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

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

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Abstract

This paper investigates the nonlinear impact of natural disasters on economic growth. Using the Quantile Local Projections (QLP) method on a panel of 68 developing countries over the period 1970-2021, we find that natural disasters have an overall nonlinear effect across economic states. In particular, while some disasters exacerbate economic downturns in low-income countries, high-income developing ones tend to exhibit more resilience to adverse impacts. We argue that the state-dependent effects of natural disasters may be influenced by business cycle phases and structural economic weaknesses, such as sectoral interdependencies and limited economic diversification, especially in low-income countries.

Keywords: Natural Disasters, Developing Economies, Quantile Local Projections

JEL: C23, E32, O11, O57, Q54

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1 Introduction

Over the last three decades, there has been a surge 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 1,730 fatalities, and the earthquakes that struck Turkey and Syria in February 2023 caused more than 59,000 deaths. Overall, economic losses due to these two disasters are expected to exceed USD 30 billion and USD 34.2 billion, respectively (The World Bank, 2022, 2023).

In this context, 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 (IPCC, 2012; NGFS, 2024). As direct consequences, a natural disaster could trigger (i) a supply shock caused by damages to the capital stock and infrastructure, and the disruption of the supply chain (Cavallo et al., 2013), and (ii) a demand shock triggered by lower wealth, disrupted trade flows, and increased uncertainty about future climate events, all of which negatively impact investment (Batten et al., 2020; Cantelmo et al., 2023; NGFS, 2024).

Most of the macroeconomic literature finds an overall negative impact of natural disasters on economic growth, although some empirical disagreements persist. For instance, using linear models, Loayza et al. (2012); Fomby et al. (2013) and Mohan et al. (2018) find contrasted responses of economic growth to natural disasters and heterogeneous effects across economic sectors. Another body of literature has focused on studying the non-linear effects of natural disasters on growth. In a seminal theoretical paper, Hallegatte and Ghil (2008) shows that during expansion phases, economies can be more vulnerable to disasters than during recession phases, when economic resources are already weakened. Similarly, Atsalakis et al. (2021), using quantile-on-quantile methodology, provide evidence on the complex relationship between varying levels of natural disaster intensity and the state of economic activity. Additionally, Ginn (2022) finds that the impact of natural disasters on the US GDP growth is state-dependent and is particularly negative in times of expansion.

This paper overlaps with this strand of the literature related to the varying impact of natural disasters on growth depending on the prevailing economic conditions at the time of the event. Given the substantial losses in both human and capital terms caused by natural disasters, and their potential economic effects, a crucial question arises: Do natural disasters pose a risk to economic growth in developing countries? To address this question, we employ the Quantile Local Projections method (QLP) that allows us to measure the evolution of the state-dependent effect of a disaster. In particular, we are interested in knowing whether a natural disaster happening at the extremes of the business cycle contributes to disrupting growth path, or to worsening the economic downturns, thus delaying recovery.

Quantile methods offer attractive features compared to other models, as they allow the impact of independent variables to vary 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 rather than at the median or mean. Concretely, using QLP, our methodology captures expected growth at high and low realizations of the GDP growth distribution.[1] Our approach consists, therefore, of moving beyond the traditional strategy of estimating the average or state-dependent effect of natural disasters on economic growth. To the best of our knowledge, we are the first to apply QLP method to study the effects of natural disasters on the evolution of the 90th and 10th percentiles of economic growth distribution of developing economies, especially low-income countries. Thus, we contribute to the literature on the economic impact of natural disasters by providing new evidence on the state-dependent effects of these events on economic growth over a projection horizon.

Capturing the economic impact of natural disasters presents significant challenges due to the heterogeneous effects experienced by different countries and their varied recovery processes. In this study, we solely focus on developing countries which are the most vulnerable, in economic terms, to natural disasters (Loayza et al., 2012). Cavallo et al. (2022) find that catastrophic natural events 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 countries. According to Noy (2009), GDP growth in small developing countries is more sensitive to natural disasters, as they struggle to implement counter-cyclical policies in the aftermath of disasters, facing issues like limited insurance coverage and insufficient population-assistance mechanisms, which worsen the adverse effects.[2] Moreover, Kabundi et al. (2022) underscores that high corruption levels contribute to higher fatalities from natural disasters, particularly in developing economies, highlighting their vulnerability due to poor institutional quality and inadequate health and risk management systems (NGFS, 2024).

Given all these considerations, our methodological approach is as follows. Firstly, we are conducting our analysis on a panel of 68 developing countries from 1970 to 2021, not only because of their institutional weaknesses, but also, as we will see below, because these countries have been widely affected by major disasters and whose costs, both human and material, are extremely high. Secondly,

[1] At the 90th and 10th percentiles, respectively.

[2] In a recent working paper Beirne et al. (2024) show that high political and institutional stability tend to mitigate the adverse effect of climate risks on fiscal space. As disasters' aftermath requires significant government spending for recovery and adaptation efforts, fiscal space is most constrained in economies highly exposed to climate risks, and sound institutions could help mitigate these adverse impacts, offering better fiscal resilience against climate-related vulnerabilities.

we are aware that structural economic disparities exist within our sample of developing countries, which is why it is necessary to take them into account in our approach. We therefore use the income level of our countries to separate them into two sub-samples, low-income and high-income developing countries. For instance, Mejia et al. (2019) find that, due to their low public sector efficiency and scarce capacity for climate adaptation, low-income countries remain the most vulnerable and the least resilient to rising temperatures, as well as to mitigating the negative impacts on output.

Our results show that natural disasters have heterogeneous state-dependent effects on economic growth depending on both the types of disasters and countries' income level. High-income developing economies exhibit overall insignificant responses to natural disasters, likely due to their stronger financial resilience, diversified economic structures, and effective institutional frameworks that help absorb shocks. This contrasts with low-income economies that witness significant disruptions. For instance, floods tend to stimulate economic growth, particularly in low-income countries, likely through increased agricultural production or reconstruction efforts, while droughts and storms are particularly detrimental during recessions, exacerbating economic downturns. We find as well that severe disasters generally amplify the negative effects on growth, especially during recessions. When studying the heterogeneous effects across sectors, our results suggest that floods support growth in agriculture and industry mainly during expansions, due to interconnections between the two sectors, while droughts depress industrial production at the 10th percentile. The services sector, meanwhile, often shows resilience in high-income countries but struggles to recover during extreme recessions in poorer economies.

This paper is structured as follows. Section 2 reviews the existing literature that investigates the macroeconomic impact of natural disasters, section 3 presents some stylized facts, and section 4 outlines our empirical approach, while results are presented in section 5, and section 6 focuses on sectoral heterogeneity. Section 7 concludes.

2 Literature Review

As natural disasters become more frequent and severe, a growing interest in gaining a more profound understanding of their impact on economic growth and providing policymakers with valuable insights on the advantages of risk reduction and mitigation, has sparked. Up to this point, the existing body of empirical macroeconomic literature is not conclusive regarding the influence of natural disasters on economic growth. While some studies indicate negative effects, others find no impact or potential positive effects of natural disasters on growth.

An early study by Skidmore and Toya (2002) suggests that disasters might boost economic growth by accelerating human capital accumulation, updating capital stock, and adopting new technologies, which can enhance productivity, while Hallegatte and Dumas (2009) show that disasters don't alter long-term growth rates. On the contrary, Noy (2009) shows that natural disasters can be detrimental to economic growth, particularly in developing and small economies that experience more significant output declines than developed and larger ones for similar disaster magnitudes.[3] 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. Interestingly, Cavallo et al. (2013) suggest that natural disasters are unlikely to affect economic growth, although they find that the only times where natural disasters caused significant declines in GDP growth were when the disaster was followed by political unrest and institutional disorganization.

Given these contradictory results regarding the overall impact of natural disasters on economic growth, some papers have offered more granular analyses. For instance, Loayza et al. (2012); Fomby et al. (2013) and Panwar and Sen (2019) examine the effect of different types of disasters on economic sectors in both developed and developing countries. They show that disasters have distinct effects across economic sectors depending on the type of disaster. They observe that these effects on growth are not exclusively adverse, and their results show that using disaster-type indices gives better statistical properties than aggregated ones. [4] This body of literature suggests that floods and droughts have contrasting effects on GDP growth, primarily through their impact on agricultural production. Moderate floods can benefit to crops by providing excess water and moist soils, leading to higher yields. However, severe floods cause destruction of capital and crops, offsetting any potential benefits. Additionally, droughts negatively affect agricultural output by reducing water availability, leading to lower productivity in the primary sector. Earthquakes and storms have more nuanced effects, as reconstruction efforts can stimulate economic growth in the disaster's aftermath. While earthquakes may boost non-agricultural sectors through rebuilding activities, storms tend to cause an initial decline in economic activity, followed by a rebound driven by recovery investments.[5]

As suggested earlier, natural disasters exhibit non-linear dynamics. Atsalakis et al. (2021) have

[3]Several theoretical macroeconomic papers consider uncertainty from time-varying disaster risk. These models suppose that disaster risk can cause a recession in case of an elasticity of intertemporal substitution larger than unity and leads to a rise in the equity premium. In other words, rational agents facing a risk of disaster would prefer to reduce contemporaneous consumption in order to increase precautionary savings (Isoré and Szczerbowicz (2017); Cantelmo et al. (2023) and Isoré (2018) for an application to Latin American countries).

