Frequency of Shocks, Resilience and Shock Persistence: Evidence from Natural Disasters

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Abstract: Volatility persistence has important welfare consequences. In this paper, we investigate the effect on volatility persistence of the frequency of shocks for which we consider exogenous natural disasters. We find that, on average, volatility persistence is about 5 percent lower in countries that have experienced one more natural disasters per year. However, there is a non-linearity in that volatility persistence initially decreases and then increases with the frequency of natural disasters. The results are explained in terms of disaster resilience—countries that experience natural disasters frequently develop resilience that shields the economy from the destruction of natural disasters and/or expedites economic recovery. Among the factors that potentially create resilience, we find significance of its structural component.

Keywords: Shock; Natural disaster; Resilience; Volatility persistence.

JEL codes: E32; H54; I38; Q54.

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1. Introduction

The welfare costs of shocks are of great importance to both researchers and policymakers. There is an emerging consensus that the welfare costs of shocks can be immense for large shocks. For example, Barro (2006; 2009) estimates that the costs associated with large shocks, such as World Wars and the Great Depression, are as large as 20% of GDP for a typical advanced economy, although those associated with smaller shocks, such as normal business cycles, are approximately 1.5% of GDP.[1] The sizable negative impact of these shocks also suggests that the effects may persist for a long period of time. Large shocks are rare but smaller shocks are frequent so the cumulative effects of smaller shocks can be non-negligible. However, the magnitude and persistence of the effects can vary across countries depending on their resilience to shocks developed over time through past exposures to shocks. The relationship between the frequency of shocks and growth volatility, especially its persistence, is unknown and this paper is intended to fill this gap. We argue and document that the effects of shocks will be less (more) persistent in countries that experience shocks more (less) frequently. More specifically, we document that the trend growth rate of real GDP is less volatile in countries that experience shocks more frequently because these countries, due to their shock resilience, incur lower damage from a given shock and/or the negative effects of the shock do not persist long compared to countries that experience shocks less frequently.

To identify the causal effects of the frequency of shocks, we consider only natural disasters, which are exogenous. There is a large literature on the effects of natural disasters on many economic aspects that include GDP growth, fiscal dynamics, trade and capital flows, stock markets, school enrolment, life expectancy and fertility (see Cavallo and Noy (2011), Klomp and Valckx (2014), Kousky (2014) and Lazzaroni and van Bergeijk (2014), among others, for surveys). There is a consensus that in the short-run, large disasters have negative effects on growth, but there is no agreement on the effects of small disasters. The effect on long-run economic growth is not well established although most studies report a negative effect (Cavallo and Noy, 2011). However, there is no study that relates the *frequency* of natural disasters to growth volatility let alone volatility persistence. A handful of studies investigate

[1] Pindyck and Wang (2013) estimate that a permanent tax on consumption of approximately 7% would be justified if the resulting revenues could be used to limit the impact of a catastrophic shock, such as nuclear attack or "a highly contagious *megavirus* that spreads uncontrollably" to a loss no greater than 15% of the capital stock.

the damage caused by the frequency of a specific type of natural disasters. For example, Hsiang and Narita (2012) and Hsiang and Jina (2014) find that the marginal losses from tropical cyclones are smaller in cyclone-prone countries and larger in countries with less historical cyclone experience. Anbarci, Escaleras and Register (2005) and Escaleras, Anbarci and Register (2007) find that on average countries that experience earthquakes more frequently experience lower marginal fatalities and damages. These authors interpret their results as evidence that frequently exposed populations learn from the experiences and adapt to climatological risks by undertaking investments that partially insulate their economies from natural disasters.

We calculate *volatility persistence* as the standard deviation of the low-frequency component of the real GDP growth; this is also referred to as *long-run (LR) volatility* (Levy and Dezhbakhsh, 2003; Ascari and Sbordone, 2014; Müller and Watson, 2017; Mallick, 2014; 2019).[2] We consider the 1990-2017 period to retain the maximum number of countries in our sample.[3] We use natural disaster data from the Emergency Events Database (EM-DAT), the most widely used and publicly available dataset on disasters. We count the number of natural disasters for the same period and define its frequency as the average number of natural disasters experienced by a country per year. We also count the frequency of natural disasters of different levels of severity (intensity). Given that the severity of different types of natural disasters is not comparable, we define it in terms of the number of deaths (see details in Section 2). Although the frequency of natural disasters is exogenous, we include a set of control variables in the regression that might potentially affect volatility and are also correlated with natural disasters. After accounting for the severity of natural disasters (see Section 3 for identification), our estimation approach captures the exogenous variations to estimate the causal effect of the frequency of natural disasters on the persistence of volatility.

We find that, on average, persistence of volatility is 4.9% lower in a country that has experienced one more natural disaster per year. The results are robust in a variety of ways that include specific types of natural disasters that occur more frequently such as floods and storms, different sub-samples defined based on different percentiles in the distribution of the frequency of natural disasters, and alternative definitions of the long-run in growth and

[2] Throughout the paper, we alternatively use persistence of volatility, LR volatility and volatility of the trend growth.

[3] Depending on the availability of the relevant variables used in the regression, we have a cross-section of 182 countries for our benchmark analysis.

business-cycle literature. Importantly, we observe significant non-linearity in the effects of the frequency of natural disasters. As the frequency of natural disasters increases, LR volatility initially decreases but increases in countries that experience natural disasters too frequently. However, the marginal effect is significant when it is negative.

We interpret our results in terms of disaster resilience. Disaster resilience minimizes the potential losses caused by a natural disaster and/or promotes quick economic recovery in the aftermath of a natural disaster. Disaster resilience develops at the individual, community and state level when a country experiences more frequent natural disasters. It is generated by several factors that include prioritized investments that limit the impact of disasters, developing early warning systems, creating fiscal buffers and pre-arranged financial instruments to manage funds for recovery in the aftermath of a disaster, and developing the capacity to respond by rapidly mobilizing physical and financial resources to limit disruption to public services. It also includes people's adaptive capacity such as diversification of economic activities in response to natural disasters. In the absence of disaster resilience, destructions will be large and/or recovery slow, which result in volatility that persists for a long period of time. At the other extreme, when natural disasters are too frequent (say, hit by another disaster before recovering from the destructions caused by the previous one), disaster resilience may not be sufficient and LR volatility will be larger.

It is hard to measure resilience at the national level, even more difficult when comparing across countries. Therefore, we take an indirect approach by considering the factors attributed to creating resilience such as government investments in critical areas such as prioritized infrastructure and early warning systems. However, given that data on such specific types of government investment are not available at the cross-country level, we instead use the share of government gross capital formation (GGFCF) in GDP as a proxy (measurement errors in GGFCF is addressed in Section 5). We find that GGFCF can explain the effect of the frequency of natural disasters on LR volatility—after including this variable in the regression, its coefficient is negative and statistically significant while the coefficient on the frequency of natural disasters becomes statistically insignificant. On the other hand, other likely candidates such as government expenditure for business-cycle stabilization, financial development or foreign aid cannot explain the disaster-volatility relationship. We also observe that GGFCF increases with the frequency of natural disasters.

Our paper is situated in several branches of literature—both macroeconomics and natural disasters. Aguiar and Gopinath (2007) posit that the volatility of the trend growth (LR volatility) is very large in the emerging market economies due mainly to sudden reversals in fiscal, monetary, and trade policies, while it is stable in developed countries. On the other hand, we find that the frequency of exogenous shocks explains the LR volatility and our measure of shocks—natural disasters—is unrelated to the country income groups. Our paper is also related to studies on economic disasters that attempt to explain several asset market puzzles. For example, Barro (2006; 2009) uses the observed probability distribution of economic disasters in the twentieth century to explain the equity-premium and risk-free rate puzzles. Gabaix (2012) extends Barro (2006) using variable severity of disasters to explain several other asset market puzzles as well as excess volatility puzzle, among others. We differ from this literature in that we explain LR volatility by the frequency of natural disasters. Our paper is also situated in the large literature on disaster resilience (see, Rose (2016) for a summary and more references). Building disaster resilience is also a high priority for many international organizations including the United Nations, World Bank and International Monetary Fund. Our results signify the role of resilience in mitigating the LR volatility.

The rest of the paper proceeds as follows. Section 2 describes the data and some key descriptive statistics. The empirical specification and identification strategy are explained in Section 3. Section 4 presents the results including several robustness checks. The role of resilience is discussed in Section 5. Section 6 concludes.

2. Data and Descriptive Statistics

We use the Emergency Events Database (EM-DAT), the most commonly used and publicly available dataset on natural disasters. The EM-DAT database is compiled from several sources that include the United Nations, governmental and non-governmental agencies, insurance companies, research institutes and press agencies. The dataset compiles information about natural disasters since 1900. In this dataset, natural disasters are recorded if at least one of the following criteria are satisfied: i) 10 or more people dead, ii) 100 or more people affected, injured or homeless, iii) declaration by the country of a state of emergency, and iv) an appeal for international assistance. We consider the following four categories of natural disasters: geophysical (earthquake, volcanic activity and mass movement), meteorological (storm, extreme temperature and fog), hydrological (flood, landslide, avalanche and wave action), and climatological (drought, glacial lake outburst and wildfire).[4]

We choose the 1990-2017 period to retain as many sample countries as possible for which data for LR volatility and other variables used in the regression analyses are available for a longer period. We count the number of natural disasters for the above period and define its frequency as the average number of natural disasters a country experienced per year. We have a cross-section of 182 sample countries. Details of other data used in the analyses are provided in Appendix B.

Descriptive statistics are presented in Table 1. On average a country has experienced 1.7 natural disasters of any type and severity per year. However, there is a wide dispersion in the frequency across countries with a maximum of 25.6 (China) and 0 (Qatar, Equatorial Guinea, Bahrain, Malta, Singapore, and Sao Tome and Principe). More details on this are in Section 4.2.1 and the footnote therein.

Insert Table 1 here

The severity of different types of natural disasters, such as floods, cyclones and earthquakes, cannot be compared as they are measured in different scales. Economic damage and the number of deaths are two obvious candidates for comparing severity. However, the majority of disasters in the EM-DAT data have missing (direct) damage estimates (this data limitation is also emphasized by others including Kousky (2014)).[5] Therefore, we define the severity of natural disasters based on the number of deaths.[6] The frequency of natural disasters decreases with the severity. For example, the mean values of the frequencies are 1.2, 0.76 and 0.66 per year in the case of natural disasters that caused at least 10, 50 and 100 deaths, respectively. Countries that experienced more frequent natural disasters also experienced more severe natural disasters. The correlations of the frequency

[4] Note that in the dataset there is no entry for the following natural disasters: fog, wave action and glacial lake outburst.

[5] There is also underreporting of economic losses in the EM-DAT data as large as 50% in low and middle income countries (UNISDR, 2013).

[6] We recognize that number of deaths depends on many factors including level of economic development and institutional development that we control in our regression analysis (details in Section 3).

of all natural disasters with more severe ones causing at least 10, 50 and 100 deaths are very large exceeding 0.97 (not reported in the table). This observation is also corroborated by Cantelmo, Melina and Papageorgiou (2019) in the context of developing countries. The most frequent natural disasters are floods and storms with a mean value of 1.2 per year, while that for less frequent earthquakes and volcanic eruptions is 0.17 per year.

Table 1 also shows that the frequency of (all types of) natural disasters has increased over time. For example, the mean frequency of natural disasters per year during 1900-1989 was 0.22. Similar findings are also documented by, among others, Bloom and Khanna (2007) and Gaiha, Hill, Thapa and Kulkarni (2015). The increased frequency is generally attributed to climate change, growing population and structures in hazardous areas, and also improved recording. Importantly, the correlation between the frequency during 1990-2017 and 1900-1989 is very large around 0.9, suggesting that countries with more historical disaster exposures also experience natural disasters more frequently.

