Is growth at risk from natural disasters? Evidence from quantile local projections

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January 2024

Abstract

This paper explores the impact of natural disasters on developing countries' GDP growth tail risk. Using quantile local projections on data for 75 developing economies from 1970-2021, our results reveal that natural disasters lead to a persistent decrease at the 10th percentile of economic growth. In addition, agricultural and industrial growth at the 10th percentile experience significant declines. However, the services sector shows a less persistent response and, in some cases, a reversal that may be due to increased demand post-disasters. When splitting countries by income level, we observe that high-income developing countries better counteract the adverse effects of natural disasters. In contrast, low-income countries appear to lack the capacity to mitigate associated risks effectively. Finally, when studying the impact of institutional arrangements and government effectiveness in mitigating natural disaster risk, we find autocratic countries have a slightly higher vulnerability to natural disasters than democratic countries. At the same time, better public institutions are associated with lower growth tail-risk.

Keywords: Natural Disasters, Growth-at-Risk, Quantile Local Projections, Economic Development
JEL: E23, O10, O40, Q54, Q56

We sincerely thank Òscar Jordà for sharing the codes of quantile local projections from his paper "Zombies at large? Corporate debt overhang and the macroeconomy", Jordà et al. (2022). We also thank Pr. Thomas B. Fomby, as well, for his helpful advice and insights.

1 Introduction

Over the last three decades, there has been a significant increase in the frequency and intensity of natural disasters. For instance, between June and September 2022, floods in Pakistan affected 33 million people, resulting in over 1730 fatalities. The World Bank estimates that the overall economic losses from these floods are expected to exceed USD 30 billion. More recently, earthquakes struck Turkey and Syria in February 2023, causing an estimated USD 34.2 billion in direct physical damages in Turkey and killing over 59,000 people.Thus, natural disasters pose a significant risk to economic activity as their effects can be widespread and highly destructive, leading to capital and infrastructure destruction and mass movement of workforce (Field (2012)).

Given the substantial losses in both human and capital terms caused by natural disasters, crucial questions arise: Is growth at risk from natural disasters? Do these events worsen the decline of low-growth outcomes in developing countries? These are the questions we intend to address throughout this paper.

Capturing the economic impact of natural disasters is challenging for different reasons. First, there is considerable heterogeneity among countries regarding the economic effects of disasters and how countries recover from them. As explained by Noy (2009), developing countries cannot implement counter-cyclical policies in the aftermath of such events, and they also face challenges related to insufficient insurance coverage and mechanisms for assisting victims, exacerbating the adverse consequences. Additionally, Kabundi et al. (2022) highlights that high levels of corruption contribute to a large number of deaths from natural disasters, especially in developing economies. This reflects the high vulnerability of these countries, given their low institutional quality and the weakness of their health and risk management systems. Therefore, countries with low social and economic resilience capacities, such as developing countries, tend to suffer most from natural disasters.

Second, damages from natural disasters exhibit probability distributions with thick tails, indicating a high degree of skewness compared to normal or exponential distributions, as pointed out by Coronese et al. (2019). Consequently, standard econometric approaches based on normal distribution assumptions are inadequate for predicting the effects of these events (Bolton et al. (2020)). Therefore, many studies argue that the effects of natural disasters cannot be adequately captured using linear statistical methods (Atsalakis et al. (2021)).

In line with these considerations, in this paper, we aim to provide new evidence on the nonlinear effects of natural disasters on economic performance for a large sample of emerging and developing countries. Following Linnemann and Winkler (2016) and Jordà et al. (2022), we employ quantile local projections, which provide the effects of natural disasters on the lower percentile of GDP growth. This methodology is inspired by the Growth-at-Risk models developed by Adrian et al. (2019) and IMF (2017b) which provide evidence that GDP growth follows a fat-tailed pattern, indicating that the lower percentile of the GDP growth distribution may suffer substantial losses conditional on certain financial conditions.

Quantile methods offer attractive features compared to linear models, as they allow to estimate the impact of variables with varying coefficients across different quantiles of the conditional distribution of the outcome variable. The quantile regressions that we use suppose that disasters may have different effects at the tails of the conditional distribution of the outcome variable than at the median or the mean.[1] This method is thus well suited to investigate whether natural disaster effects are nonlinear, in the sense that there exist quantile-specific parameters that lead to different responses if the output growth is low and thus in a lower percentile of its conditional distribution. Concretely, GaR is the conditional growth at a lower percentile of the GDP growth distribution, and thus captures expected growth at a low realization of the GDP growth distribution of developing economies.

In the context of existing literature, Kiley (2021) investigates Growth-at-Risk associated with climate change, specifically focusing on the impact of rising temperatures. His findings suggest an increase in the likelihood of experiencing low GDP growth with global warming. Nevertheless, to the best of our knowledge, we are the first to use Quantile Local Projections method to study the effects of natural disasters on the evolution of the 10th percentile of GDP per capita growth distribution. This is what we call the growth-at-risk.

[1]This question was addressed by Atsalakis et al. (2021), and their findings reveal that the effect of natural disasters on GDP growth varies depending on the quantile they examine.

While the intuitive expectation might be that natural disasters have consistent adverse effects, some empirical studies argue that disasters could be assimilated into Schumpeter's destructive creation notion, thus boosting economic growth. Consequently, using standard empirical tools, the literature does not offer conclusive answers.

Moving beyond the traditional strategy of estimating the average effect of natural disasters on economic growth, we seek to measure how the 10th percentile of its distribution changes over the projection horizon as a function of natural disasters. We contribute to the literature on the economic impact of natural disasters by forecasting the effects of these events on the 10th percentile of growth using the Quantile Local Projections technique. This methodology allows us to study the growth path at the 10th percentile in the aftermath of a natural disaster shock on a panel of 75 developing countries.

Our results suggest that that natural disasters cause a lasting decrease in economic growth in the 10th percentile, particularly affecting agricultural and industrial sectors. However, the services sector displays a less persistent response, possibly due to increased post-disaster demand. High-income developing countries are better equipped to offset these effects than low-income countries. Moreover, autocratic countries exhibit slightly higher vulnerability to the long-term impacts of natural disasters than democratic economies, suggesting institutional quality influences resilience.

This paper is structured as follows. Section 2 presents some stylized facts on natural disasters, and section 3 reviews existing literature on their impact on economic growth. Section 4 outlines the quantile local projections method and describes the data used. The benchmark results are presented in section 5, and section 6 provides the results when accounting for sectoral, macroeconomic, and institutional heterogeneity. Finally, section 7 concludes.

2 Stylized Facts

Global climate is changing, making directly related natural disasters more frequent and intense. While climate change does not directly cause earthquakes (Buis (2019)), it is likely to increase the intensity and frequency of droughts, floods, and storms, along with the vulnerability of countries (Field (2012)).

Figure 1a shows a sharp increase in natural disasters by the beginning of the 21^{st} century. This acceleration is more pronounced for developing countries, while the evolution of the number of disasters seems to remain stable for developed countries.

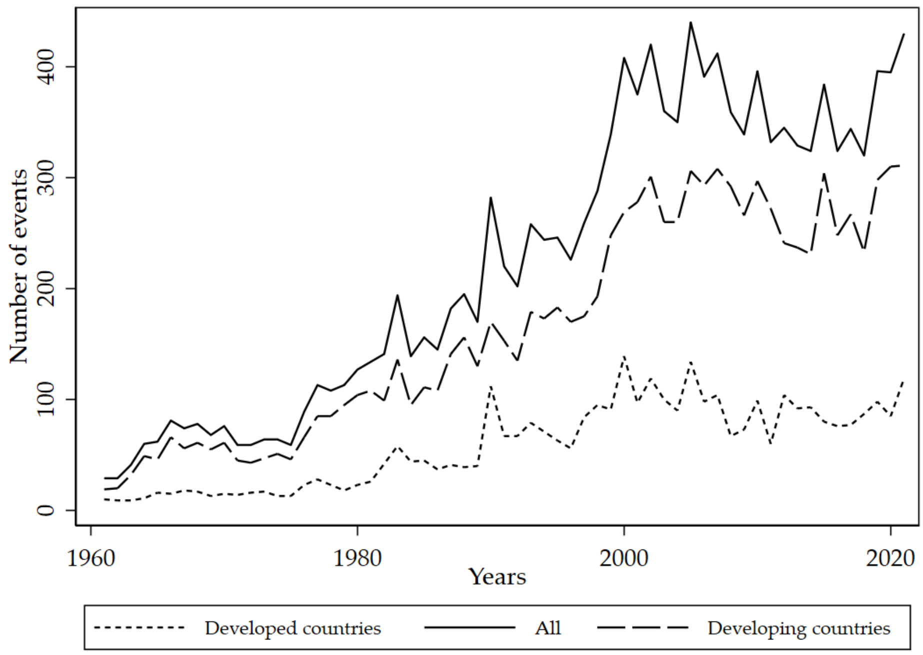
Our analysis will only focus on earthquakes, droughts, floods, and storms for various reasons. In fact, these disasters represent 85% of all natural disasters between 1961 and 2021. 9% of these events are earthquakes, 5.5% are droughts, 40% are floods and 31% are storms. Additionally, as shown in Figure 1b, these disasters are omnipresent in both developed and developing countries, with a predominance of storms in developed countries and floods in developing countries. On the other hand, the preponderance of these disasters can be attributed to climate change (IPCC (2013, 2014); IMF (2017a)).

The determinants of natural disasters are influenced by their social and economic impact. For a climate shock to be considered a natural disaster, it must significantly affect society and the economy. The magnitude of these impacts depends on the vulnerability of countries and the nature of the hazard itself. Vulnerability is assessed based on factors such as infrastructure quality, population concentration in urban areas, and the effectiveness of early prevention systems. Hazards transform into disasters when they result in loss or harm to human lives and cause damage or destruction to livelihoods and infrastructure (Cavallo et al. (2022)).

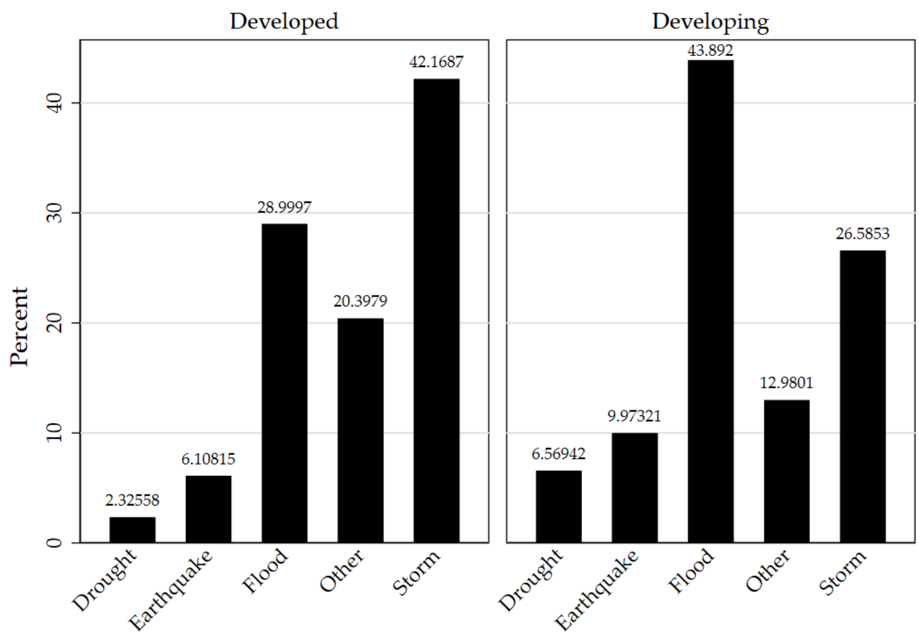
Advanced economies have enhanced their resilience and reduced vulnerability by adopting counter-cyclical fiscal and monetary measures to address adverse shocks such as natural disasters. Inversely, developing countries have experienced increased vulnerability primarily due to population growth over the past century (Perrow (2011)) and the low quality of their institutions. This could elucidate why these countries tend to have a higher average population affected by natural disasters, as shown in Figure 2a.

