Do Natural Disasters Increase the Risk of Financial Crises?

Daniel Fichmann

May 2023 | Most recent version

1 Introduction

Natural disasters pose a serious threat to the stability and prosperity of economies around the world. They are a familiar and well-studied shock. While previous studies have examined how natural disasters affect economic growth, employment, and credit (Botzen et al., 2019; Klomp & Valckx, 2014), this paper is the first to directly investigate their impact on crisis-risk. Doing so is important because the frequency of natural disasters has drastically increased in the last half century and is projected to continue to increase as a result of climate change (see Figure 1). By identifying the channels through which natural disasters increase crisis-risk, this line of research can help inform policies that are aimed at making our economies more climate resilient.

My aim is to estimate the effect that natural disasters have on the risk that a financial crisis occurs. To do so I use the Emergency Events Database (EM-DAT) and a historical dataset constructed by Schularick and Taylor (2012). The merged data covers 18 countries over 120 years. In the analysis I proceed as follows: First, I estimate a set of logit and linear probability models with a binary crisis indicator as the dependent variable. The key explanatory variables are a set of lagged disaster measures and I also control for other macroeconomic indicators and fixed effects. Second, I use local projections to analyze the dynamic impact disasters have on credit, bank equity return, and growth. And third, I conduct in and out-of-sample crisis prediction.

I find that a 0.1% of GDP increase in damages from natural disasters increases the odds of a crisis occurring two years later by 6% to 18%. Moreover, when I interact credit growth with disaster damages the estimated effect is positive and significant, while the effect of the disaster shock alone shrinks. The results support the hypothesis that natural disasters increase the risk of financial crises, and that this risk is amplified by periods of rapid credit expansion. The dynamic analysis shows that disasters have a persistent negative effect on economic growth and bank equity returns, but only a very small, positive, and mostly insignificant impact on credit. The logit model had some predictive power both in and out-of-sample even when including only fixed effects and disaster variables.

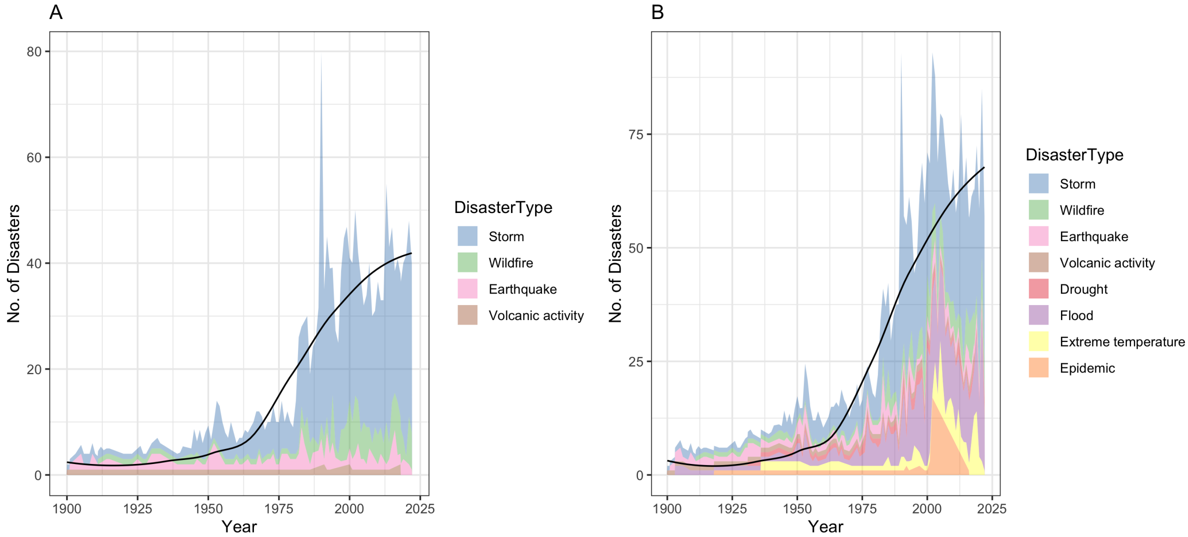
This research and its findings are especially important in light of the fact that natural disasters are quickly becoming more damaging and more frequent. Since 1950, climate change has drastically increased the frequency and damage of storms, wildfires, droughts, floods, extreme temperatures, and even epidemics (IPCC, 2022). According to projections by the International Panel on Climate Change, the increase in frequency and ferocity of disasters will only further accelerate. Deepening our understanding of the impact that these disasters have on the financial system is therefore a crucial component to mitigating and preparing for the costs of future climate induced disasters.

1.1 Historic Examples

Noteworthy historic examples of extreme natural disasters that have had a significant impact on crisis-risk, include the 1906 San Francisco earthquake, the 1923 and 1995 earthquakes in Japan, and the 1999 earthquake in Turkey. In Turkey, the earthquake in 1999 coincided with a number of adverse financial conditions: In the late 1990s the Asia Crisis and Russian debt default put pressure on the portfolios of Turkish banks, which were also holding a quickly increasing level of public debt. When the Marmara earthquake caused damages of up to US$20 billion (11% of GDP) in 1999, the exposure of banks to government debt in combination with the heightened fear of sovereign default looming, eventually led to a panic that pushed eight banks into insolvency, triggering a financial crisis in 2001 (Akyüz & Boratav, 2002; Koch et al., 2001).

The 1995 Kobe earthquake in Japan, shocked the country's capital stock with damages estimated as high as US$100 billion (Horwich, 2000). The reduction of capital belonging

Figure 1: Frequency and Type of Natural Disasters



to firms and households, put pressure on banks' balance sheets, reducing their lending capacity and decreasing their financial health (Hosono et al., 2016). Additionally, over 30% of bank branches in the affected regions were unable to operate in the aftermath of the quake because their physical infrastructure was destroyed (Hosono et al., 2016). This directly weakened the banking system's ability to respond and further worsened its financial stability. The country eventually experienced a banking crisis in 1997 (Nelson & Tanaka, 2014). Earlier in 1923, the Great Kanto earthquake in Japan caused vast destruction of real and financial capital, which is said to have contributed to a spike in non-performing loans that eventually led to a panic followed by a systemic banking crisis in 1927 (Schularick & Taylor, 2012; Tamaki, 1995).

Going even further back in history, some economic historians have argued that the 1906 San Francisco earthquake triggered a chain of events that led to the 1907 panic and financial crisis. The 1906 earthquake ignited a fire that left over half of San Francisco's residents homeless and caused damages of up to 1.8% of GNP (Odell & Weidenmier, 2004). A majority of the costs was actually borne by British, German, and French insurance companies that were liable for the claims. The quake therefore led to a very large (14% of the gold money stock of England) and sudden transfer of gold from the UK to San Francisco in the months following the disaster (Odell & Weidenmier, 2004). To counteract the gold outflows and protect its exchange rate under the gold standard, the Bank of England doubled its discount rate and discriminated against American finance bills (Friedman et al., 1963; Wicker & Tallman, 2009). When Germany and France followed suit it effectively halted the flow of gold to the United States, which led to a liquidity crisis, stock market crash, recession, and finally the panic of 1907 (Friedman et al., 1963; Odell & Weidenmier, 2004).[1]

More recent examples are the Covid-19 pandemic or the 2023 earthquake in Turkey, whose full impact on the financial system we have yet to see. The point of these narratives and this paper is not to argue that natural disasters are the sole cause of crises, but rather to highlight the channels through which they have increased crisis-risk or acted as triggers in combination with other factors. What follows is an empirical investigation of whether this is an observable pattern in the data.

Roadmap

Section II reviews the literature and highlights the contributions of my research approach and results. Section III defines the key variables, gives an overview of the data, and describes the main models and specifications. In Section IV I present and discuss the main empirical results. Section V analyzes the robustness of the earlier findings. Finally, Section VI discusses the weaknesses of the paper and summarizes its findings as well as highlights ways to further extend this line of research.

2 Literature Review

The paper with an aim most similar to mine is Klomp (2014), who uses country-level panel data from 1997 to 2010 across 160 countries to study the effect natural disasters have on bank stability, measured by the World Bank's z-score[2]. Klomp (2014) finds that a large natural disaster significantly decreases the z-score of a country's banking sector, which suggests that they increase the default-risk of banks. Since bank defaults are a known precursor and symptoms of panics, this highlights one of the channels through which natural disasters may increase crisis-risk. Klomp (2014), however, only uses data

[1] To ensure that the United States would not be as vulnerable to future shocks to the money supply, the government put in place institutions that formed the basis of the Federal Reserve System (Odell & Weidenmier, 2004).

[2] Defined as the number of standard deviations that a bank's return on assets has to drop below its expected value before the bank is considered insolvent

that spans 13 years and finds no evidence that natural disasters have an impact on banking crises.[3]

A recent paper by Baron et al. (2020) constructs a historical dataset on bank equity returns for 46 countries. It shows that large declines in bank equity returns are indeed a key feature of banking crises as well as a cause of the associated panics. Combined with the findings of Klomp (2014) that natural disasters decrease bank equity returns, this suggests a potential channel through which disasters increase crisis-risk: If large natural disasters are a negative shock to bank equity returns (as found by Klomp (2014)) and a bank capital crunch can lead creditors to run on banks and trigger a crisis (as shown in Baron et al. (2020)), then that is a clear channel through which strong natural disasters may increase crisis-risk. It also echoes the historic narratives presented in the previous section.

I contribute to this literature by directly testing this link between natural disasters and financial crises using a macrohistory database developed by Schularick and Taylor (2012) that contains an indicator variable for systemic financial crises. Combined with the data on disasters, my analysis uses long-run data on crises, key macroeconomic variables, and natural disasters from 1900 to 2020 for 18 countries, making it, to the best of my knowledge, the first in-depth quantitative analysis of the effect that natural disasters have on systemic financial crises. To test the hypothesis that natural disasters impact crisis-risk through their effect on bank equity returns, I also employ local projections (Jordà, 2005) to analyze the dynamic effects of a disaster shock on returns.

Furthermore, my paper also provides new empirical evidence in support of the financial-accelerator model, developed by Bernanke and Gertler (1989), Bernanke et al. (1999), and Kiyotaki and Moore (1997) who argue that periods of financial fragility and credit expansions amplify shocks. According to the model proposed by Bernanke and Gertler (1989), an economy with adverse financial conditions can experience amplified effects from shocks due to their impact on the cash flows of borrowers. Kiyotaki and Moore (1997) model such a negative feedback loop but focus more on the role of asset prices than on cash flows. In their model, an initial reduction in the total worth of assets from agents

[3] In the final paragraph of the paper, Klomp (2014) use data from Laeven and Valencia (2013) to test the impact of natural disasters on a bank crisis and do not find a statistically significant result. The analysis is more of an extension to the rest of the paper and the lack of significant results is not surprising given that the time period analysed only covers 13 years and banking crises are rare.

who face financial constraints leads to a drop in asset prices, which further reduces the wealth of those agents.