Insert Figures 1A and 1B here

There are also geographic variations in the frequency of natural disasters. For example, the Asia Pacific and South Asia are the most disaster-prone regions in the world followed by Latin and North America, and while Scandinavia is the least disaster-prone as shown in Figure 1A. The above pattern of the regional distributions of the frequency of natural disasters also holds for different levels of severity (Appendix Figure A.1-A.3), and in the 1900-1989 period (Figure 1B), When comparing floods and storms, the Caribbean region is also more disaster-prone (Appendix Figure A.4). Earthquakes and volcanic activities are more frequent in the Asia Pacific and in few Middle-Eastern and Latin American countries (Appendix Figure A.5).

3. **Empirical Specification and Identification**

Our benchmark empirical specification is the following:

$$\ln \sigma_i^{LR} = \alpha + \beta \overline{S}_i + \boldsymbol{\delta}' \mathbf{X}_i + \varepsilon_i . \tag{1}$$

Here, σ_i^{LR} is the LR volatility in country *i*. For each country *i*, the growth rate of real GDP (Y) is calculated as $g_t = \ln(Y_t / Y_{t-1})$. The long-run (low-frequency) value of g_t (g_t^{LR}) is extracted by employing a low-pass filter (which is a special case of the Baxter and King (1999) band-pass filter)[7] at the zero-frequency. The LR volatility (σ^{LR}) or alternatively, the persistence of volatility is then calculated as the standard deviation of g_t^{LR}. $\overline{S}_i$ is the average number of natural disasters per year in country *i* over the 1990-2017 period.

Although the frequency of natural disasters is exogenous (also see Noy, 2009; Cantelmo, Melina and Papageorgiou, 2019), our regression specification may suffer from omitted variables that potentially affect σ_i^{LR} and are also correlated with $\overline{S}_i$. We carefully choose a vector of control variables, $\mathbf{X_i}$, to address the omitted variables.

The first set of variables in $\mathbf{X_i}$ includes the size of the country proxied by (log) land area (in square kilometres) and (log) population in the initial period. Macroeconomic impacts of natural disasters are likely to be modest in larger countries since such impacts are usually localized, thus large land size provides a "natural shelter". In contrast, many disaster-prone countries have a very small land size (e.g. small Pacific or Caribbean islands) with a small population and also their key sectors depend on weather conditions (Cantelmo, Melina and Papageorgiou, 2019; IMF, 2019). The number of deaths caused by a disaster (as we define the severity of natural disasters by the number of deaths) also depends on the population size, especially living in hazardous areas.

Although poor countries do not experience more natural disasters than rich countries (Kahn, 2005), the economic and human losses from natural disasters (and the speed of recovery) depend on economic development.[8] We control for the initial level of per capita real GDP (log) to account for the level of economic development.

Institutional development is influenced by natural disasters and is also a channel that mediates the effect of natural disasters on volatility. There is a large literature on

[7] For details of the low-pass filter, please see Chirinko and Mallick (2017).

[8] The exact relationship is debated. Noy (2009) finds that countries experience less impact on the macroeconomy if they have higher per capita incomes. However, Kellenberg and Mobarak (2008) find that damages from floods, landslides, and windstorms increase with GDP per capita until a certain level and then decline. Raschky (2008), on the other hand, finds that initial level of development can reduce losses, and economic damages increase at higher wealth level.

retrospective voting behavior that argues that (in mature democracies) voters hold politicians responsible for the damage caused by a natural disaster, but reward them when they react promptly by taking actions that limit the negative consequences (See Klomp (2020) for a review). In nascent democracies, citizens who suffer damage from natural disasters tend toward lower evaluations of democratic institutions, lower support for democratic values and practices, and stronger dispositions toward action (Carlin, Love and Zechmeister, 2014). Yamamura (2014) finds that natural disasters that cause substantial damage increase public sector corruption in both developing and developed countries, and the impact is greater in developed than in developing countries. On the other hand, countries with a higher quality of institutions suffer fewer deaths from natural disasters (Kahn, 2005; Raschky, 2008; Noy, 2009).[9]

We control for *Voice and Accountability* as a proxy for institutions. This variable captures "perceptions of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media (WGI, 2019)."[10] Values range from approximately -2.5 (weak) to 2.5 (strong) performance. This is one of the indicators of governance in the Worldwide Governance Indicators (WGI) research dataset of the World Bank. Note that *Polity2, Constraint on Executives* or *Governance* are the most common proxies for institutions in the literature. However, using any of these variables reduces our sample size; in our data the correlation between our proxy and the above alternatives is the largest for *Polity2* at 0.87.[11]

In addition to their role in shaping the institutions, natural disasters also affect discretionary fiscal policy. In the aftermath of a disaster, fiscal support might not always only be provided to improve the economic condition of the affected population; rather, in many instances, this is motivated by securing political gains. Klomp (2020) estimates that approximately 10 percent of the disaster-related public spending provided in an election year is attributed to rent-seeking rather than need. Fiscal behavior that is not related to the stabilization of

[9] Kahn (2005) conjectures corruption as one possible mechanism as government corruption could raise death counts through the lack of enforcement of building codes, infrastructure quality, and zoning. Disbursement and efficient utilization of reconstruction resources for post-disaster recovery also depend on the institutional quality (del Valle, Janvry and Sadoulet, 2020).

[10] Besley and Burgess (2002) observe that in India impacts of flood are negatively correlated with newspaper circulation. They argue that when newspaper circulation is higher, politicians are more accountable and therefore the government is more active in both preventing and mitigating the impacts of natural disasters.

[11] All the results are strongly robust if *Polity2* is used as the proxy for institution. However, the sample size decreases to 145 countries.

business cycles is referred to as "policy volatility" or "fiscal activism" by Fatás and Mihov (2013) and has negative effects on growth and volatility. Following these authors, we calculate policy volatility[12] and include it as a control. This variable also captures domestic macroeconomic policy shocks.[13]

Finally, we control for the share of agriculture in GDP as agricultural output is dependent on weather conditions, especially in developing countries, and therefore their economies are more susceptible to natural disasters. For example, many low-income countries in sub-Saharan Africa that are dependent on rain-fed agriculture suffer considerable damage from repeated droughts and floods (IMF, 2019). Based on the estimates of the Food and Agricultural Organization of the United Nations (FAO), the impact of natural disasters on agriculture (broadly defined in terms of crops, livestock, fisheries and forestry) is also very large especially in developing countries constituting approximately 22 percent of total damage (FAO, 2015). Disasters not only destroy agricultural output, critical agricultural assets and infrastructure but also alter agricultural trade flows, and lead to losses in agricultural-dependent manufacturing subsectors such as the textile and food processing industries (FAO, 2015).

One potential concern is that all natural disasters may not be strong enough to negatively affect economic growth and volatility. Since the majority of disasters in the EM-DAT data have missing damage estimates, we include the average number of deaths per disaster to control for the severity of natural disasters in the regressions. We also run separate regressions for severe natural disasters that caused at least 10, 50 and 100 deaths. However, these cut-off based on the number of deaths are ad-hoc and therefore may not be informative enough about natural disasters that caused fewer or no deaths but had damaging effects on the

[12] For each country, *i*, in the sample, the following regression is run:

$\ln(G_{i,t} / G_{i,t-1}) = \alpha_i + \beta_i \ln(Y_{i,t} / Y_{i,t-1}) + \nu_{i,t}$, where *G* is the real government consumption spending and *Y* is the real GDP. The standard deviation of the predicted residual $\hat{\nu}_{i,t}$ is the measure of policy volatility.

[13] Given that the effect is usually localized, as opposed to economy wide, governments rely on fiscal rather than monetary policy. Moreover, there is no single monetary policy instrument implemented by all countries; the instrument also changes over time. For example, many developed countries having an independent central bank introduced interest rate as the monetary policy instrument in 1990s. On other hand, many developing countries use monetary aggregate as the instrument for monetary policy. Fatas and Mihov (2013) also highlight the difficulties in constructing a consistent measure of monetary policy volatility at the cross-country level.

economy. Failure to account for the true severity may lead to measurement errors, which in turn lead to endogeneity.

Our IV is historical natural disasters prior to 1990—the average number of natural disasters per year a country experienced during the 1900-1989 period ($\overline{S}_i^P$). The argument for using $\overline{S}_i^P$ as the IV is the following. Due to the difficulty of information gathering (poor record-keeping), fewer natural disasters in the past were recorded and the reported ones are more severe in affecting lives and the economy. However, the distribution of countries in terms of disaster probability[14] has not changed; countries and regions that experienced natural disasters more frequently than others in the pre-1990 period still experience the same more frequently. This pattern also holds for different types of natural disasters such as floods or earthquakes, and disasters of different levels of severity. In the data, the correlation between $\overline{S}_i$ and $\overline{S}_i^P$ is 0.89. This correlation is almost the same for severe disasters and also for floods and storms, and earthquakes and volcanic eruptions (see Table 1 and discussions in Section 2). It is conceivable that $\overline{S}_i^P$ does not have any direct effect on current volatility, σ_i^{LR}, but affects σ_i^{LR} only through $\overline{S}_i$. More specifically, after controlling for $\mathbf{X_i}$, $\overline{S}_i^P$ extracts the exogenous variations in the severity of $\overline{S}_i$ to obtain its consistent estimate (β). The first-stage regression is given by equation (2):

$$\overline{S}_i = \phi + \eta \overline{S}_i^P + \boldsymbol{\theta}'\mathbf{X_i} + \mu_i . \quad (2)$$

Equation (2) regresses the average number of natural disasters a country experienced during the 1990-2017 period ($\overline{S}_i$) on the average number of natural disasters experienced during the 1900-1989 period ($\overline{S}_i^P$) and the vector of control variables $\mathbf{X_i}$. In the second stage, equation (1) is estimated substituting $\overline{S}_i$ with its predicted value obtained in the first stage.

4 Results

4.1 Benchmark results

[14] We alternatively use disaster probability and the frequency of natural disasters throughout the paper.

The OLS results for equation (1) are presented in the first eight columns in Table 2 for different combinations of the control variables. The standard errors are clustered at the regional level (only heteroskedascity-corrected robust standard errors are also reported in brackets). In Columns (1)-(5), $\overline{S}_i$ includes all recorded natural disasters irrespective of their severity. Column (1) is estimated without any control variables. Column (2) controls for the initial level of per capita real (log) GDP and the level of institutional development. Column (3) additionally controls for policy volatility. In all cases, the coefficient on $\overline{S}_i$ is negative and statistically significant at the 10% level. In column (4), country size as measured by land area (log) and initial population (log), and the share of agriculture in GDP are additionally controlled. Cols. 5 additionally includes the average number of deaths per disaster to account for the severity of natural disasters and a dummy indicating whether a country experienced any natural disaster during the sample period (this dummy is included in all subsequent regressions). The coefficient on $\overline{S}_i$ is negative but statistically insignificant. Importantly, adding the average number of deaths per disaster as a proxy for the severity of natural disasters does not change either the magnitude or standard error of $\overline{S}_i$.

Insert Table 2 here

In Columns (6)-(8), different levels of severity of $\overline{S}_i$ in terms of numbers of deaths are included—at least 10, 50 and 100, respectively. The coefficient on $\overline{S}_i$ is now statistically significant except for at least 100 or more deaths. These results suggest that, once the intensity of natural disasters is accounted for, countries that experience more natural disasters have less volatile long-run growth. In column (9), we report the results estimated by the IV method using the frequency of natural disasters in the 1900-1989 period ($\overline{S}_i^P$) as the IV for $\overline{S}_i$. The result shows that a negative and statistically significant coefficient on $\overline{S}_i$.[15] Quantitatively, the volatility of LR growth is, on average, 4.9% lower in a country that has experienced one more natural disaster per year.