Using quantile regressions, Coronese et al. (2019) prove that extreme damages from natural disasters are increasing. They uncover compelling evidence of a gradual shift towards the right and an increase in the thickness

Figure 1: *Natural disasters: level and percentage. 1961-2021.*



(a)

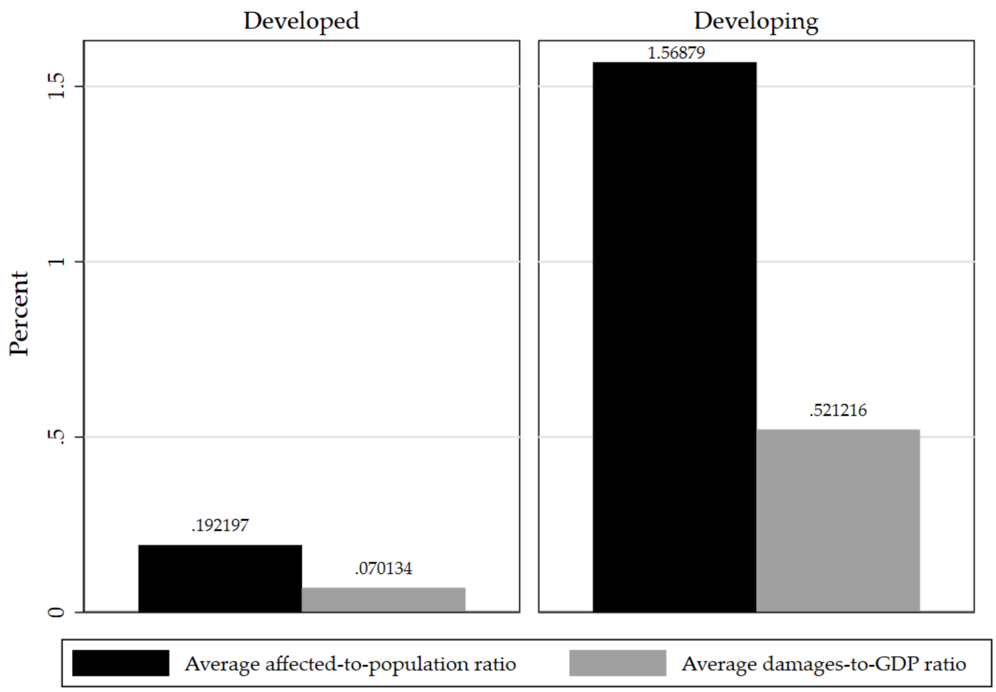


(b)

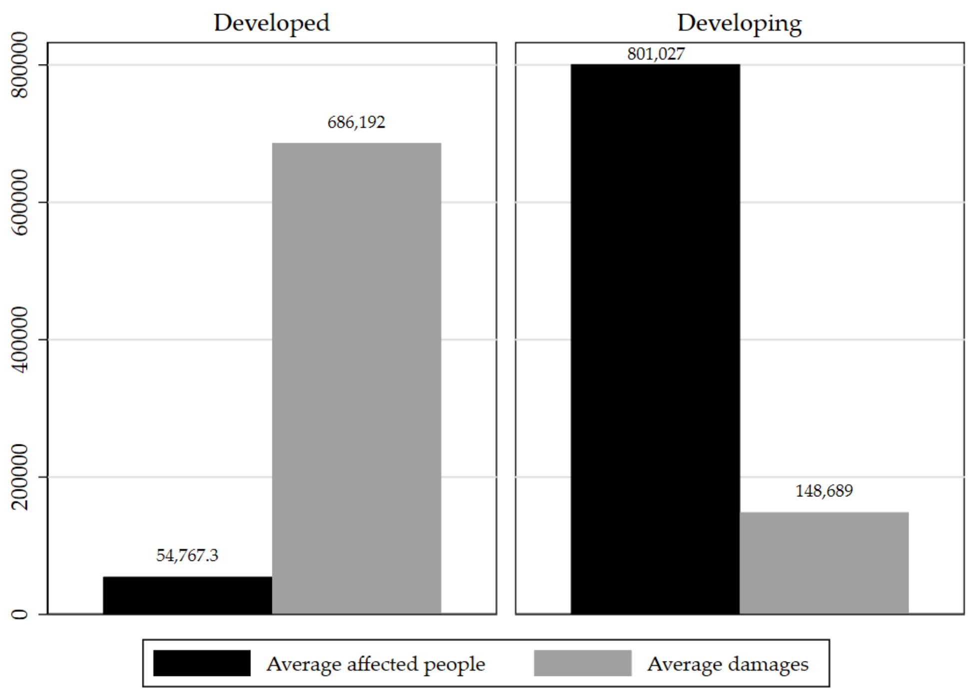
Source: EM-DAT and author's calculations.

of the damage distribution tail over time. Although it is difficult to discern any significant time-related impact on averages, the effects on extreme damage levels are substantial. Figure 2 shows that the material cost of natural disasters (2b) is higher in developed countries. At the same time, monetized damages in terms of GDP are, on average, much higher in developing countries (2a), thus highlighting the significant vulnerability of emerging economies to natural disasters. This could be explained by the incapacity of these countries to increase their ability to anticipate and engage *ex-ante* actions likely to reduce their vulnerability (Noy (2009)). That

Figure 2: *Average affected-to-population and damages-to-GDP. 1961-2021.*



(a)

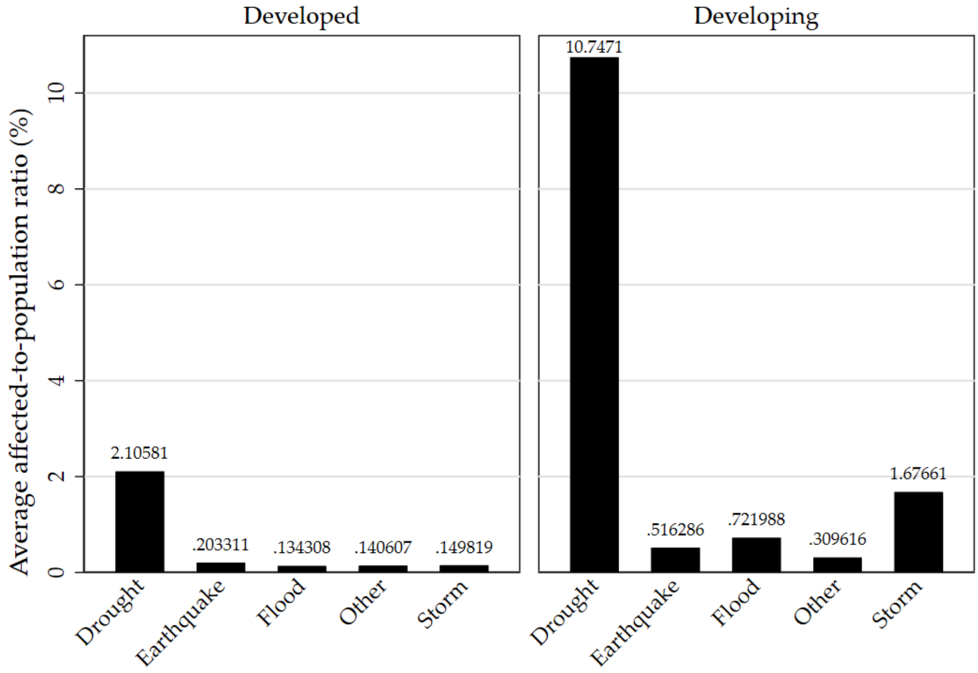


(b)

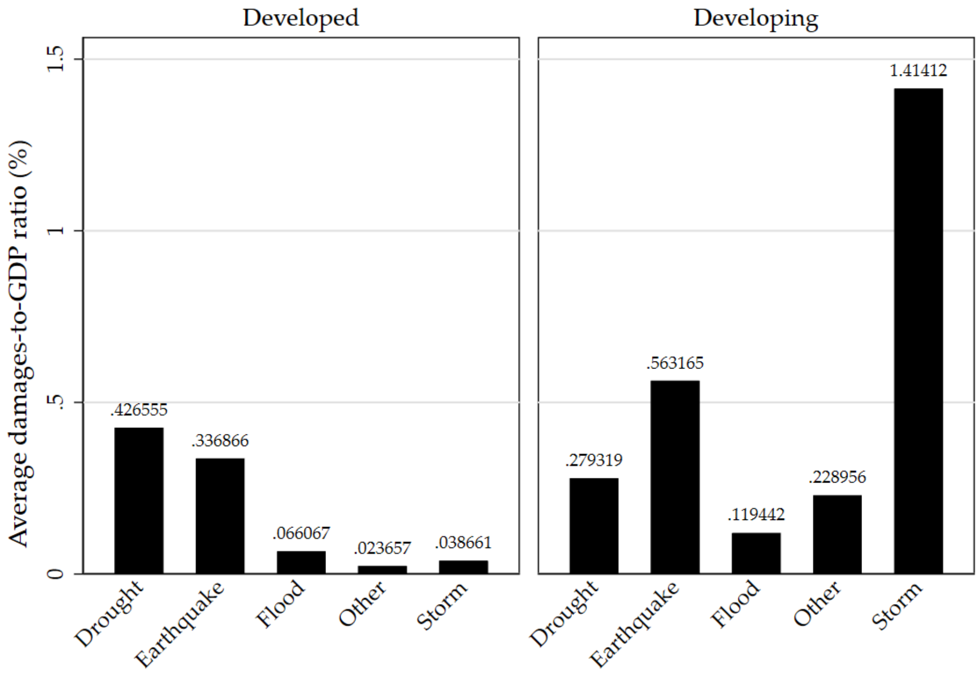
Source: EM-DAT and author's calculations.

said, recall that developing countries are poor, hotter, and exposed to more natural disasters than developed countries (Cavallo et al. (2022); IMF (2017a); Kiley (2021)). Figure 3 presents data on the average proportion of people affected (panel 3a) and the damages to GDP (panel 3b). Notably, droughts affect an average of 10.7%

Figure 3: *Average affected-to-population and damages-to-GDP by type of disaster. 1961-2021.*



(a)



(b)

Source: EM-DAT and author's calculations.

of the population in developing countries, while only 2% of the population in advanced economies is affected by droughts. Although droughts have the highest impact in terms of affected population, they only account for an average cost of 0.43% of developed countries' GDP and 0.28% for developing economies. In contrast, storms affect an average of 1.67% of developing countries' population, ranking third in human damage following floods. Earthquakes take second place in developed countries. Material damages reveal that storms, on average, destroy 1.41% of developing countries' GDP, while earthquakes account for 0.56%, floods for 0.12%, and other natural disasters combined for 0.23%. In developed countries, earthquakes incur a cost of 0.34% of GDP on average, followed by floods at 0.06%, storms at 0.04%, and other natural disasters at 0.24%.

3 Literature Review

As natural disasters become more frequent and severe, a growing interest in gaining a more profound comprehension of their impact on economic growth, aiming to provide policymakers with valuable insights into the advantages of risk reduction and mitigation, has sparked. Up to this point, the existing body of empirical macroeconomic literature still needs to reach a definitive consensus regarding the influence of natural disasters on economic growth. While some studies indicate detrimental effects, others also present findings of no impact or potential positive effects of natural disasters on growth.

Early studies argue that disasters can have a positive impact on economic growth. Skidmore and Toya (2002) explain that they can be associated with higher rates of human capital accumulation, updated capital stock, and adoption of new technologies, leading to improved total factor productivity and economic growth. Noy (2009) shows that developing and smaller economies experience more significant output declines than developed and larger economies of similar disaster magnitudes. The observed heterogeneity of the impact of natural disasters between developed and developing countries is attributed to the capability of developed ones to implement counter-cyclical fiscal and monetary policies in response to adverse shocks, a capacity often lacking in developing economies. Noy (2009) explores the contribution of institutional and structural factors to output declines following extreme natural events. The study finds that countries with higher illiteracy rates experience more significant negative impacts on output growth post-disaster. Furthermore, robust institutions and higher per capita incomes are associated with lower macroeconomic costs after such events.

Loayza et al. (2012) examine the effect of each type of disaster on various economic sectors in both developed and developing countries. They discovered that disasters have distinct effects on economic growth depending on the type of disaster and the economic sector in question. Their research suggests that developing countries are more susceptible to the influence of natural disasters on economic growth. They observed that these effects on growth are not exclusively adverse. Loayza et al. (2012)'s results support using natural disaster measures segregated by event type. Indeed, their results show that using segregated indices gives better statistical properties than an aggregated index. Similarly, in examining the annual response of GDP growth to natural disasters, Fomby et al. (2013) find varying effects across economic sectors, with more pronounced impacts on developing economies. Droughts negatively impact overall GDP growth, particularly affecting agriculture immediately, while floods tend to have a positive effect, with significant responses in agricultural growth occurring one year after the event. The effects of earthquakes and storms are weaker, with earthquakes leading to a positive response in non-agricultural growth due to reconstruction efforts and storms having a brief negative impact followed by signs of positive growth driven by reconstruction efforts.

Panwar and Sen (2019) address the ambiguity in the existing literature regarding the impact of natural disasters on the economy, re-examining the relationship and contributing to the literature on the economy-wide and sector-specific consequences in the short-to-medium term. They organize their data into 5-year, non-overlapping periods to assess the growth effects of floods, droughts, storms, and earthquakes. The results indicate diverse economic impacts across sectors, with statistically stronger effects in developing countries, suggesting policymakers need to explore effective *ex-ante* disaster risk financing tools for safeguarding populations, assets, and adherence to sustainable development goals. A recent study by Cavallo et al. (2022) utilizing event study methodology on panel data finds that catastrophic natural disasters have a more pronounced adverse impact on economic growth in developing countries, leading to an average decline of 2.1 to 3.7 percentage points. This effect is particularly evident when assessing disaster severity based on mortality rates, underscoring the significant relationship between natural disasters and economic development in poorer nations.

As suggested above, natural disasters exhibit non-linear dynamics. Atsalakis et al. (2021) have acknowledged these non-linearities and employ quantile-on-quantile approach to investigate the relationship between natural disasters and economic growth. Atsalakis et al. (2021)'s paper sheds light on the complex relationship between natural disasters and economic activity. Findings reveal mitigating impacts across different combinations of quantiles. Ginn (2022) assumes that natural disasters' effects on US growth are state-dependent.[2] He investigates the impact of disaster damages on economic conditions, finding that, during an expansionary phase, disaster aftermath is associated with a slight reduction in output and an increase in inflation. The study also suggests that the Federal Reserve's interest rate remains unchanged in response to a disaster shock, proportionally aligned with changes in output growth and inflation, resulting in a heightened Economic Policy Uncertainty index (EPU) during expansion but indicating greater resilience during a recessionary period.

