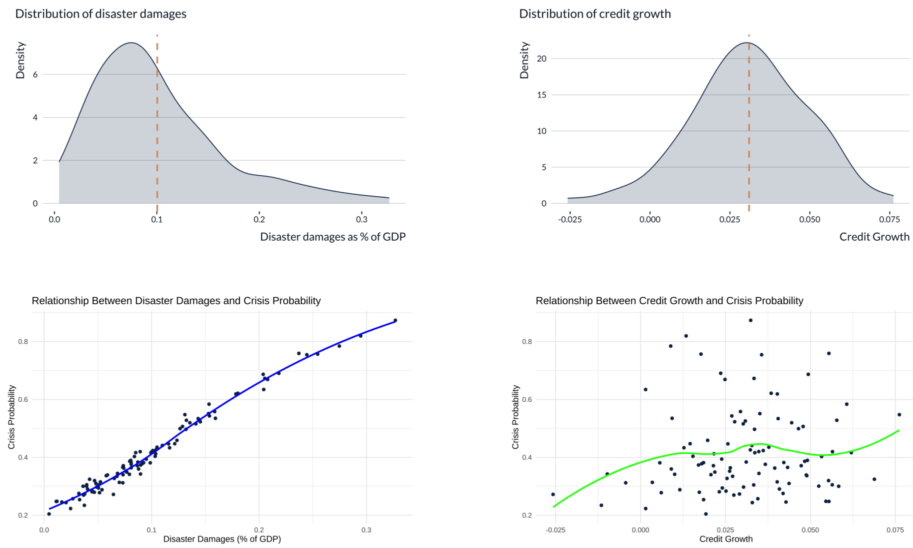
We began with a basic simulation, including only two variables: `disaster_damages` and `credit_growth`. Disaster damages were modeled using a right-skewed gamma distribution, consistent with the paper's emphasis on the rare but extreme nature of natural disasters. Credit growth was generated using a normal distribution, reflecting economic variability in credit expansion. The results highlighted how these variables influenced crisis probability, with disaster damages showing a stronger effect, which aligns with the paper's hypothesis on the critical role of disasters in triggering financial instability.

Next, we implemented the Credit Role Model from the paper, which interacts disaster damages and credit growth to explore their combined impact on crisis risk. The parameters for the interaction term were chosen to reflect a moderate reinforcing effect, as suggested by the theoretical discussion in the paper. By coding this interaction explicitly, we observed that credit growth amplified the effect of disaster damages, supporting the paper's findings that credit booms exacerbate financial vulnerabilities in the presence of natural disasters.

In a subsequent simulation, we refined the relationship between `disaster_damages` and `credit_growth` by making credit growth a function of disaster damages. This adjustment acknowledges the possibility that disasters may directly influence economic conditions, including credit markets, through mechanisms such as reduced fiscal space or banking system stress. When we omitted `disaster_damages` from the regression model, the results revealed clear signs of omitted variable bias. Specifically, the effect of disaster damages was absorbed into the `credit_growth` coefficient, inflating its magnitude and significance. This exercise highlighted the importance of including key explanatory variables to avoid misattribution of effects, aligning with the paper's methodology and caution about model design.

Finally, we introduced fiscal capacity as an additional explanatory variable, hypothesizing that higher fiscal capacity could mitigate the impact of disasters on crisis risk. Fiscal capacity was modeled using a gamma distribution and normalized, representing institutional resilience. Credit growth was then modeled as a function of fiscal capacity, reflecting its stabilizing influence on the economy. When included in the model, fiscal capacity had a modest but statistically insignificant effect, while disaster damages remained significant. However, omitting fiscal capacity caused slight changes in the coefficients for credit growth and disaster damages, demonstrating how neglecting structural variables could bias results and lead to incomplete conclusions. This finding emphasizes the importance of controlling for fiscal capacity when analyzing the interplay of disasters and financial crises.

To validate our assumptions and highlight the relationships, we will include graphs showing the distributions of the key variables (`disaster_damages`, `credit_growth`) and their relationships with crisis probability.



4 Conclusion

Our analysis confirms that natural disasters significantly impact financial crises, particularly when combined with rapid credit growth. Simulations validated the paper's findings, highlighting the importance of including key variables like fiscal capacity to avoid omitted variable bias. While fiscal capacity had limited direct effects, its role in mitigating crisis risk was evident.