[15] The *F*-statistic in the first-stage regressions is also large exceeding a cut-off value of 10 as recommended by Stock, Wright and Yogo (2002) suggesting that the instrument is highly relevant. The coefficient on $\overline{S}_i^P$ in the reduced form regression ($\ln \sigma_i^{LR} = \tau + \lambda \overline{S}_i^P + \boldsymbol{\pi}'\mathbf{X}_\mathbf{i} + e_i$) is negative and statistically significant at the 5% level.

In our subsequent analyses, we account for the severity of natural disasters by employing IV estimation for the frequency of all natural disasters, and by employing OLS estimation for the frequency of natural disasters causing at least 10, 50 and 100 deaths. In the following, we first check robustness of our benchmark results in several different ways.

4.2.1 Alternative definitions of the long-run (alternative periodicities / frequencies)

We have defined the long-run at the zero frequency. This is consistent with the concept of the long-run in growth theory. However, in the business-cycle literature, the business cycle is usually defined at the periodicity of 2-8 years (periodicity is inversely related to the frequency as $p = 2\pi/\omega$, where p and ω are periodicity and frequency, respectively), and the long-run is defined by the periodicity of 8+ years. Outside these two conventional definitions, Comin and Gertler (2006) and Comin, Loayza, Pasha and Serven (2014) use a non-standard definition of the long-run in terms of the periodicity of 50+ years (200+ quarters).[16] We re-estimate our benchmark IV regressions using these alternative definitions of the long-run. The results for the periodicity of 50+ and 8+ years are presented in Appendix Tables A.1 and A.2, respectively. The results are robust to the baseline results in Table 2. The coefficients on $\overline{S}_i$ are almost identical in the case of 50+ years of periodicity, although in the case of 8+ years of periodicity, the coefficient is significant only in the IV regression.[17]

4.2.2 Alternative filtering methods

We extracted the long-run growth component using the Baxter-King (1999) filter modified for the low-pass filtering. To see if the results are driven by our filtering method, we use the most commonly employed filtering method to extract the long-run component—the Hodrick-Prescott (HP) (1997) filter. Note that the HP filter is used to isolate the business cycle frequencies in quarterly data. There is a substantial divergence between the HP and band-pass filters, and the choice of smoothing parameter is not clear when applying to annual data

[16] These authors refer to the periodicities up to 50 years as the medium-term business cycle—periodicities up to 8 years as the high-frequency component of the medium-term, and periodicities between 8 and 50 years as the medium-frequency component of the medium-term.

[17] The results (not reported) are strongly robust to the results in the quadratic specification reported in Table 4.

(Baxter and King 1999, Section V.C).[18] With these caveats, we nonetheless apply the HP filter to first extract the business cycle frequencies and then recover the long-run (trend) component as the residual. The results, presented in Appendix Table A.3 are robust in terms of both the sign and statistical significance of the coefficient on $\overline{S}_i$; however, the magnitudes are now much larger than those in the benchmark results.[19]

4.2 Different disaster probabilities

Countries vary in terms of disaster probability. Some countries had been tormented by natural disasters several times a year. The maximum frequency of natural disasters of any level of severity in our sample is 25.6; in contrast, a few countries did not experience natural disasters at all during this period.[20] One valid concern might be whether our results are driven by these countries. To address this concern, we re-estimate using different combinations of sample countries selected based on their disaster probability: i) dropping 10% of sample countries with largest disaster probability (N= 164; max. $\overline{S}_i$=3.21), ii) dropping 25% of sample countries with largest disaster probability (N= 137; max. $\overline{S}_i$=1.86), iii) further dropping top 50% of sample countries with largest disaster probability (N= 95; max. $\overline{S}_i$=0.82), iv) dropping the countries that did not experience any natural disaster (N= 176), v) dropping bottom 10% of countries with lowest disaster probability (N= 166; min. $\overline{S}_i$=0.14), and finally, vi) dropping 10% of both largest and smallest disaster probability (N= 148; max. $\overline{S}_i$=3.21 and min. $\overline{S}_i$=0.14).

[18] We use 6.25 as recommended by Ravn and Uhlig (2002) for annual data.

[19] Unobserved Component Model is another alternative candidate for trend-cycle decomposition but this method relies on specific assumption about the data generating process. On the other hand, the Christiano-Fitzgerald (2003) band-pass filter is based on the assumption that the raw data follow a random walk. We therefore do not pursue these methods. Cochrane (1988) variance ratio, in our case, will be defined as the ratio of the variance of the long-difference to the variance of the first-difference of log GDP. The long-difference is another way of low-pass filtering. Therefore, our LR variance is similar to the numerator of the Cochrane variance ratio.

[20] The sample countries in order that experienced more than 10 natural disasters per year in the 1990-2017 period are China, United States, Philippines, India and Indonesia. Bangladesh follows next with 7.07 natural disasters per year. On the other hand, Singapore, Qatar, Bahrain, Equatorial Guinea, Sao Tome and Principe and Malta did not experience any natural disaster in the above period. The sample countries in order that experienced the highest number of floods and storms per year are United States, China, Philippines, India and Bangladesh. The sample countries in order that experienced the highest number of earthquakes and volcanic activities per year are China, Indonesia, Iran, Japan and Philippines (also see Figure 1A).

Since our variable of interest is the frequency of all recorded natural disasters having impacts on the economy, regressions are estimated by the IV method to account for the severity of natural disasters. These results can be compared with that in column (9) in Table 2. In all cases, the results, presented in Table 3, are robust both in terms of the sign and significance of the coefficient on $\overline{S}_i$. However, an important pattern emerges when comparing the magnitudes of the coefficient on $\overline{S}_i$. When countries with lower disaster probability are excluded, the magnitudes in columns (4) and (5) are very close to that in the full sample (column (9) in Table 2). On the other hand, the magnitude increases 10 times when 10% of the sample countries with the largest disaster probability are excluded (column (1)). The magnitude further increases several times when 25% and 50% of the sample countries with the largest disaster probability are excluded (columns (2) and (3)). This pattern suggests an important non-linearity in the effect of the frequency of natural disasters in that the effect on volatility persistence is less for countries with higher disaster probabilities.

Insert Table 3 here

4.3 Non-linear effects

To test the non-linearity of the effects of natural disasters, we augment equation (2) by the square of the average number of natural disasters per year ($\overline{S}_i^2$). The specification is written as:

$$\ln \sigma_i^{LR} = \alpha + \beta_1 \overline{S}_i + \beta_2 \overline{S}_i^2 + \boldsymbol{\delta}'\mathbf{X_i} + \varepsilon_i . \tag{3}$$

The results are presented in Table 4. Column (1) reports the IV result for the frequency of all natural disasters. Given that both $\overline{S}_i$ and $\overline{S}_i^2$ are now endogenous, our additional IV is the square of $\overline{S}_i^P$. Columns (2)-(4) report the OLS results for the frequency of natural disasters causing at least 10, 50 and 100 deaths, respectively.

The coefficients on $\overline{S}_i$ are negative and those on $\overline{S}_i^2$ are positive and both are significant at least at the 5% level. This suggests a non-linear effect of natural disasters on LR volatility—as the frequency of natural disasters increases, LR volatility first decreases and then increases.[21] The critical frequency of natural disasters per year for which the LR volatility reaches its minimum is calculated as ($-\beta_1 / 2\beta_2$). In the IV estimation, the critical frequency is 12.8 in the case of all natural disasters, which is close to the one for at least 10 deaths (11.6). This critical frequency declines as the severity of natural disasters increases—6.4 and 5.2 for the frequency of natural disasters causing at least 50 and 100 deaths, respectively. However, the marginal effect of the frequency of natural disasters on the LR volatility is not statistically significant at all ranges of the frequency. Figures 2A-2D display the marginal effects with 95% confidence intervals for different severity of natural disasters. In the cases of natural disasters causing at least 10, 50 and 100 deaths, the marginal effect is significant when it is negative at lower frequency of natural disasters—up to 9, 4.5 and 3.5 per year causing at least 10, 50 and 100 deaths, respectively.[22]

Insert Table 4 and Figures 2A-2D

4.4 Frequent vs. infrequent natural disasters

We have found that countries experiencing natural disasters more frequently have lower LR volatility, and also an important non-linearity in the effect. However, some types of natural disasters are more frequent than others and these also differ in terms of their predictability. To gain further support of our results, we classify all natural disasters into two groups—the ones that are more frequent and can also be forecasted in advance allowing precautions to be undertaken and have a relatively long onset, and the ones that are less frequent, unpredictable and have a relatively fast onset (Skidmore and Toya, 2002; Raddatz, 2007). We include floods and storms in the first category, and earthquakes and volcanic activities in the second

[21] So far, all our results are based on cross-section regressions. To check if our results are robust in panel data, we divide the sample period into two equal intervals—1990-2003 and 2004-2017—and calculate LR volatility and average of the control variables for each interval. Both the linear and non-linear results estimated by the FE method, presented in Appendix Table A.4, are strongly robust to the results presented in Tables 2 and 4. We do not pursue this approach further since data for some control variables are not available for longer periods, so the averages for the first interval (1993-2003) are based on fewer number of years. It is important to note that the results (not reported) are also strongly robust for each interval separately.

[22] Note that there are relatively small number of countries in the sample that experienced natural disasters too frequently. This may be the reason for the insignificance of the marginal effects at the higher frequencies of natural disasters.

category. We expect that the first category of natural disasters will lower LR volatility, while the second category will have no effect.

Insert Table 5 here

Both the OLS and IV results are presented in Table 5. Columns (1) and (2) present the OLS results for the linear and quadratic specifications, respectively. The same results for the IV estimation are presented in columns (3) and (4), respectively. In the linear specification, the coefficient on the frequency of floods and storms is negative and insignificant in OLS estimation but significant in IV estimation, which are also similar to the results in the case of all natural disasters. In addition, a similar non-linear pattern in the effect on volatility persistence is also apparent for the frequency of floods and storms. The LR volatility initially decreases and then increases with the frequency of floods and storms with a critical frequency of 10.1 per year in the IV estimation. On the other hand, there is no effect of earthquakes and volcanic activities both in the linear and quadratic specifications.

4.5 Do natural disasters change the long-run growth trajectory?

LR volatility can be lower if either output losses from natural disasters are lower and/or post-disaster economic recovery is quicker. There can be another possibility in which frequent natural disasters permanently lower the long-run growth trajectory around which the growth rate remains stable.[23] In such a scenario, LR volatility will also be lower. However, this investigation requires constructing an appropriate counterfactual trajectory that output would have followed without natural disasters. This exercise is beyond the scope of the current paper, and we, therefore, draw on past research instead. One influential study is Cavallo, Galiani, Noy and Pantano (2013) that employed an innovative approach. These authors constructed a counterfactual for each affected country from a group of countries that had the same secular trends in GDP and would have the same secular behavior in the absence of

[23] In endogenous growth models with aggregate capital externality that exploit increasing returns to capital, destruction of capital leads to permanent deviation from the previous balanced growth path to a new one characterized by a lower growth rate. Note that different variants of growth models, such as models based on exogenous technological change or creative destruction, have different predictions about the balanced growth path (see, Appendix Table 1 in Botzen, Wouter and Sanders, 2019). We do not stress on this issue since our objective is not to test predictions of different growth models.

natural disasters. They studied the impact of large natural disasters and documented that natural disasters do not change the long-run growth trajectory of a country (two exceptions are Iran and Nicaragua where radical political revolutions followed the disasters.).[24]

5. Role of resilience

The channels through which the impact of natural disasters on volatility is mediated is difficult to understand without an economic theory. We do not intend to develop a formal model here but in the following, we argue for disaster resilience as a dampening factor that minimizes the effect of natural disasters and/or helps quickly recover from destruction in the post-disaster period.