Several empirical studies address other economic implications of natural disasters. For instance, Akyapi et al. (2022) find that high daily temperatures produce a pro-cyclical effect, reducing government revenue. At the same time, droughts and floods lead to increased government spending and debt, mitigating the shocks to GDP. Klomp (2014) finds that natural disasters elevate the likelihood of bank defaults, with financial development mitigating this risk. Avril et al. (2022) analyzes financial stress following storms and floods, revealing a significant rise in external finance premium after storms but a less pronounced effect for floods in relaxed macroprudential regulatory environments. Inflation dynamics following natural disasters are also studied. Beirne et al. (2022) find that extreme natural events significantly raise food and beverage inflation in the euro area, with no long-lasting effects observed six months after the shock. Fratzscher et al. (2020) provide empirical evidence supporting inflation targeting as a shock absorber, showing lower inflation, higher output, and reduced fluctuations during natural disasters. Kabundi et al. (2022) explore climate shocks, noting that droughts tend to increase inflation, mainly affecting food prices, while floods are more likely to decrease inflation. Klomp (2020) investigates the influence of earthquakes on central banks' policy interest rates, indicating a drop in the first year post-earthquake.[3] Lastly, Mallucci (2022) studies sovereign default risk after extreme hurricanes in seven Caribbean countries, finding that such events hinder government borrowing capacity, potentially leading to a substantial decrease in the public debt-to-GDP ratio and broader spreads. Mallucci (2022) 's subsequent study on disaster clauses[4] suggests that debt reduction clauses, post-disasters, significantly improve government borrowing capabilities and overall well-being, proving more effective than coupon suspension.

4 Empirical Approach

This section presents the methodology employed and then presents our data.

4.1 Local Projections from Panel Quantile Regressions

Quantile regression is a statistical analysis technique offering a broader scope than conventional procedures by detecting additional effects on the dependent variable. Unlike traditional methods that focus solely on the conditional mean, quantile regression allows for estimating heterogeneous quantile-specific parameters of a response variable.

It also presents advantages over nonlinear state-dependent methods by avoiding the need to pre-classify economic regimes and allowing for the estimation of shock impacts across the entire distribution of the outcome

[2]He uses a non-linear VAR model with local projections.

[3]For this purpose, he estimates a dynamic panel model including about 400 major earthquakes from about 85 countries that occurred between 1960 and 2015.

[4]It is a provision included in certain types of bonds (CAT Bonds) or debt instruments. This clause addresses the impact of unexpected and severe natural disasters, such as earthquakes, hurricanes, floods, or other catastrophic events, on the issuer's ability to meet its financial obligations related to the bond. It mainly allows for an immediate and temporary suspension of coupon payments or debt reduction.

variable. This approach provides a comprehensive assessment of potential nonlinearities. It allows researchers to explore how independent variables affect different quantiles of the outcome distribution, contrasting with traditional linear regression, which focuses solely on the average impact.

Quantile regression is commonly employed in various models, such as value-at-risk in finance and, more recently, growth-at-risk. GaR, initiated by Adrian et al. (2019, 2022) and Loria et al. (2022), focuses on lower quantiles of the economic growth distribution to assess potential financial risks to growth. Quantile regression analysis enables the investigation of factors impacting growth rate, specifically in the lower percentile of the conditional distribution, shedding light on drivers that may hinder growth during adverse conditions.

By concentrating on lower quantiles, researchers can understand factors contributing to economic resilience, identify challenges that need addressing, and inform targeted policies for sustainable growth. Growth-at-risk expressed as the value-at-risk of future GDP growth, provides a flexible platform to explore the risk of negative GDP growth rates. This paper aims to assess the downside risk to the economy after a natural disaster shock, using Quantile Impulse Response Functions (QIRFs) estimated by local projections to measure the effect on response variables at the quantile of interest (Linnemann and Winkler (2016); Jordà et al. (2022) and Loria et al. (2022)). This analysis contributes to a deeper understanding of the implications of natural disasters on the macroeconomic landscape.

Classical regression concentrates on the expectation ($\mathbb{E}$) of a variable Y given the values of a set of variables X, denoted as $\mathbb{E}(Y \mid X)$, which is known as the regression function. This function can vary in complexity, but it only provides information about a specific location within the conditional distribution of Y. Quantile regression expands upon this approach, enabling the study of the conditional distribution of Y on X at different locations.[5] As a result, it offers a comprehensive understanding of the relationships between Y and X.

Quantile regressions aim to evaluate the variations in conditional quantiles $Q^{\tau}(Y|X)$ when the vector X of determinants of Y change. It is important to note that the influence of a particular feature X on the different quantiles of the conditional distribution of Y may not be identical.

In our study, we are interested in studying the impact of natural disasters on low macroeconomic outcomes of a panel of developing countries. Precisely, we consider a regression of $\Delta y_{i,t+h}$, the annualized average growth rate of GDP per capita for country i, between t and $t+h$, on $x_{i,t}$ a vector of control variables that will be described below. Thus, the regression slope, δ_{τ}, is chosen to minimize the quantile-weighted absolute value of errors:

$$\hat{\delta}_{\tau} = \arg\min \sum_{t=1}^{T-h} (\tau \times \mathbb{1}_{\Delta y_{i,t+h} > x_{i,t}\delta_{\tau}} \mid \Delta y_{i,t+h} - x_{i,t}\delta_{\tau} + (1-\tau) \times \mathbb{1}_{\Delta y_{i,t+h} > x_{i,t}\delta_{\tau}} \mid \Delta y_{i,t+h} - x_{i,t}\delta_{\tau} \mid), \quad (1)$$

where $\mathbb{1}_{(.)}$ denotes an indicator variable and $\tau \in (0,1)$ indicates the τ^{th} quantile of interest. The predicted value from the regression is the quantile of $\Delta y_{i,t+h}$ conditional on $x_{i,t}$, such as :

$$\hat{Q}_{\Delta y_{i,t}|x_{i,t}}(\tau \mid x_{i,t}) = x_{i,t}\hat{\delta}_{\tau} + \epsilon_{\tau}, \quad (2)$$

$\hat{Q}_{y_{i,t+h} > x_{i,t}}(\tau)$ is then a consistent linear estimator of the quantile function of $\Delta y_{i,t+h}$ conditional on $x_{i,t}$.

Now, suppose the following traditional panel local projections estimation function:

$$\Delta y_{i,t+h} = \alpha_{i,h} + \beta_h DS_{i,t} + \delta_h x_{i,t} + \epsilon_{i,t}, \quad (3)$$

where $\alpha_{i,h}$ is the country-fixed effects, $DS_{i,t}$ the disaster variable and $X_{i,t}$ the vector of control variables.[6] Using the quantile local projection method (QLP) proposed by Jordà et al. (2022), we analyze the impacts of natural disaster shocks on the 10th percentile of the output growth variable. Let $\omega_{i,t}$ collect the shock, control variables, and the fixed effects. Given (1) and (3), quantile local projections can be estimated based on

[5] For an introduction to quantile regressions, see Koenker (2005) and our Appendix.

[6] All the regressors are demeaned by their full-sample average.

$$\hat{\theta}_\tau = \arg\min_{\theta_\tau} \sum_{t=1}^{T-h} \left(\tau \mathbb{1}(\Delta y_{i,t+h} \geq \omega_{i,t}\theta_\tau) |\Delta y_{i,t+h} - \omega_{i,t}\theta_\tau| + (1-\tau)\mathbb{1}(\Delta y_{i,t+h} < \omega_{i,t}\theta_\tau) |\Delta y_{i,t+h} - \omega_{i,t}\theta_\tau| \right). \quad (4)$$

To establish a baseline, we conduct a linear regression as inspired by Jordà et al. (2022):

$$\hat{Q}^{\tau}_{i,t+h} = \omega_{i,t}\theta_{h,\tau}, \quad (5)$$

for $h = 0, ..., H$. The coefficients $\theta_{h,\tau}$ measure the effect of the ω variables on the τ-th quantile of the conditional distribution of $\Delta y_{i,t+h}$. Specifically, we intend to examine how natural disasters affect the distribution of GDP per capita growth conditional on observables.

4.2 Data Description

Data on natural disasters are drawn from the Emergency Disasters Database (EM-DAT), managed by the Center for Research on the Epidemiology of Disasters (CRED) of the University of Louvain. It classifies the following events as natural disasters: Earthquakes, Extreme temperatures, Droughts, Floods, Glacial lake outbursts, Landslides, Mass movement (Dry), Volcanic activity, Storms, and Wave action. The EM-DAT database is a comprehensive global database that includes information on all natural disasters between 1900 and 2023. This database provides a clear definition of disasters. To be recorded as a disaster, a natural event must meet at least one of the following criteria: causing the death of 10 or more people, affecting 100 or more people, or leading to a declaration of a state of emergency and/or a call for international assistance.

$DS_{i,t}$ in Equation (3) represents our measure of natural disasters intensity calculated as in Fomby et al. (2013), given by:

$$intensity^{dis}_{i,t} = \begin{cases} 1, & \text{if } \frac{fatalities^{dis}_{i,t} + 0.3 \times affected^{dis}_{i,t}}{population_{i,t}} > 0.01\% \\ 0, & \text{otherwise.} \end{cases}$$

An aggregated yearly index by disaster is then calculated, such as:

$$DS^{dis}_{i,t} = \sum_{k=1}^{K} intensity^{dis}_{i,t},$$

where K is the total number of specific natural event dis that took place in country i during year t.

Gauging the intensity of disasters involves considering two fundamental components – the number of fatalities and the number of people affected. Fatalities and non-fatal affected people are not equivalent, and their impact on growth is not equivalent. Fomby et al. (2013) consider a threshold of 30%, speaking to the equivalency of 3.33 non-fatal affected people, which affects growth to the same extent as one fatality.[7]

Fomby et al. (2013) and Panwar and Sen (2019) highlight that the effects of moderate and extremely severe disasters on economic performance differ in terms of their scale and dynamic characteristics. In order to effectively capture the downside risk to growth, in addition to the above index, we consider using an adjusted measure to study the impact of severe disasters on the 10th percentile of growth distribution. Instead of the 0.01% threshold, we have chosen a higher one of 1%. The revised threshold allows us to focus specifically on severe natural disasters and their impact on the 10th quantile of growth distribution. We apply the same methodology described to identify and categorize severe natural disasters.

The literature on economic development and natural disasters mainly focuses on the number of people affected rather than data on economic damages, although EMDAT reports it. In fact, material damages in the EM-DAT database is prone to missing data in this category. According to Jones et al. (2022), there is a significant proportion of missing data in EM-DAT for events between 1990 and 2020, particularly in reporting economic losses. Although the missing data on economic damages can be attributed to challenges

[7] Although this is a subjective assessment, exhaustive checks for robustness using diverse thresholds demonstrated no noteworthy alterations in results.

in data collection, reporting bias, varying data availability across regions, and the ongoing data compilation and updates process, data on human losses is relatively complete. In addition, Felbermayr and Gröschl (2014) raised concerns about accurately measuring natural disasters. They argue that reliance on damage records from insurance companies may introduce biases, proposing a comprehensive database compiling information from geophysical and meteorological sources to offer a more reliable basis for analysis. This database, the *ifo GAME*, covering 36 developing countries from 1979 to 2010, is used in our analysis of the robustness of our results.

We identified four variables to characterize economic activity: real per capita GDP growth, real per capita agricultural value-added growth, real per capita industrial value-added growth, and real per capita services value-added growth. The common practice in the development literature is to look at economic growth on a per capita basis. In addition of being widely used in the natural disasters literature, using per capita growth rate enables comparison of economic performance across countries and considering population changes, especially over a long period such as the one considered in our study: 1970-2021. This measure highlights the average economic well-being and helps policymakers making informed decisions regarding disaster management and recovery.[8] In addition, this approach will enable us to map better the transmission channels through which the impact of natural disaster shocks is propagated in economic activity.

$x_{i,t}$ in Equation (3) is the matrix of control variables containing gross fixed capital formation, government size, trade openness, financial depth, and inflation rate. According to Fomby et al. (2013); Noy (2009) and Panwar and Sen (2019), these variables are considered as major growth determinants. We also control for the nominal exchange rate variation as an important determinant of economic growth via its impact on the trade balance and terms of trade. We also include a measure of human capital captured by the ratio of enrollment in secondary classes[9], and an indicator of capital account openness measured by the Chinn and Ito (2008) index, as it is usually done by the literature and to mitigate the risk of omitted variable bias. This approach allows for a more robust analysis that considers the potential confounding effects of human capital development and financial openness, providing a more accurate understanding of the real effects of natural disasters on economic growth.[10] All economic data is drawn from the World Development Indicators database of the World Bank. All of them are measured in their logarithmic form.[11]

Our panel covers 75 developing countries on an annual basis from 1970 to 2021.[12] We provide in Table 1 the correlations of sectoral production with the disaster indexes. As described in the table below, growth performance strictly varies across sectors and types of disasters. Earthquakes are positively and statistically significantly correlated with agricultural and industrial production. In contrast, droughts and floods (except for agricultural production) negatively correlate with production in all sectors. The positive correlation of floods with agricultural production could be explained by the fact that floods are likely to cause an abundance of water needed for agriculture. However, excessive floods harm crops, hence the insignificance of the correlation between severe flooding and agricultural production. Storms seem not to have any statistically significant correlation with production. The rest of the correlation coefficients for the different production sectors with severe disasters are more or less similar to those for moderate disasters. As per Fomby et al. (2013) and Panwar and Sen (2019), the variations observed in growth performances indicate the potential for disasters to have varying impacts on

[8]Jaramillo (2007) explains that capital losses due to natural disasters do not show up in national accounting, while the surge in investment does. Therefore, one might find a positive net effect on level GDP. However, this effect is of limited duration, and it should only concern the level of GDP rather than its long-term growth path, which he expects to be negative. Thus, he proposes and justifies using the GDP per capita in empirical research to study the impact of disasters.

[9]Including education attainment as a metric is reasonable due to the belief that it exerts a delayed impact on economic growth via technological progress, as supported by growth theories. Therefore, using education enrollment as a proxy for human capital is a justifiable way to account for its potential role in affecting economic growth.

[10]Table A1 summarizes the main characteristics of our variables and Table A2 presents a full description of data used in this paper.