[4]Similarly, Mohan et al. (2018) find that aggregate analyses are likely to mask different responses of the components of GDP to hurricane shocks.

[5]Other empirical studies address many economic implications of natural disasters such as employment (Barattieri et al., 2023), government revenue and consumption (Akyapi et al., 2022) and sovereign default risk (Mallucci, 2022), financial stress and bankruptcy (Klomp, 2014; Avril et al., 2022), inflation dynamics (Fratzscher et al., 2020; Beirne et al., 2022; Kabundi et al., 2022) and monetary policy (Klomp, 2020).

acknowledged these non-linearities by employing a quantile-on-quantile approach to investigate the relationship between natural disasters and economic growth. Their results shed light on the complex relationship between natural disasters and economic activity by finding mitigating impacts across different combinations of quantiles. Similarly, Ginn (2022) shows that natural disasters' effects on US growth are state-dependent. Using a non-linear VAR-LP model, 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.

Our paper adopts a novel approach by using Quantile Local Projections on a panel of 68 developing countries to study the nonlinear effects of natural disasters on GDP growth. Quantile methods allow to study the impact of a treatment on extreme economic states, formally the 10th and 90th percentile of economic growth distribution. This means that the focus is more on the tail of the growth rate distribution, where the most severe downturns/booms in economic activity occur. Linnemann and Winkler (2016) use Quantile VAR and QLPs to investigate how government spending shocks influence US macroeconomic activity. They find that a fiscal policy shock effect is greater at lower quantiles of GDP growth distribution. On the other hand, Adrian et al. (2019, 2022) develop the Growth-at-Risk model to asses the risk to growth from financial conditions. The model, using quantile regressions, provide evidence that GDP growth follows a fat-tailed pattern, indicating that the lower percentile of the GDP growth distribution may suffer substantial losses under certain financial conditions.

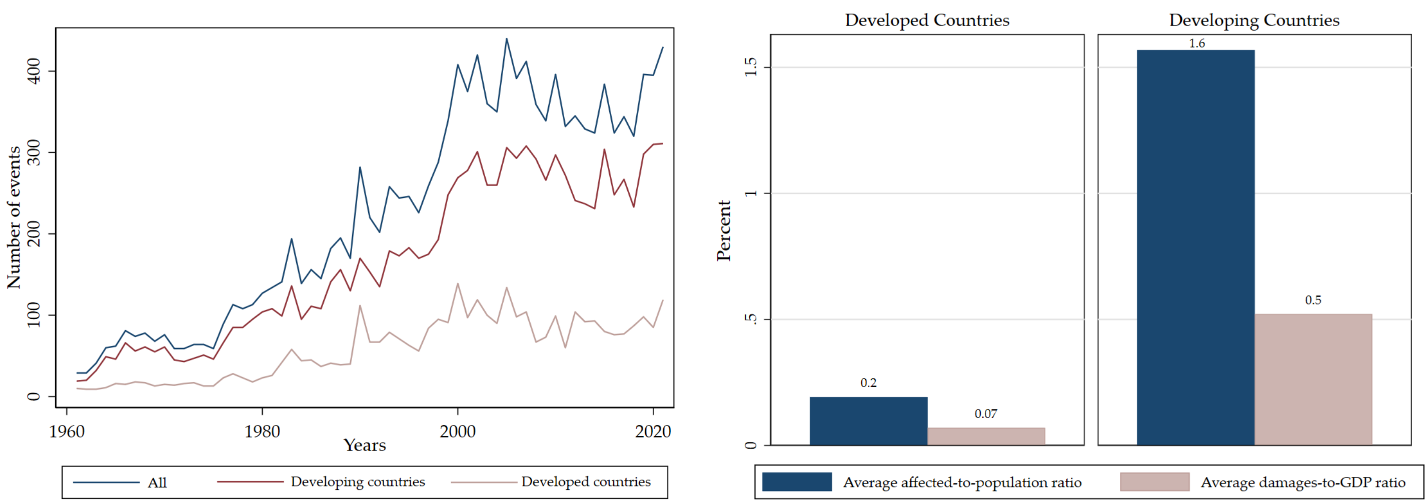
Our research closely follows the approaches and ideas presented in the literature on natural disasters and quantile local projections in order to estimate the nonlinear effects of a disaster shock on a panel of developing countries. This approach allows us to assess their impact during periods of expansion and recession, verifying findings from previous studies and determining whether such events halt growth or prolong downturns. Unlike traditional strategies, this methodology provides a more precise analysis of shock propagation by targeting specific points in the growth distribution rather than relying on average trends. This is particularly relevant in contexts where extreme risks play a critical role. Finally, it presents advantages over nonlinear state-dependent methods by avoiding the need to pre-classify economic regimes and allowing for the estimation of impacts across the entire distribution of the outcome variable.

3 Stylized Facts

Global climate is changing, making natural disasters more frequent and intense. While global warming 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 affected countries (IPCC, 2012, 2013, 2014; IMF, 2017). In this section, we present some stylized facts on natural disasters.

The data used in this paper to account for 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. To be recorded as a disaster, a natural event must meet at least one of the following criteria: causes the death of 10 or more people, affects 100 or more people, or leads to a declaration of a state of emergency and/or a call for international assistance.[6] Figure 1a shows a sharp increase in the number of natural disasters since the beginning of the 21^{st} century. As seen, this acceleration is more pronounced for developing countries, while the evolution of the number of disasters seems to remain stable for developed countries.

Figure 1: *Some statistics on natural disasters between 1961-2021.*



(a) Number of natural disasters

(b) Average cost of natural disasters

Source: EM-DAT and author's calculations.

The interplay between vulnerability and the nature of the hazardous event itself plays a crucial role in determining the impact of a natural disaster. Vulnerability factors, such as economic conditions, infrastructure, and preparedness, define a country's level of risk (Cavallo et al., 2022; NGFS, 2024). Indeed, Noy (2009) and Kabundi et al. (2022) explain extreme losses from natural disasters by the countries' structural and institutional vulnerabilities. Meanwhile, the nature and intensity of hazards, such as the magnitude of an earthquake or the strength of a hurricane, significantly influence the outcomes. Schumacher and Strobl (2011) corroborate this argument, further suggesting that the losses-development relationship exhibits a non-linear pattern conditional on hazard inten-

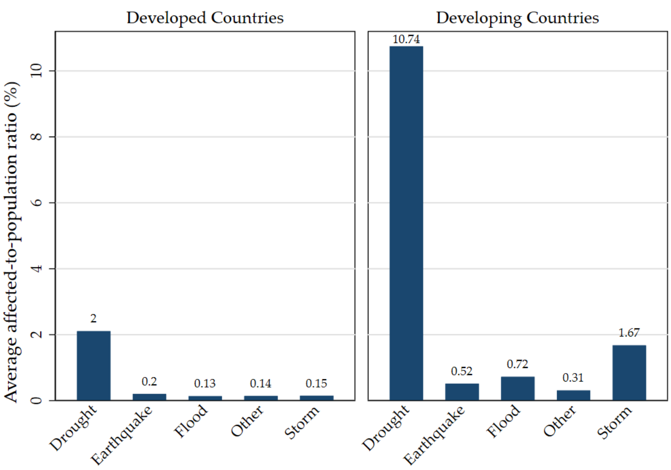
[6]EM-DAT classifies the following events as natural disasters: Earthquakes, Extreme temperatures, Droughts, Floods, Glacial lake outbursts, Landslides, Mass movement (Dry), Volcanic activity, Storms, and Wave action. The EM-DAT database is a comprehensive global database that includes information on all natural disasters between 1900 and 2023. The database can be accessed here.

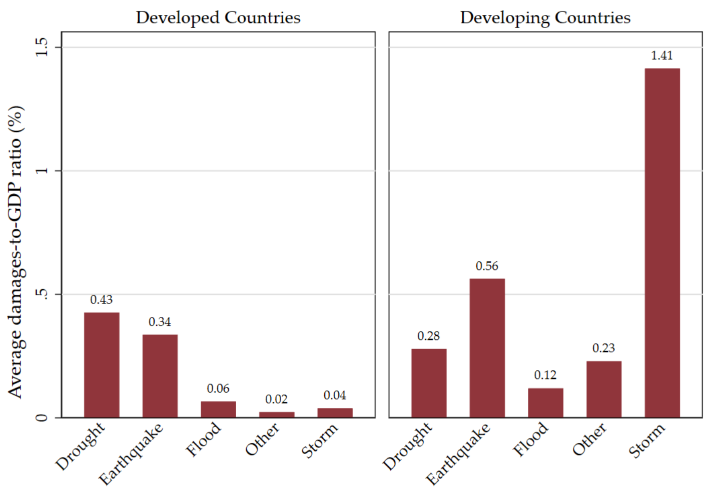
sity, meaning that better-developed countries remain vulnerable to extreme disasters. Understanding both aspects is, therefore, essential for effective disaster management and mitigation strategies.