Building on this foundation, newer models show that the state of the financial system can have non-linear effects on the impact of shocks to the economy (Brunnermeier & Sannikov, 2014; He & Krishnamurthy, 2013; Mendoza, 2010). Barnichon et al. (2016) show that the impact of a negative shock to the economy is larger when the financial system is in a fragile state. Furthermore, there is substantial empirical evidence that a large expansion in credit may not only amplify shocks, but itself be a source of them (Baron et al., 2020; Krishnamurthy & Muir, 2017; Schularick & Taylor, 2012). In particular, the findings of Schularick and Taylor (2012) show that past credit expansion is a significant predictor of financial crises and suggest that they could indeed be shocks themselves.

I use natural disasters to identify a shock in order to understand if the negative effect of the shock is larger when it coincides with a credit expansion. In other words, does a natural disaster have a crisis-triggering effect when the financial system is weak? This is unique because (1) it is the first paper to do so using natural disasters as a shock. And (2) natural disasters have the added benefit of truly identifying a stochastic and exogenous shock because the probability of a disaster occurring is unrelated to the current state of economy.

Other studies have used natural disasters as an instrument for local credit demand and shown that they lead to an increase in bank lending in affected areas (Cortés & Strahan, 2017). Given what we know about credit expansions, this could suggest yet another channel through which natural disasters effect crisis-risk. That said, when analysing the dynamic effects of natural disasters on credit growth using local projections, I find almost no significant result.

Regarding the exogenous characteristics of natural disasters, some may argue that since the frequency of disasters has rapidly increased over the last decades (see Figure 1) their occurrence is not entirely stochastic and agents may be able to predict a higher likelihood of disaster in the future. That said, I find it convincing that while economic agents may have a good approximation of the risk that a disaster could occur at any given moment, they generally do not foresee the exact date or year of extreme storms, wildfires, earthquakes, or volcanic activity years or even months in advance. Therefore, these extreme events do indeed qualify as a stochastic and exogenous shock.

3 Data and Empirical Strategy

To estimate the impact natural disasters have on the likelihood of financial crises, I merged the Emergency Events Database (EM-DAT) with historic financial data from Schularick and Taylor (2012). The EM-DAT is a project of the Centre for Research on the Epidemiology of Disasters (CRED) and contains detailed data on over 20 000 natural disasters worldwide between 1900 to the present day. It is also one of the most commonly used databases for research on disasters (Botzen et al., 2019; Klomp, 2014; Noy, 2009). For an event to be recorded in EM-DAT, it has to cause 10 or more deaths, affect 100 or more people, or be declared as an emergency by the country. The data collected for each disaster includes its year and start month, the type of disaster, and the total cost of its damages.

3.1 Data

Identifying a Natural Disaster Shock

For the baseline analysis presented in this paper, I consider an event to be a natural disaster if it meets the following two conditions: (1) it is classified as a: storm, wildfire, earthquake, or volcanic activity. (2) The estimated cost of direct damages associated with the disaster are above the country median. The first condition limits natural disasters to events that stochastically shock the economy for a limited amount of time. A more extensive list of natural disasters would also include droughts, floods, extreme temperatures, and epidemics, but these types of disasters may occur gradually and over long periods of time and are therefore usually not considered a natural disaster shock in the literature (Bremus & Rieth, 2022). Nevertheless, I include the full list of disasters in the robustness-check section and the results do no not meaningfully change. The second condition aims to reduce noise and ensures that the disasters are indeed substantially large shocks. Only including above median disasters is a common strategy in the literature

(Bremus & Rieth, 2022). However, to account for cross-country differences in size and economy, my strategy differs from past disaster studies in that I include all disasters with estimated damages above the country median as opposed to the overall median. The results are, nevertheless, robust to using the standard approach or relaxing the condition all together. Table 1 shows that across the 18 countries included in the main analysis, there are 374 natural disasters that meet the first condition and 238 that qualify as strong enough to meet the second one.

Environmental economics distinguish between direct and indirect economic effects of disasters (Botzen et al., 2019). The former captures the physical destruction of assets and lives. The latter relates to interrupted economic activities and reconstruction efforts that were brought about by these direct effects. The estimated damages from each disaster reported in the EM-DAT database capture only the direct damages to property, crops, and livestock. This is good for identification purposes, because in order for the disaster measure to properly identify the shock, it should not also capture its indirect effect, which is in part what this paper intends to estimate.

Furthermore, I weigh the estimated damage (measured in thousands of (current) U.S. Dollars) by the onset month of the disaster. This captures the idea that since the main analysis uses annual data, a disaster in January will have a bigger impact on the financial stability of that calendar year than the same disaster in December. The weighted damages are calculated using the same formula as Noy (2009): $\widetilde{d} = d(12 - OM)/12$, where OM denotes the onset month of the disaster and d is the estimated damage.

To construct the final disaster measure, $D_{i,t}$, I sum the weighted damages from (qualifying) natural disasters by country and year, divide by the price level to adjust for inflation and divide by real GDP to standardize.[4] The formula is as follows:

$$D_{i,t} = \frac{\left(\sum_{i,t} \widetilde{d}_{i,t}\right) \frac{1}{cpi_{i,t}}}{rGDP_{i,t}} \times 1000 \tag{1}$$

The subscripts i and t denote the country and year respectively. Multiplying the measure by 1000 is merely for convenience such that a one unit change in $D_{i,t}$ represents 0.1% of GDP. The average damage from a qualifying disaster is approximately 0.19% of GDP

[4] The base year for both real damages and real GDP is 1990.

(see Table 1). The disaster with the highest estimated damages in the sample is the 2011 earthquake and tsunami in Japan which is estimated to have cost 5.98% of GDP.[5]

The main issue with the EM-DAT is the quality of the data collection. Collecting information on natural disasters worldwide over the last 120 years is an ambitious undertaking and although the database is one of the most trusted sources of disaster events in the literature, it is not without gaps. The first issue is that the quality of the data is not consistent over time (it is easier to keep a record of all disasters in 2010 than in 1910). The second issue is that studies have shown that the quality of data collection is not consistent across countries and that low-income countries are likely to have more missing data (Jones et al., 2022). This is not a significant problem since I mainly use data on the 18 high-income countries in the Schularick and Taylor (2012) database for which the data collection is likely to be fairly similar. To account for any remaining systematic differences in data collection across countries I include country-fixed effects in all the main specifications. Finally, another issue is that there is a significant amount of missing data on the estimated damages of disasters, which consequently effects my main disaster measure. I address this issue in two ways: Since the missing data is a particularly large problem for early years, I also test the model with a restricted sample including only observations after 1949 as a robustness check. Additionally, I also check that my results are robust to different measures of disasters including a binary indicator variable that does not rely on the availability of estimated damages.

Crisis Data

The Schularick and Taylor (2012) macrohistory database (from now on JST database) contains macroeconomic data on 18 countries from 1870 to 2020 and is one of the most comprehensive macroeconomic long-run time series datasets available. Most importantly for this paper, it also contains an indicator variable for systemic financial crises, which is 1 for the first year of the crisis and 0 otherwise. Schularick and Taylor (2012) use a narrative-approach to coding the systemic banking crises, which they define as an episode of banking distress "characterized by major bank failures, banking panics, substantial losses in the banking sector, significant recapitalization, and/or significant government

[5]This figure is in line with other available estimates.

intervention." Observe that in this definition, the failure of only a few small banks without broader economic consequences is not considered a systemic crisis. The summary statistics presented in Table 1 show that there are 63 crises included in the sample from (1900 - 2020).

Table 1: Summary Statistics

Statistic	N	Mean	Median	Pctl(75)	Min	Max	St. Dev.
Crisis Indicator (JST)	2,158	0.029	0	0	0	1	0.168
Disaster Indicator	2,158	0.173	0	0	0	1	0.379
Strong Disaster Indicator	2,158	0.110	0	0	0	1	0.313
Damages (in millions US)	596	923.047	151.950	580.415	0.002	37,279.920	3,056.656
Strong Damages (in millions US)	285	1,813.045	573.835	1,371.900	16.095	37,279.920	4,241.096
Weighted Damages (pc GDP)	357	0.121	0.016	0.079	0.00000	5.987	0.426
Disaster Measure (pc GDP)	225	0.185	0.039	0.154	0.00000	5.980	0.528
Strng Disaster Measure (pc GDP)	237	0.336	0.112	0.324	0.00001	8.044	0.743
Strng Disaster Measure 5yr ma (pc GDP)	2,084	0.192	0.000	0.000	0.000	19.953	1.082
Log change in credit	2,059	0.040	0.041	0.086	−1.675	0.779	0.107
Log change in credit 5yr ma	2,025	0.041	0.045	0.075	−0.474	0.412	0.064

To test the robustness of the results and analyze a broader set of countries, I also conduct the analysis using data from Baron et al. (2020), which covers 46 countries from 1870 to 2016. In their definition, an event is considered a financial crisis if there is a bank panic or a bank equity crash (defined as a cumulative 30% decline) in combination with widespread bank failures.[6] Baron et al. (2020) define a banking panic as an event in which large banks face considerable funding pressures in the form of depositor (or creditor) withdrawals. This crisis identification approach differs from the narrative-based approach of Schularick and Taylor (2012). The dataset also covers a wider set of countries, including lower and upper middle income. This allows me to test whether developing countries' financial systems are more or less vulnerable to disasters than those of high-income countries. A disadvantage of covering a wider set of countries is that it does not include as many other macroeconomic variables (including long-run GDP data). I therefore use GDP data from the World Bank - available from 1960 onwards - to construct the disaster measure for the Baron et al. (2020) sample.

[6] A detailed explanation of how their indicators are constructed is given in their online appendix.

3.2 Model and Methods

The Basic Model

The empirical evidence in the literature suggests that the disruption in the production of goods and services in the wake of disaster event's negatively affects growth, employment, and trade (Botzen et al., 2019; Hsiang & Jina, 2014; Strobl, 2011) but generally leads to an increase in private and public debt (Klomp & Valckx, 2014). I want to know whether the economic consequences of a natural disaster make the financial system more vulnerable to financial crises. Schularick and Taylor (2012) show that large increases in credit predict a higher risk of a financial crisis occurring. Baron et al. (2020) show that shocks in the form of bank losses can be a key driver of financial crises. Given the evidence of the effect a disaster has on the macroeconomy I propose that the combination of disrupted production, lower growth, and higher levels of debt put pressure on the financial system and increase crisis-risk. To test, this I estimate the following logit models based on Schularick and Taylor (2012) with an added measure of natural disasters as the key explanatory variable of interest:

$$\text{logit}\,(p_{i,t}) = \alpha_i + \sum_{j=0}^{4} \beta_j D_{i,t-j} + \phi \mathbf{X}_{i,t} + e_{i,t} \tag{2}$$

$$Crisis_t = \alpha_i + \gamma_t + \sum_{j=0}^{4} \beta_j D_{i,t-j} + \phi \mathbf{X}_{i,t} + e_{i,t} \tag{3}$$

In equation (2), the dependent variable p_{it} denotes the probability of a crisis occurring, such that $\text{logit}\,(p_{it}) = ln(p_{it}/1 - p_{it})$ is the log odds ratio of a crisis occurring in country i at time t. The logit function transforms probabilities from the range (0, 1) to the entire real line $(-\infty, \infty)$, such that the specification can model probabilities as a linear combination of the independent variables. α_i denotes country-fixed effects, and $\mathbf{X}_{i,t}$ represents a set of lagged controls including credit growth and economic growth. Finally, the variables of interest, $D_{i,t}$, are four measures of annual damages from a disaster (defined above) at time t, $t-1$, $t-2$, and $t-3$.