To define disaster resilience, we follow the United Nations International Strategy for Disaster Risk Reduction (UNISDR): "The capacity of a system, community or society potentially exposed to hazards to adapt, by resisting or changing in order to reach and maintain an acceptable level of functioning and structure. This is determined by the degree to which the social system is capable of organizing itself to increase this capacity for learning from past disasters for better future protection and to improve risk reduction measures" (UNISDR, 2005).[25]

IMF (2019b) categorized resilience in three categories: structural, financial and post-disaster resilience.[26] Structural resilience is created through appropriately chosen and prioritized investments that limit the impact of disasters that include upgrading infrastructure, developing irrigation systems, developing early warning systems, customizing building codes and zoning rules. A prime example is Bangladesh where far fewer people (3,000) were killed by a cyclone in 2008 than by a similar one in 1970 which killed almost half a million people (Ashdown, 2011). Financial resilience entails the use of fiscal buffers and pre-arranged financial instruments to manage funds for recovery in the aftermath of a disaster. In the absence of financial resilience, financing post-disaster recovery becomes more difficult

[24] Hsiang and Jina (2014) find negative and persistent effects of tropical cyclones; however, losses are magnified in countries with less historical cyclone experience, which is consistent with our findings.

[25] Similar definitions are also given by Manyena (2006) and DFID (2011). For a nice review of the concept of resilience and its measurement, see Rose and Krausmann (2013) and Rose (2016).

[26] Resilience has also been categorized in different alternative ways such as inherent vs. adaptive, and static vs. dynamic (see Rose, 2016).

because credit-worthiness is also adversely affected in the post-disaster period. Mexico's indexed disaster fund (*Fonden*) is a prime example of the creation of financial resilience that has been proven to be very effective to accelerate economic recovery after a disaster (del Valle, Janvry and Sadoulet, 2020). Post-disaster resilience entails the ability to respond by rapidly mobilizing physical and financial resources to limit disruptions to public services such as utilities, medical services, schools, law and order, and critical financial services. This also includes countercyclical fiscal spending to mitigate the indirect economic damages and facilitate recovery. Therefore, development of resilience reduces the need for, and cost of, financial protection and ex-post assistance (IMF, 2019b).

The capacity for learning, termed as adaptive capacity by Manyena (2006), also develops intrinsically among the population. There is ample anecdotal evidence. For example, communities in the Zambezi Valley of Zimbabwe have adapted to drought spells experienced during the rainy season by switching from production of traditional maize to "nzembwe", a drought-resistant type of millet (Manyena, 2006).

Testing the relationship between the frequency of natural disasters and disaster resilience at the macroeconomic level is a daunting challenge as an aggregate measure of disaster resilience at the cross-country level is very difficult to conceptualize and construct.[27] In the absence of counterfactuals, it is also not possible to measure the amount of damage/destruction avoided due to increased resilience, and also the speed of recovery.[28] Given this difficulty, we investigate the role of the factors that create resilience. We consider proxies for factors that create each of the structural, financial and post-disaster resilience, and alternatively include these variables in our regression. If inclusion of any of this variable makes the coefficient on the frequency of natural disaster insignificant and also its own coefficient becomes significant, we can infer this as a channel (mediator) through which natural disasters affect LR volatility. The proxy for structural resilience is government gross fixed capital formation (GGFCF) as a share of GDP (I_g/Y), the proxy for financial resilience is financial development measured as the ratio of private credit to GDP, and the proxies for

[27] Rose and and Krausmann (2013) summarize different resilience indices employed in the literature. The macroeconomic indices (that can be compared across countries) comprise the variables that are mostly captured by economic development of a country, which we control in our regression.

[28] Few studies attempted to calculate the counterfactual but at the specific incident level; for example, counterfactual business interruptions in the context of 9/11 terrorist attack by Rose, Oladosu, Lee and Asay (2009), and the same from a nine-month closure of a major US seaport by Rose and Wei (2013).

post-disaster resilience are government consumption expenditure as a share of GDP, and the ratio of foreign aid (net official development assistance and official aid) to GDP.

Insert Tables 6 and 7 here

The results are presented in Table 6.[29] Note that I_g/Y is also endogenous, and the source of endogeneity is measurement errors because I_g/Y is a proxy for government's prioritized investment on areas such as critical infrastructure and early warning system that creates resilience. Assuming that in disaster-prone countries' governments invested more in critical infrastructure (documented in Table 8),[30] the frequency of natural disasters in the 1900-1989 period ($\overline{S}_i^P$) is also a candidate for valid instrument for I_g/Y. We need a second instrument as both I_g/Y and $\overline{S}_i$ are now treated as endogenous. Therefore, we use squared $\overline{S}_i^P$ as the second instrument.[31] This result is presented in column (1). The coefficient on $\overline{S}_i$ is insignificant with a positive sign. If we re-estimate this specification without instrumenting I_g/Y, the previous result also holds (the coefficient on $\overline{S}_i$ is insignificant but now it is negative); however, the coefficient on I_g/Y increases by more than six-folds from -33.1 to -4.97, which suggests considerable measurement errors in I_g/Y as measurement errors bias a coefficient towards zero.[32]

In contrast, in the specifications that include government expenditure, financial development or foreign aid as a potential mediator variable, the sign, magnitude and statistical significance of the coefficient on $\overline{S}_i$ remains robust (both in terms of magnitude and significance) and the

[29] Note that sample size differs across specifications after including these mediator variables. In each of the specifications, the results are robust if regression is run excluding the mediator variables but restricting the sample to the same countries except in the case of foreign aid (columns 2a-5a). These results, including the one with foreign aid, also hold if the quadratic specification is estimated (not reported).

[30] There is anecdotal evidence that fraction of I_g/Y is quite large for countries experiencing frequent natural disasters. For example, in Dominica, about half of the public investment since *Hurricane Maria* in 2017 has been allocated for disaster-resilient projects (IMF, 2019).

[31] Some papers suggest to use a single instrument that jointly affects the treatment and the mediator but identification holds under particular structural restrictions (Frölich and Huber, 2017). We therefore do not follow this approach.

[32] Since the marginal effect of $\overline{S}_i$ is significant only when it is negative, we do not estimate a quadratic speciation. In addition, endogeneity of I_g/Y cannot be addressed in such as a specification because of the lack of enough instruments.

coefficients on these mediator variables are insignificant which rules out their role as a mediating factor (columns 2-5).

It may be likely that when countries experience natural disasters too frequently, resilience may not work and therefore I_g/Y may not mediate the effects of natural disasters. To investigate such a possibility, we divide the sample countries in two groups—below and above the median value of the frequency. The results are presented in Table 7. We find that for countries below the median value of the frequency, the coefficient on I_g/Y is negative and statistically significant; the coefficient on $\overline{S}_i$ decreases in (absolute) magnitude although remains statistically significant (which suggests partial mediation). On the contrary, for countries above the median value of the frequency, the coefficient on I_g/Y is statistically insignificant (and positive), and also the coefficient on $\overline{S}_i$ remains unchanged both in terms of its magnitude and standard error.

Insert Table 8 and Figures 3A-3D here

To further explore the relationship between the frequency of natural disasters and I_g/Y, we regress I_g/Y on the frequency of natural disasters ($\overline{S}_i$) and the variables in $\mathbf{X_i}$ defined in Section-3. The results, presented in Table 8, show that the coefficients on $\overline{S}_i$ are positive and significant, and robust for all levels of severity of natural disasters. The predicted values of I_g/Y are plotted in Figures 3A-3D from estimation of a quadratic specification augmented by the square of $\overline{S}_i$. For natural disasters of all levels of severity, the predicted values secularly increase with $\overline{S}_i$. These results further corroborate the role of the structural resilience.

6. Concluding remarks

In this paper, we investigate the relationship between the frequency of shocks and volatility persistence, which is also referred to as long-run (LR) volatility. In our empirical analyses, we consider natural disasters as exogenous shocks. We find that, on average, LR volatility is 4.9% lower in a country that has experienced one more natural disasters per year of any level of severity. We also observe a non-linear effect—LR volatility initially decreases with the frequency of natural disasters but increases in countries that experience natural disasters very frequently but the marginal effects are significant in the range of frequencies at which LR volatility is decreasing.

We argue that countries that experience natural disasters frequently will develop resilience that shields the economy from the destruction of natural disasters and/or expedites economic recovery (we cannot disentangle these two effects). Therefore, the output level will rapidly revert to the trend, which in turn implies lower persistence of volatility. Given the difficulty in quantifying disaster resilience, we investigate the factors that create resilience as possible mediating factors. We find that only the structural component among the possible factors that create resilience is important. More specifically, this is government gross fixed capital formation invested in prioritized areas such as, among others, upgrading critical infrastructure and developing early warning systems. This type of investment acts like an insurance for the citizens and the economy especially in developing countries where the private insurance market is incomplete or absent. But when countries experience natural disasters too frequently, resilience may not be sufficient to reduce volatility persistence.

We have considered only natural disasters and narrowly defined welfare in terms of volatility persistence. It is yet to be known if our results can be replicated for different types of shocks, such as epidemics, and terms-of-trade or other macroeconomic shocks, to have an impact on many other dimensions of development. Although there is a large literature relating macroeconomic and other exogenous shocks to volatility, there is no study exploring the effect of the frequency of shocks and how that creates resilience. Our results have also important implications for the global Covid-19 pandemic. Pindyck and Wang (2013) calculated very large welfare costs of a catastrophic event such as "a highly contagious *megavirus* that spreads uncontrollably." Rates of infection and deaths from the Covid-19 greatly vary across countries even after controlling for factors including measures undertaken to contain the spread of the virus (and reporting errors). It would be interesting to see how such variations across countries are related to the frequency of epidemic and prevalence of infectious diseases in the past that have created disease resilience among the population in different parts of the world.