[11]Everything suggests that our control variables are stationary since they are largely expressed as a ratio to GDP (see Table 1).

[12]The development classification is done according to UNCTADstat country classification.

different economic sectors, thus emphasizing diversifying growth measures. However, this remains a simplistic correlation analysis between different variables. In what follows, we turn to a formal analysis of the effect of natural disasters on GDP growth.

Table 1: *Correlations of sectoral production with the disasters indexes.*

	GDP	Agriculture	Industry	Services
Earthquakes	0.0407	0.0730***	0.0649***	0.0383
Droughts	-0.137***	-0.0762***	-0.121***	-0.133***
Floods	-0.132***	0.0501**	-0.116***	-0.123***
Storms	0.00501	0.0310	0.00637	0.0208
Severe earthquakes	0.0281	0.0268	0.0245	0.0320
Severe droughts	-0.140***	-0.101***	-0.127***	-0.139***
Severe floods	-0.0707***	0.00921	-0.0622**	-0.0686***
Severe storms	0.0208	0.0466*	0.00747	0.0290

Notes: The significance of correlations is tested using the Pearson test: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5 Results

Results presentation is structured according to different types of disasters, namely droughts, earthquakes, floods, and storms. We examine the dynamic effects on the 10th percentile of GDP growth and its key components for each type: agricultural, industrial, and services value-added per capita growth. Our analysis covers a panel of 75 developing countries, of which 41% are lower-middle income economies, 29% are upper-middle income, 20% are low income, and 10% are high-income economies.[13]

5.1 Time Series of average tail-risk

We chose our percentile of interest to ensure the presentations' readability and focus the discussion on the most interesting aspects. In the case $\tau = 0.1$, the output is in the lowest 10% of its conditional distribution, and if $\tau = 0.5$, we assess natural disaster effects at the median, which is close to its mean. Similarly, when $\tau = 0.9$, the output is predicted to be booming such that it is in the highest 10% of its conditional distribution.

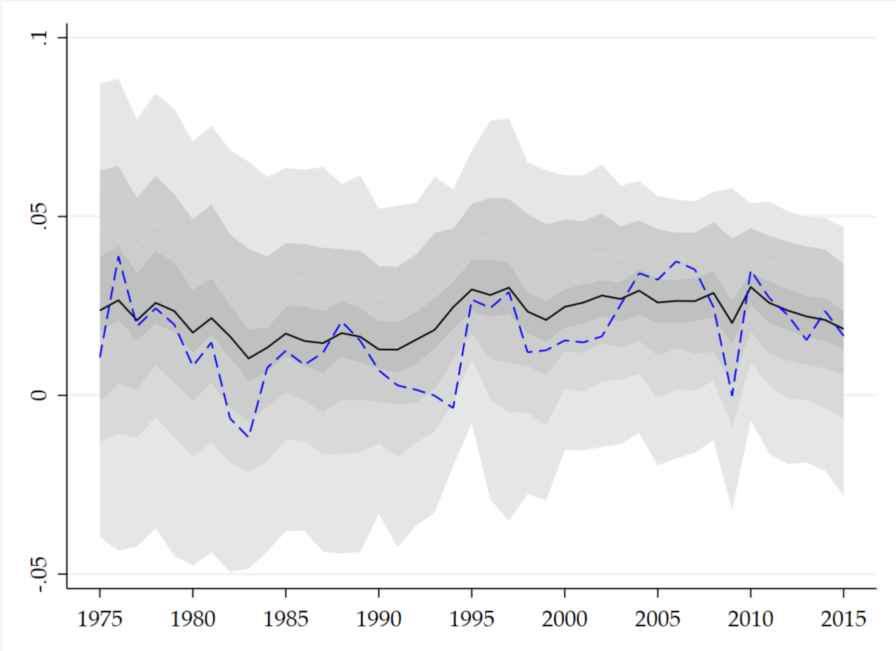
Before discussing the effects of disaster shocks, we aim to understand the quantiles of the conditional distribution of GDP deviations from the trend. Figure 4 shows the time series of average tail-risk estimates (averaged across countries) at the projection horizon of one year. Also plotted are the conditional median, the 90th percentile, and realized growth (shifted one-year forward). Here, we compare fitted values for the lower and upper conditional output decile to actual output realizations. More precisely, we use the estimated quantile regressions to compute one-year-ahead forecasts for the 10th and 90th percentile.

The figure illustrates an asymmetry between the upper and lower conditional quantiles. The time series analysis further indicates that lower projected median growth is linked to a decreased growth-at-risk, aligning with a consistent pattern of conditional growth and negatively correlated volatility. In contrast, the 90th percentile displays limited variability, indicating a more pronounced fluctuation for downside than upside risk. In addition, Figure 4 shows that output realization closely matched the conditional 10th percentile forecasts. It reveals periods when shocks occurred, pushing output well below its conditional mean forecasts. This pattern is predominant during business cycles, where output growth records significant declines. Therefore, lower quantiles of conditional output growth distribution coincide with cycle downturns and vice versa.

Over the sample period, the mean GaR for developing economies stands at -3%, with a standard deviation of 1.24 (see Table 2). The standard deviation of the 90th percentile is slightly lower at 1.21 despite a significantly

[13] In what follows, we add upper-middle-income economies to our high-income economies subgroup.

Figure 4: *Average 10th Percentile, Median, and 90th Percentile at $h = 1$.*



Notes: The figure shows the time series evolution of the predicted distribution of real GDP per capita growth one year ahead. Extreme lines refer to lower (10th percentile) and upper (90th percentile) output, the solid line refers to median output, and the small-dashed line refers to actual output.

Table 2: *Average 10th Percentile, Median, and 90th Percentile at $h = 1$: descriptive statistics.*

	Mean	Std. Dev.	CV
Realized growth	2%	1.60	-
90th percentile	6.2%	1.21	19%
Conditional mean	2%	0.60	28%
10th percentile	-3%	1.24	41%

Notes: CV stands for Coefficient of Variation given by the ratio of the standard deviation to the mean. A high CV suggests that the standard deviation (the measure of volatility) is relatively large compared to the mean. Thus, this kind of variability typically implies higher volatility.

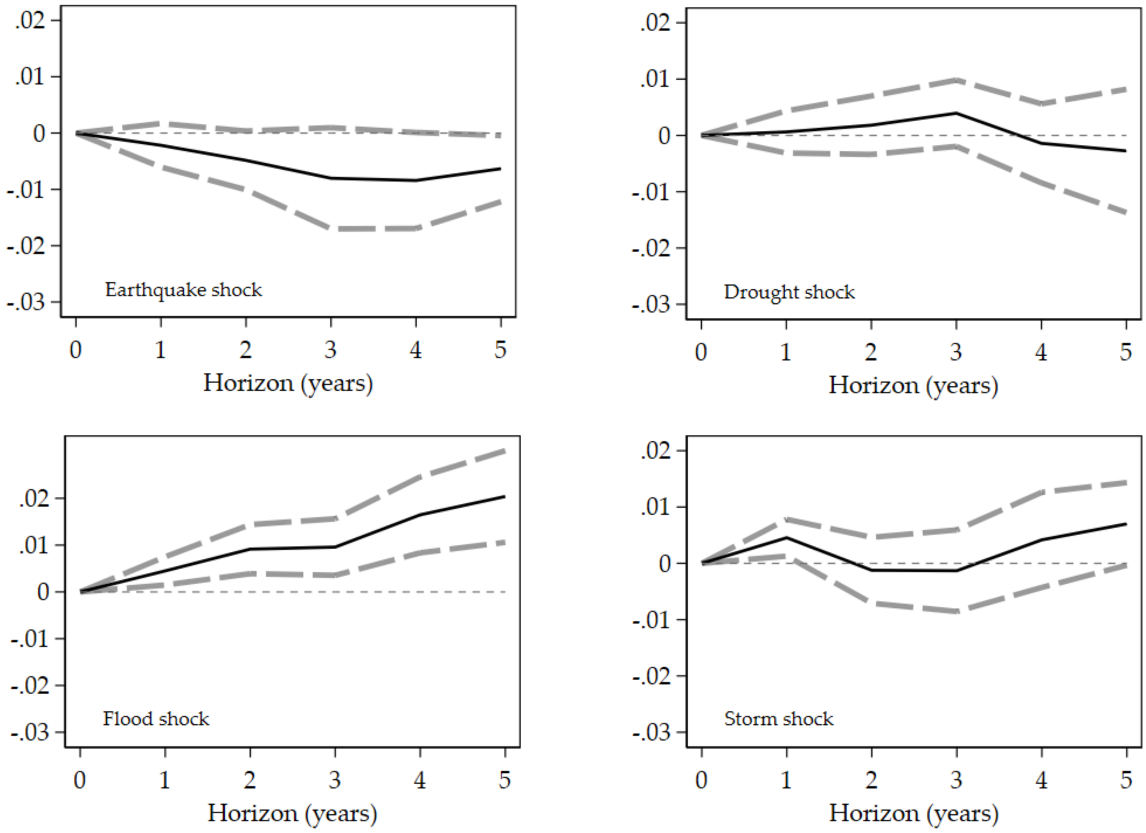
higher mean of 20%. However, we are more interested in the coefficients of variations of the upper and lower percentiles, as they are good measures of relative variability. Indeed, a high coefficient of variation can indicate higher volatility. Essentially, GaR displays a high level of variability (41%) compared to the 90th percentile (19%).

By considering the effect on the 10th percentile, we thus can gain a comprehensive understanding of the effects of natural disasters on low economic growth outcomes. It allows us to uncover the nuanced relationships between natural disasters and macroeconomic outcomes, shedding light on the diverse ways in which different states of the economy are affected.

5.2 The Average Effect

We begin with a brief presentation of the results of traditional local projections. Figure 5 plots predicted IRFs for the average GDP growth rate following a one-standard-deviation natural disaster shock for our sample of developing countries. As seen, the effect of disasters on the average GDP growth is mitigated. The impact of earthquakes and droughts on GDP growth is not statistically significant, while storms have only a direct positive impact on the year after the shock. Interestingly, floods have a positive and persistently increasing

Figure 5: *Natural disasters, responses at 50-th percentile of real GDP per capita growth.*



Notes: Figures show the predictive effects of a one-SD natural disaster shock on GDP growth based on the LPs technique. Dashed lines denote the 95% confidence interval based on bootstrap replications.

effect on economic growth.

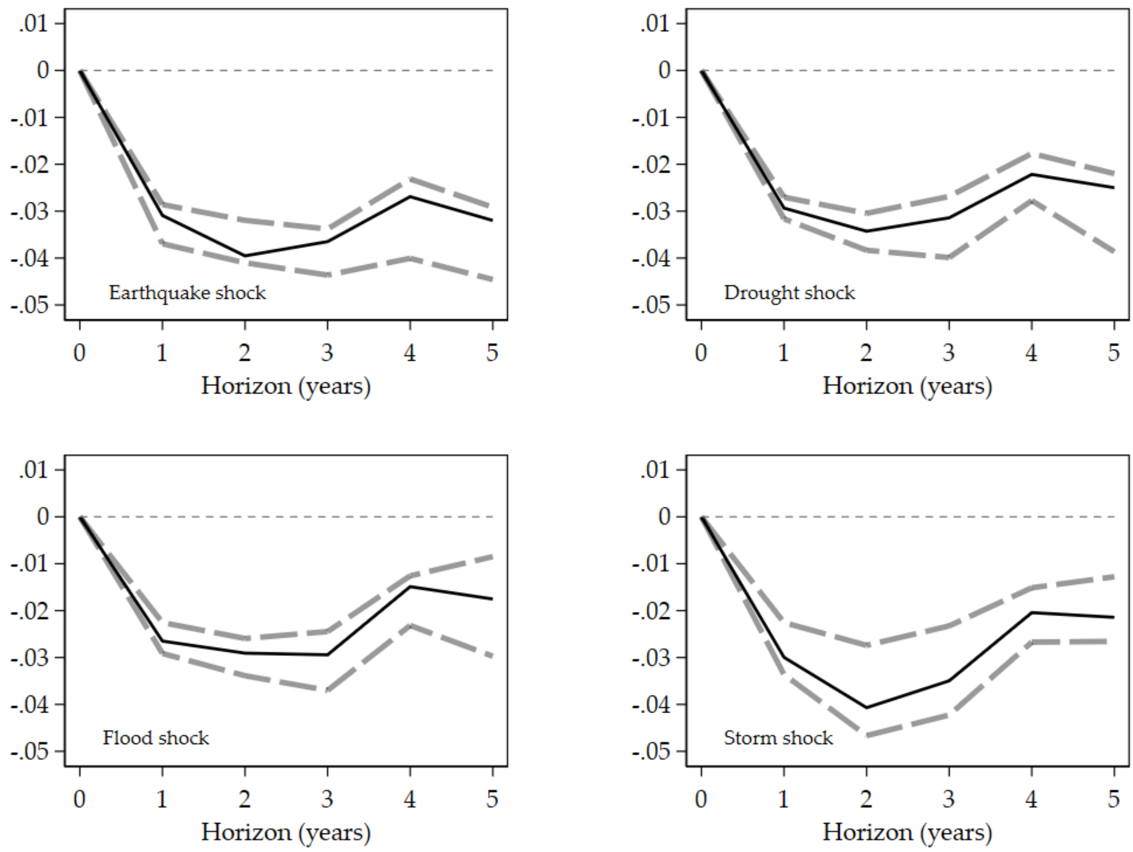
Consequently, floods stimulate higher GDP growth on average, mainly through transmission mechanisms. According to the literature, floods have mitigating effects on agriculture. Water is essential to life, but too much of it can harm crops. Therefore, as Fomby et al. (2013); Loayza et al. (2012) and Panwar and Sen (2019) point out, the effect of floods on GDP can be more or less beneficial for economic growth if they do not occur at the same time as land cultivation.