The logit model specified in equation (2), includes country fixed effects to control for unobserved heterogeneity across countries. Observe that the inclusion of country fixed effects here does not result in the incidental parameters' problem because the number of countries is relatively small compared to the sample size (Lancaster, 2000; Schularick & Taylor, 2012). This means that the number of fixed effects parameters to be estimated is small relative to the number of observations, which allows for consistent estimation of the model parameters.

In contrast, including time fixed effects in the logit model, would result in a large number of fixed effects parameters relative to the sample size, which would indeed lead to the incidental parameters' problem. However, since only 18 countries are covered in the dataset, this cannot be addressed by using conditional logit or the analytical bias corrections derived in Cruz-Gonzalez et al. (2017). This leaves using the linear probability model (LPM) in equation (3) to test whether the estimates are robust to including year and country fixed effects. The crisis indicator variable is denoted $Crisis_{i,t}$ and γ_t represents the added year effects. The LPM, however, suffers from well-known limitations including that it assumes that the relationship between the independent variables and the probability of a crisis occurring is linear, which is a particularly weak assumption given that the probability of a crisis occurring is low to begin with. Additionally, the error term in LPMs is inherently heteroscedastic, which, if left unaddressed, can lead to biased standard errors.[7] For those reasons, the main specifications and results in this paper are logistic regressions and I use the LPMs predominately as an additional robustness check and to address potential measurement error (discussed in the next section).

The Role of Credit

To test the hypothesis that natural disasters are particularly risky if they occur in combination with a credit boom, I follow the approach of (Krishnamurthy & Muir, 2017) and interact the disaster variable with the measure for credit growth:

$$\mathrm{logit}\left(p_{i,t}\right) = \alpha_i + \beta\left(\overline{D}_{MA5}\right) + \delta\left(\overline{C}_{MA5}\right) + \lambda\left(\overline{D}_{MA5} \times \overline{C}_{MA5}\right) + \phi \mathbf{X}_{i,t} + e_{i,t} \tag{4}$$

[7] LPMs are inherently heteroscedastic because the variance of the error term is not constant across the range of predicted probabilities. This occurs because the LPM assumes that the relationship between the independent and dependent variables is linear and thus the variance of the error term changes as the predicted probability moves closer to 0 or 1. Therefore, I also include results with heteroscedasticity-robust standard errors in the robustness test section

In equation (4) above, the disaster measure is a 5 year, backward looking, moving average of annual damages from natural disasters denoted $\overline{D}_{MA5} = \frac{1}{5}\sum_{j=0}^{4} D_{i,t-j}$. Similarly, credit is denoted as the 5-year moving average of the log change in real total debt, $\overline{C}_{MA5} = \frac{1}{5}\sum_{j=1}^{5} \Delta C_{i,t-j}$. The moving average of the disaster measures includes damages from the current year t since natural disasters are exogenous to crisis-risk. On the other hand, the moving average of the credit measure is calculated using only past values. As before, $\mathbf{X}_{i,t}$ denotes a vector of further control variables, which for this specification consists of only a 5-year moving average of the log change of GDP, denoted $\overline{GDP}_{MA5} = \frac{1}{5}\sum_{j=1}^{5} \Delta GDP_{i,t-j}$

Dangerzones

One of the weaknesses of the models above is that there are multiple lagged disaster variable such that the results focus on details that do not add much value to the aim of the paper. In other words, to understand the relationship between natural disasters and financial crises, it is not so important whether the 1-year or 2-year lagged disaster variable is significant. Therefore, I re-define the dependent variable by trading precision for efficiency and capture a financial crisis "dangerzone" (or risk period):

$$dangerzone_t = \begin{cases} 1 & \text{if } Crisis_t = 1,\ Crisis_{t+1} = 1,\ \text{or } Crisis_{t+2} = 1 \\ 0 & \text{otherwise} \end{cases}$$

I then re-estimate the previous specifications but only including the one-period lagged independent variables. The logit model, for example, becomes:

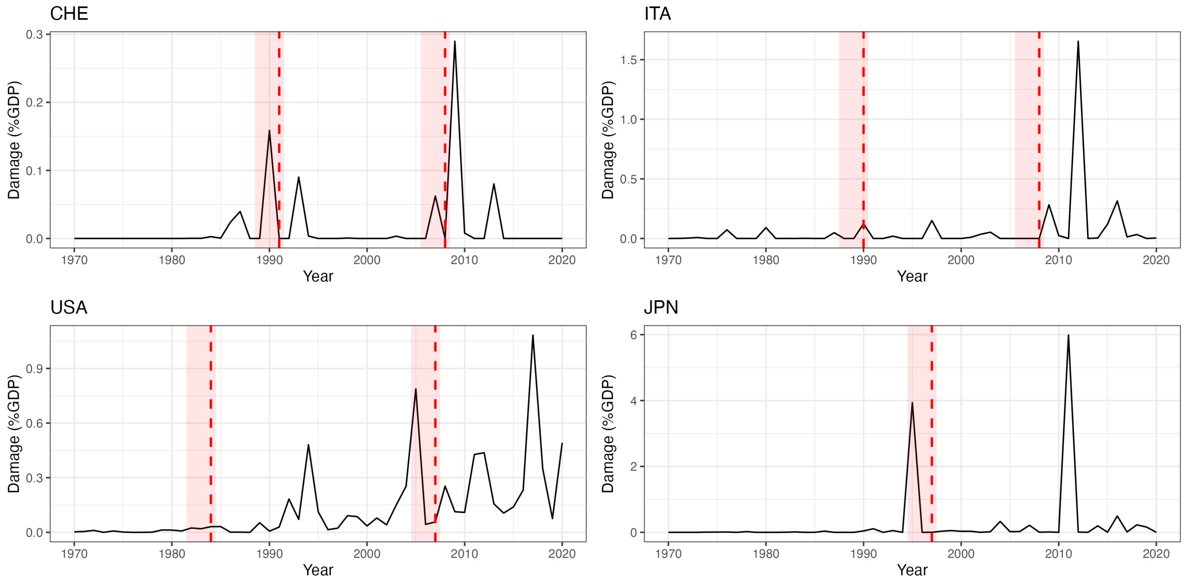
$$\text{logit}\left(p^*_{i,t}\right) = \alpha_i + \beta\left(D_{i,t-1}\right) + \delta\left(C_{i,t-1}\right) + \lambda\left(D_{i,t-1} \times C_{i,t-1}\right) + \phi\left(GDP_{i,t-1}\right) + e_{i,t} \quad (5)$$

where p_{it} denotes the probability of a crisis occurring in the current year, next year, or the year after. Figure 2 shows this visually for four example countries.

Local Projections

I also test the impact of a disaster on the log change in GDP, the change in credit to GDP ratio, and the percentage change in bank equity returns (taken from Baron et al.

Figure 2: Crises "Dangerzones" and Natural Disasters



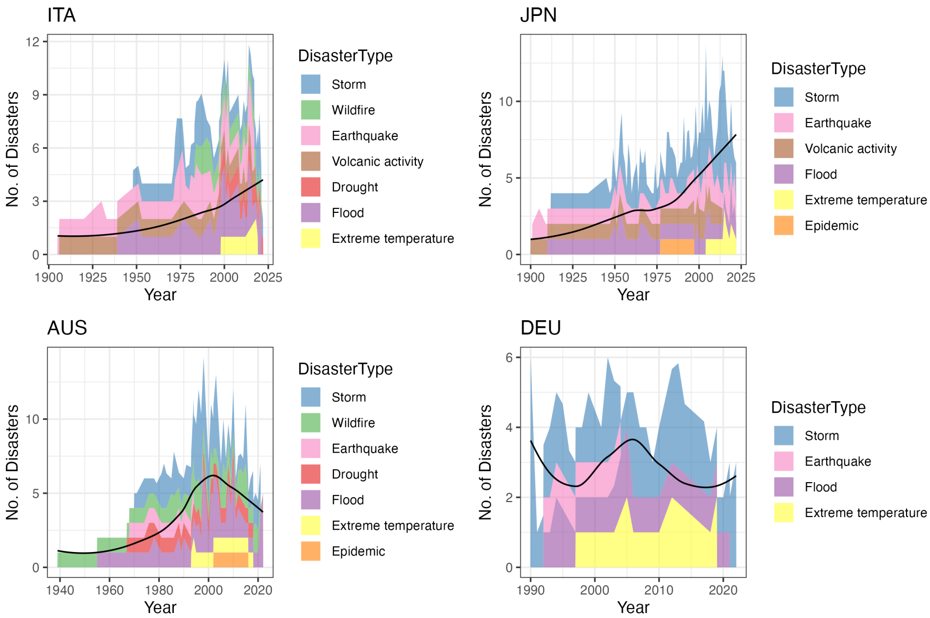
Note: The four graphs show an example of the crisis "dangerzone" and the disaster measure (weighted annual damages from natural disasters standardized by GDP) for Switzerland, Italy, the United States, and Japan. The dotted red line indicates the year in which the crisis occurred.

(2020)) using Jordà (2005) local projections:

$$\Delta_h y_{i,t+h} = \alpha_i + \sum_{j=0}^{3} \beta_j DISASTER_{i,t-j} + \gamma \mathbf{X}_{i,t} + e_{i,t}, \ \forall \, h \in \{0,1,2,...,5\} \tag{6}$$

The outcome variable in equation (6) is the cumulative log change in GDP, change in credit-to-GDP, or percentage change in bank equity return denoted $\Delta_h y_{i,t+h} = y_{i,t+h} - y_{i,t-1}$ for any h in $\{0,1,2,...,5\}$. To further test the underlying mechanisms (as well as to check the robustness of the results), I also estimate the model in equation (1) for banking panics and bank equity crashes. A local projection is a series of projections of the cumulative change in the endogenous variable shifted forward in time (Jordà, 2005). They are a useful tool for this analysis because they allow for the estimation of the impact of a disaster on the outcome variable over a range of horizons. In fact, Jordà et al. (2022) recently used local projections to analyze the long-run impact of pandemics on economic growth (Jordà et al., 2022).