Advanced economies have enhanced their resilience and reduced their 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 explain why these countries tend to have a higher average population affected by natural disasters.

Figure 1b shows that the material cost of natural disasters in terms of GDP are, on average, much higher in developing countries, 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). At the same time, developing countries are poorer, have in general higher temperatures, and are exposed to more natural disasters than developed ones, making their economies more vulnerable to climate change and, *in fine*, to natural disasters (IMF, 2017; Kiley, 2021; Cavallo et al., 2022).

Figure 2: *Average cost by type of disasters. 1961-2021.*





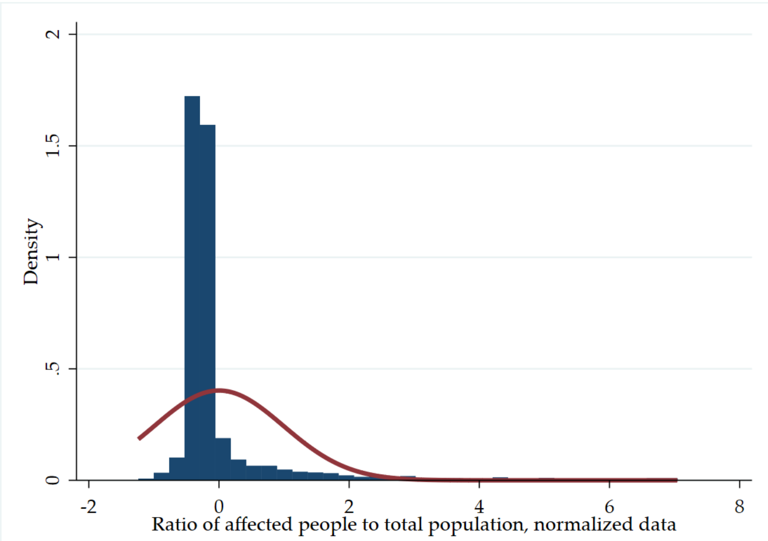
Source: EM-DAT and author's calculations.

Figure 2 presents the average proportion of people affected and the damages to GDP by type of disasters, according to the EM-DAT data. Notably, droughts affect an average of 10.7% of the population in developing countries, while only 2% of the population in advanced economies is affected by this type of disasters. 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, while earthquakes are the second most harmful disaster, in terms of humanitarian cost, 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%.

Our analysis will only focus on droughts, earthquakes, floods, and storms for various reasons. First, 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. Second, these disasters are omnipresent in both developed and developing countries, with a predominance of storms in developed countries and floods in developing ones.[7]

Figure 3 plots the probability density function (PDF) for the number of people affected (including number of deaths) as a percentage of total population in developing countries. This figure shows clearly that the disasters' human cost are non-normally distributed, with the presence of a "heavy-tail" pattern and a highly skewed distribution.[8]

Figure 3: *PDF of natural disaster cost in developing countries.*



Source: EM-DAT and author's calculations.

Our focus on examining the state-dependent reaction of GDP growth to natural disasters is justified as follows. First, as show in Table 1, our data show that the average ratio of the human cost of disasters to the population is marginally higher in recessions and during low growth periods, at the 10th percentile, than in other periods. Second, Table 1 below contains the correlation coefficients

[7] Author's calculations based on the EM-DAT data. Available upon request.

[8] We use the human cost of natural disasters as a measure of their intensity, because of the structural bias of data on economic damages (Refer to the variables description section below). However, studies have shown that extreme material damages from natural disasters are increasing overall exhibiting a gradual shift towards the right and an increase in the thickness of the damage distribution tail over time (Coronese et al., 2019).

between GDP per capita growth and the human cost of natural disasters delineated by economic activity. We notice that across the whole sample, disasters' human cost is negatively correlated with economic growth, and the correlation coefficient is about -6.45. However, the correlation differs across the states of the economy. For instance, the correlation coefficients during expansion is of -1.30, while it is higher during recessions (-10.65). Finally, although the correlation between human cost and real GDP growth rate is positive during periods (2.11) of high GDP growth (at the 90th percentile of economic growth), it is negative and more pronounced (-17.72) at its 10th percentile.

Table 1: *Disasters' Human Cost and Economic Activity.*

	All sample		***High income***		***Low income***	
	Mean	Correl.	Mean	Correl.	Mean	Correl.
All periods	6.83%	-6.45	2.64%	-0.70	9.63%	-9.61
Expansion	5.03%	-1.30	2.56%	-2.06	6.66%	-0.28
90th percentile	4.80%	2.11	5.00%	-16.06	11.47%	15.24
Recession	19.73%	-10.65	3.17%	6.41	32.12%	-15.27
10th percentile	15.14%	-17.72	0.67%	3.37	27%	-24.21

Note : The table presents state-dependent means of the ratio of affected and killed people to total population and correlation coefficients of the ration with GDP p.c. growth for our sample of 68 developing countries. The ratio affected people / population was normalized in order to control for outliers. Expansion and Recession phases are determined using the Bry and Boschan (1971) algorithm that determines the local maxima and minima of GDP per capita in levels. Recessions go from peak to trough, expansions from trough to peak.

The last two columns of Table 1 feature interesting results. According to the table, low income countries witness higher human cost from natural disasters overall (9.63%) than high income developing countries (2.64%). The same pattern implies for correlation coefficients (-9.61 v.s. -0.70). On another note, a quick glance at the correlation coefficients reveals an interesting characteristic. In line with the literature on the state-dependent effects of natural disasters, we note that these are negatively correlated with economic growth in high-income developing countries in times of expansion, whereas in periods of recession, the correlation coefficients are positive but of small magnitude. The opposite is true, however, and is more pronounced for low-income countries. During periods of expansion, the human cost of natural disasters is weakly negatively correlated with the growth rate, whereas it is positively and highly correlated at the 90th percentile of the growth rate distribution. Nevertheless, in periods of both moderate and severe recession, we expect to observe a greater reduction in the GDP growth rate as a result of natural disasters in low-income countries, given the magnitude of the correlation coefficients. These features highlight that our proposed methodology is well-suited for studying the nonlinear effects of natural disasters on economic growth, given the evidence above.

4 Data and Empirical Approach

Our empirical approach is twofold. First, we built a comprehensive natural disasters index for identifying the shocks. We create a disaggregated index by type of natural disaster, since these are assumed to have different effects on GDP. Second, we estimate quantile IRFs using quantile regression on the 90th and 10th percentiles of GDP growth distribution to study the impact of a natural disaster shock on high-growth regimes and extreme downturns.

4.1 Natural Disaster Index

Let $DS^{dis}_{i,k,t}$ be our measure of natural disasters intensity calculated as in Fomby et al. (2013) using data from the EM-DAT:

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

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

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

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

Assessing the severity of disasters involves evaluating two key elements: the number of fatalities and the number of people affected. Fatalities and non-fatalities affected individuals do not have the same weight, nor do they impact growth similarly.[9]

Fomby et al. (2013) and Panwar and Sen (2019) highlight that the effects of moderate and severe disasters on economic performance differ in terms of their scale and dynamic characteristics. In order to effectively capture the impact of disasters on growth, in addition to the above index, we use an adjusted measure to identify severe natural disasters. To ensure a sufficiently large number of observations, we have opted to select the 90th percentile of $intensity^{dis}_{i,k,t}$ to identify the most severe disasters.

The literature on economic development and natural disasters mainly focuses on the number of people affected rather than data on economic damages. 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

[9] Fomby et al. (2013) propose a threshold of 30%, suggesting that 3.33 non-fatally affected individuals affect growth to a degree equivalent to one fatality. Although this is a subjective assessment, exhaustive checks for robustness using diverse thresholds demonstrated no noteworthy alterations in results.

in reporting economic losses. Although the missing data on economic damages can be attributed to challenges 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.[10]

The dependent variable of our model is the growth rate of the GDP per capita. 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 aids policymakers in making informed decisions regarding disaster management and recovery. While capital losses due to natural disasters may not appear in national accounting, the surge in investment typically does, potentially leading to a temporary positive net effect on GDP levels. However, this effect is often short-lived and should primarily concern GDP levels rather than its long-term growth trajectory, which is expected to be negative in the aftermath of disasters. Therefore, using GDP p.c. in empirical research to study the impact of disasters is endorsed for its suitability in capturing the broader implications beyond level GDP fluctuations. In addition, this approach will enable us to map better the drivers of the propagation of disasters' impact on economic activity.

4.2 Control Variables

Our vector of control variables contains the inflation rate, domestic debt to GDP, nominal effective exchange rate[11] and an indicator of capital account openness measured by the Chinn and Ito (2008) index. Plus, we control for climate change using the annual surface temperature change from the climate change dashboard. We also include a measure of human capital drawn from the Penn World Table. The first difference of the logarithmic form of these variables is considered to ensure stationarity, except for the Chinn and Ito (2008) index. According to the literature, these variables are considered as major GDP growth determinants. The nominal exchange rate variation is an important determinant of economic growth through its impact on the trade balance and terms of trade. The capital account openness indicator is considered as financial openness is a key driver of growth.

[10] This database, the *ifo GAME*, covering 17 developing countries from 1979 to 2010, were used to check the robustness of our results. No significant variations from our results were found.