Transitioning from traditional local projections to quantile local projections on the 10th percentile of the GDP growth distribution, we focus on exploring the specific dynamics at the left tail of economic growth. While traditional local projections offer insights into average responses to shocks, quantile local projections delve deeper by examining how natural disaster shocks impact economic activity when output is depressed and thus in a lower quantile of its conditional distribution. This transition allows us to uncover nuanced patterns and vulnerabilities in the economy, particularly in the face of adverse events, providing a more comprehensive understanding of the distributional effects of such shocks and emphasizing the non-linearity of the effects of natural disasters.

5.3 Tail Risk from Natural Disasters

This section presents and discusses our findings regarding the risk to growth from natural disasters. Figure 6 plots predicted trajectories for the 10th percentile of GDP growth rate following a one-standard-deviation natural disaster shock for developing countries. While the effect of disasters on the average response, shown

Figure 6: *Natural disasters, responses at 10-th percentile of real GDP per capita growth.*



Notes: Figures show the predictive effects on growth of a one-SD natural disaster shock based on a LP series of quantile regressions. Dashed lines denote the 95% confidence interval based on bootstrap replications.

above, is mitigated, Figure 6 makes it unequivocal that the effects of different natural shocks on the 10th percentile of growth are considerable. We can see that the peak is reached two years after the shock for all types of disasters except floods, which is reached three years after the shock.

We can see that earthquakes and storms have the most negative impact on the lower growth percentile two years post-shock. This can be attributed to the particularly devastating effect of these two events. Indeed, while earthquakes destroy productive capital and infrastructure, storms typically involve strong wind gusts and violent hailstorms capable of causing significant destruction to plantations and crops. Losses can be notably higher when they occur during the flowering period. With that said, it is essential to highlight a sudden reversal in the IRFs after reaching the peak for both types of events. Indeed, the current body of literature on natural disasters occasionally underscores a positive impact on economic growth after earthquakes and storms. This is attributed to the necessity for reconstruction efforts, including restoring damaged capital and crops, which tends to favor economic growth in the medium term. Moreover, viewed through the lens of growth theory, the concept of "creative destruction" likely comes into play in this context.

For floods and storms, recovery is faster and more significant, reducing downside risk to economic growth. Nevertheless, we note that the reaction of the 10th percentile of growth rate to the flood shock is relatively stable and not very pronounced compared to other disasters, recalling the positive role of floods as explained above.

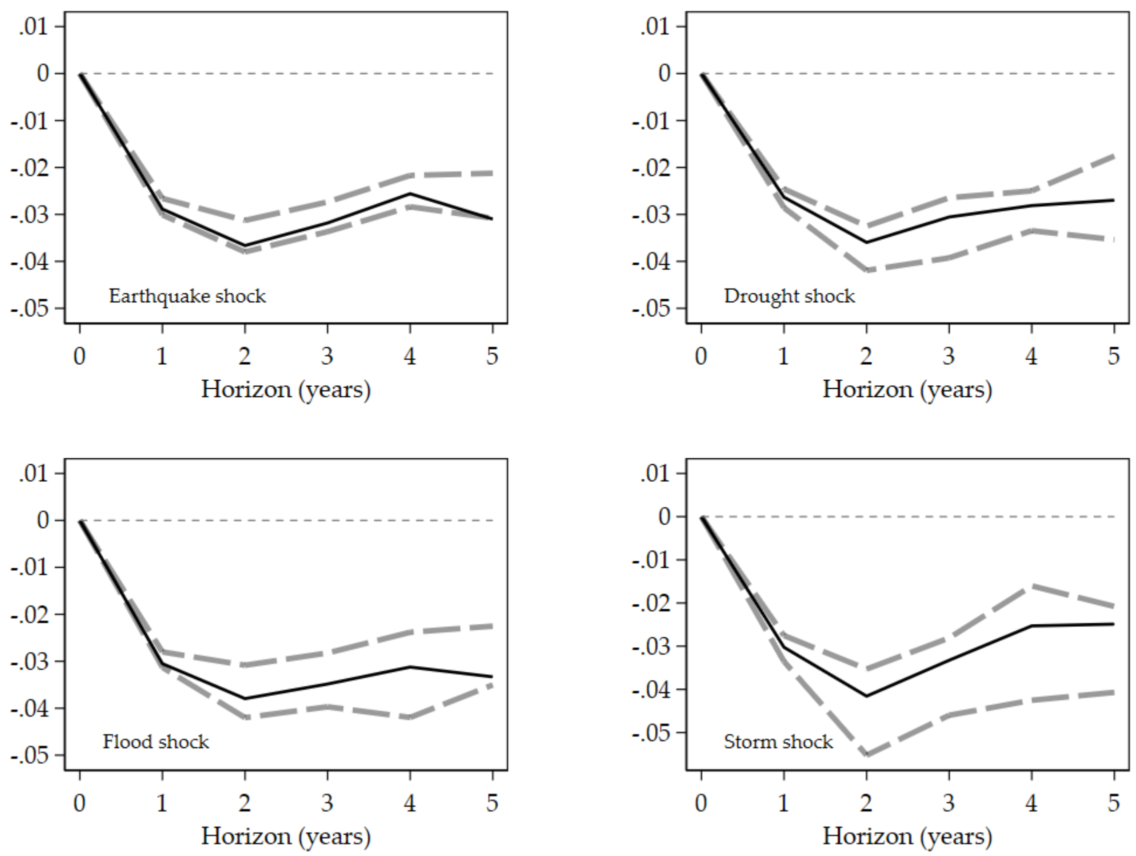
Figure A1 in the Appendix shows the QIRFs of the 10th percentile of GDP growth rate following a disaster shock, measured using *ifo GAME* database (Felbermayr and Gröschl (2014)). Impulse response functions exhibit broad confidence intervals, possibly stemming from the limitation in the panel covered by the *GAME* database.

The latter focuses on natural disasters occurring annually between 1979 and 2010 and on a narrowed sample of countries. Comparing the two databases, however, allows us to verify the accuracy of our initial estimate, as well as its robustness. Indeed, there is a downside risk to economic growth, which is also shown to be persistent.

5.4 Moderate versus Severe Natural Disasters

We now examine the effect of the severe natural disasters index on the 10th percentile of growth. According to Figure 7, the downside risk to GDP growth is more pronounced with severe events, exhibiting more remarkable persistence and prolonged effects than moderate ones. This is true even for floods, which had shown positive effects on average economic growth in Figure 5 and a stable downside risk one year after the shock (Figure 6). The seemingly consistent impacts on lower macroeconomic output caused by moderate floods, such as providing ample water supply for multiple cropping seasons, seem to be counteracted by the damage and devastation inflicted by severe floods two years after the event, which is the point at which the IRF peaks.

Figure 7: *Severe natural disasters, responses at 10-th percentile of real GDP per capita growth.*



Notes: Figures show the predictive effects on 10th percentile of GDP growth of a one-SD severe natural disaster based on a LP series of quantile regressions. Shaded areas denote the 95% confidence interval based on bootstrap replications.

Looking at Figures 7, we can further corroborate our earlier results that severe earthquakes and storms considerably increase the downside risk to economic growth. Moreover, the reversal in the QIRF that we see in Figure 6 is also present here but on a lower scale.

According to Figure 7, the downside risk to GDP growth is more pronounced with severe events, exhibiting more remarkable persistence and prolonged effects than moderate ones. This is true even for floods, which had shown positive effects on average economic growth in Figure 5 and a stable downside risk one year after the shock (Figure 6). The seemingly consistent impacts on lower macroeconomic output caused by moderate floods, such as providing ample water supply for multiple cropping seasons, seem to be counteracted by the damage and devastation inflicted by severe floods two years after the event, which is the point at which the IRF peaks.

6 Tail Risk and Macroeconomic Heterogeneity

in this section, we present a detailed investigation of tail risk, considering macroeconomic heterogeneity. This transition refines our focus from a broad perspective to a more specific examination, considering factors like different economic sectors' growth and income levels. By doing so, we aim to unveil varied patterns and vulnerabilities across developing economies, offering a better understanding of the macroeconomic implications associated with tail risk.

6.1 Heterogeneity Across Production Sectors

We now study the downside risk of growth in the various production sectors. Impulse response functions for agricultural, industrial, and services value-added growth are reported in Figures 8 and 9.

These results support our previous assessment. Indeed, natural disasters have an important negative impact on capital (both public and private) and crops. This also explains the increasing and persistent risk to growth in agricultural and industrial production, while we note a lesser effect on the downward risk to growth in services. There are, therefore, several explanations to be drawn here. Firstly, a transmission channel between the agricultural and industrial sectors negatively affects the downside risk to economic growth in developing countries following natural disasters.

In developing countries, a close interconnection exists between the agricultural and industrial sectors. The industrial sector is frequently influenced by the agri-food industry, which relies heavily on agricultural production. Furthermore, agricultural output is contingent on the industrial sector's intermediate inputs, such as tools and fertilizer. Hence, these inter-dependencies elucidate why natural disasters impacting agriculture are likely to parallel affect industrial growth (Loayza et al. (2012)). Secondly, the weak reaction of the 10th percentile growth rate in the services sector and the rapid turnaround in the IRF might be explained by increased demand for services in the aftermath of disasters, reducing the downside risk to services growth. Natural disasters can impact the services sector's growth through a mechanism where relief resources and activities increase the demand for service-related industries such as transport, communications, banking, and insurance. Notably, the resilience of the services sector is primarily attributed to the fact that, unlike industry, it is less dependent on physical capital, which is directly impacted by destructive natural disasters (Loayza et al. (2012)).

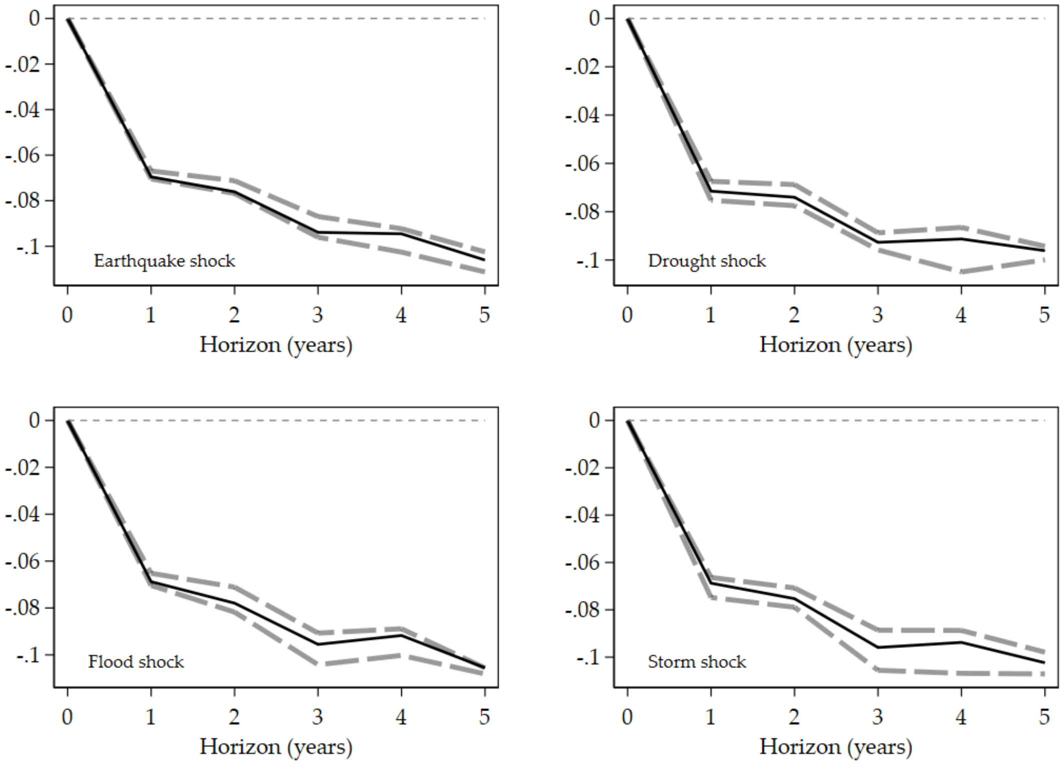
6.2 Heterogeneity Across Income Level

To expand and deepen our analysis, we divide our sample of countries according to income level. This approach allows us to homogenize the countries in our database. Indeed, out of 75 developing countries in our sample, 29 are classified as high-income countries (e.g., China, India, Hong Kong...), and 15 are classified as low-income countries, generally referred to as "least developed countries (LDCs)" (e.g., Burkina Faso, Rwanda, Mali...).[14] This allows us to consider heterogeneous macroeconomic dynamics among developing economies. It is worth noting that the results for "lower-middle income countries" are very similar to those of our benchmark analysis in Figure 6, so we have decided not to carry them forward.