Figure 3: Country-level Frequency and Type of Natural Disasters



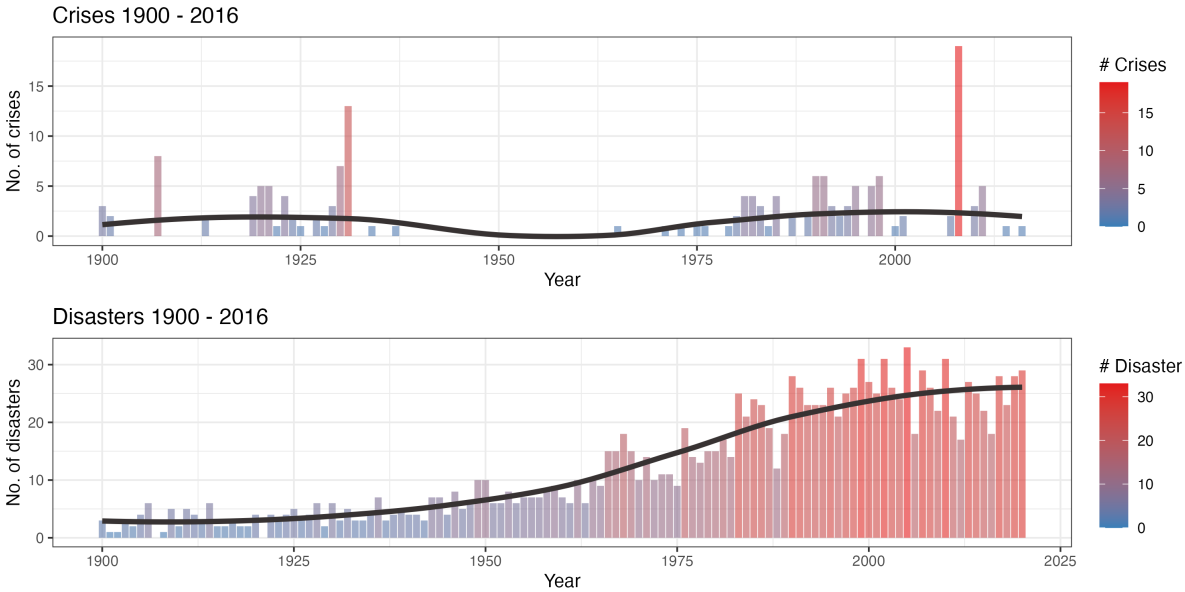
Note: The four graphs in the panel show the frequency and trend of qualifying natural disasters in Italy, Japan, Australia, and Germany.

Challenges

There are three main challenges that I need to address in the analysis. Firstly, the impact natural disasters have on countries is heterogeneous and correlated with other macroeconomic indicators (Botzen et al., 2019; Hsiang & Jina, 2014). Kahn (2005), for example, finds that higher income countries have smaller economic growth consequences, although their total damages from disasters are larger. This is an issue because the frequency of natural disasters systematically varies by country. For example, Figure 3 shows that the frequency, type, and trend of natural disasters is heterogeneous across countries. Earthquakes, for instance, are common in Italy and Japan but rare in Australia and Germany. To address this I include country fixed effects in all estimations (except to explicitly show the effect of adding them).

Secondly, it seems fairly obvious that natural disasters are exogenous to crisis-risk. If this were not the case, one would have to argue that financial crises cause natural disasters. I see no reason why such a reverse causality would exist and therefore assume that natural disasters are exogenous to crises (Noy (2009), Raddatz (2007), and Skidmore and Toya (2002) adopt a similar logic for different macroeconomic outcome variables) Nevertheless, the model could suffer from omitted variable bias if there are factors in

Figure 4: Frequency of Crises vs Disasters



the economy that arguably increase the risk of a financial crisis as well as accelerate climate change or worsen the damages from natural disasters (which then increases the frequency of natural disasters). This is also largely addressed by including fixed effects, which control for static country-level differences. Additionally, given the global nature of climate change, its uneven impacts, and the lack of empirical evidence that would suggest that macroeconomic variables are determinants of natural disasters, this is likely not a large concern. There is, however, some empirical evidence that economic growth is a determinant of the damage caused by natural disasters (Botzen et al., 2019; Skidmore & Toya, 2002). To account for this, I control for GDP growth in the specifications.

Lastly, it is likely that the drastic increase in the frequency of natural disasters after the 1950s is partially driven by a significant amount of measurement error. In other words, technology likely improved global data collection for natural disasters. This would be worrisome if the data collection for crises suffered from similar measurement error. However, unlike natural disasters, the frequency of crises has not increased meaningfully over the last century (see Figure 4). As a robustness check, however, I include year effects in the LPMs, which would account for this type of correlated measurement error. Overall the main results appear to be robust to this issue.

4 Results

The Basic Model

In this section I present the main results and discuss their strengths and limitations. Columns (1) through (3) in Table 2 show the results of the logit model introduced in equation (2). Columns (4) and (5) show the results of the LPM specified in equation (3). The standard errors are clustered by country, which is a standard approach for estimating effects of natural disasters in panel data (Klomp, 2014). The most noteworthy finding in Table 2 is that the two-period lagged damage measure is positive and significant at the 0.01 level across all different specifications with and without year and fixed effects. This result indeed suggests that a large natural disaster is associated with higher crisis-risk in the future.

Examining columns (1) and (2), it is noteworthy that including fixed effects in the logit model does not change the estimate for the coefficient of the two-year lagged disaster measure. This suggests that the time-invariant unobserved characteristics of countries included in the analysis are not correlated with both the disaster and crisis variable. This would be the case if, for example, countries that are consistently more likely to have higher damages from natural disasters are also more likely to experience financial crises. Similarly, for the LPM, including year and country fixed effects only increased the estimates from 0.005 to 0.006, which indicates that the bias, if any, from country-specific (time-invariant) and time-specific (country-invariant) unobserved characteristics is directed downward.

The coefficients in the logit model represent the marginal change in the log-odds of a crisis occurring associated with a one-unit change in the corresponding disaster variable (holding all other variables constant). And since a one unit increase in the disaster measure represents 0.1% of GDP, the results in column (2) can be interpreted as follows: A 0.1% of GDP increase in damages from natural disasters, increases the odds of a crisis occurring two years later by 6.2%.[8] Column (3) depicts the results of the same logit model as in column (2) but restricting the sample to observations after 1949. I do this to address concerns regarding the data collection on natural disasters during the first half of the century and therefore test the results using only more recent data of the last 70

[8]The formula for converting log odds is simply: $\exp(0.063) = 1.062$.

Table 2: Effect of a strong natural disaster on crisis risk (1900 - 2020)

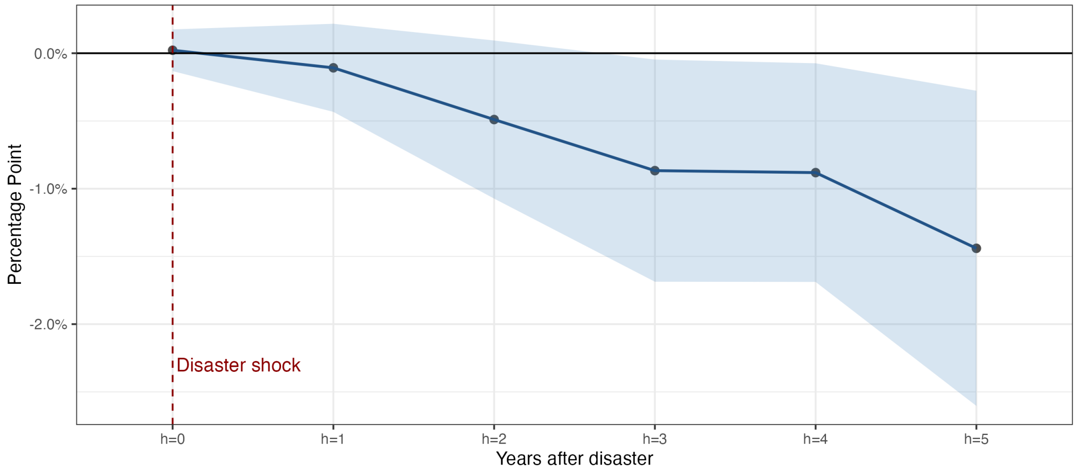
	Dependent Variable: Crisis in $year = t$				
	logistic			*OLS*	
	(1)	(2)	(3)	(4)	(5)
$Damages(pcGDP)_t$	-0.171	-0.148	-0.111	-0.001	-0.0002
	(0.185)	(0.176)	(0.202)	(0.001)	(0.0004)
$Damages(pcGDP)_{t-1}$	0.009	0.012	0.098*	-0.00002	0.00004
	(0.030)	(0.033)	(0.059)	(0.001)	(0.001)
$Damages(pcGDP)_{t-2}$	0.058***	0.060***	0.165***	0.005***	0.006***
	(0.006)	(0.006)	(0.054)	(0.002)	(0.002)
$Damages(pcGDP)_{t-3}$	0.060*	0.062	0.166*	0.005	0.002
	(0.036)	(0.040)	(0.095)	(0.006)	(0.002)
Country fixed effects	*No*	*Yes*	*Yes*	*No*	*Yes*
Year fixed effects	*No*	*No*	*No*	*No*	*Yes*
Restricted sample	*No*	*No*	*Yes*	*No*	*No*
Observations	2,084	2,084	1,278	2,084	2,084
Adjusted R^2				0.005	0.204
Log Likelihood	-268.928	-262.137	-113.029		
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.

years, which has the added benefit of (1) reducing any additional noise coming from the weaknesses in data collection between 1900 and 1950 and (2) excluding both World Wars. The result for the lagged disaster measure remains statistically significant at the 0.01 level and also significantly increases from 0.060 to 0.165. This would suggest that a 0.1% of GDP increase in disaster damages is associated with a 17.9% increase in the odds that a crisis occurs two years later.

The interpretation of the coefficients in the LPM reported in columns (4) and (5) is different, but the overall conclusion is the same. A one unit increase in the two-year lagged disaster measure is associated with a 0.006 percentage point increase in the probability that there is a crisis. While the estimated coefficients of the LPM are fairly small, one has to consider that the probability of a crisis occurring in any given year is not large to begin with and that the shock variable is scaled such that a one unit increase represents 0.1% of GDP. Consequently, scaling the shock variable differently would increase or decrease the size of the coefficients. I set it to 0.1% of GDP because that was close to the mean for damages from qualifying natural disasters (see Table 1).

Figure 5: Local Projection of Disaster Shock on bank equity returns



Note: The outcome variable is the cumulative percentage change in bank equity returns from year -1.

Next, Figure 5 visualizes the results of local projections of a disaster shock on bank equity returns. The figure confirms the finding of previous studies (Klomp, 2014) that disasters have a negative effect on bank equity returns. Moreover, the results show that the effect is persistent and only starts to sets in one period after the shock. Interestingly the timing is in line with the fact that the coefficients for the two-period lagged disaster variable were the most significant crisis predictors in Table 2. The figure therefore gives credence to the narrative that strong disasters put pressure on bank's balance sheets, which heightens crisis-risk. Although the effect is negative for all time horizons, it is only statistically significant after 3 years. The outcome variable in the local projection is the cumulative percentage change in bank equity returns from year -1. The light blue shaded area represents the 90% confidence interval computed using cluster-robust standard errors (as in Jordà et al. (2020)).[9]

4.0.1 The Role of Credit

Table 3 adds the log-change of credit growth as controls and tests if there are interaction effects between credit growth and disasters. Columns (1) and (2) simply extend the previous specification by adding 4 lagged credit covariates and an interaction term for the disaster and credit growth variable at $t-2$. The results in the first column show

[9]However, the results are robust to using White and Newey West standard errors for both heteroscedasticity and autocorrelation in all the local projections presented in this paper.

that controlling for the change in credit does not change the statistical significance of the disaster shock coefficients and slightly increases the magnitude of the two-year lagged disaster coefficient (from 0.060 in column (2) of Table 2 to 0.074). Additionally, the estimated coefficients of the log-change in credit are very similar to those found by Schularick and Taylor (2012) who find a coefficient of 7.14 for the two-year lagged credit (compared to 8.14).[10] Including the interaction term in column (2) does not produce any statistically significant differences to column (1). Table 15 also controls for GDP growth, but the results are not meaningfully different either.