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Tables

Table 1: Descriptive Statistics (N = 182)

Number of Natural Disasters per year	Mean (St. Dev.)	Median	[Min, Max]	Skewness	Corr. between (1900-1989) and (1990-2017) periods
	1990-2017 Period				
Any Intensity	1.697 (3.193)	0.821	[0, 25.643]	5.177	0.894
Causing at least 10 deaths	1.215 (2.417)	0.536	[0, 20.821]	5.258	0.881
Causing at least 50 deaths	0.757 (1.321)	0.429	[0, 10.786]	5.029	0.895
Causing at least 100 deaths	0.659 (1.078)	0.393	[0, 8.536]	5.043	0.870
Flood and Strom (any intensity)	1.201 (2.355)	0.571	[0, 19.857]	5.390	0.901
Earthquake and Volcanic eruption (any intensity)	0.165 (0.492)	0.036	[0, 4.393]	6.013	0.893
Volatility of trend real GDP growth rate (log) at 0-freq.	0.388 (0.692)	0.301	[-1.224, 2.371]	0.412	
	1900-1989 Period				
Any Intensity	0.224 (0.464)	0.078	[0, 3.378]	4.065	
Causing at least 10 deaths	0.198 (0.424)	0.067	[0, 3.067]	4.194	
Causing at least 50 deaths	0.145 (0.305)	0.044	[0, 2.056]	4.170	
Causing at least 100 deaths	0.122 (0.247)	0.044	[0, 1.678]	4.071	
Flood and Strom (any intensity)	0.137 (0.334)	0.033	[0, 2.789]	5.132	
Earthquake and Volcanic eruption (any intensity)	0.044 (0.129)	0	[0, 0.856]	4.358	

Table 2: Effect of the frequency of natural disasters on the (log) LR volatility.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS								IV
	All					Natural disasters causing at least			All
						10 deaths	50 deaths	100 deaths	
$\overline{S}_i$	-0.047	-0.048	-0.031	-0.029	-0.029	-0.040	-0.063	-0.064	-0.049
	(0.017)**	(0.017)**	(0.016)*	(0.018)	(0.017)	(0.022)*	(0.035)*	(0.041)	(0.027)*
	[0.016]***	[0.015]***	[0.013]**	[0.014]**	[0.014]**	[0.017]**	[0.030]**	[0.038]**	[0.022] **
R^2	0.048	0.156	0.253	0.264	0.267	0.266	0.262	0.259	
N	182	182	182	182	182	182	182	182	182

Notes: Figures in parentheses are clustered robust standard errors. Figures in brackets are heteroskedasticity-corrected robust standard errors. *** p<0.01, ** p<0.05, * p<0.1. All regressions include a constant. $\overline{S}_i$ = Average number of natural disasters per year in the 1990-2017 period.
Col. 1 does not include any control variable; Col. 2 includes (log) initial per capita GDP and institution.
Col. 3 includes (log) initial per capita GDP, policy volatility and institution. Col. 4 includes for (log) initial GDP per capita, policy volatility, institution, (log) population, (log) land area in sq. km. and share of agricultural value-added in GDP. Cols. 5-9 additionally include a dummy (0=no natural disaster; 1 = otherwise). Cols. 5 additionally includes average number of deaths per disaster.
The instruments is $\overline{S}_i^P$ (average number of natural disasters per year in the 1900-1989 period). First-stage regression for col. 9 (coefficient on $\overline{S}_i^P$): 5.749 (0.580) [0.786], F = 98.42 [53.57]. Reduced-form regression for col. 9 (coefficient on $\overline{S}_i^P$): -0.284 (0.141) [0.110].

Table 3 (IV Regressions): Effect of the frequency of natural disasters on the (log) LR volatility (for different sample distribution of the frequency).

	(1)	(2)	(3)	(4)	(5)	(6)
	Dropping largest 10%	Dropping largest 25%	Dropping largest 50%	Dropping without any natural disasters	Dropping smallest 10%	Dropping largest 10% and smallest 10%
	A: Second-stage regressions					
$\overline{S}_i$	-0.416	-0.995	-2.809	-0.052	-0.050	-0.450
	(0.098)***	(0.475)**	(1.496)*	(0.026)**	(0.026)*	(0.098)***
	[0.125]***	[0.242]***	[1.285]**	[0.023]**	[0.023]**	[0.135]***
N	164	137	95	176	166	148
	B: First-stage regressions					
$\overline{S}_i^P$	2.078	1.227	1.715	5.750	5.733	1.976
	(0.704)***	(0.557)**	(0.554)***	(0.581)***	(0.587)***	(0.685)***
	[0.696]***	[0.690]*	[0.543]***	[0.784]***	[0.785]***	[0.670]***
F-statistic	8.710 [8.905]	4.846 [3.159]	9.567 [9.956]	97.866 [53.74]	95.496 [53.272]	8.331 [8.694]
	C: Reduced-form regressions					
$\overline{S}_i^P$	-0.865	-1.221	-4.817	-0.298	-0.285	-0.890
	(0.377)**	(0.917)	(1.971)**	(0.136)**	(0.137)**	(0.360)**
	[0.373]**	[0.709]*	[1.582]***	[0.114]**	[0.113]**	[0.377]**
R^2	0.262	0.289	0.346	0.257	0.256	0.243

Notes: Figures in parentheses are clustered robust standard errors. Figures in brackets are heteroskedasticity-corrected robust standard errors. *** p<0.01, ** p<0.05, * p<0.1. All regressions include (log) initial GDP per capita, policy volatility, institution, (log) population, (log) land area in sq. km., share of agricultural value-added in GDP and a constant. Cols. 1-3 additionally include a dummy (0=no natural disaster; 1 = otherwise). $\overline{S}_i$ = Average number of natural disasters per year in the 1990-2017 period. $\overline{S}_i^P$ = Average number of natural disasters per year in the 1900-1989 period. The instruments is $\overline{S}_i^P$.

Col. 1: Maximum number of natural disasters per year experienced by a country is 3.214286.
Col. 2: Maximum number of natural disasters per year experienced by a country is 1.857143.
Col. 3: Maximum number of natural disasters per year experienced by a country is 0.8214286.
Col. 4: Minimum number of natural disasters per year experienced by a country is 0.1428571.
Col. 6: Number of natural disasters per year experienced by a country is between 3.214286 and 0.1428571.

Table 4: Non-linear effect of the frequency of natural disasters on the (log) LR volatility.

	(1)	(2)	(3)	(4)
	IV	OLS		
		Natural disasters causing at least		
	All	10 deaths	50 deaths	100 deaths
$\overline{S}_i$	-0.283	-0.154	-0.224	-0.238
	(0.103)***	(0.063)**	(0.100)**	(0.107)**
	[0.082]***	[0.062]**	[0.125]*	[0.150]
Squared $\overline{S}_i$	0.011	0.007	0.018	0.023
	(0.004)***	(0.003)*	(0.009)*	(0.011)*
	[0.003]***	[0.003]**	[0.011]	[0.016]
Critical no. of $\overline{S}_i$	12.797	11.578	6.387	5.234
	(0.821)***	(1.509)***	(0.884)***	(0.649)***
	[0.969]***	[1.531]***	[0.953]***	[0.666]***
Kleibergen-Paap rk LM statistic (*p*-value)	0.036 [0.013]			
Kleibergen-Paap rk Wald F statistic†	22.854 [22.413]			
R^2		0.282	0.272	0.267
N	182	182	182	182

Notes: Figures in parentheses are clustered robust standard errors. Figures in brackets are heteroskedasticity-corrected robust standard errors. *** p<0.01, ** p<0.05, * p<0.1. All regressions include (log) initial GDP per capita, policy volatility, institution, (log) population, (log) land area in sq. km., share of agricultural value-added in GDP, a dummy (0=no natural disaster; 1 = otherwise) and a constant. Cols. 1 additionally includes average number of deaths per disaster.

The estimating equation: $\ln \sigma_i^{LR} = \alpha + \beta_1 \overline{S}_i + \beta_2 \overline{S}_i^2 + \boldsymbol{\delta}'\mathbf{X_i} + \varepsilon_i$. Critical no. of $\overline{S}_i$ is calculated as $-\beta_1 / 2\beta_2$ (where β_1 is the coefficient on $\overline{S}_i$ and β_2 is the coefficient on squared $\overline{S}_i$), and its standard error is calculated by the delta method. The instruments are $\overline{S}_i^P$ (average number of natural disasters per year in the 1900-1989 period) and its square.

† Stock-Yogo weak ID test critical values: 10% maximal IV size = 7.03.

Table 5: Effect of the frequency of natural disasters on the (log) LR volatility: Comparing frequent and infrequent natural disasters.

	(1)	(2)	(3)	(4)
	OLS		IV	
Floods and Storms	-0.058 (0.038)	-0.276 (0.089)**	-0.070 (0.041)*	-0.398 (0.124)***
	[0.031]*	[0.058]***	[0.036]**	[0.086]***
Squared Floods and Storms		0.012 (0.004)**		0.020 (0.006)***
		(0.003)***		(0.005)***
Critical no. of Floods and Storms		11.200 (0.403)***		10.121 (0.868)***
		[0.568]***		[0.882]***
Earthq. and Volc.	0.107 (0.098)	0.197 (0.321)	0.083 (0.094)	-0.105 (0.327)
	[0.088)	[0.216)	[0.092)	[0.321)
Squared Earthq. and Volc.		-0.015 (0.074)		0.075 (0.086)
		[0.056]		[0.101]
Critical no. of Earthq. and Volc		6.714 [23.112]		0.707 [1.394]
		(18.951)		(1.308)
Kleibergen-Paap rk LM statistic (*p*-value)			0.101 [0.003]	0.067 [0.001]
Kleibergen-Paap rk Wald F statistic†			12.462 [16.726]	2.584 [3.828]
R^2	0.275	0.317		
N	182	182	182	182

Notes: Figures in parentheses are clustered robust standard errors. Figures in brackets are heteroskedasticity-corrected robust standard errors. *** p<0.01, ** p<0.05, * p<0.1.
All regressions include (log) initial GDP per capita, policy volatility, institution, (log) population, (log) land area in sq. km., share of agricultural value-added in GDP, a dummy (0=no natural disaster; 1 = otherwise) and a constant. Cols. 1 and 2 (OLS regressions) additionally include average number of deaths per disaster. The instruments are $\overline{S}_i^P$ (average number of floods and storms/earthquakes and volcanic activities per year in the 1900-1989 period) and its square.
† Stock-Yogo weak ID test critical values: 10% maximal IV size = 7.03.

Table 6: (IV Regressions): Possible channels through which natural disasters affect LR volatility.

	(1)	(2)	(2a)	(3)	(3a)	(4)	(4a)	(5)	(5a)
$\overline{S}_i$	0.081	-0.027	-0.046	-0.054	-0.051	-0.049	-0.049	-0.075	-0.073
	(0.057)	(0.020)	(0.026)*	(0.028)*	(0.028)*	(0.026)*	(0.027)*	(0.056)	(0.056)
	[0.063]	[0.019]	[0.022]**	[0.022]**	[0.023]**	[0.022]**	[0.022]**	[0.029]***	[0.028]***
I_g/Y	-33.092	-4.971	No						
	(15.493)**	(2.227)**							
	[15.378]**	[1.887]***							
Private credit/Y				0.002	No				
				(0.002)					
				[0.001]					
G/Y						0.666	No		
						(0.585)			
						[0.565]			
Aid/Y								0.460	No
								(0.538)	
								[0.634]	
N	158	158	158	172	172	182	182	157	157
First-stage *F*-statistic		58.265 [62.660]	92.738 [52.821]	98.778 [61.942]	95.812 [53.412]	102.571 [53.635]	98.417 [53.565]	42.302 [26.633]	39.716 [26.337]
Kleibergen-Paap rk LM statistic (*p*-value)	0.085 [0.059]								
Kleibergen-Paap rk Wald F statistic†	3.469 [2.944]								

Notes: Figures in parentheses are clustered robust standard errors. Figures in brackets are heteroskedasticity-corrected robust standard errors. *** p<0.01, ** p<0.05, * p<0.1.All regressions include (log) initial GDP per capita, policy volatility, institution, (log) population, (log) land area in sq. km., share of agricultural value-added in GDP, a dummy (0=no natural disaster; 1 = otherwise) and a constant. $\overline{S}_i$ = Average number of natural disasters per year in the 1990-2017 period. The instrument for col (2) is $\overline{S}_i^P$ (average number of natural disasters per year in the 1900-1989 period). Col. 1: Squared $\overline{S}_i^P$ is the additional instrument.

Table 7: (IV Regressions): Possible channels through which natural disasters affect LR volatility—Low and high frequencies of natural disasters.

	(1)	(2)	(3)	(4)
	Below median		Above median	
$\overline{S}_i$	-3.888 (1.459)***	-4.327 (1.655)***	-0.036 (0.022)*	-0.036 (0.022)*
	[1.849]**	[2.025]**	[0.026]	[0.025]
I_g/Y	-6.916 (2.453)***	No	0.167 (2.262)	No
	[3.294]**		[2.591]	
Kleibergen-Paap rk LM statistic (*p*-value)	0.105 [0.027]	0.113 [0.024]	0.055 [0.027]	0.047 [0.012]
Kleibergen-Paap rk Wald F statistic†	5.630 [5.037]	6.103 [5.232]	28.138 [35.707]	50.712 [46.722]
N	78	78	80	80

Notes: Figures in parentheses are clustered robust standard errors. Figures in brackets are heteroskedasticity-corrected robust standard errors. *** p<0.01, ** p<0.05, * p<0.1.
All regressions include (log) initial GDP per capita, policy volatility, institution, (log) population, (log) land area in sq. km., share of agricultural value-added in GDP, a dummy (0=no natural disaster; 1 = otherwise) and a constant. The instruments are $\overline{S}_i^P$ (average number of floods and storms/earthquakes and volcanic activities per year in the 1900-1989 period.
† Stock-Yogo weak ID test critical values: 10% maximal IV size = 7.03.