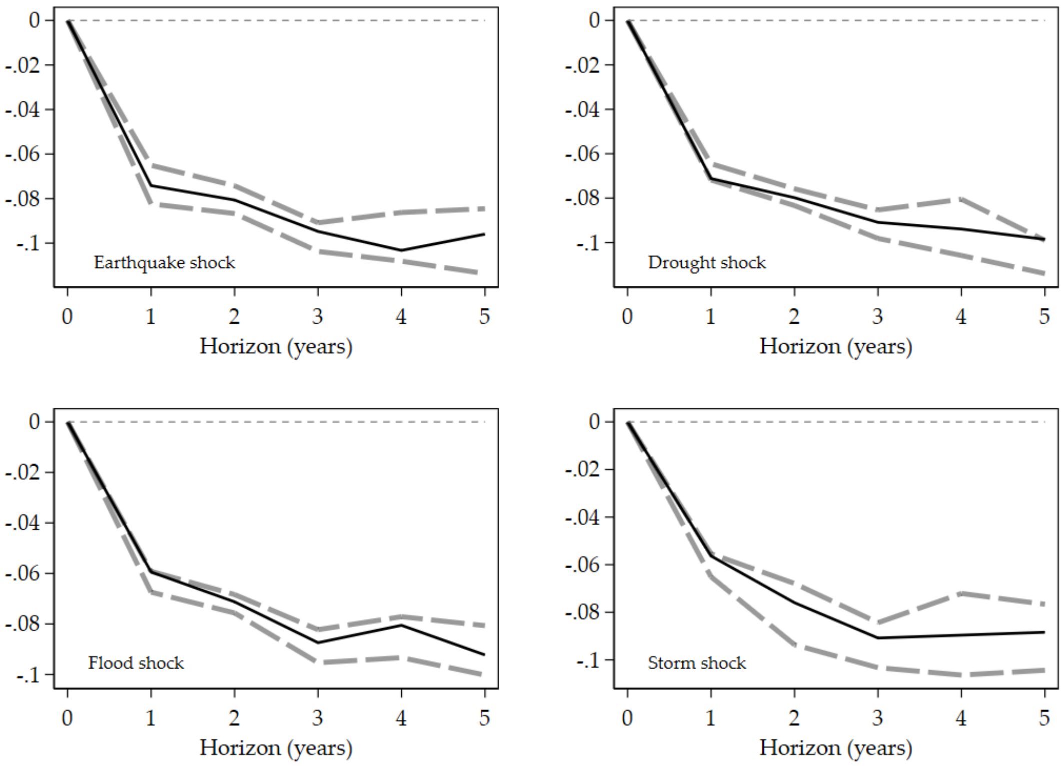
In addition, cross-country heterogeneity is also evident in terms of natural disasters. For instance, the LDCs in our sample are affected by very few earthquakes (our $DS^k_{t,i}$ indicator considers only three such events), making it impossible to include them in our quantile regression.

[14] See Table A3 for a list of the countries we consider in our sample.

Figure 8: *Agricultural and Industrial Value-Added Growth*



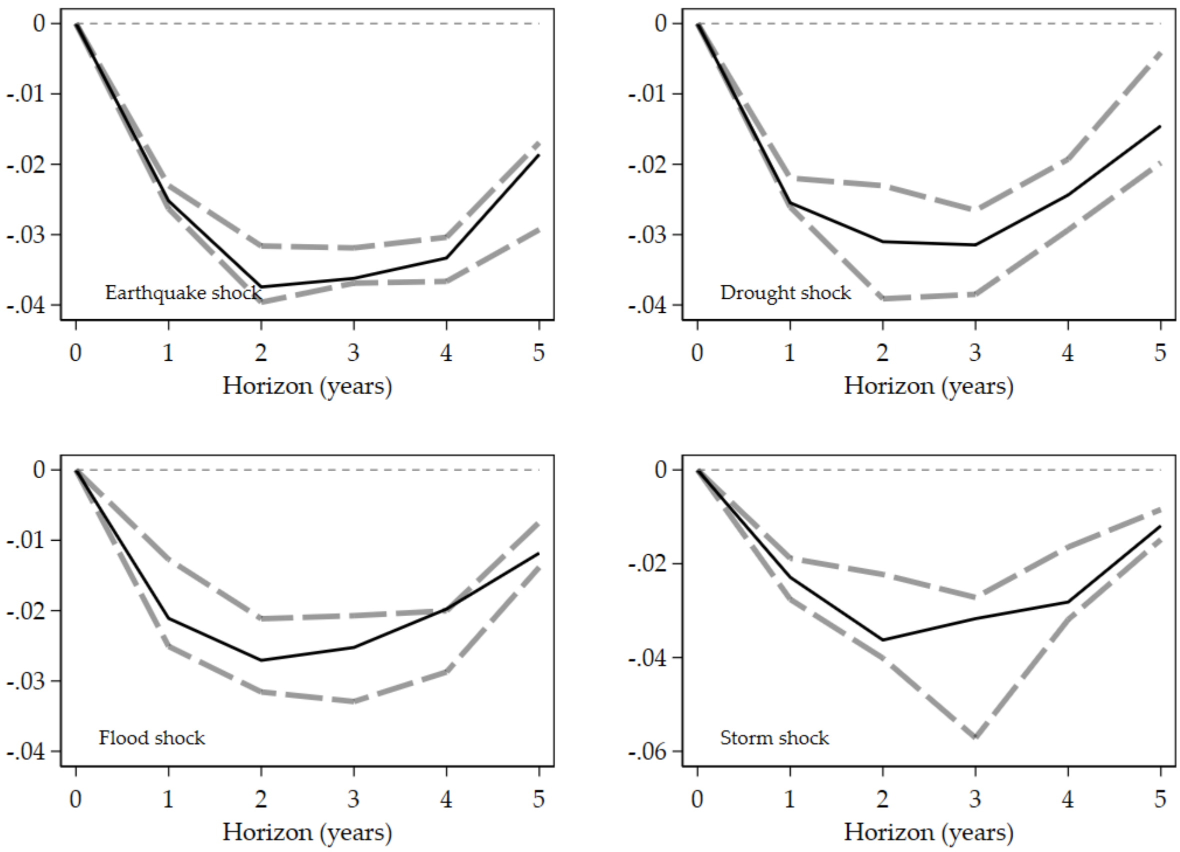
(a) *Agricultural value-added growth*



(b) *Industrial value-added growth*

Notes: Figures show the predictive effects on a one-SD natural disaster's 10th percentile sectoral production growth based on a LP series of quantile regressions. Dashed lines denote the 95% confidence interval based on bootstrap replications.

Figure 9: *Services value-added growth*



Notes: Figures show the predictive effects on a one-SD natural disaster's 10th percentile sectoral production growth based on a LP series of quantile regressions. Dashed lines denote the 95% confidence interval based on bootstrap replications.

The results are shown in Figure 10 below and are striking. The peak of downside risk for high-income developing countries is reached one year after the shock, except for storms, which are reached in the second year and are of greater magnitude (-4 p.p.). From Figure 3, we see that storms are enormously costly, in terms of human (panel 3a) and property damage (panel 3b) in developing countries, which could explain the apparent delay in replacing destroyed capital and the reversal of corresponding QIRF.

The QIRFs for LDCs, on the other hand, decrease sharply, indicating that the shock to downside risk for these countries is persistent. The reaction of the 10th percentile of the growth rate is even more severe, with an average decrease of 12.5 p.p. in the second year. It is also crystal clear that in the long term, i.e., beyond three years after the shock, the economic growth of LDCs remains highly vulnerable. The downside risk to economic growth remains very high and very persistent. In contrast, the downside risk to growth in rich countries is reduced in the long term, with the reaction of the 10th percentile even becoming positive.

Natural disasters have a more widespread impact on low-income countries' entire economies than on high-income economies. This is because low-income countries, with their smaller economies in size but also in terms of income, are more vulnerable to disasters and experience a more extreme range of damages. Hence, natural disasters are regarded as crucial factors influencing the development process of LDCs (Cantelmo et al. (2023)). While Noy (2009) explains the difference in GDP growth reaction between developed and developing countries by the former's ability to implement counter-cyclical policies to mitigate the risk of recession following natural disasters and the latter's inability to do the same, a significant contribution of our paper is to have shown that there is heterogeneity in *ex-post* reactions even within developing countries since the downside risk to growth in “rich” countries seems to fade out in the long term, while that of low-income countries being highly persistent.

The high-income countries in our sample have relatively large diversified economies, both in size and surface area. The extent of natural disasters, therefore, remains very limited locally and rarely spreads to the whole country at the same time[15]. The macroeconomic characteristics of these countries also appear to play a role in mitigating the risk associated with natural disasters. High-income developing countries often have more diversified economies, with a broader range of industries contributing to their GDP. This diversification can provide greater stability and resilience to economic shocks.

On the other hand, low-income countries benefit from an increase in inward remittances and international financial aid after natural disasters (Bettin and Zazzaro (2018)), which are likely to act like a fiscal buffer reducing the global negative impact on average GDP growth (Ebeke and Combes (2013); Mejia et al. (2019)). Despite the mobilization of international aid and increased remittance inflows, the downside risk to LDC growth remains significantly persistent following natural disasters. With this in mind, it would be legitimate to attribute this to institutional quality and level of development Noy (2009) refers to.

6.3 Heterogeneity Across Institutional Arrangements and Quality

High-income countries have stronger institutions, including effective governance, legal frameworks, and regulatory systems, contributing to economic stability and efficient resource allocation through social welfare programs and insurance mechanisms. In low-income countries, institutional quality tends to be lacking. The importance of public institutions can be linked either to the immediate efficacy of public intervention in the aftermath of an event, such as distributing aid to the homeless and offering secure housing, or to the indirect influence of an efficient government response in shaping the private sector’s response to the disaster. This is particularly relevant in events like droughts, where longer-term interventions such as policies to support farmers become essential.

To investigate the effect of institutional strength on mitigating risk to growth from natural disasters, we use an interaction term of the natural disaster index and a categorical variable of democracy. We use this measure as a proxy for institutional quality since we assume democracies have better public institutions than autocratic regimes.

We use an ordered categorical variable based on the democracy index by the Polity 5 database (Herre (2022)). It captures the extent to which open, multi-party, and competitive elections choose a chief executive facing comprehensive institutional constraints, and competitive political participation is competitive. It ranges from -10 to 10 (fully democratic). From this, and following the recommendations of the database managers, our dummy variable ($democ_{i,t}$) takes the value of 0 when the index is below or equal to -6 (autocracy), one if the Polity index is higher or equal to 6 (democracy).[16]

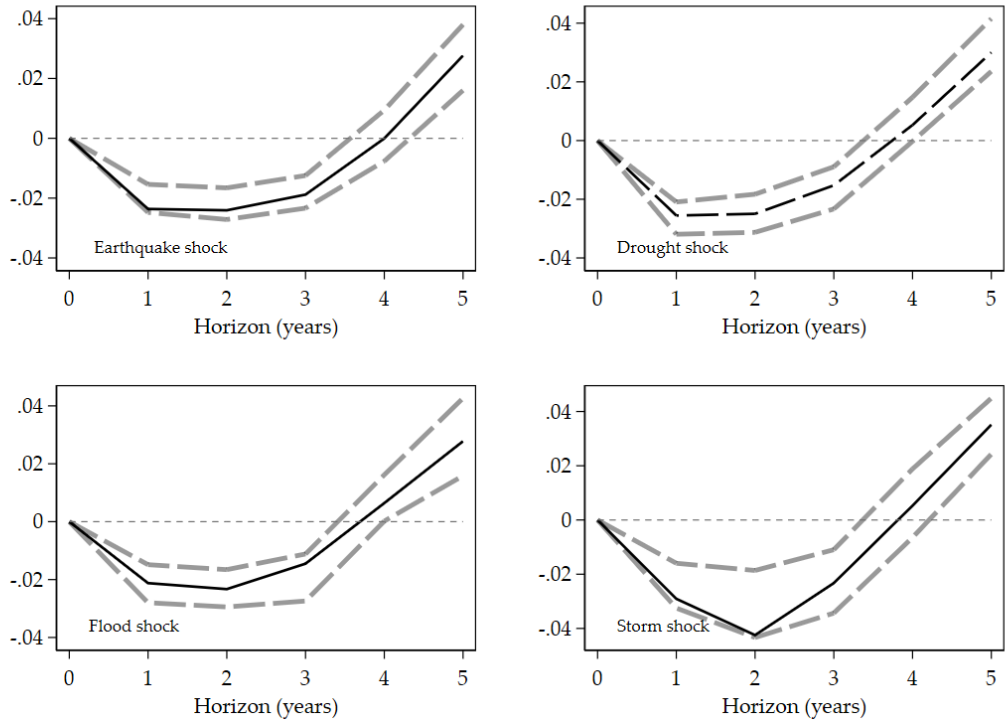
Figure 11 below shows that although the IRFs undergo similar changes one year after droughts for both democracies, following droughts and earthquakes, the 10th percentile of GDP growth decreases more for autocratic countries in the long term than others. This highlights the challenges these countries face in dealing with the consequences of droughts. Such climatic events are characterized by prolonged and persistent adverse effects, particularly on agricultural production, severely impacted by droughts (Gallic and Vermandel (2020)). Consequently, the significance of implementing agricultural policies and support measures for farmers is emphasized, a task that autocratic countries appear to struggle with. Our results also suggest that while there is no evidence of a differentiated effect between democracies and autocracies one year after a flood or storm shock, the impact of these events is statistically insignificant for autocracies in the longer term.