[11] These data come from the World Bank's World Development Indicators database.

In addition, including human capital as a control variable is reasonable because it exerts a delayed impact on economic growth via technological progress, as supported by growth theories.[12]

Our panel covers 68 developing countries on an annual basis from 1970 to 2021.[13] As explained above, we account for heterogeneity across developing economies using income level classification. The latter is done according to the UNCTADstat country classification.[14]

4.3 Panel Local Projections

Since Jordà, 2005, local projections have proved to be an effective method and an increasingly convenient way to estimate how an exogenous shock can affect an outcome over a horizon of time. LPs are also well suited to the analysis of state-dependent impulse responses.

As a single-equation methods, LPs can be advantageous when specifying the full system using VARs is inconvenient due to data limitations or model complexity, and can conveniently be useful in the presence of nonlinearities and state-dependence (Jordà and Taylor, 2024). In addition, LP confidence intervals exhibit notable robustness against model misspecification compared to VARs, especially when the latter are not specified with a sufficient number of lags (Olea et al., 2024). Li et al. (2024) find that usual LPs estimated by OLS have lower bias than the least-squares VAR estimator, though they exhibit a higher variance. To sum up, LPs offer a more robust alternative in the presence of potential misspecification.

4.3.1 Benchmark Model

Our first estimates use OLS estimation with the LP method, based on what is our variable of interest, the GDP per capita growth rate. The typical LP equation that we estimate has the form

$$y_{i,t+h} - y_{i,t-1} = \alpha_{i,h} + \beta_h DS^{dis}_{i,k,t} + \delta_h x_{i,t} + \epsilon_{i,t}, \tag{1}$$

for $h = 1, \dots, 5$, and where $\Delta_h y_{i,t+h} = y_{i,t+h} - y_{i,t-1}$ denotes the cumulative change from time $t-1$ to $t+h$ in the log of real GDP p.c, that is the overall percentage change in the outcome since the shock.[15] $\alpha_{i,h}$ are country-fixed effects, $DS^{dis}_{i,k,t}$ the disaster variable and $x_{i,t}$ the vector of control variables.[16]

[12] Table A1 presents a full description of data used in this paper.

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

[14] See Table A2 for a list of the countries we consider in our sample.

[15] We consider this long-difference specification to control for unobserved fixed effects, and reducing biases caused by autocorrelation or near-unit-root variables (Jordà, 2023).

[16] All the regressors are demeaned by their full-sample average to ensure that cross-sectional dependence in our panel is removed, allowing us to focus on estimating the effects of time-varying variables. In addition, all estimates are conditional on contemporaneous and two lags of GDP per capita growth and controls.

4.3.2 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 state-dependent methods by avoiding the need to pre-classify economic regimes and allowing for the estimation of impacts across the entire distribution of the outcome variable. Moreover, this approach provides a comprehensive assessment of potential non-linear effects. Therefore, it allows researchers to explore how independent variables affect different quantiles of the outcome distribution, contrasting with traditional linear regression.

By estimating the impact of a disaster shock on the high and low quantiles of the GDP growth distribution, we can understand how disasters affect periods of high/low growth and outline factors contributing to economic resilience. This approach also informs targeted policies to mitigate any negative growth impacts following disasters. In particular, this technique aims to provide evidence on whether the effect of natural disasters is state-dependent in extreme economic scenarios, using Quantile Impulse Response Functions (QIRFs) estimated by local projections to measure the impact on the 90th and 10th percentiles of the growth rate.

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. The latter 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.[17] 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 changes. 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 this paper, we consider a regression of $\Delta_h y_{i,t+h}$ on $x_{i,t}$, our vector of control variables. Thus, the regression slope, δ_τ, is chosen to minimize the quantile-weighted absolute value of errors:

$$\hat{\delta}_\tau = \arg\min \sum_{t=1}^{T-h} (\tau \times \mathbb{1}_{\Delta y_{i,t+h} \geq x_{i,t}\delta_\tau} \mid \Delta y_{i,t+h} - x_{i,t}\delta_\tau \mid + (1-\tau) \times \mathbb{1}_{\Delta y_{i,t+h} < x_{i,t}\delta_\tau} \mid \Delta y_{i,t+h} - x_{i,t}\delta_\tau \mid), \quad (2)$$

[17]For an introduction to quantile regressions, see Koenker (2005) and Appendix 7.

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 $\Delta_h y_{i,t+h}$ conditional on $x_{i,t}$, such as:

$$\hat{Q}_{\Delta y_{i,t+h}|x_{i,t}}(\tau \mid x_{i,t}) = x_{i,t}\hat{\delta}_\tau + \epsilon_\tau, \tag{3}$$

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

Now, from equation (1), which represents the traditional panel local projections estimation function, and using the quantile regression method presented above in equation (2), quantile local projections can be estimated based on

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

with $\omega_{i,t}$ a vector that collects the shock, control variables, and the fixed effects.

To establish a baseline, we conduct the following linear regression (see Appendix 7):

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

for $h = 0, \ldots, 5$. The coefficients $\theta_{h,\tau}$ measure the effect of the ω variables on the τ-th quantile of the conditional distribution of $\Delta_h y_{i,t+h}$. Specifically, we intend to examine how natural disasters affect the distribution of GDP per capita growth conditional on observables.[18]

5 Results

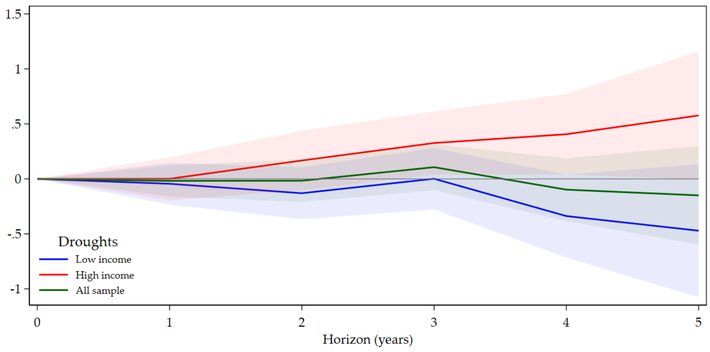
5.1 Benchmark Results

We begin with a brief presentation of the results of our benchmark panel LPs model as expressed by equation (1). Figure 4 plots the estimated IRFs for the GDP growth rate following a one-standard-deviation natural disaster shock for our sample of developing countries. The figure shows that the effect of disasters on the average GDP growth is mixed. The impact of droughts and storms on GDP growth is positive for high income countries, while the impact is only significant 4 years after the shock for droughts and starting the fourth year for storms. Interestingly, floods have a positive effect on economic growth for all our sample's countries, while the response remains persistently

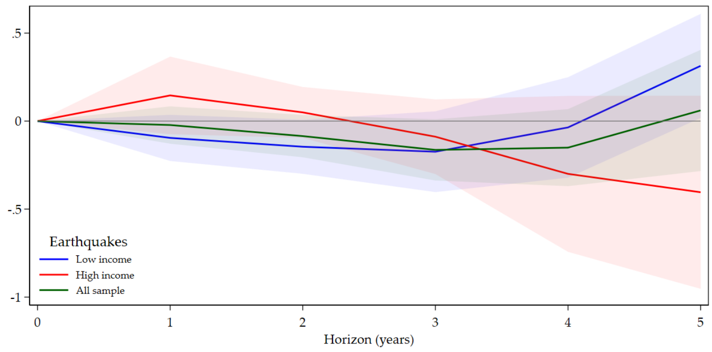
[18] Note that our approach is not intended to make a causal argument about whether natural disasters directly influence the likelihood of being in an expansion or a slump. Instead, we are examining how the impact of disasters differs across these states without asserting that they cause these states to occur.

increasing for low income countries. Accordingly, floods stimulate GDP growth, mainly through transmission mechanisms. In accordance with the literature, floods have mitigating effects on agriculture. Water is essential to life, but too much of it can harm crops. Therefore, as pointed out in the literature, the impact 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.

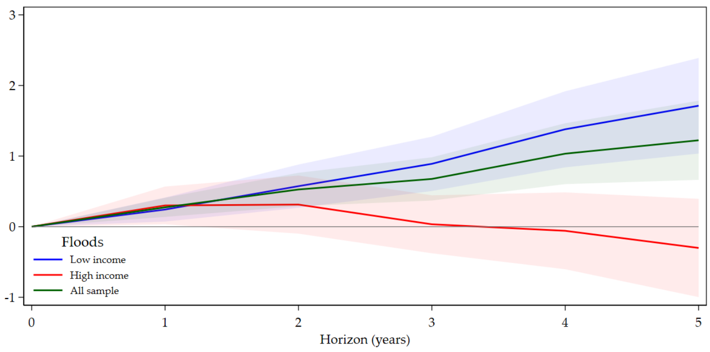
Figure 4: *Natural disasters, responses of real GDP per capita growth.*



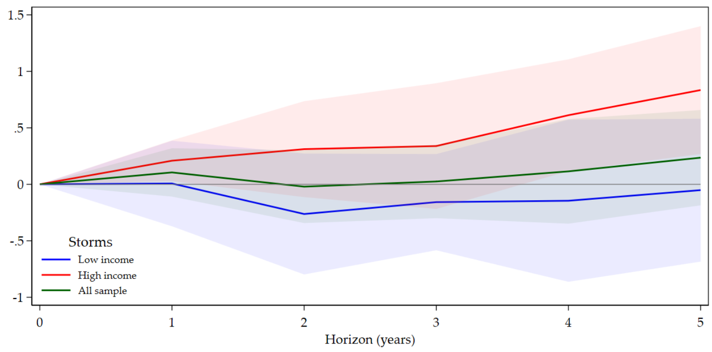
(a) Drought shock



(b) Earthquake shock



(c) Flood shock



(d) Storm shock

Notes: Figures show the predictive effects of a 1-SD disaster shock on GDP growth estimated by local projections. Shaded areas denote the 90% confidence interval.