Table 8: Relationship between the frequency of natural disasters Government GFCF/GDP ratio.

	(1)	(2)	(3)	(4)
		Natural disasters causing at least		
	All	10 deaths	50 deaths	100 deaths
$\overline{S}_i$	0.004	0.006	0.010	0.012
	(0.001)***	(0.001)***	(0.002)***	(0.004)**
	[0.002]**	[0.002]***	[0.004]***	[0.005]**
R^2	0.332	0.354	0.338	0.319
N	158	158	158	158

Notes: Figures in parentheses are clustered robust standard errors. Figures in brackets are heteroskedasticity-corrected robust standard errors. *** p<0.01, ** p<0.05, * p<0.1. All regressions include (log) initial GDP per capita, policy volatility, institution, (log) population, (log) land area in sq. km., share of agricultural value-added in GDP, a dummy (0=no natural disaster; 1 = otherwise) and a constant. Col. 1 additionally includes average number of deaths per disaster. $\overline{S}_i$ = Average number of natural disasters per year in the 1990-2017 period.

Figures

Figure 1A: Frequency of natural disasters (All) for the 1990-2017 period (25, 50, 75, 90, 95, 95+ percentiles).

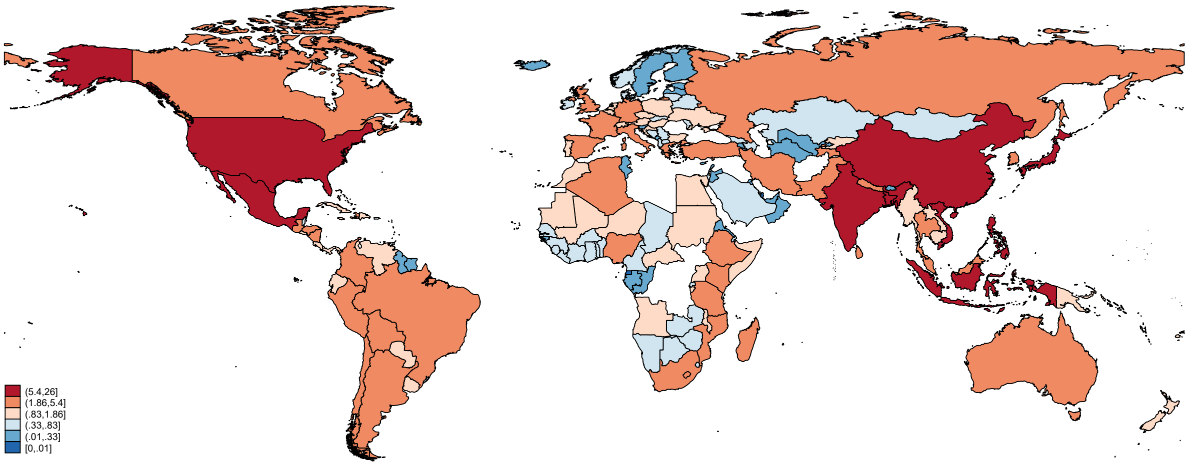


Figure 1B: Frequency of natural disasters (All) for the 1900-1989 period (25, 50, 75, 90, 95, 95+ percentiles).

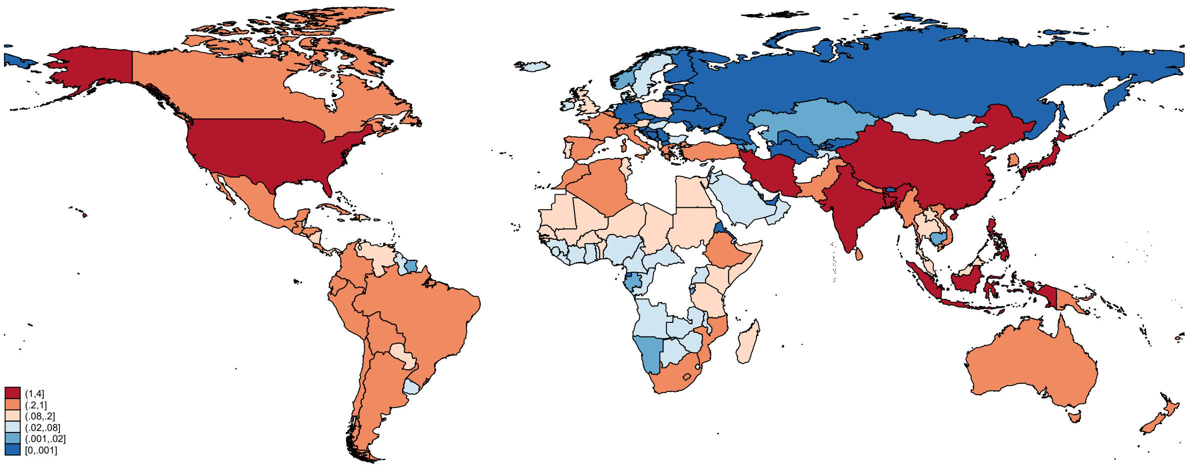


Figure 2A: Marginal effects of natural disasters on LR volatility (All natural disasters)

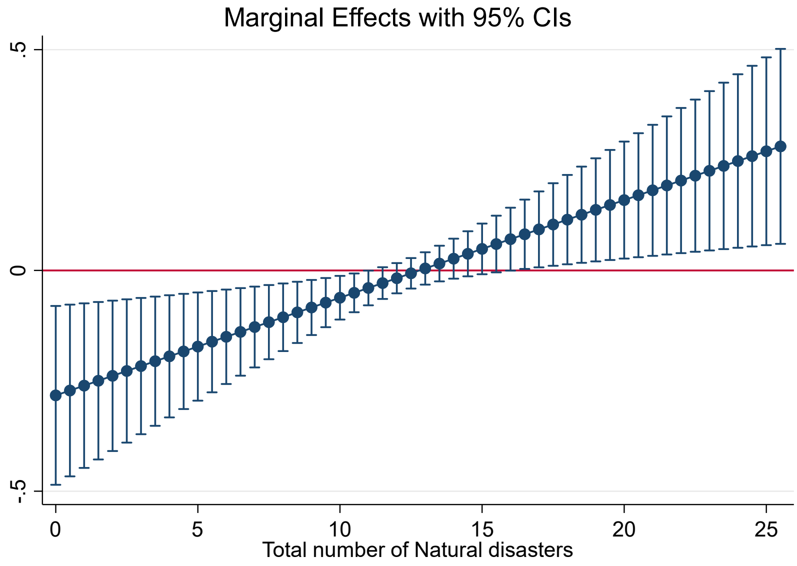


Figure 2B: Marginal effects of natural disasters on LR volatility (Natural disasters causing at least 10 deaths)

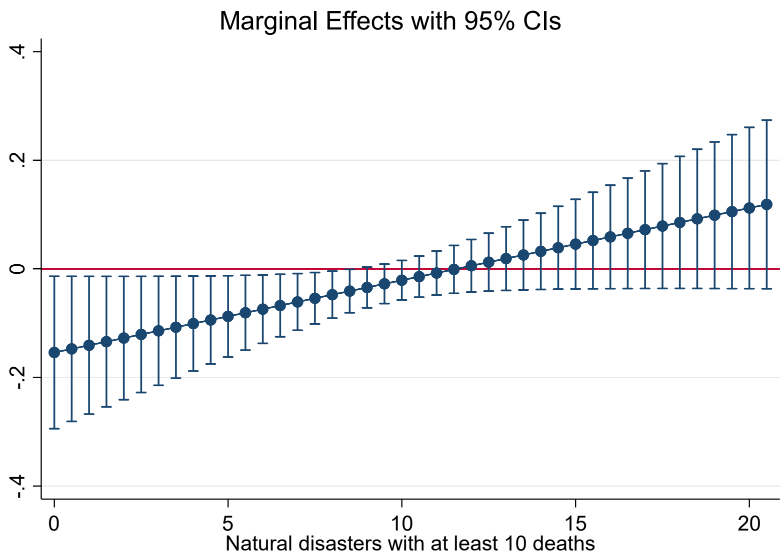


Figure 2C: Marginal effects of natural disasters on LR volatility (Natural disasters causing at least 50 deaths)

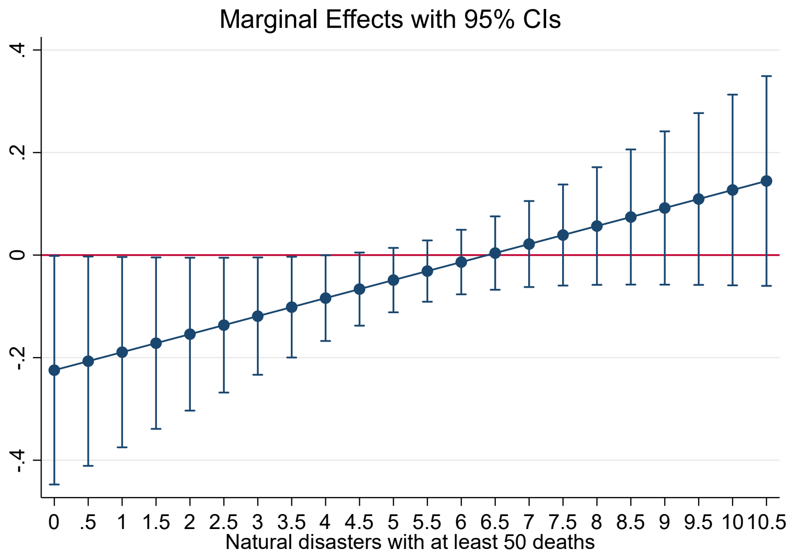


Figure 2D: Marginal effects of natural disasters on LR volatility (Natural disasters causing at least 100 deaths)

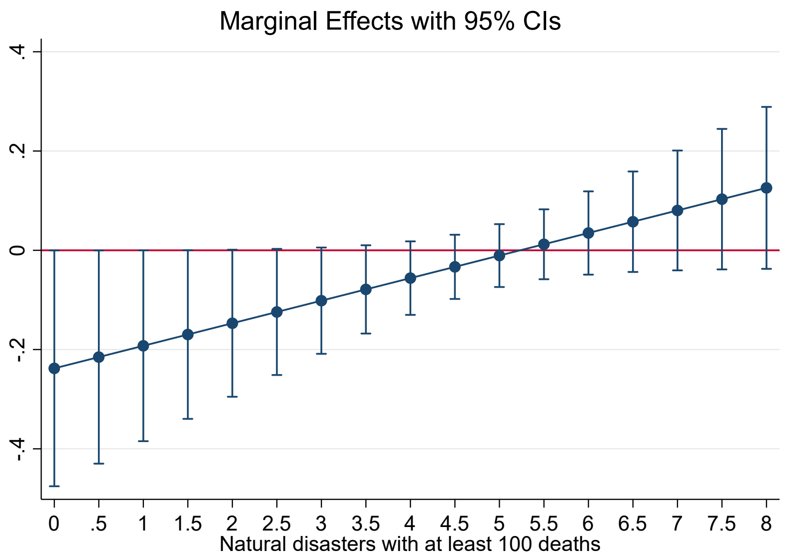


Figure 3A: Predicted values of GGFCF/GDP for the frequency of natural disasters (All).