Our findings indicate that the disparity in 10th quantile growth responses between democratic and autocratic

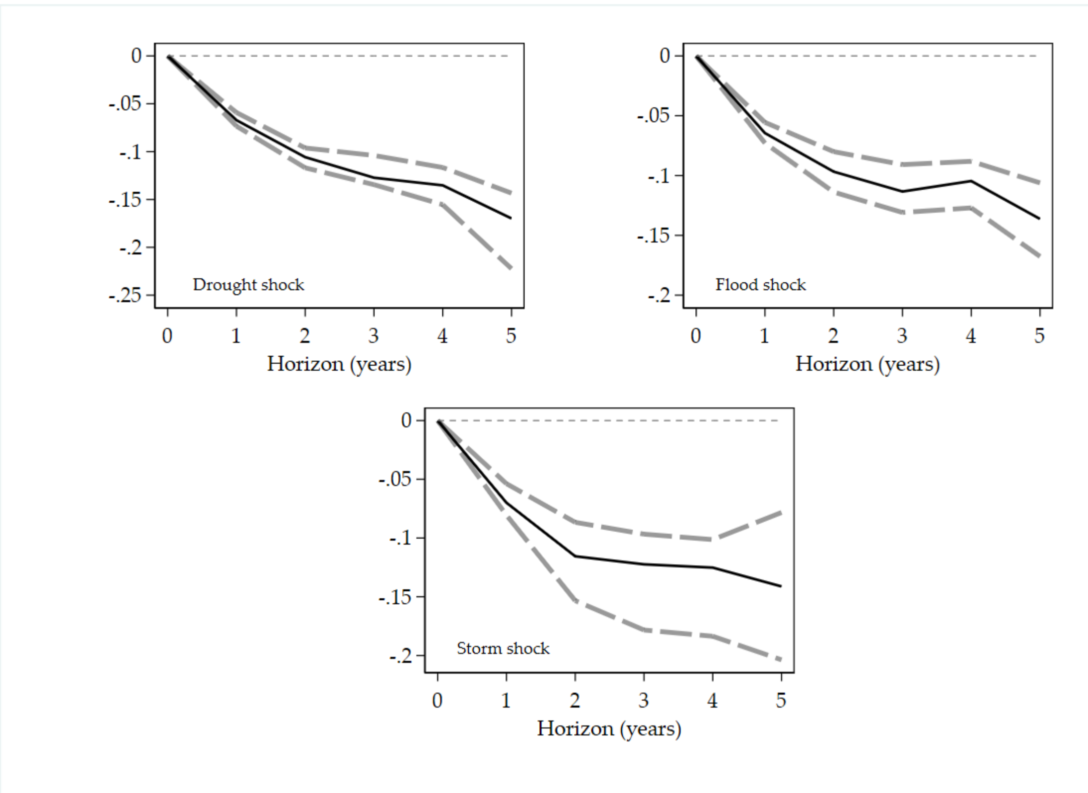
[15]See Felbermayr et al. (2022) and Naguib et al. (2022) for an analysis of the impact of natural disasters on local GDP.

[16]According to the Polity 5 website, if the index ranges between -5 and 5, the country is considered as anocracy, an incoherent authority regime as opposed to mixed authority regimes referred to as autocracies. The corresponding results are of little interest to us; thus, they are not reported.

Figure 10: *Natural disasters, responses at 10-th percentile of real GDP growth according to income level.*



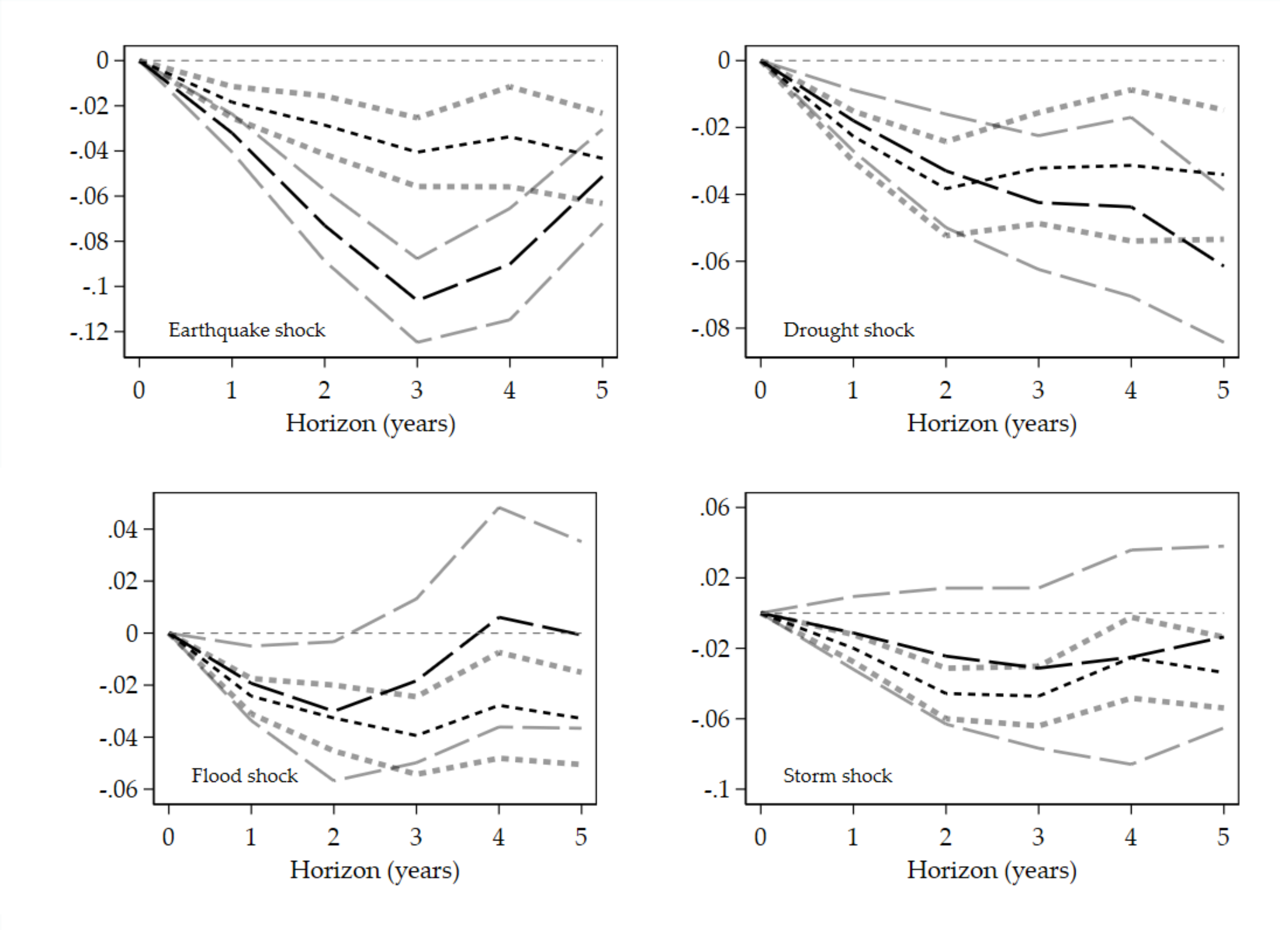
(a) High income countries



(b) Low income countries

Notes: Figures show the predictive effects on the 10th percentile growth of a one-SD natural disaster based on a LP series of quantile regressions. Dashed lines denote the 95% confidence interval based on bootstrap replications.

Figure 11: *Natural disasters and democracy, responses at 10-th percentile of real GDP per capita growth.*



Notes: Figures show the predictive effects of a one-SD natural disaster's 10th percentile of GDP growth based on a LP series of quantile regressions. Long dashed lines refer to the reaction of autocratic countries' GDP growth, whereas short dashed lines refer to democratic countries. Faded dashed lines denote the corresponding 95% confidence interval based on bootstrap replications.

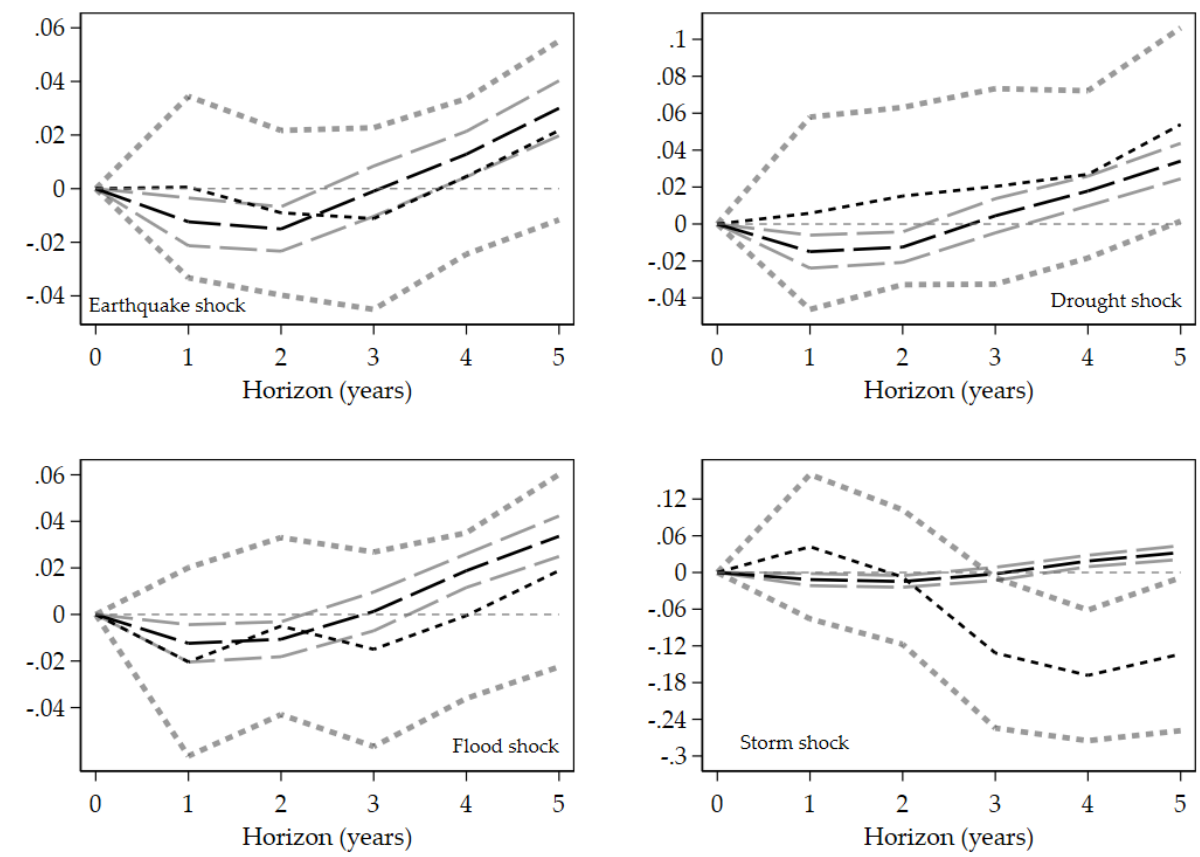
countries becomes evident solely in the long run, explicitly following droughts and earthquakes. This partially supports our previous assertion regarding the significance of institutional quality in mitigating the adverse impact on growth.

We are aware that the democracy indicator is of little relevance in studying the mechanisms driving the difference in reactions between growth in rich and poor countries and could be somehow misleading. Indeed, this indicator places several rich countries (China, for example) in the autocratic category, thus constraining our approach. However, this indicator is the only continuous qualitative one that covers a broad period.[17]

We now use the government effectiveness index in our interaction term to control for the quality of public institutions. The World Bank constructs this indicator, among others, in the Worldwide Governance Indicators database. Government effectiveness indicator captures perceptions of the quality of public services, the quality of civil service, the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies. The government effectiveness index is a ranking of state capacity including 193 countries, each scored from -2.5 (less effective) to 2.5 (more effective). It is, a good measure of public institutions' quality and can effectively measure governments' capacity (or incapacity) to adopt policies aiming to mitigate natural disaster risk on economic growth. We also

[17]We tried to run the model with China excluded from the sample, but the results were not significantly altered.

Figure 12: *Natural disasters and government effectiveness, responses at 10-th percentile of real GDP per capita growth.*



Notes: Figures show the predictive effects of a one-SD natural disaster shock on the 10th percentile of GDP growth based on a LP series of quantile regressions. Long dashed lines refer to the reaction of autocratic countries' GDP growth, whereas short dashed lines refer to democratic countries. Faded dashed lines denote the corresponding 95% confidence interval based on bootstrap replications.

consider a binary variable that takes the value of 1 if the government's efficiency indicator is greater than 1, i.e., if the government is perceived as efficient, and 0 otherwise.

It is worth noting that natural disasters are associated with lower growth outcomes in less effective countries, at least in the short term. Droughts cause the highest decline in the 10th percentile growth of less effective governments one year after the shock (-1.2%), while earthquakes and storms have greater effects two years later (a decline of 1.5%). The impact of natural disasters on more effective governments' growth tail risk is not significant. Although the results of ineffective governments are not significant three years after the storm shock, in the long term, the effect is negative and significant in the 10th percentile of the GDP growth of these countries.

Our results are unequivocal and support that, in the short term, political regimes and better quality of public institutions are important factors that can mitigate adverse effects of natural disasters and are associated with lower growth tail risk. Democracies encourage leaders to act effectively and transparently, as they will be held accountable. At the same time, the importance of public institutions can be attributed either to the direct effectiveness of public intervention after the event, such as implementing policies and taking measures to reduce the adverse economic impact, or to the indirect impact in shaping the private sector's response to the disaster.

7 Conclusion

In this study, we analyze the impact of natural disasters on the tail risk of output growth in developing countries. Our research extends the literature on the consequences of natural disasters by revealing tail risks arising from such events. Relying on quantile local projections techniques as proposed by Linnemann and Winkler (2016) and Jordà et al. (2022), our findings indicate that disaster shocks tend to decrease low growth outcomes at the 10th percentile, with persistently enduring effects.

Our study identifies transmission channels of tail risk to economic growth following natural disasters by examining the dynamics of various GDP components. In particular, we show that natural shocks induce extreme declines in lower output growth, particularly evident in the agricultural and industrial sectors. The imbrication of these sectors accentuates the sharp decline in the 10th percentile of production growth. While this trend holds for agricultural and industrial production, the downside risk to services growth is less persistent compared to the rest of the sectors. Our results even suggest a reversal of impulse response functions, indicating a diminishing tail risk on growth in this sector. This result could be attributed to the increasing demand for services post-disaster, as they are vital for the reconstruction process (banking, insurance, telecommunications, transport, etc.). Moreover, services are also less dependent on physical capital and, thus, less affected by its destruction.