The results highlight the diverse and nuanced effects of natural disasters on GDP growth, with differences across income levels. Furthermore, our findings underline the importance of considering heterogeneity in the impacts of disasters, prompting the need for a more refined approach. In the following section, we address this by estimating a QLP model to capture how the economic effects of natural disasters vary with underlying economic conditions.

5.2 QLP Results

We now turn to the results obtained by quantile local projections. Transitioning from traditional local projections to quantile LP on the 90th and 10th percentiles of the GDP growth distribution, we focus on exploring the specific dynamics at the tails of economic growth which correspond to the most extreme scenarios of business cycles, i.e., booms and downturns. This transition allows us to uncover nuanced patterns and vulnerabilities in the economy, prone to adverse events, providing a more comprehensive understanding of the effects of such shocks on low (high) growth periods and emphasizing the non-linearity of the effects of natural disasters. The QLP enables us to understand how natural disasters affect economic activity differently during periods of booms and downturns. This approach is particularly important for understanding the asymmetric nature of disaster effects, as countries may react differently to shocks depending on their initial economic situation, as stipulated in the literature. Figure 5 plots the predicted trajectories for the 90th and 10th percentiles of GDP p.c. growth rate after a moderate disaster shock, while figure A1 presents the results for severe disasters.[19]

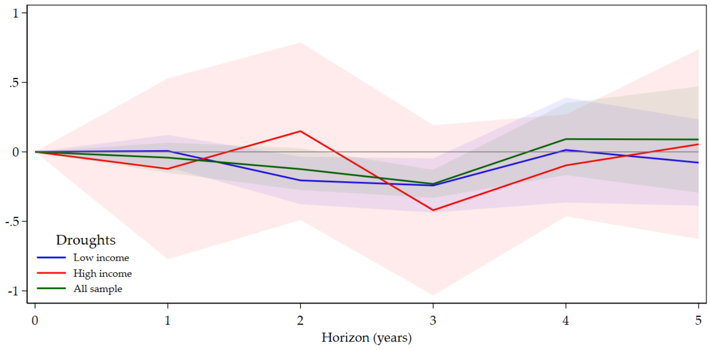
Starting with the impact of droughts, we find that these events affect negatively the low-income economies at the 90th percentile and are likely to worsen severe recessions. For instance, the cumulative response of the 10th percentile of GDP growth to droughts is of nearly -1% at year 4 for low-income countries, while during high expansions it is marginally lower, but negative, between second and third year. Severe droughts corroborate this result with a negative impact of 0.5% during booms and a persistent decrease in the long-run (between years 4 and 5) during downturns. This finding aligns with Mejia et al. (2019), who emphasize that low-income countries are disproportionately affected by extreme climate events due to limited adaptation capacity and the lack of institutional and economic buffers to mitigate their impacts on global output, such as enough fiscal space which allows governments to respond effectively to economic shocks, and high international reserves sufficient to cover several months of imports.

While the impact of earthquakes is not significant,[20] floods remain expansionary for low-income countries. They have no significant impact for wealthier developing economies, except for severe ones. Finally, moderate storms appear to have the most interesting impact during periods of severe downturns. In fact, their effect on low-income GDP growth is persistently negative at the 10th percentile, which implies that these events tend to worsen economic downturns. However, the cumulative response for high-income countries is positive and significant starting the fourth year, highlighting the gap that exists between these two types of countries in absorbing the adverse effects of storms during recessionary periods. Moreover, the impact of severe storms is insignificant, which shows that, given the scale of the damage caused, even rich countries have difficulty in managing the adverse effects of catastrophe in times of low growth.

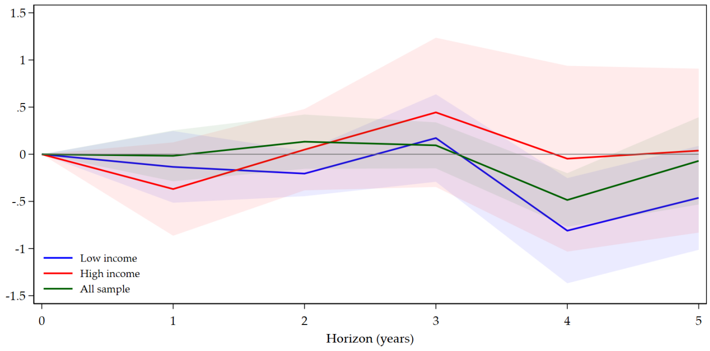
[19] Q-IRFs for the 80th and 20th percentiles are also reported in Figure A2.

[20] This is mainly due to the low number of earthquakes identified during periods of high and low growth in our sample.

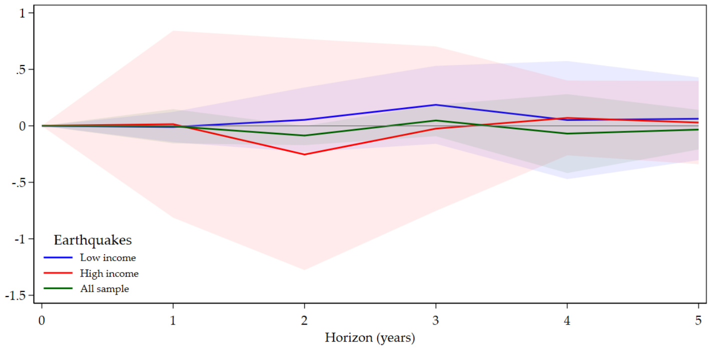
Figure 5: *Natural disasters, responses of the 90th and 10th percentiles of real GDP per capita growth.*



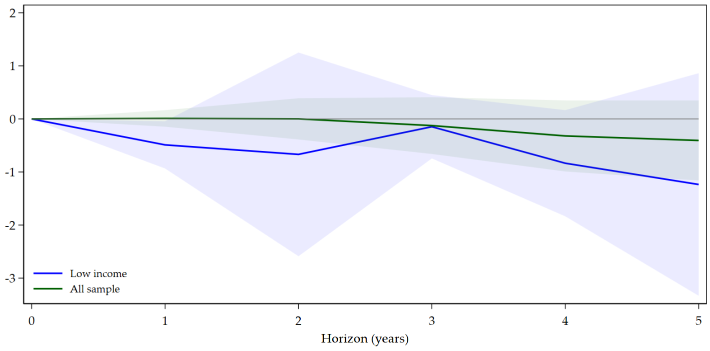
Drought shock at the 90th p.



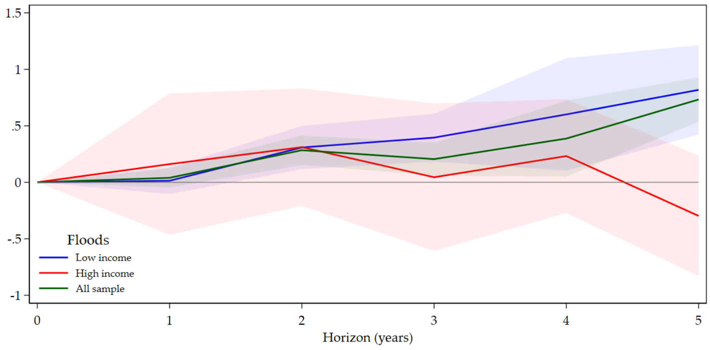
Drought shock at the 10th p.



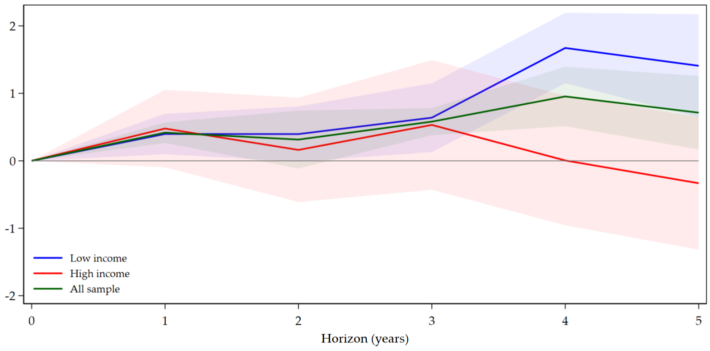
Earthquake shock at the 90th p.