Table 3: 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.					

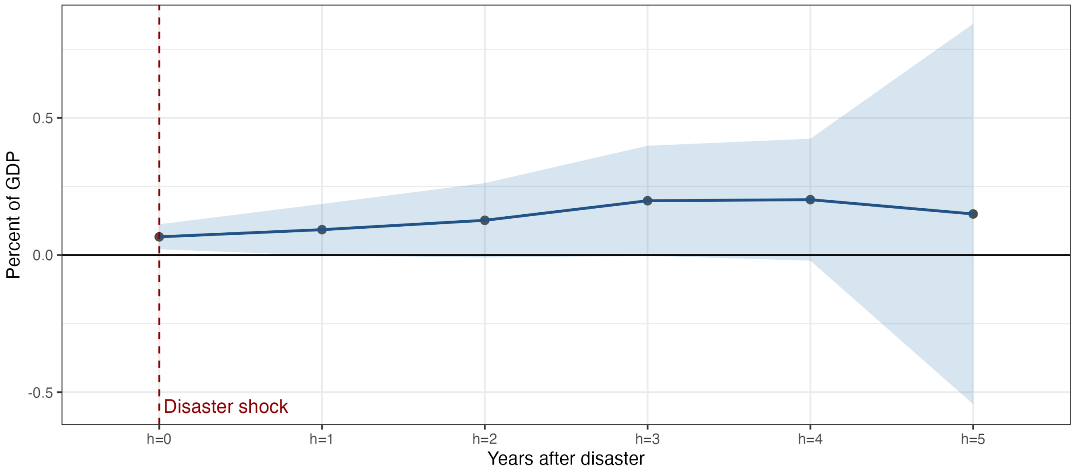
[10] The minor differences between the two estimates could be attributed to the inclusion of the disaster measures or the fact that the sample in Schularick and Taylor (2012) covered 1870-2008, whereas my sample covers 1900-2020.

The lack of significant results in the specifications with the lagged variables may be because I only interacted the two-period lags. Therefore, Columns (3) and (4) of Table 3 present the results from the logit model introduced in equation (4) with the 5-year moving averages for disasters and credit. As expected, the estimated coefficients for the 5-year moving average of the disaster shock and credit expansion are both statistically significant (and larger than the estimates for the lagged shocks). The main result from this table is that including the interaction term in column (4) makes the disaster variable statistically insignificant while the coefficient for the interaction is positive, larger than either of the other coefficients was in column (3), and statistically significant at the 0.01 level. Additionally, including the interaction term also reduces the magnitude of the credit coefficient. Overall the estimates in columns (3) and (4) support the hypothesis that a credit boom amplifies the effect of a natural disaster shock (and/or vice versa). A natural disaster during a period of credit expansion, increases crisis-risk. Additionally, the fact that the disaster variable becomes insignificant may imply that the interaction is one of the main channels through which disasters cause crises.

Next, I test whether this result is robust to adding year effects in a linear probability model (LPM). Indeed, the estimates in columns (5) and (6) of Table 3 show the same development when I include the interaction term. The disaster shock coefficient is positive and significant in column (5) and when the interaction term is included its magnitude decreases and is no-longer significant. As before, the interaction term in column (6) is significant and larger than the coefficient for the credit variable.

The results so far identify a credit expansion as an amplifier of the effect of natural disasters on crisis-risk. But could credit booms themselves be a channel through which natural disasters increase crisis-risk? In other words, natural disasters may lead to an increase in credit due to economic disruptions and reconstruction costs. If this resulting increase in credit increases crisis-risk, it would mean that part of the observed effect of disasters on crises is actually coming from the resulting increase in credit. But comparing the estimates of column (2) of Table 2 to those of column (1) of Table 3 shows that the estimated coefficient for the disaster shock is larger when controlling for credit and therefore does not indicate that credit expansions are a channel through which disasters negatively affect crisis-risk. Additionally, I analyze the effect that natural disasters have on the credit-to-GDP ratio using the local projections approach as in Jordà et al. (2020).

Figure 6: Local Projection of Disaster Shock on Credit-to-GDP Ratio



Note: The outcome variable is the difference of credit-to GDP ratio from year -1.

Figure 6 visually shows the local projections of the disaster shock on the change in the credit-to-GDP. While the effect is positive throughout the 5 year time horizons, it is small and only slightly significant in the year of the shock.

4.0.2 The Role of economic growth

Table 4 shows the results for the logit model in equation 4 when controlling for the five-year moving average of GDP growth. Unsurprisingly, economic growth is negatively related to crisis-risk. But interestingly, including GDP growth as a control reduces the size of the disaster coefficient in column(1). In column (2), where the interaction term is also included, the coefficient actually becomes negative (although not statistically significant). Together this may imply yet another channel through which natural disasters increase crisis-risk. To briefly re-estimate a well-established result in the literature that natural disasters decrease growth, I use a two-way fixed effects OLS model to test the effect of natural disasters on economic growth as well as a local projection to analyze the dynamic effects of its impact. The result of the two-way fixed effects model is reported in column (3) and is consistent with well established finding that natural disasters lead to a reduction in growth. Figure 7 shows a local projection on 100 $\times$ log change of GDP from year -1. The impulse response function clearly shows that the effect of a natural disaster shock on GDP growth is negative and statistically significant for all 5 time horizons. The effect appears to slow in the fourth year after the shock. This result is consistent with other empirical findings in the environmental economics literature that the destructive effect of strong natural disasters outweighs the positive effect of reconstruction efforts and therefore leads to a reduction in economic growth Klomp and Valckx (2014). Coupled with the effect that including GDP growth had on the logit regression, this also supports the narrative that the reduction in output after a disaster is a potential channel through which crises become more likely.

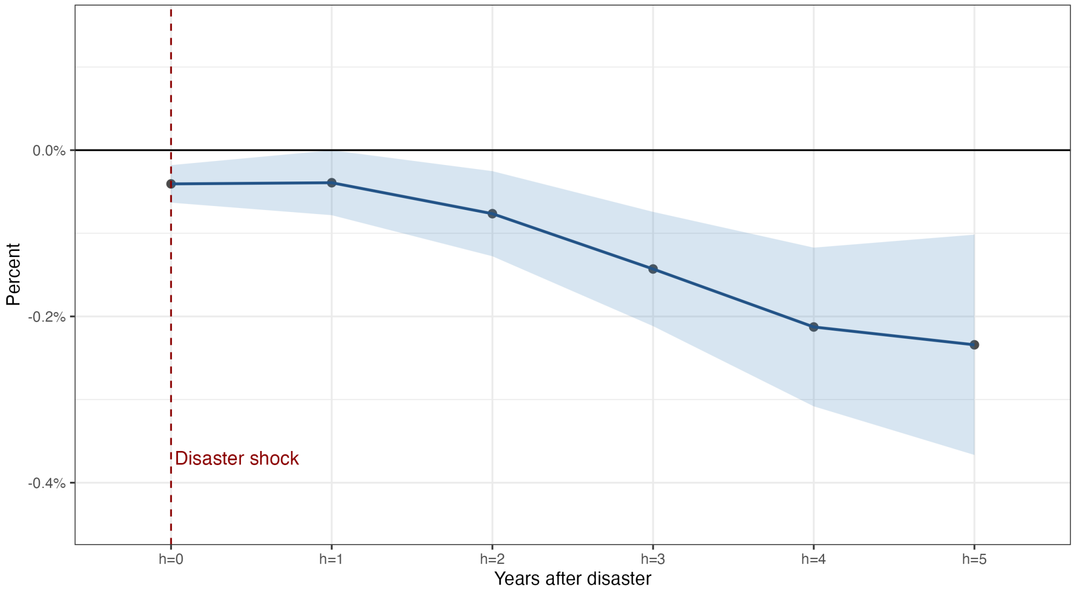
Table 4: Controlling for economic growth

	Dependent variable:		
	logistic		*OLS*
	(1)	(2)	(3)
Damages 5yr ma	0.149***	−0.099	−0.002***
	(0.057)	(0.080)	(0.0004)
Credit 5yr ma	14.854***	13.572***	
	(3.120)	(2.886)	
Δ GDP ma	−17.747***	−17.939***	
	(5.181)	(5.267)	
Damages ma $\times \Delta Credit$ ma		9.636***	
		(1.945)	
Constant	−5.085***	−5.397***	0.034***
	(0.206)	(0.199)	(0.004)
Country fixed effects	Yes	Yes	Yes
Year fixed effects	No	No	Yes
Observations	1,900	1,900	2,003
Adjusted R^2			0.245
Log Likelihood	-230.713	-225.531	
Residual Std. Error			0.033
F Statistic			5.924***
Note:	*p<0.1; **p<0.05; ***p<0.01 Cluster-robust standard errors are shown in parentheses.		

Danger Zone

Columns (1) and (2) of Table 5 show the estimates of the specification defined in equation (5) where the dependent variable is re-coded as a crisis "Danger Zone". Overall both the magnitude and the significance of the estimates in all the columns is similar to those presented in previous models. The estimates in column (1) indicate that a natural disaster shock (with damages of 0.1% of GDP) is associated with a 7% increase in the odds that a crisis occurs in the following three years. When including the interaction of the disaster and credit shock, the shock coefficient decreases and is no longer significant while the coefficient for the interaction term is positive and significant. The LPMs with year and country effects in columns (3) and (4) are also similar.

Figure 7: Local Projection of Disaster Shock on GDP Growth



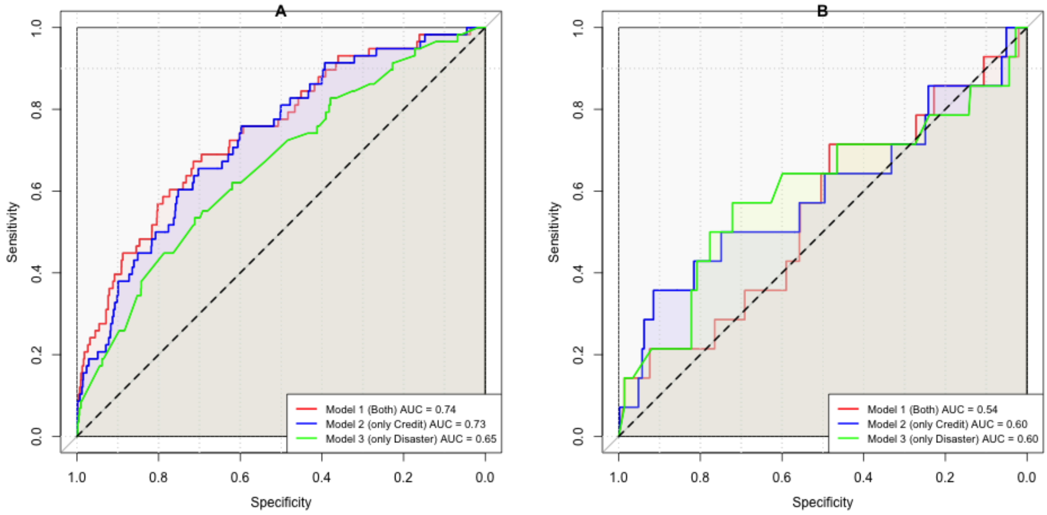
Note: The outcome variable is 100 × log change of GDP from year -1.