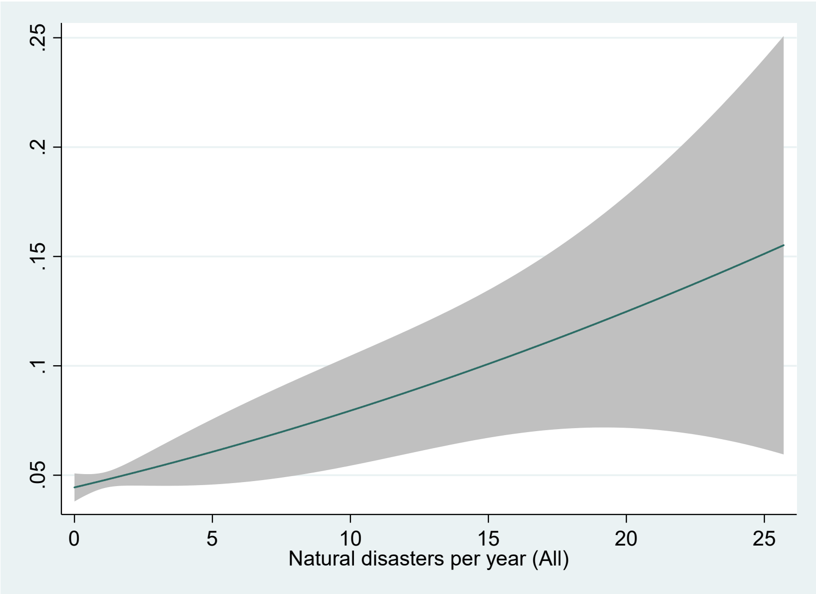


Figure 3B: Predicted values of GGFCF/GDP for the frequency of natural disasters causing at least 10 deaths.

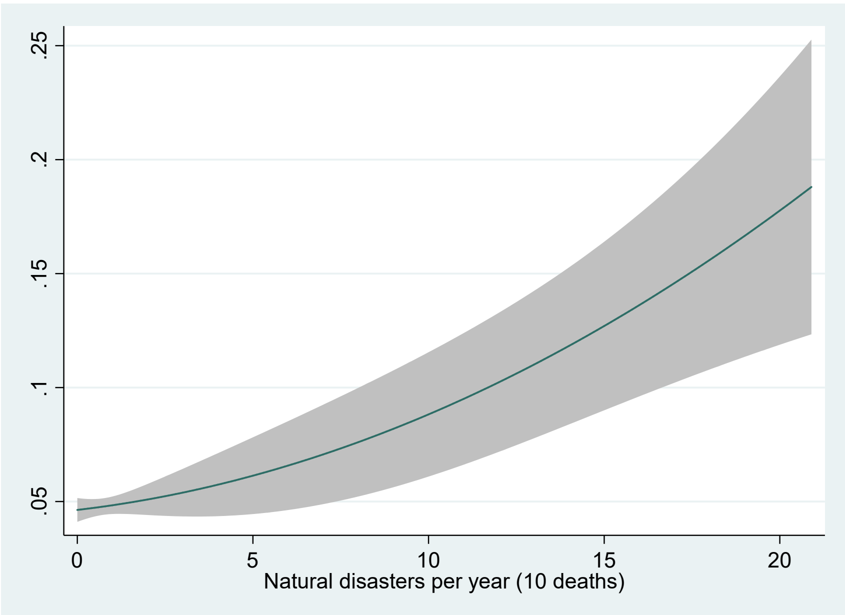


Figure 3C: Predicted values of GGFCF/GDP for the frequency of natural disasters causing at least 50 deaths.

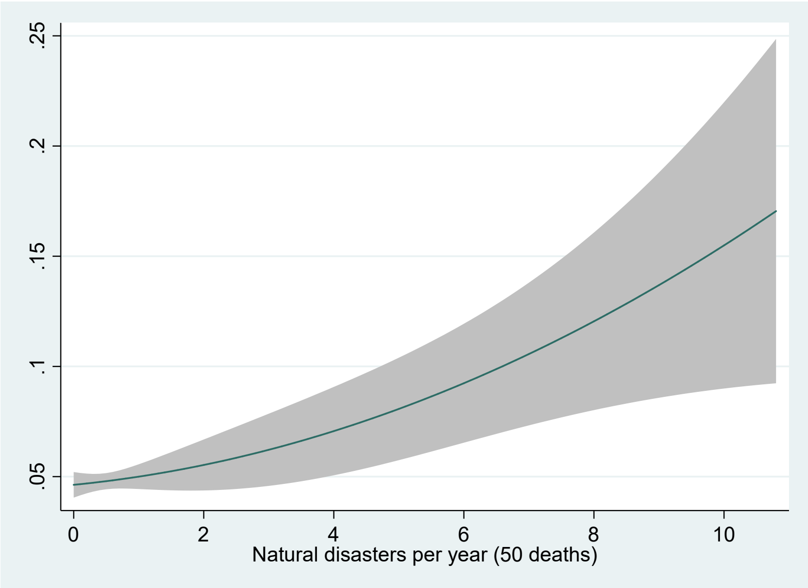
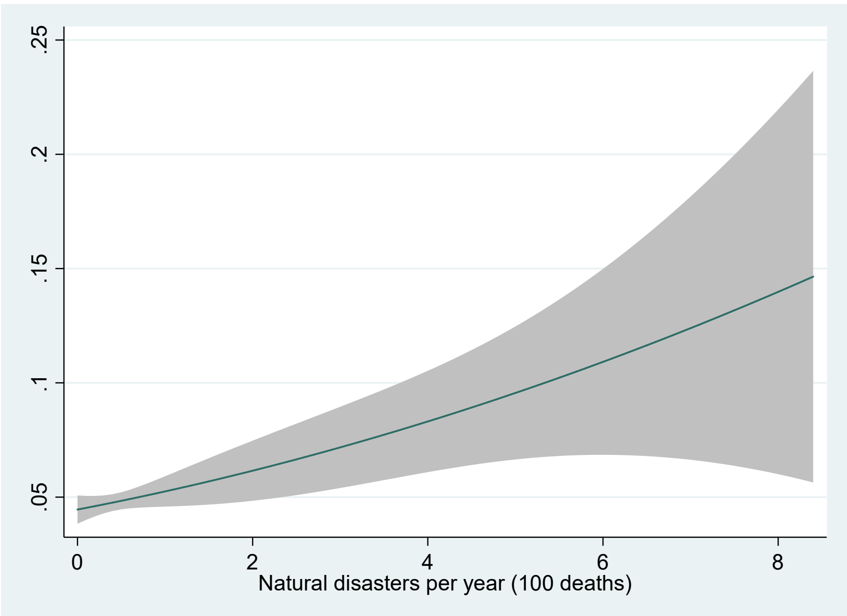


Figure 3D: Predicted values of GGFCF/GDP for the frequency of natural disasters causing at least 100 deaths.



Appendix

Appendix Table A.1: Table 2: Effect of the frequency of natural disasters on the (log) LR volatility at the 50+ year periodicity.

	(1)	(2)	(3)	(4)	(5)
	All	Natural disasters causing at least			All
		10 deaths	50 deaths	100 deaths	
	OLS				IV
$\overline{S}_i$	-0.029	-0.040	-0.063	-0.064	-0.049
	(0.017)	(0.022)*	(0.035)*	(0.041)	(0.027)*
	[0.014]**	[0.017]**	[0.030]**	[0.038]**	[0.022]**
R^2	0.267	0.266	0.262	0.259	
N	182	182	182	182	182

Notes: Figures in parentheses are clustered robust standard errors. Figures in brackets are heteroskedasticity-corrected robust standard errors. *** p<0.01, ** p<0.05, * p<0.1. Figures in brackets are robust standard errors clustered at the region level. All regressions include (log) initial GDP per capita, policy volatility, institution, (log) population, (log) land area in sq. km., share of agricultural value-added in GDP, a dummy (0=no natural disaster; 1 = otherwise) and a constant. Col. 1 additionally includes average number of deaths per disaster. $\overline{S}_i$ = Average number of natural disasters per year in the 1990-2017 period.
The First-stage regression is the same as in Col. 9 in Table 2.

Appendix Table A.2: Table 2: Effect of the frequency of natural disasters on the (log) LR volatility at the 8+ year periodicity.

	(1)	(2)	(3)	(4)	(5)
	All	Natural disasters causing at least			All
		10 deaths	50 deaths	100 deaths	
	OLS				IV
$\overline{S}_i$	-0.025	-0.035	-0.055	-0.055	-0.044
	(0.017)	(0.021)	(0.034)	(0.039)	(0.025)*
	[0.013]**	[0.017]**	[0.030]*	[0.036]	[0.021]**
R^2	0.269	0.268	0.266	0.263	
N	182	182	182	182	182

Notes: Figures in parentheses are clustered robust standard errors. Figures in brackets are heteroskedasticity-corrected robust standard errors. *** p<0.01, ** p<0.05, * p<0.1. Figures in brackets are robust standard errors clustered at the region level. All regressions include (log) initial GDP per capita, policy volatility, institution, (log) population, (log) land area in sq. km., share of agricultural value-added in GDP, a dummy (0=no natural disaster; 1 = otherwise) and a constant. Col. 1 additionally includes average number of deaths per disaster. $\overline{S}_i$ = Average number of natural disasters per year in the 1990-2017 period.
The First-stage regression is the same as in Col. 9 in Table 2.

Appendix Table A.3: Effect of the frequency of natural disasters on the (log) LR volatility (based on Hodrick–Prescott filter).

	(1)	(2)	(3)	(4)	(5)
	All	Natural disasters causing at least			All
		10 deaths	50 deaths	100 deaths	
	OLS				IV
$\overline{S}_i$	-0.105	-0.144	-0.228	-0.252	-0.169
	(0.056)*	(0.070)**	(0.106)*	(0.124)*	(0.099)*
	[0.035]***	[0.047]***	[0.080]***	[0.098]**	[0.060]***
R^2	0.281	0.275	0.272	0.270	
N	182	182	182	182	182

Notes: Figures in parentheses are clustered robust standard errors. Figures in brackets are heteroskedasticity-corrected robust standard errors. *** p<0.01, ** p<0.05, * p<0.1. Figures in brackets are robust standard errors clustered at the region level. All regressions include (log) initial GDP per capita, policy volatility, institution, (log) population, (log) land area in sq. km., share of agricultural value-added in GDP, a dummy (0=no natural disaster; 1 = otherwise) and a constant. Col. 1 additionally includes average number of deaths per disaster. $\overline{S}_i$ = Average number of natural disasters per year in the 1990-2017 period.
The First-stage regression is the same as in Col. 9 in Table 2.