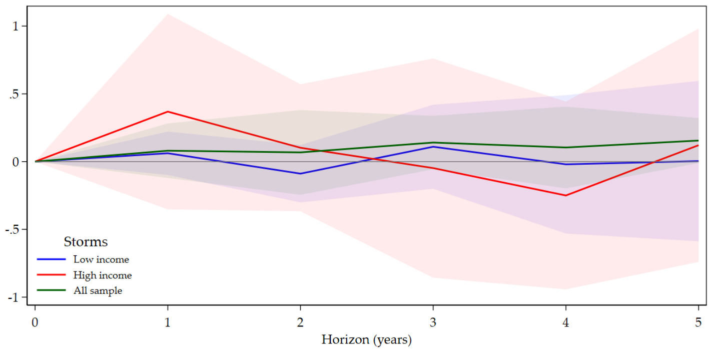
Earthquake shock at the 10th p.



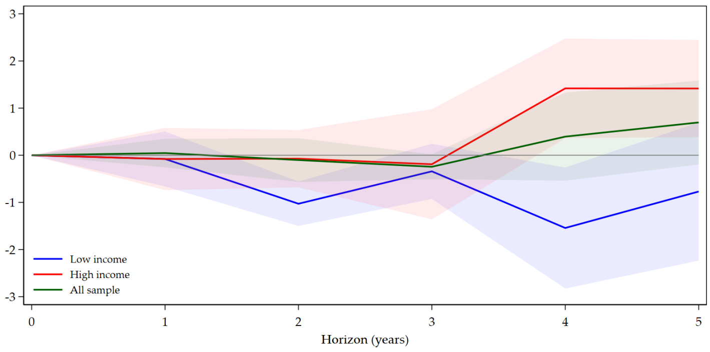
Flood shock at the 90th p.



Flood shock at the 10th p.



Storm shock at the 90th p.



Storm shock at the 10th p.

Notes: Figures show the predictive effects of a 1-SD disaster shock on 90th and 10th percentiles of GDP growth estimated by quantile local projections. Shaded areas denote the 90% confidence interval.

The absence of significant effects from a severe storm shock at the extremes of the growth rate distribution highlights the crucial role of economic conditions in mitigating the adverse effects of natural disasters. While the effect on the 90th percentile growth rate of poor countries is insignificant, indicating a possible resilience due to the positive effects of booming period, we can say that the growth of these countries is at risk after a severe storm shock, given the negative and significant result at the 10th percentile.

Although 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. According to Loayza et al. (2012) it is reasonable to expect a positive effect from storms and earthquakes, attributed to the necessity of reconstruction, including the restoration of damaged capital and crops, which would stimulate economic growth. Moreover, according to the "creative destruction" concept of the growth theory, the positive impacts witnessed in our Q-IRFs - especially for floods and storms (4 years after the shock during slumps) - could be explained by the positive impact of these events on the activity, as described above. However, this is not always the case with severe disasters, where adverse effects can be amplified, or the significant impacts often dissipate.

5.3 Notes on the Nonlinear Effects of Natural Disasters

The nonlinear effects of natural disasters on economic growth can be influenced by several factors inherent to the phase of the business cycle. In an early theoretical study, Hallegatte and Ghil (2008) conclude that economies are more resilient to disasters' shock during recessionary periods as unused resources like low employment and excess inventory can mitigate their impacts by facilitating a quicker recovery through reconstruction activities. However, during booms, supply chains and labor markets may already be under stress, limiting the ability to react to disruptions, such as sudden declines in output (Barattieri et al. (2023)) and inflationary pressures (Beirne et al. (2022); Kabundi et al. (2022)) caused by natural disasters. More recently, Atsalakis et al. (2021) tend to agree with Hallegatte and Ghil (2008)'s argumentation. In fact, they highlight that natural disasters' impact on growth depend on the phase of the business cycle in which a disaster happens, reinforcing the idea of the presence of a "vulnerability paradox" where economies in periods of recessions are more resilient to the adverse effects of natural disasters.

However, our paper brings out new evidence on the state-dependent effects of natural disasters, in the sense that it shows varying effects across states for countries divided by their income level. In fact, we find that only low-income countries' growth experience significant declines due to natural disasters shock. While high-income countries tend to have robust infrastructure, diversified economies, and effective disaster management system, their low-income counterparts lack sufficient infrastructure, financial resources, and institutional capacity, making them more vulnerable to natural disasters (Noy, 2009; Mejia et al., 2019; Atsalakis et al., 2021). Especially during downturns, they struggle to mobilize resources for recovery, leading to prolonged recessionary phases. The results we presented earlier corroborate this pattern, while the overall insignificant effect to disasters' shock in high-income developing countries is potentially due to their capacity to leverage financial buffers and fiscal space to stimulate recovery and efficient reconstruction (Beirne et al., 2024), resulting in infrastructure upgrades potentially yielding medium to long-term growth benefits, during recessions (The Q-IRF for storm shock at the 10th percentile in figure 5 shows a net diverging reactions of growth between high-income and low-income developing countries, corroborating our argument).

6 Heterogeneous Effects of Natural Disasters across Economic Sectors

Developing countries generally exhibit interconnections across economic sectors. While one can expect richer countries to have a relatively more diversified economic structure, low-income countries are mostly reliant on primary sectors, which are highly susceptible to disruptions from natural disasters, and they manifest high interdependence between sectors (Loayza et al. (2012)). In what follows, we examine the impact of natural disasters on different economic sectors to assess whether cross-sectoral transmission effects exist, and influence the GDP growth responses.

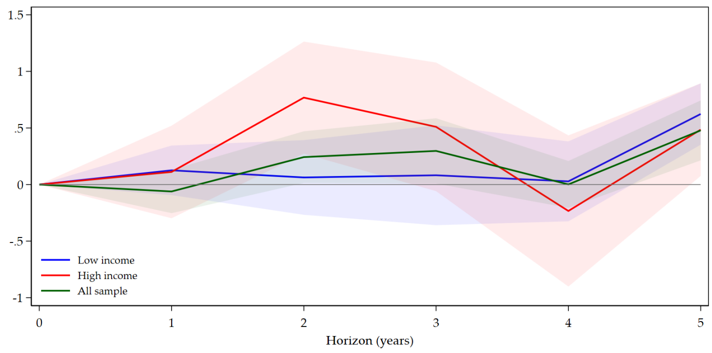
Thus, we intend to examine the transmission mechanisms that could explain our previous results. To do so, we conduct an in-depth investigation by studying the state-dependent response of sectoral production growth to natural disasters. We aim here to identify diverse patterns and vulnerabilities across developing economies, thereby providing a deeper understanding of the macroeconomic implications associated with risk from natural disasters.

6.1 Agricultural sector

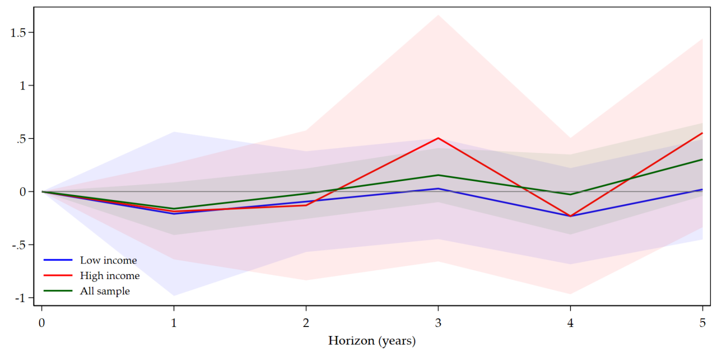
Starting with the agricultural sector, we find that droughts have a significant positive cumulative impact on agricultural value-added at the 90th percentile only at year 2 for high-income developing economies. This rather counter-intuitive effect is in line with the observation that droughts may present bargain effect from investments in resilient infrastructure in high-income countries. For instance, during 2015-2018 drought in South Africa, significant investments in water infrastructure, innovative technologies, and sustainable agricultural practices helped drive economic activity, and enhance long-term resilience (Theron et al., 2023). Interestingly, we don't find any significant effects for droughts on agricultural sector in low-income countries.

As one can expect, earthquakes do not have any significant effect on agricultural production. However, the long term cumulative impact of floods is significantly positive (starting year 3) at the 90th percentile for low-income countries, while it is only significant one year after the shock when GDP is depressed. When storms occur during high-growth periods, high-income developing countries see their agricultural value-added excessively grow from year 2 to 4 after the shock. However, the impact is different for low-income economies that witness a significant reduction of their agricultural v.a. simultaneously at the 90th and 10th percentiles, caused by the destruction of crops and the inability of these countries to implement rapid and effective measures to address the losses caused by storms.