Table 5: Effect on a Crisis "Danger Zone" (1900 - 2020)

	Dependent Variable: Crisis Danger Zone			
	logistic		*OLS*	
	(1)	(2)	(3)	(4)
$Damages(pcGDP)_{t-1}$	0.068*	−0.009	0.008***	0.006***
	(0.038)	(0.017)	(0.001)	(0.001)
$\Delta Credit_{t-1}$	5.493***	5.219***	0.213***	0.209***
	(1.514)	(1.470)	(0.080)	(0.080)
ΔGDP_{t-1}	−4.269**	−4.253**	−0.046	−0.044
	(1.782)	(1.800)	(0.111)	(0.111)
$Damages_{t-1} \times \Delta Credit_{t-1}$		5.377***		0.108
		(1.500)		(0.076)
Constant	−3.812***	−4.023***	−0.078***	−0.079***
	(0.086)	(0.140)	(0.014)	(0.015)
Country fixed effects	*Yes*	*Yes*	*Yes*	*Yes*
Year fixed effects	*No*	*No*	*Yes*	*Yes*
Restricted sample	*No*	*No*	*No*	*No*
Observations	1,985	1,985	1,985	1,985
Adjusted R^2			0.312	0.312
Log Likelihood	-544.567	-537.591		
Residual Std. Error			0.234	0.234
F Statistic			7.612***	7.569***

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

Figure 8: In and Out of Sample ROC plots



Note: Figure A shows the ROC curves for the in-sample predictions and Figure B shows the ROC curves for the out-of-sample predictions. The out-of-sample prediction model is trained on data from 1900-1995 and then used to predict crises from 1995-2020

Prediction

Another way to test what effect natural disasters have on crisis-risk, is to test how well they predict them. This not only provides a different way to test the main hypothesis, but also test the robustness of the previous results. I use the logit model specified in equation 2 to predict the probability of a crisis occurring. Following the approach of Schularick and Taylor (2012), I then compare the predicted crises to the actual crises using Receiver Operating Characteristic (ROC) curves presented in Figure 8. The ROC curve plots the true positive rate (sensitivity) against the false positive rate (specificity) for different thresholds of the predicted probability. The area under the curve (AUC) is a measure of the accuracy of the model. The closer the AUC is to 1, the more accurate the model.

Panel A in Figure 8 shows the ROC curves for the in-sample prediction for a model including only the lagged disaster shocks (Model 3 in green), a model including only the lagged credit variables (Model 2 in blue), and a model including both (Model 1 in red). Observe that even the model with only disaster shocks has some predictive power (AUC = 0.65). This is a striking result. Furthermore, adding disaster shocks to a model with only credit variables (i.e. comparing the blue and red line), increases the predictive power of the model.[11]

[11] The results of the in-sample and out-of-sample prediction of the model including only credit are in line with the results from Schularick and Taylor (2012).

Going a step further, I want to check whether I have overfitted the model. Thus, Panel B in Figure 8 shows the ROC curves for the out-of-sample prediction using the same models. In other words, I trained on data from 1900 - 1995 and then used the result to predict crises from 1995 - 2020. The AUC for the out-of-sample prediction of the model using only disasters is 0.6 indicating that natural disasters have some predictive power even in the out-of-sample prediction.

All the models perform worse in the out-of-sample prediction. This is not surprising since the out-of-sample prediction has less information available and is trained on a smaller sample. Consequently, the fact that model 3 in the out-of-sample prediction is even just somewhat predictive about when a financial crisis is going to occur, is a good result in favour of my main hypothesis.

5 Robustness checks

Recall that I limited the analysis to storms, wildfires, earthquakes, and volcanic activities. In Table 6 I test whether the main logit models are robust to also including droughts, floods, extreme temperatures and epidemics. Although the magnitude of the estimates is somewhat smaller, Table 6 shows that the estimates reported in Table 2 and 3 are robust to including these additional types of disasters.

Next, Table 7 presents the estimates of model 2 when I don't exclude disasters with damages under the country-specific median. Here too, the results are robust and almost identical to the baseline estimates. Table 8 shows estimates for the same model but using unweighted damages to compute the disaster measure, which also produces similar coefficients and standard errors.

To see what happens when I use a different measure of financial crises for the same list of 18 countries, I estimate equation 2 using the crisis indicator from Baron et al. (2020) as the dependent variable and report the results in column 1 of Table 9. Although the estimated coefficients are smaller, the two-period lagged disaster measure is still a statistically significant predictor of financial crises.

A key issue with the disaster measure I used so far is that it relies on the availability of damage data, which is not consistent across the listed disaster events in the EM-DAT

Table 6: Robust: Main results including other types of disasters

	Dependent Variable: Crisis in $year = t$			
	(1)	(2)	(3)	(4)
$Damages(pctGDP)_t$	-0.095	-0.060		
	(0.177)	(0.205)		
$Damages(pctGDP)_{t-1}$	-0.001	0.066		
	(0.037)	(0.055)		
$Damages(pctGDP)_{t-2}$	0.055***	0.136***		
	(0.007)	(0.040)		
$Damages(pctGDP)_{t-3}$	0.059	0.140*		
	(0.037)	(0.081)		
Damages 5yr ma			0.175***	-0.022
			(0.050)	(0.078)
Credit 5yr ma			9.577***	8.416***
			(2.473)	(2.300)
Damages ma $\times \Delta Credit$ ma				7.721***
				(2.022)
Constant	-4.757***	-4.620***	-5.369***	-5.939***
	(0.121)	(0.423)	(0.201)	(0.247)
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	No	No	No	No
Restricted sample	No	Yes	No	No
Observations	2,084	1,278	1,966	1,966
Log Likelihood	-262.455	-113.835	-240.963	-237.029

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

Table 7: Robust: Effect of a natural disaster on crisis risk (1900 - 2020)

	Dependent Variable: Crisis in $year = t$				
	logistic			*OLS*	
	(1)	(2)	(3)	(4)	(5)
$Damages(pcGDP)_t$	-0.190	-0.167	-0.135	-0.001	-0.0003
	(0.198)	(0.192)	(0.226)	(0.001)	(0.0005)
$Damages(pcGDP)_{t-1}$	0.019	0.021	0.113*	0.0004	0.0002
	(0.026)	(0.029)	(0.059)	(0.001)	(0.001)
$Damages(pcGDP)_{t-2}$	0.058***	0.060***	0.163***	0.005***	0.006***
	(0.006)	(0.006)	(0.054)	(0.002)	(0.002)
$Damages(pcGDP)_{t-3}$	0.061*	0.062	0.165*	0.005	0.002
	(0.036)	(0.040)	(0.094)	(0.005)	(0.002)
Constant	-3.550***	-4.762***	-4.612***	0.027***	-0.023***
	(0.119)	(0.069)	(0.307)	(0.003)	(0.003)
Country fixed effects	No	Yes	Yes	No	Yes
Year fixed effects	No	No	No	No	Yes
Restricted sample	No	No	Yes	No	No
Observations	2,102	2,102	1,278	2,102	2,102
Adjusted R^2				0.005	0.204
Log Likelihood	-269.469	-262.680	-113.037		
Residual Std. Error				0.166	0.149
F Statistic				3.391***	4.904***

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

Table 8: Robust: Effect of a strong natural disaster (unweighted) on crisis risk (1900 - 2020)

	Dependent Variable: Crisis in $year = t$				
	logistic			*OLS*	
	(1)	(2)	(3)	(4)	(5)
$Damages(pcGDP)_t$	-0.098	-0.090	-0.064	-0.001^{**}	-0.0004
	(0.079)	(0.080)	(0.096)	(0.001)	(0.0005)
$Damages(pcGDP)_{t-1}$	-0.027	-0.029	0.002	-0.001	-0.0004
	(0.048)	(0.047)	(0.052)	(0.001)	(0.0003)
$Damages(pcGDP)_{t-2}$	0.042^{***}	0.041^{***}	0.076^{***}	0.003^{**}	0.004^{***}
	(0.009)	(0.010)	(0.018)	(0.001)	(0.001)
$Damages(pcGDP)_{t-3}$	0.044^{*}	0.043	0.077^{*}	0.003	0.001
	(0.025)	(0.026)	(0.041)	(0.003)	(0.001)
Constant	-3.545^{***}	-4.739^{***}	-4.355^{***}	0.027^{***}	-0.022^{***}
	(0.123)	(0.058)	(0.137)	(0.003)	(0.003)
Country fixed effects	No	Yes	Yes	No	Yes
Year fixed effects	No	No	No	No	Yes
Restricted sample	No	No	Yes	No	No
Observations	2,102	2,102	1,278	2,102	2,102
Adjusted R^2				0.003	0.203
Log Likelihood	-269.530	-262.843	-114.884		
Residual Std. Error				0.166	0.149
F Statistic				2.844^{**}	4.887^{***}

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

database. To address this, columns (2) through (4) in Table 9 present the results for different disaster measures, all of which support the main hypothesis that disasters increase crisis-risk. The model reported in column (2) codes the disaster measure as a dummy variable that takes the value of 1 if there was a disaster in country i and time t. Column (3) uses a count measure of the number of disasters each year. Finally, the disaster measure in column (4) is just the estimated sum of damages measured in billions of current US dollars. Next to the fact that the results are robust to using different measures for the dependent and independent variables, the main takeaway is that in the estimates that do not rely on damage data, it is the one-period (as opposed to two-period) lagged coefficient that is significant. It is unclear what is driving this change in chronology but the direction of the effect remains the same.

Finally, the findings may depend on the 18 countries included in the sample, which all have very advanced-economies. To account for this I take advantage of the fact that the crisis indicator from Baron et al. (2020) covers 46 countries. The results from testing the model using this larger sample and their crisis indicator, are presented in Table 10. Note

Table 9: Robust: Additional Robustness checks (1900 - 2020)

	Dependent Variable: Crisis in $year = t$			
	BVX		JST	
	(1)	(2)	(3)	(4)
$Damages(pcGDP)_t$	-0.119			
	(0.121)			
$Damages(pcGDP)_{t-1}$	0.013			
	(0.027)			
$Damages(pcGDP)_{t-2}$	0.042^{***}			
	(0.006)			
$Damages(pcGDP)_{t-3}$	0.041			
	(0.038)			
$Disaster_t$		-0.682		
		(0.444)		
$Disaster_{t-1}$		0.672^{**}		
		(0.333)		
$Disaster_{t-2}$		-0.012		
		(0.435)		
$Disaster_{t-3}$		-0.080		
		(0.473)		
$No.ofDis_t$			-0.065	
			(0.100)	
$No.ofDis_{t-1}$			0.214^{*}	
			(0.118)	
$No.ofDis_{t-2}$			-0.123	
			(0.078)	
$No.ofDis_{t-3}$			-0.096	
			(0.089)	
$DamB(US)_t$				-0.056^{*}
				(0.033)
$DamB(US)_{t-1}$				-0.018
				(0.015)
$DamB(US)_{t-2}$				0.019^{***}
				(0.006)
$DamB(US)_{t-3}$				0.005
				(0.006)
Constant	-3.897^{***}	-4.610^{***}	-4.598^{***}	-4.604^{***}
	(0.042)	(0.190)	(0.034)	(0.008)
Country fixed effects	Yes	Yes	Yes	Yes
Observations	1,798	1,818	1,818	1,818
Log Likelihood	-299.511	-250.675	-251.288	-250.316

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

that the coefficients are now no longer statistically significant. This may, however, be due to the lack of available damage data for less advanced economies and not because the finding doesn't hold for a larger sample of countries. To test this I use a dummy variable as the disaster measure (as before) and find that the one-period lagged disaster coefficient is indeed positive and significant (see Table 11 column (1)).