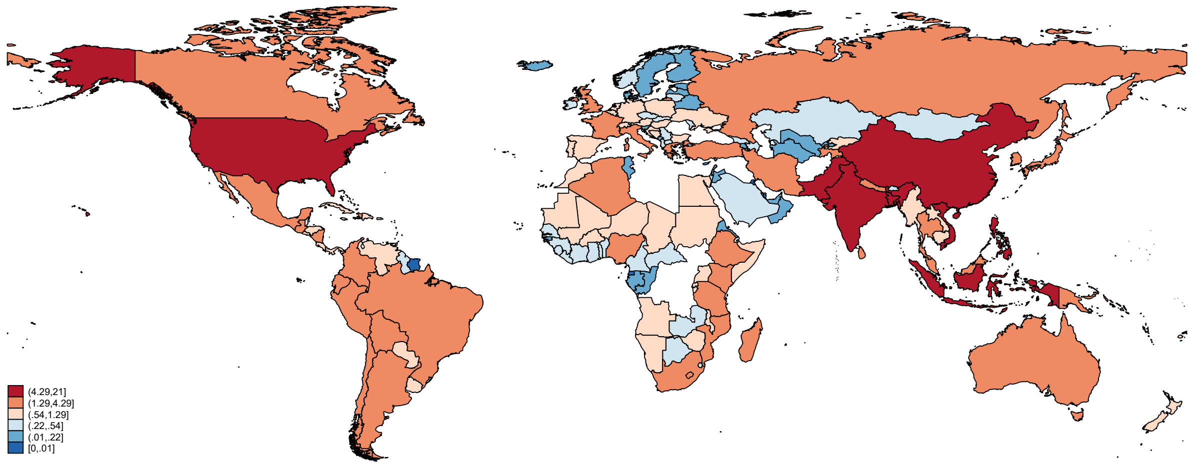
Appendix Table A.4: Fixed effect regressions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All		10 deaths		50 deaths		100 deaths	
$\overline{S}_i$	-0.059	-0.150	-0.101	-0.263	-0.097	-0.337	-0.099	-0.343
	(0.020)**	(0.047)**	(0.037)**	(0.085)**	(0.062)	(0.134)**	(0.062)	(0.127)**
	[0.047]	[0.090]*	[0.055]*	[0.111]**	[0.062]	[0.161]**	[0.063]	[0.160]**
Squared $\overline{S}_i$		0.003***		0.007		0.018		0.019
		(0.001)		(0.002)***		(0.008)**		(0.009)*
		[0.002]		[0.003]**		[0.009]**		[0.009]**
Critical no. of $\overline{S}_i$		25.419		18.520		9.484		8.833
		(2.539)***		(2.037)***		(0.895)***		(0.831)***
	[]	[5.966]***		[2.451]***		[0.716]***		[0.633]***
R^2 (within)	0.211	0.217	0.212	0.225	0.206	0.216	0.206	0.217
No. of countries	175	175	175	175	175	175	175	175

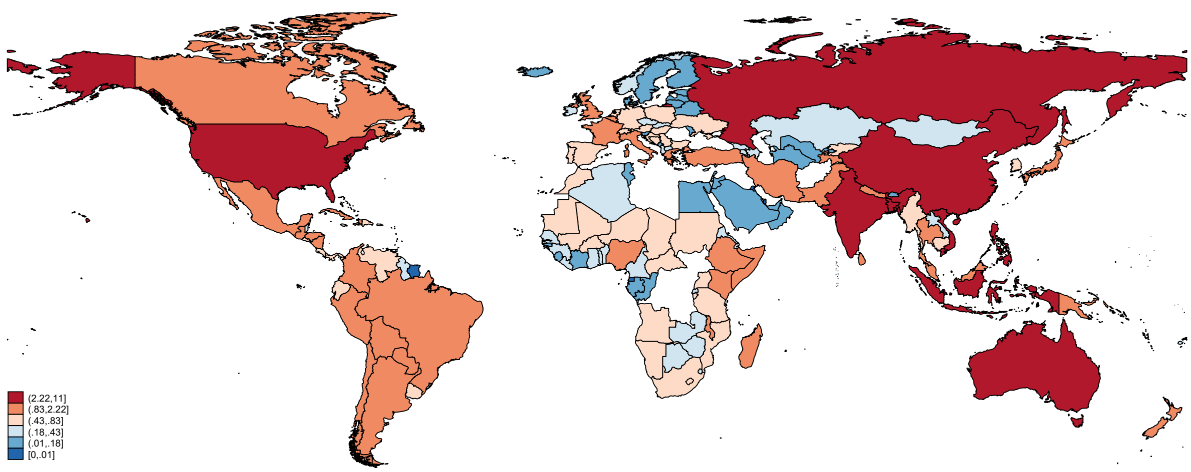
Notes: Figures in parentheses are clustered robust standard errors. Figures in brackets are heteroskedasticity-corrected robust standard errors. *** p<0.01, ** p<0.05, * p<0.1. All regressions include (log) initial GDP per capita, policy volatility, institution, (log) population, share of agricultural value-added in GDP, a dummy (0=no natural disaster; 1 = otherwise), interval dummy and a constant. Cols. 1-2 additionally includes average number of deaths per disaster.

The estimating equation: $\ln \sigma_i^{LR} = \alpha + \beta_1 \overline{S}_i + \beta_2 \overline{S}_i^2 + \boldsymbol{\delta}'\mathbf{X_i} + \varepsilon_i$. Critical no. of $\overline{S}_i$ is calculated as $-\beta_1 / 2\beta_2$ (where β_1 is the coefficient on $\overline{S}_i$ and β_2 is the coefficient on squared $\overline{S}_i$), and its standard error is calculated by the delta method.

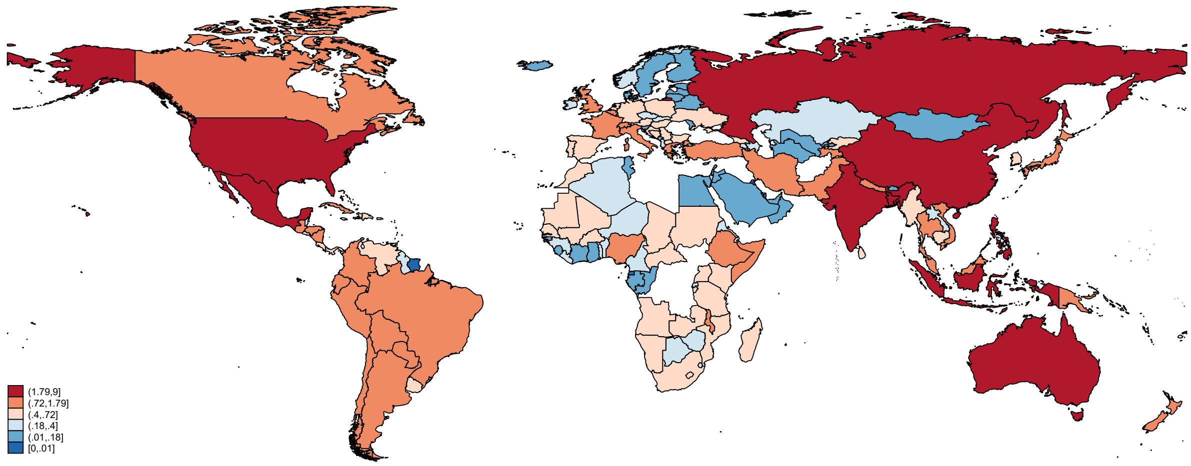
Appendix Figure A.1: Frequency of natural disasters (At least 10 deaths) for the 1990-2017 period (25, 50, 75, 90, 95, 95+ percentiles).



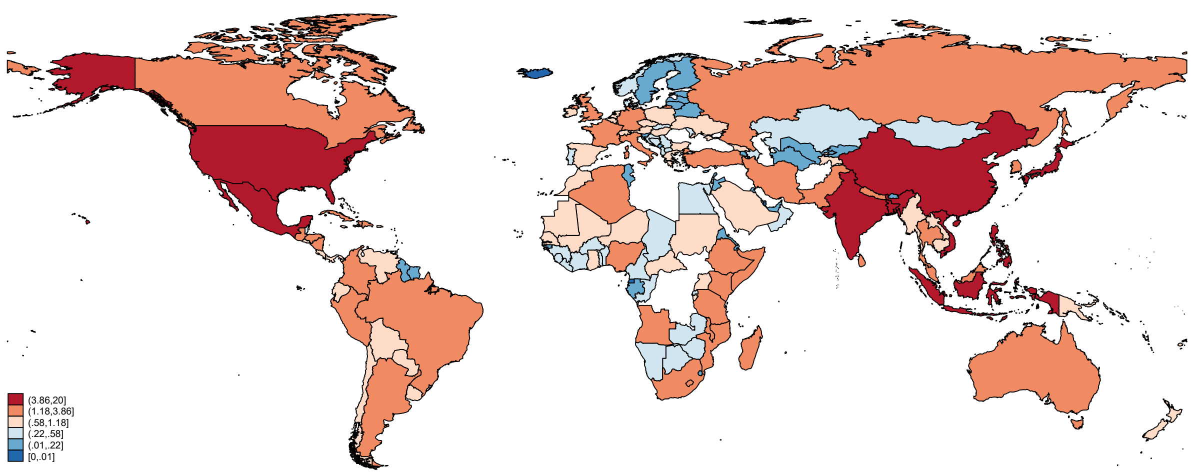
Appendix Figure A.2: Frequency of natural disasters (At least 50 deaths) for the 1990-2017 period (25, 50, 75, 90, 95, 95+ percentiles).



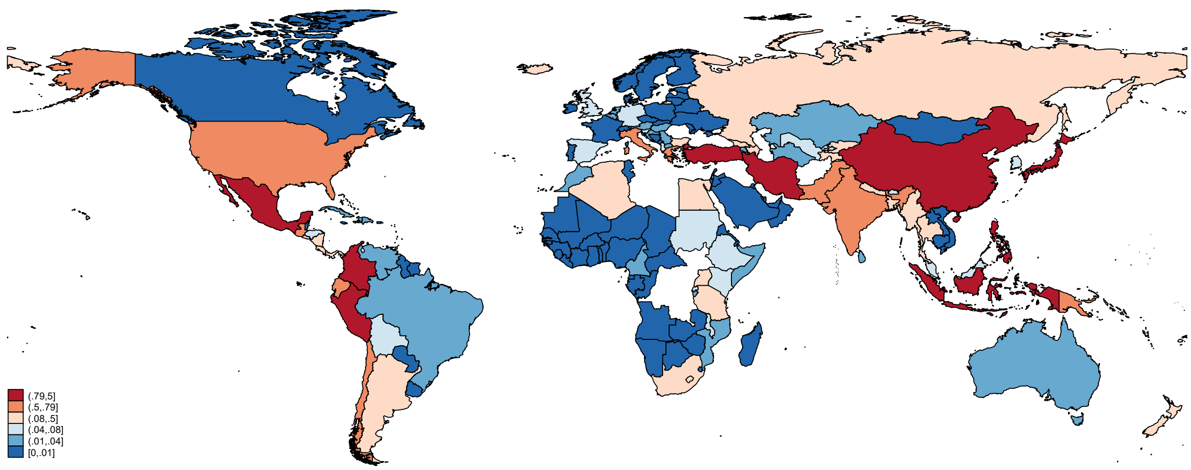
Appendix Figure A.3: Frequency of natural disasters (At least 100 deaths) for the 1990-2017 period (25, 50, 75, 90, 95, 95+ percentiles).



Appendix Figure A.4: Frequency of floods and storms (All) for the 1990-2017 period (25, 50, 75, 90, 95, 95+ percentiles).



Appendix Figure A.5: Frequency of earthquakes and volcanic activities (All) for the 1990-2017 period (25, 50, 75, 90, 95, 95+ percentiles).



Appendix B: Data definitions and sources

Variable and definition	Source
Natural Disasters	Emergency Events Database (EM-DAT)
GDP at constant national 2011 prices; Government consumption at constant national 2011 prices;	PWT9.1 (National Accounts Data)—see Feenstra, Inklaar and Timmer (2015)
Population; Total Factor Productivity; Human Capital	PWT9.1
Government Gross Fixed Capital Formation as a share of GDP	International Monetary Fund
Voice and Accountability	Worldwide Governance Indicators (WGI), World Bank
Ratio of private credit to GDP; Share of agricultural value-added in GDP; Net official development assistance and official aid	World Development Indicators
Polity2	Center for Systematic Peace (CSP) / Integrated Network for Societal Conflict Research (INSCR) http://www.systemicpeace.org/inscrdata.html