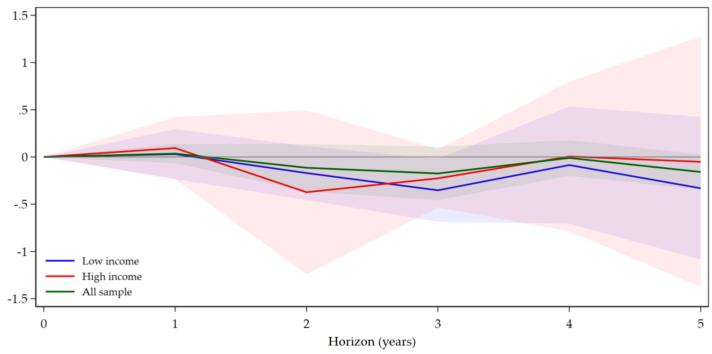
Figure 6: *Natural disasters, responses of the 90th and 10th percentiles of real Agriculture V.A. per capita growth.*



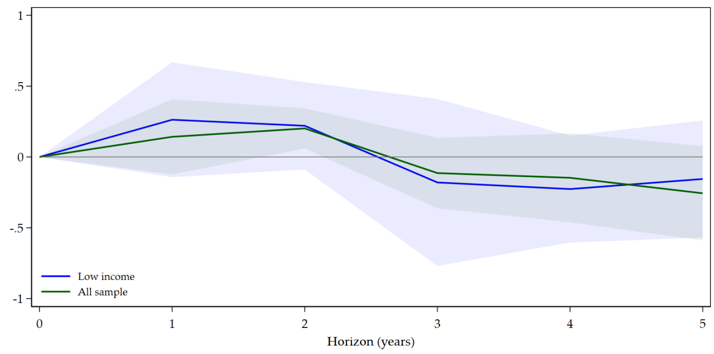
Drought shock at the 90th p.



Drought shock at the 10th p.



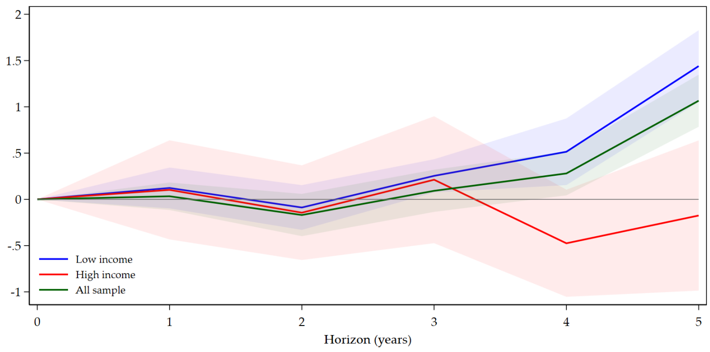
Earthquake shock at the 90th p.



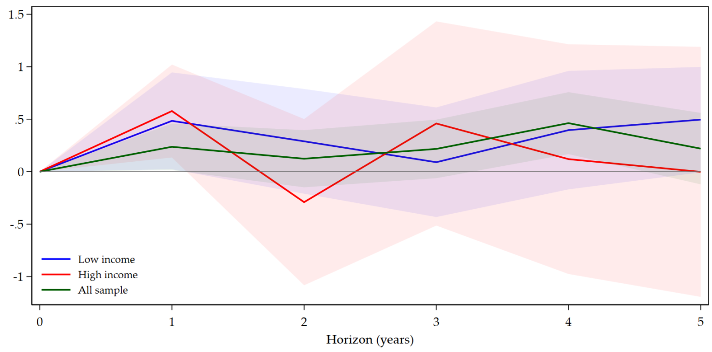
Earthquake shock at the 10th p.

Notes: Figures show the predictive effects of a 1-SD disaster shock on 90th and 10th percentiles of Agriculture value-added growth estimated by quantile local projections. Shaded areas denote the 90% confidence interval.

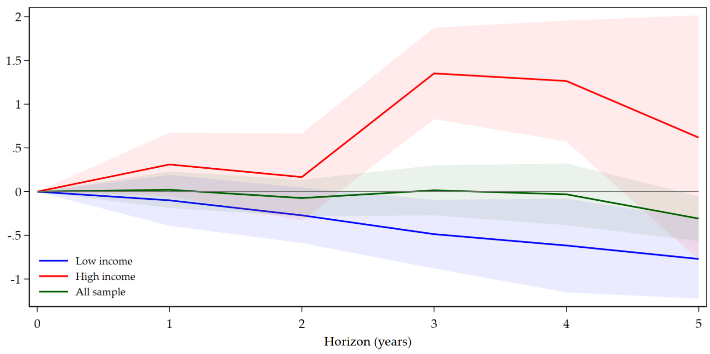
Figure 6 - continued: *Natural disasters, responses of the 90th and 10th percentiles of real GDP per capita growth.*



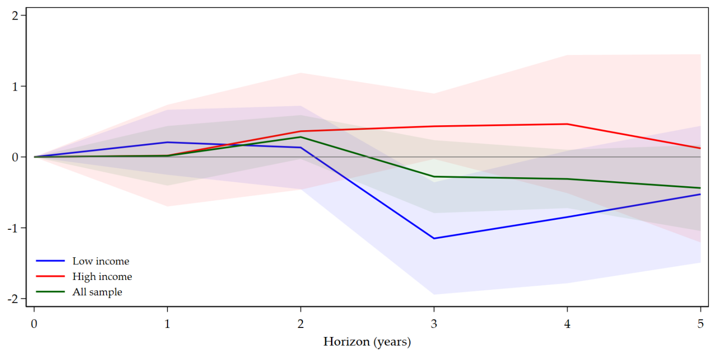
Flood shock at the 90th p.



Flood shock at the 10th p.



Storm shock at the 90th p.



Storm shock at the 10th p.

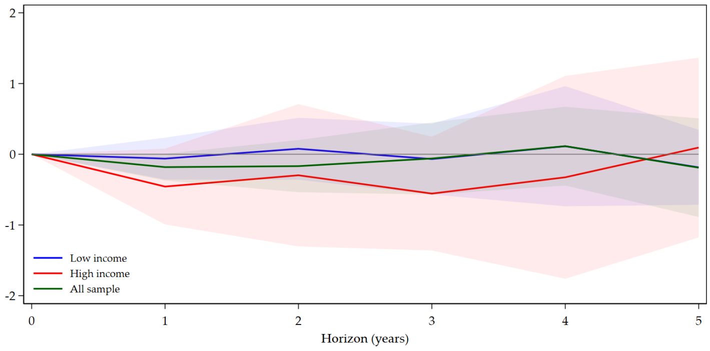
Notes: Figures show the predictive effects of a 1-SD disaster shock on 90th and 10th percentiles of Agriculture value-added growth estimated by quantile local projections. Shaded areas denote the 90% confidence interval.

6.2 Industrial sector

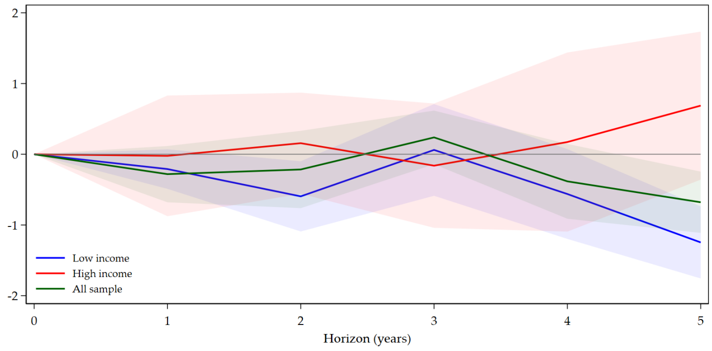
As for the industrial production growth, droughts tend to depress the outcome significantly at the 10th percentile for low-income countries. This could be explained by the loss of productivity jointly induced by the drought itself,[21] and by the fact of being in a depressed economic state. The image reverses after a seismic shock. During a period of expansion, the industrial added value of low-income countries increases significantly (this is the case from year 4 onward at the 90th percentile). However, during recessions, as is to be expected from the destruction of productive capital, earthquakes cause an immediate and significant loss. On the other hand, results for floods closely follow the previous observations with an overall positive cumulative impact across states for low-income countries, the response being more pronounced at the 10th percentile. This final result suggest that floods stimulate industrial production growth in low-income countries over time.

[21]See Mejia et al. (2019); Tintchev and Jaramillo (2024), and Letta and Tol (2019) that analyze the nexus between climate change and TFP losses. They find a negative relationship only in poor countries, where a 1°C annual increase in temperature decreases TFP growth rates by about 1.1–1.8 percentage points.

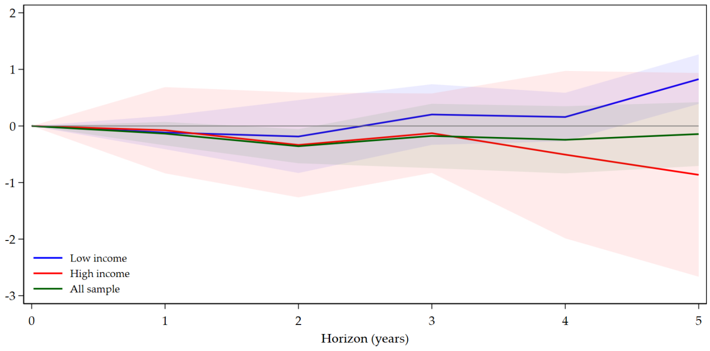
Figure 7: *Natural disasters, responses of the 90th and 10th percentiles of real Industrial V.A. per capita growth.*



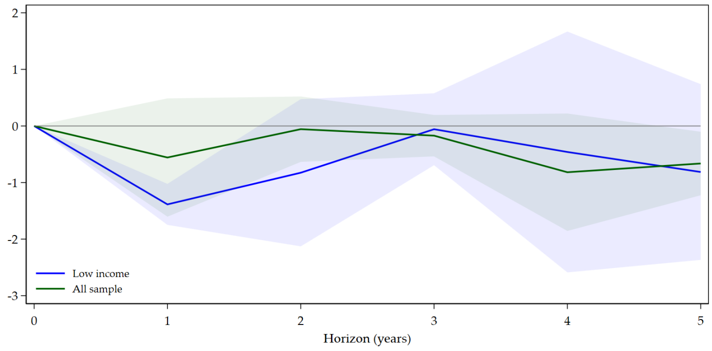
Drought shock at the 90th p.