Additionally, I check whether the results hold for a dummy variable for above median disasters for all, high-income, and low-income countries. I present the results in Table 11 columns (2), (3), and (4) respectively. Interstingly the coefficient for the one-period lagged disaster measure is significant for all countries and high-income countries but not for low-income countries. Again, this may be due to data collection issues which is why it is hard to draw any strong conclusions from these results.

Table 10: Robust: Effect of a strong natural disaster on crisis risk (with additional countries) (1960 - 2020)

	Dependent Variable: Crisis in $year = t$	
	(1)	(2)
$Damages(pcGDP)_t$	−0.063	−0.075
	(0.076)	(0.094)
$Damages(pcGDP)_{t-1}$	−0.006	−0.006
	(0.013)	(0.016)
$Damages(pcGDP)_{t-2}$	0.007	0.008
	(0.012)	(0.013)
$Damages(pcGDP)_{t-3}$	−0.005	−0.005
	(0.012)	(0.014)
Constant	−3.125***	−2.219***
	(0.094)	(0.0003)
Country fixed effects	*No*	*Yes*
Observations	2,220	2,220
Log Likelihood	-382.465	-363.889
Note:	*p<0.1; **p<0.05; ***p<0.01 Cluster-robust standard errors are shown in parentheses.	

In the specifications presented so far, I used cluster-robust standard errors as is standard in the literature. As a robustness check, I conducted both the Breusch-Pagan and White test on the main specifications, which indicated that there may indeed be some heteroscedasticity in the models. Since the clustered standard errors may therefore not be robust enough, Tables 12, 13, and 14 present the results using heteroskedasticity-consistent standard errors and shows that, although the main findings are robust, a few of the coefficients become less significant or insignificant all-together. This is particularly an issue for the LPMs including the interaction terms. The estimates for the logit models with and without the interaction terms, however, are robust to using heteroskedasticity-consistent standard errors.

Table 11: Robust: Disaster Dummies (1900 - 2020)

	Dependent Variable: Crisis in $year = t$			
	(1)	(2)	(3)	(4)
$Disaster_t$	-0.023			
	(0.214)			
$Disaster_{t-1}$	0.740^{***}			
	(0.212)			
$Disaster_{t-2}$	0.021			
	(0.249)			
$Disaster_{t-3}$	0.028			
	(0.253)			
$StrongDisaster_t$		0.257	0.155	0.465
		(0.269)	(0.293)	(0.612)
$StrongDisaster_{t-1}$		0.861^{***}	0.888^{**}	0.786
		(0.300)	(0.380)	(0.491)
$StrongDisaster_{t-2}$		-0.412	-0.485	-0.240
		(0.316)	(0.357)	(0.654)
$StrongDisaster_{t-3}$		0.411	0.334	0.574
		(0.309)	(0.388)	(0.513)
Constant	-2.853^{***}	-2.626^{***}	-4.245^{***}	-2.634^{***}
	(0.111)	(0.010)	(0.183)	(0.023)
Country fixed effects	*Yes*	*Yes*	*Yes*	*Yes*
Income group	*All*	*All*	*High*	*Low*
Observations	4,671	4,671	3,151	1,520
Log Likelihood	-657.948	-657.073	-456.994	-199.690

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

Table 12: Robust: Effect of a strong natural disaster on crisis risk (1900 - 2020)

	Dependent Variable: Crisis in $year = t$				
	logistic			*OLS*	
	(1)	(2)	(3)	(4)	(5)
$Damages(pcGDP)_t$	-0.171	-0.148	-0.111	-0.001^{*}	-0.0002
	(0.162)	(0.154)	(0.172)	(0.001)	(0.0005)
$Damages(pcGDP)_{t-1}$	0.009	0.012	0.098	-0.00002	0.00004
	(0.026)	(0.029)	(0.062)	(0.001)	(0.001)
$Damages(pcGDP)_{t-2}$	0.058^{*}	0.060^{*}	0.165^{***}	0.005	0.006
	(0.034)	(0.035)	(0.061)	(0.005)	(0.006)
$Damages(pcGDP)_{t-3}$	0.060^{**}	0.062^{*}	0.166^{*}	0.005	0.002
	(0.030)	(0.033)	(0.093)	(0.004)	(0.002)
Constant	-3.542^{***}	-4.756^{***}	-4.603^{***}	0.027^{***}	-0.023^{*}
	(0.133)	(1.014)	(1.141)	(0.004)	(0.012)
Country fixed effects	*No*	*Yes*	*Yes*	*No*	*Yes*
Year fixed effects	*No*	*No*	*No*	*No*	*Yes*
Restricted sample	*No*	*No*	*Yes*	*No*	*No*
Observations	2,084	2,084	1,278	2,084	2,084
Adjusted R^2				0.005	0.204
Log Likelihood	-268.928	-262.137	-113.029		
Residual Std. Error				0.167	0.149
F Statistic				3.542^{***}	4.898^{***}

Note: *p<0.1; **p<0.05; ***p<0.01
Heteroskedasticity-robust standard errors are shown in parentheses.

Table 13: Robust: 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				
	(0.138)	(0.137)				
$Damages(pctGDP)_{t-1}$	0.033	0.033				
	(0.027)	(0.028)				
$Damages(pctGDP)_{t-2}$	0.074^{**}	0.078^{**}				
	(0.036)	(0.039)				
$Damages(pctGDP)_{t-3}$	0.078^{**}	0.078^{**}				
	(0.035)	(0.035)				
$\Delta Credit_{t-1}$	-0.333	-0.319				
	(1.244)	(1.257)				
$\Delta Credit_{t-2}$	8.137^{***}	8.155^{***}				
	(1.522)	(1.530)				
$\Delta Credit_{t-3}$	-0.537	-0.526				
	(1.405)	(1.410)				
$\Delta Credit_{t-4}$	1.931^{*}	1.929^{*}				
	(1.022)	(1.022)				
Damages 5yr ma			0.184^{***}	-0.080	0.008	0.003
			(0.064)	(0.162)	(0.006)	(0.004)
Credit 5yr ma			9.554^{***}	8.293^{***}	0.199^{***}	0.179^{***}
			(2.596)	(2.536)	(0.067)	(0.068)
$Damages_{t-2} \times \Delta Credit_{t-2}$		-0.245				
		(0.724)				
Damages ma $\times \Delta Credit$ ma				9.948^{***}		0.299
				(3.438)		(0.196)
Constant	-5.321^{***}	-5.319^{***}	-5.320^{***}	-5.688^{***}	-0.033^{**}	-0.037^{***}
	(1.025)	(1.025)	(1.002)	(1.098)	(0.014)	(0.014)
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 Heteroskedasticity-robust standard errors are shown in parentheses.					

Table 14: Robust: Effect on a Crisis "Danger Zone" (1900 - 2020)

	Dependent Variable: Crisis Danger Zone			
	logistic		*OLS*	
	(1)	(2)	(3)	(4)
$Damages(pcGDP)_{t-1}$	0.068	−0.009	0.008	0.006
	(0.052)	(0.035)	(0.006)	(0.006)
$\Delta Credit_{t-1}$	5.493***	5.219***	0.213***	0.209***
	(1.073)	(1.079)	(0.079)	(0.079)
$\Delta GDPCredit_{t-1}$	−4.269	−4.253	−0.046	−0.044
	(2.645)	(2.675)	(0.154)	(0.154)
$Damages_{t-1} \times \Delta Credit_{t-1}$		5.377***		0.108
		(1.400)		(0.083)
Constant	−3.812***	−4.023***	−0.078***	−0.079***
	(0.593)	(0.647)	(0.024)	(0.024)
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	No	No	Yes	Yes
Restricted sample	No	No	No	No
Observations	1,985	1,985	1,985	1,985
Adjusted R^2			0.312	0.312
Log Likelihood	-544.567	-537.591		
Residual Std. Error			0.234	0.234
F Statistic			7.612***	7.569***
Note:	*p<0.1; **p<0.05; ***p<0.01 Heteroskedasticity-robust standard errors are shown in parentheses.			

6 Conclusion

The key remaining challenges and opportunities for research are: (1) To better identify the granular channels through which disasters affect the financial system and when. (2) Expand the analysis to a broader set of countries and overcome the issue of including year effects in the probit models. (3) Use empirical methods to identify which crises were affected by natural disasters and analyze if and how they were different to those that weren't.

Additionally, given the correlation between disasters and crises discovered in this study, an extension of this research could be to explore whether disasters are a viable instrument for crises. My findings already show that disasters would be a relevant instrument (although the correlation is fairly small). Disasters are also exogenous to the financial system and therefore unlikely to be correlated with the error term. Yet, the main challenge is to overcome the exclusivity conditions since disasters, almost by definition, have such a wide-ranging effect on the economy.

The main goal of my research was to see whether the historic narratives natural disasters leading up to financial crises, were a more general phenomenon that could be identified in the data. Indeed, the results show that the two-period lagged damage measure from natural disasters is consistently positive and statistically significant across different model specifications, indicating that large natural disasters are associated with higher crisis-risk in the future. This effect is amplified during periods of credit expansions. Furthermore, my results suggest that the reduction in economic output after a disaster and the ensuing fall in bank equity returns are potential channels through which natural disasters increase the likelihood of financial crises. When I control for GDP growth, for example, the size and significance of the disaster coefficient shrink.

I conclude by noting that the relationship between disasters and crises presented in my research hopefully further motivates and supports existing efforts by central banks to study the impact of climate change on the stability of the financial system and prepare for the challenges ahead.