We extend our analysis by categorizing countries by income level and studying the impact of various natural disasters on the 10th percentile of their growth distribution. Our results clearly show that within developing economies, high-income countries exhibit better resilience to the adverse effects of natural disasters on the growth tail risk compared to low-income countries. For the more vulnerable countries, institutional shortcomings result in struggles to address the needs of their population's post-disaster, increasing the likelihood of highly adverse economic growth outcomes. Moreover, we demonstrate a higher vulnerability of autocratic countries to natural disasters in the long term compared to more democratic countries making evident the importance of the quality of public institutions to deal with adverse shocks such as natural disasters. In fact, better institutions appear to be better able to withstand the initial disaster shock and prevent its effects from increasing probability of witnessing a significant drop in growth as a consequence of a natural disasters.

Policy implications of our analysis can be summarized as follows. International frameworks to assist less developed countries in enhancing their resilience to natural disasters are crucial, given that these countries experience a higher frequency of devastating events. Resilience initiatives should focus on modernizing infrastructure and formulating emergency response plans to ensure prompt assistance to affected areas. Additionally, our findings suggest that diversifying economic activities, especially in agricultural and industrial production, would yield more significant advantages for all developing economies compared to maintaining concentration. Further research at both institutional and microeconomic levels is necessary to provide a more refined characterization and explanation of the observed reactions. From a broader macroeconomic perspective, exploring how fiscal policies can enhance social well-being in the aftermath of natural disasters is reasonable. Examining potential interplays between budgetary and monetary policies in this context becomes particularly pertinent.

A Appendix

A.1 Quantile Regressions

Consider we are interested in a random variable Y with a distribution function τ conditional on X defined by $F_{Y|X}(y) = \mathcal{P}(Y \leq y|X)$.[18] And if $F_{Y|X}$ is continuous and strictly increasing, then $F^{-1}_{Y|X}(\tau)$ is the unique real number y such that, the following cumulative density function

$$\mathcal{P}(Y < Q^{\tau}(Y|X)) = F_{Y|X}(y) = F(y) = \mathcal{P}(Y \leq y|X) = \tau.$$

Quantiles are then defined as particular locations of the distribution.

In conventional quantile regression, the assumption is made that the quantiles of the conditional distribution follow a linear structure (Koenker (2005)) such as:

$$Q^{\tau}(Y|X) = X'\beta_{\tau} + \epsilon_{\tau}, \;\; \text{with } Q^{\tau}(\epsilon_{\tau}|X) = 0. \tag{6}$$

A significant distinction from standard linear regression is that in this case, the coefficients are permitted to vary across different quantiles. This enables the extraction of additional insights that cannot be obtained through a basic linear regression model. Let's now turn to a more specific presentation of quantiles as particular locations of the distribution, minimizing the weighted absolute sum of deviations. In such a situation, the τ-th quantile is equal to:

$$\hat{Q}^{\tau} = \arg\min_{b} E\left[\rho_{\tau}(Y - b)\right], \tag{7}$$

where ρ_{τ} represents a loss function such as:

$$\begin{aligned} \rho_{\tau}(y) &= \left[\tau - \mathbb{1}(y < 0)\right] y \\ &= \left[(1-\tau)\mathbb{1}(y \leq 0) + \tau\mathbb{1}(y > 0)\right] |y|. \end{aligned} \tag{8}$$

Such loss function is then an asymmetric absolute loss function, that is a weighted sum of absolute deviations, where a $(1 - \tau)$ weight is assigned to the negative deviations and a τ weight is used for the positive deviations. For instance, if we are interested in the median - $\tau = 0.5$ - the loss function simply corresponds to the half absolute value. The benefit of this definition is that it seamlessly extends to the conditional framework that is of interest to us. $\hat{Q}^{\tau}$ and b can be respectively replaced by $Q^{\tau}(Y|X)$ and a function $b(X)$. Considering the previous linearity assumption in (6), we have[19]:

$$\beta_{\tau} = \arg\min_{\beta} E\left[\rho_{\tau}(Y - X'\beta)\right]. \tag{9}$$

In quantile regression, the quadratic loss function utilized in ordinary least squares regression is substituted with a different loss function (ρ_{τ}). The latter exhibits a linear increase with the residual, rather than a quadratic one. As a result, significantly large deviations are penalized to a lesser extent.[20] The estimator used herein is then called the *Least Absolute Deviation Estimator*. It is important to clarify that the estimation in quantile regression is based on the entire sample. It does not involve dividing the sample into subgroups based on quantiles of the variable of interest and performing separate linear regressions on each subgroup. Indeed, this

[18] Recall that the quantile of order $\tau \in (0, 1)$ is generally defined by: $Q^{\tau}(Y|X) = inf\{y : F_{Y|X}(y) \geq \tau\}$ and if $F_{Y|X}$ is continuous and strictly increasing we have $Q^{\tau}(Y|X) = F^{-1}_{Y|X}(\tau)$.

[19] Recall that in an OLS framework, estimators are defined as follows:

$$\beta_0 = \arg\min_{\beta} E\left[(Y - X'\beta)^2\right].$$

[20] This characteristic accounts for the robustness of quantile regression in handling extreme values.

would be incoherent as it would constrain the lower and upper values of the variable of interest within each group, rather than studying how the variable of interest varies in relation to its explanatory variables.[21] We can then estimate any quantile of order $\tau \in [0, 1]$. It is noteworthy while there may be an infinite number of possible quantile regressions in theory, the actual number of quantiles estimated in practice is influenced by the sample size and data availability.

[21]This misconception is often linked to confusion between the quantile levels (interval limits) and the individuals whose variable of interest falls within those intervals. For more about this issue see D'haultfœuille and Givord (2014); Koenker (2005)

A.2 Descriptive Statistics of the Variables, Data Description and Countries List

Table A1: *Descriptive statistics*

	Mean	Std. Dev.	Min	Max
Full sample				
Real p.c GDP growth	0.01666	0.05346	-0.60377	0.47057
Real p.c agricultural growth	0.00461	0.07945	-1.09705	0.42672
Real p.c industrial growth	0.01805	0.08827	-0.89928	0.67483
Real p.c services growth	0.02264	0.06100	-0.68631	1.03049
Gross fixed capital formation	3.02662	0.39722	0.65782	4.53847
Government consumption	2.56209	0.42934	-0.09295	4.00915
Trade openness	4.05051	0.60427	-0.27856	6.09271
Inflation rate	0.10925	0.22538	-0.13991	4.77488
Financial depth	-1.55368	0.88405	-4.64293	0.95275
Secondary enrollment	-0.96474	0.89622	-6.28321	0.35078
Financial openness	-0.42978	1.32737	-1.92703	2.31061
Change in nominal exchange rate	0.06159	0.26470	-9.37474	2.96214
Earthquakes	0.04974	0.25238	0.00000	4.00000
Droughts	0.07692	0.27503	0.00000	3.00000
Floods	0.37564	0.73854	0.00000	7.00000
Storms	0.18128	0.69528	0.00000	13.00000
Severe earthquakes	0.00410	0.06782	0.00000	2.00000
Severe droughts	0.04667	0.21216	0.00000	2.00000
Severe floods	0.03436	0.18772	0.00000	2.00000
Severe storms	0.02077	0.15304	0.00000	2.00000
N	3900			
i	75			

Table A2: *Data description*

Variable	**Description**	**Source**
Real GDP growth	Real GDP per capita annual growth rate in logarithmic form.	WDI[1]
Real agricultural growth	Real agricultural value-added per capita growth rate in logarithmic form.	WDI
Real industrial growth	Real industrial value-added per capita annual growth rate in logarithmic form.	WDI
Real services growth	Real services value-added per capita annual growth rate in logarithmic form.	WDI
Investment-to-gdp	The ratio of gross fixed capital formation to GDP in logarithmic form.	WDI
Trade openness	The ratio of the sum of exports and imports to GDP in logarithmic form.	WDI
Government consumption	General government consumption to GDP in logarithmic form.	WDI
Inflation rate	The growth rate of the logarithmic form of CPI.	WDI
Financial depth	Domestic credits to GDP ratio in logarithmic form.	WDI
Education	The ratio of total enrollment in secondary to the population of the age group in logarithmic form.	WDI
Financial openness	Chinn-Ito index measuring a country's degree of capital account openness.	Chinn and Ito (2008)
Nominal effective exchange rate	Log difference of the nominal effective exchange rate.	WDI
Disasters data	Number of people affected by natural disasters.	EM-DAT
Population	Total population.	WDI

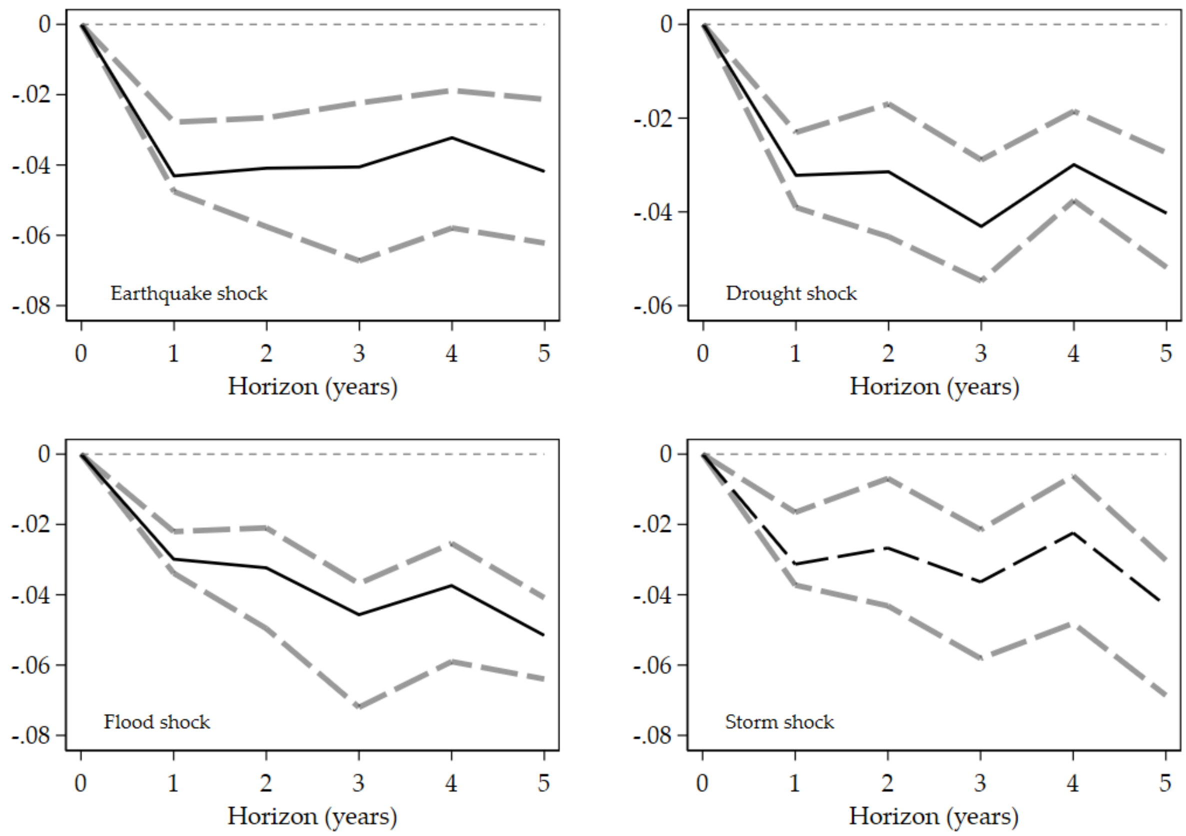
[1] World development indicators.

Table A3: *Country list*

Continent	**High-income economies**	**Low-income economies**	**Lower-middle-income economies**	**Upper-middle-income economies**
Africa		Burkina Faso, Burundi, Central African Republic, Chad, Guinea, Madagascar, Mali, Mozambique, Niger, Rwanda, Sudan, The Gambia, Togo, Uganda	Benin, Cambodia, Cameroon, Eswatini, Ghana, Ivory Coast, Kenya, Lesotho, Nigeria, Republic of the Congo, Senegal, Tanzania	Botswana, Gabon, Mauritius, South Africa
Asia	Hong Kong, Oman, Seychelles	Syria	Bangladesh, Bhutan, India, Indonesia, Iran, Kyrgyzstan, Laos, Mongolia, Nepal, Pakistan, Philippines, Sri Lanka	China, Jordan, Malaysia, Thailand, Turkey
Central America	Barbados, The Bahamas		Belize, El Salvador	Dominican Republic, Guatemala, Jamaica, Mexico
Europe				Georgia
North Africa			Algeria, Egypt, Mauritania, Tunisia	
Oceania				Fiji
South America	Chile, Uruguay		Bolivia	Brazil, Colombia, Costa Rica, Ecuador, Panama, Paraguay, Peru
	9.3%	20%	41.3%	29.3%

A.3 QIRF using *ifo GAME* Database

Figure A1: *GAME natural disasters, responses at 10-th percentile of real GDP per capita growth.*



Notes: Figures show the predictive effects on the 10th percentile of GDP growth of a one-SD *ifo GAME* natural disaster (Felbermayr and Gröschl (2014)) based on a LP series of quantile regressions. Shaded areas denote the 95% confidence interval based on bootstrap replications. The sample size here is reduced. It comprises 36 developing countries, spanning 31 years (1979-2010).

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