References

Akyüz, Y., & Boratav, K. (2002). The Making Of The Turkish Financial Crisis. *UNCTAD Discussion Papers*, (158). Retrieved May 15, 2023, from https://ideas.repec.org//p/unc/dispap/158.html

Barnichon, R., Matthes, C., & Ziegenbein, A. (2016, December 1). *Theory Ahead of Measurement? Assessing the Nonlinear Effects of Financial Market Disruptions*. Retrieved May 7, 2023, from https://papers.ssrn.com/abstract=2879284

Baron, M., Verner, E., & Xiong, W. (2020). Banking crises without panics. *The Quarterly Journal of Economics*, *136*(1), 51–113. https://doi.org/10.1093/qje/qjaa034

Bernanke, B., & Gertler, M. (1989). Agency Costs, Net Worth, and Business Fluctuations. *The American Economic Review*, *79*(1), 14–31. Retrieved May 9, 2023, from https://www.jstor.org/stable/1804770

Bernanke, B., Gertler, M., & Gilchrist, S. (1999, January 1). Chapter 21 The financial accelerator in a quantitative business cycle framework. In *Handbook of Macroeconomics* (pp. 1341–1393, Vol. 1). Elsevier. https://doi.org/10.1016/S1574-0048(99)10034-X

Botzen, W. J. W., Deschenes, O., & Sanders, M. (2019). The economic impacts of natural disasters: A review of models and empirical studies. *Review of Environmental Economics and Policy*, *13*(2), 167–188. https://doi.org/10.1093/reep/rez004

Bremus, F., & Rieth, M. (2022, December 22). *Integrating Out Natural Disaster Shocks.*

Brunnermeier, M. K., & Sannikov, Y. (2014). A Macroeconomic Model with a Financial Sector. *American Economic Review*, *104*(2), 379–421. https://doi.org/10.1257/aer.104.2.379

Cortés, K. R., & Strahan, P. E. (2017). Tracing out capital flows: How financially integrated banks respond to natural disasters. *Journal of Financial Economics*, *125*(1), 182–199. https://doi.org/10.1016/j.jfineco.2017.04.011

Cruz-Gonzalez, M., Fernández-Val, I., & Weidner, M. (2017). Bias Corrections for Probit and Logit Models with Two-way Fixed Effects. *The Stata Journal: Promoting communications on statistics and Stata*, *17*(3), 517–545. https://doi.org/10.1177/1536867X1701700301

Friedman, M., Schwartz, A. J., & Friedman, M. (1963). *A Monetary History of the United States, 1867-1960.* Princeton University Press. Retrieved May 16, 2023, from http://ebookcentral.proquest.com/lib/sciences-po/detail.action?docID=590813

He, Z., & Krishnamurthy, A. (2013). Intermediary Asset Pricing. *American Economic Review*, *103*(2), 732–770. https://doi.org/10.1257/aer.103.2.732

Horwich, G. (2000). Economic Lessons of the Kobe Earthquake. *Economic Development and Cultural Change*, *48*(3), 521–542. https://doi.org/10.1086/452609

Hosono, K., Miyakawa, D., Uchino, T., Hazama, M., Ono, A., Uchida, H., & Uesugi, I. (2016). Natural Disasters, Damage to Banks, and Firm Investment. *International Economic Review*, *57*(4), 1335–1370. Retrieved May 15, 2023, from https://www.jstor.org/stable/44280155

Hsiang, S. M., & Jina, A. S. (2014, July). *The causal effect of environmental catastrophe on long-run economic growth: Evidence from 6,700 cyclones* (Working paper No. 20352). National Bureau of Economic Research. http://www.nber.org/papers/w20352

IPCC. (2022). *Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change.* (H.-O. Pörtner, D. C. Roberts, M. M. B. Tignor, E. S.

Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, & B. Rama, Eds.).

Jones, R. L., Guha-Sapir, D., & Tubeuf, S. (2022). Human and economic impacts of natural disasters: Can we trust the global data? *Scientific Data*, *9*(1), 572. https://doi.org/10.1038/s41597-022-01667-x

Jordà, Ò. (2005). Estimation and Inference of Impulse Responses by Local Projections. *American Economic Review*, *95*(1), 161–182. https://doi.org/10.1257/0002828053828518

Jordà, Ò., Schularick, M., & Taylor, A. M. (2020). The effects of quasi-random monetary experiments. *Journal of Monetary Economics*, *112*, 22–40. https://doi.org/10.1016/j.jmoneco.2019.01.021

Jordà, Ò., Singh, S. R., & Taylor, A. M. (2022). Longer-Run Economic Consequences of Pandemics. *The Review of Economics and Statistics*, *104*(1), 166–175. https://doi.org/10.1162/rest_a_01042

Kahn, M. E. (2005). The Death Toll from Natural Disasters: The Role of Income, Geography, and Institutions. *The Review of Economics and Statistics*, *87*(2), 271–284. https://doi.org/10.1162/0034653053970339

Kiyotaki, N., & Moore, J. (1997). Credit Cycles. *Journal of Political Economy*, *105*(2), 211–248. https://doi.org/10.1086/262072

Klomp, J. (2014). Financial fragility and natural disasters: An empirical analysis. *Journal of Financial Stability*, *13*, 180–192. https://doi.org/10.1016/j.jfs.2014.06.001

Klomp, J., & Valckx, K. (2014). Natural disasters and economic growth: A meta-analysis. *Global Environmental Change*, *26*, 183–195. https://doi.org/10.1016/j.gloenvcha.2014.02.006

Koch, L., Chaudhary, M. A., & Bilquees, F. (2001). February 2001 Crisis in Turkey: Causes and Consequences [with Comments]. *The Pakistan Development Review*, *40*(4), 467–486. Retrieved May 15, 2023, from https://www.jstor.org/stable/41260347

Krishnamurthy, A., & Muir, T. (2017). How Credit Cycles across a Financial Crisis. *NBER*, w23850. https://doi.org/10.3386/w23850

Laeven, L., & Valencia, F. (2013). Systemic Banking Crises Database. *IMF Economic Review*, *61*(2), 225–270. Retrieved May 9, 2023, from https://www.jstor.org/stable/43302165

Lancaster, T. (2000). The incidental parameter problem since 1948. *Journal of Econometrics*, *95*(2), 391–413. https://doi.org/10.1016/S0304-4076(99)00044-5

Mendoza, E. G. (2010). Sudden Stops, Financial Crises, and Leverage. *American Economic Review*, *100*(5), 1941–1966. https://doi.org/10.1257/aer.100.5.1941

Nelson, B., & Tanaka, M. (2014, March 14). *Dealing with a Banking Crisis: What Lessons Can Be Learned from Japan's Experience?* Retrieved May 16, 2023, from https://papers.ssrn.com/abstract=2416213

Noy, I. (2009). The macroeconomic consequences of disasters. *Journal of Development Economics*, *88*(2), 221–231. https://doi.org/10.1016/j.jdeveco.2008.02.005

Odell, K. A., & Weidenmier, M. D. (2004). Real Shock, Monetary Aftershock: The 1906 San Francisco Earthquake and the Panic of 1907. *The Journal of Economic History*, *64*(4), 1002–1027. Retrieved May 16, 2023, from https://www.jstor.org/stable/3874987

Raddatz, C. (2007). Are external shocks responsible for the instability of output in low-income countries? *Journal of Development Economics*, *84*(1), 155–187. Retrieved May 8, 2023, from https://econpapers.repec.org/article/eeedeveco/v_3a84_3ay_3a2007_3ai_3a1_3ap_3a155-187.htm

Schularick, M., & Taylor, A. M. (2012). Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870-2008. *American Economic Review*, *102*(2), 1029–61. https://doi.org/10.1257/aer.102.2.1029

Skidmore, M., & Toya, H. (2002). Do Natural disasters promote long-term growth? *Economic Inquiry*, *40*(4), 664–687. https://doi.org/10.1093/ei/40.4.664

Strobl, E. (2011). The economic growth impact of hurricanes: Evidence from US coastal countes. *The Review of Economics and Statistics*, *93*(2), 575–589. Retrieved November 30, 2022, from http://www-jstor-org.acces-distant.sciencespo.fr/stable/23015955

Tamaki, N. (1995, September 7). *Japanese Banking: A History, 1859-1959*. Cambridge University Press.

Wicker, E., & Tallman, E. W. (2009, July 31). *Banking and Financial Crises in United States History: What Guidance can History Offer Policymakers?* https://doi.org/10.2139/ssrn.1544015

A Appendix

Table 15: Robust: Interaction credit expansions and natural disasters with GDP controls (1900 - 2020)

	Dependent Variable: Crisis in $year = t$					
	logistic				*OLS*	
	(1)	(2)	(3)	(4)	(5)	(6)
$Damages(pctGDP)_t$	-0.134	-0.133				
	(0.151)	(0.151)				
$Damages(pctGDP)_{t-1}$	0.018	0.018				
	(0.030)	(0.030)				
$Damages(pctGDP)_{t-2}$	0.067***	0.070***				
	(0.011)	(0.014)				
$Damages(pctGDP)_{t-3}$	0.072*	0.072				
	(0.043)	(0.044)				
$\Delta Credit_{t-1}$	1.882	1.899				
	(2.211)	(2.231)				
$\Delta Credit_{t-2}$	8.426***	8.443***				
	(2.603)	(2.614)				
$\Delta Credit_{t-3}$	1.272	1.282				
	(1.632)	(1.643)				
$\Delta Credit_{t-4}$	2.842**	2.840**				
	(1.314)	(1.313)				
ΔGDP_{t-1}	-5.766**	-5.770**				
	(2.680)	(2.689)				
ΔGDP_{t-2}	-1.998	-1.997				
	(2.851)	(2.849)				
ΔGDP_{t-3}	-5.357**	-5.354**				
	(2.252)	(2.251)				
ΔGDP_{t-4}	-3.489	-3.486				
	(2.772)	(2.770)				
Damages 5yr ma			0.149***	-0.099	0.008***	0.003
			(0.057)	(0.080)	(0.001)	(0.002)
Δ Credit 5yr ma			14.854***	13.572***	0.273***	0.251***
			(3.120)	(2.886)	(0.066)	(0.060)
Δ GDP 5yr ma			-17.747***	-17.939***	-0.093	-0.094
			(5.181)	(5.267)	(0.110)	(0.110)
$Damages_{t-2} \times \Delta Credit_{t-2}$		-0.219				
		(0.708)				
Damages ma $\times \Delta Credit$ ma				9.636***		0.299*
				(1.945)		(0.180)
Constant	-5.131***	-5.130***	-5.085***	-5.397***	-0.039***	-0.042***
	(0.238)	(0.237)	(0.206)	(0.199)	(0.006)	(0.008)
Country fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year fixed effects	*No*	*No*	*No*	*No*	*Yes*	*Yes*
Observations	1,929	1,929	1,900	1,900	1,900	1,900
Adjusted R^2					0.220	0.222
Log Likelihood	-224.321	-224.304	-230.713	-225.531		
Residual Std. Error					0.149	0.149
F Statistic					5.004***	5.019***

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

A.0.1 Multicollinearity

Although the main specifications in this paper include lagged independent variables, there should not be a multicollinearity problem because the disaster shocks capture one disaster each and are therefore unlikely to be correlated with their lags. In other words, the probability of having a disaster this year is likely fairly uncorrelated with having a disaster the next year. This is confirmed in the following correlation matrix among the lagged disaster variables. The results indicate that there is no significant multicollinearity issue the correlation coefficients all have values close to zero. This indicates that the independent variables included the models can be considered as distinct explanatory variables.

Table 16: Correlation Matrix of Variables

	Disaster	DisasterL1	DisasterL2	DisasterL3
Disaster	1.00			
DisasterL1	0.03	1.00		
DisasterL2	0.04	0.03	1.00	
DisasterL3	0.05	0.04	0.03	1.00