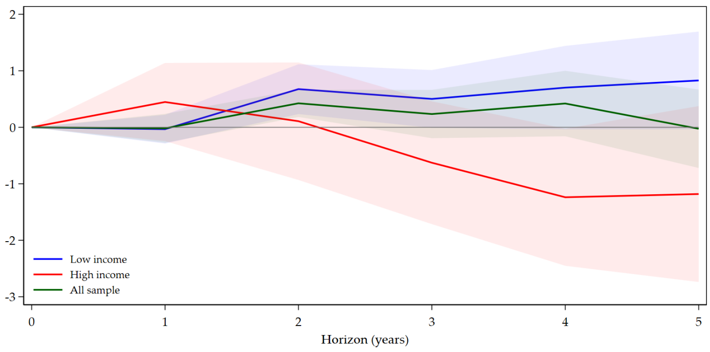
Drought shock at the 10th p.



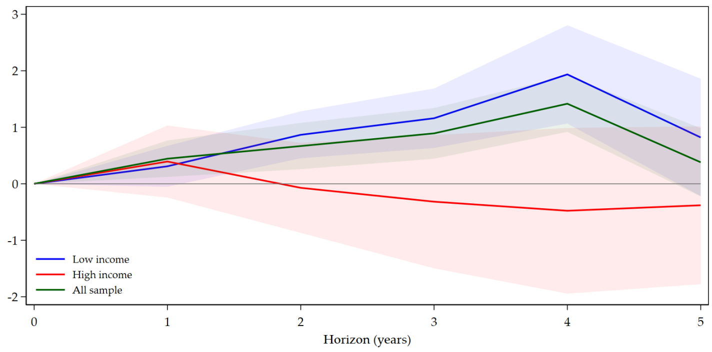
Earthquake shock at the 90th p.



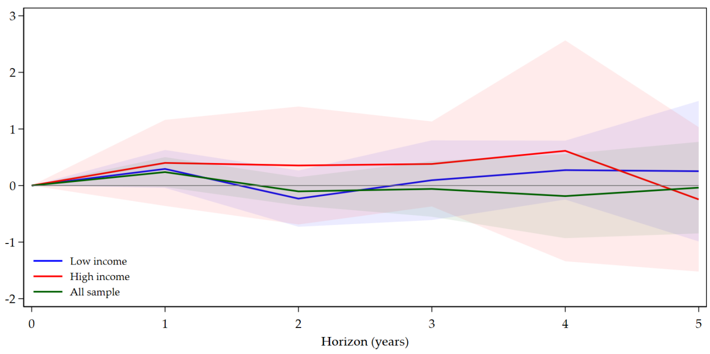
Earthquake shock at the 10th p.



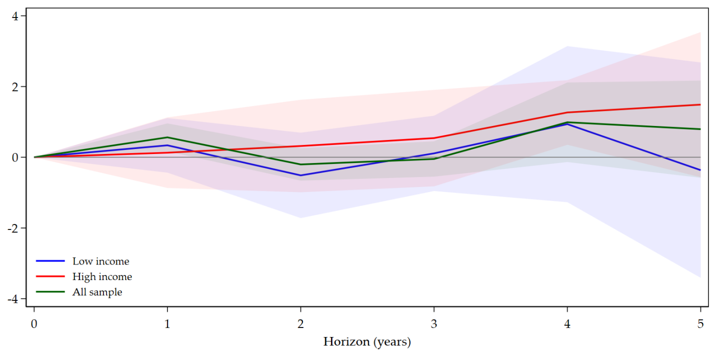
Flood shock at the 90th p.



Flood shock at the 10th p.



Storm shock at the 90th p.



Storm shock at the 10th p.

Notes: Figures show the predictive effects of a 1-SD disaster shock on 90th and 10th percentiles of Industrial value-added growth estimated by quantile local projections. Shaded areas denote the 90% confidence interval.

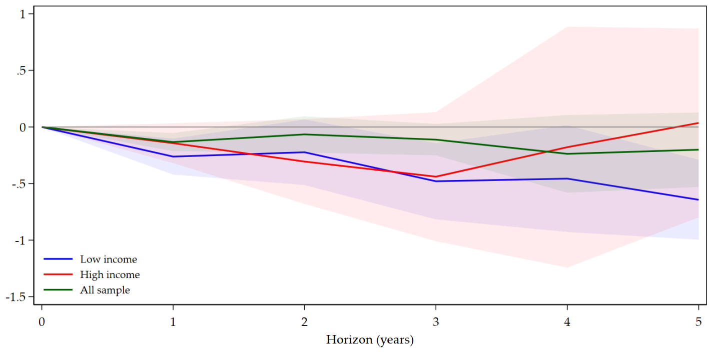
Interconnections between economic sectors plays a critical role in amplifying or mitigating the effects of natural disaster shocks in developing countries (Loayza et al., 2012). For instance, agriculture and industry are closely interconnected. The industrial sector depends heavily on the agri-food industry, which, in turn, relies significantly on agricultural production. Additionally, agricultural output is dependent on intermediate inputs from the industrial sector, such as tools and fertilizers. These interdependencies explain why natural disasters affecting agriculture are likely to similarly impact industrial growth, further exacerbated by the destruction of infrastructure.

6.3 Services sector

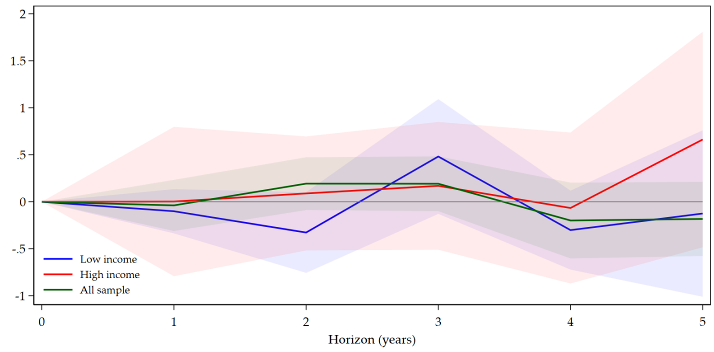
Figure 8 includes Q-IRFs for the services sector's responses to natural disasters. The analysis highlights the differentiated impact of natural disasters on services sector. For instance, droughts have a prolonged negative effect on the services sector in low-income economies at the 90th percentile. Earthquakes generally cause disruption to the services sector, particularly in low-income countries, due to damage to infrastructure and destruction of services centers. Responses in these cases are insignificant during downturns, but the cumulative Q-IRF at year 2 is significantly negative during boom periods, indicating the vulnerability of growth to an earthquake shock. Q-IRFs for floods shock follow the same pattern as earlier. They typically lead to a significant positive response in the services sector in the short term, particularly in low-income countries during expansion, while the response for both types of countries is delayed during slumps, with a faster boost for high-income economies. Floods have a positive immediate effect in high-income developing countries at the 10th percentile, although the responses for these countries are overall insignificant. At the tails of the growth distribution, the significance of the positive responses for low-income economies is delayed, reflecting structural vulnerabilities and institutional weaknesses that impede immediate recovery. Finally, in periods of recessions, the cumulative response of the services sector in low-income countries is negative at year 4 following a storm shock, as seen successively in figures 5 and 6. Worsening downturns from storms (as seen in Figure 5) suggests the importance of transmission mechanisms based on supply chain relationships across sectors.

While its dependency on physical capital is relatively lower than that of industry, the reliance of services sector on agricultural supply chains, particularly in agrarian economies makes it vulnerable. Droughts, for example, can severely disrupt transportation, retail, and financial services in rural areas due to reduced farming activity (Fomby et al., 2013). However, in the aftermath of a destructive disaster, the services sector may experience increased demand driven by relief efforts and recovery activities to meet the immediate needs of affected populations.

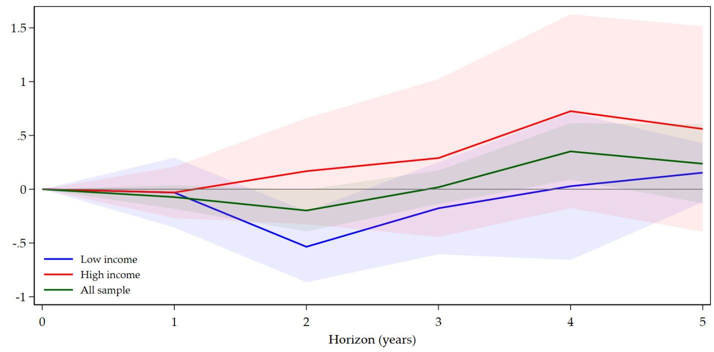
Figure 8: *Natural disasters, responses of the 90th and 10th percentiles of real Services V.A. per capita growth.*



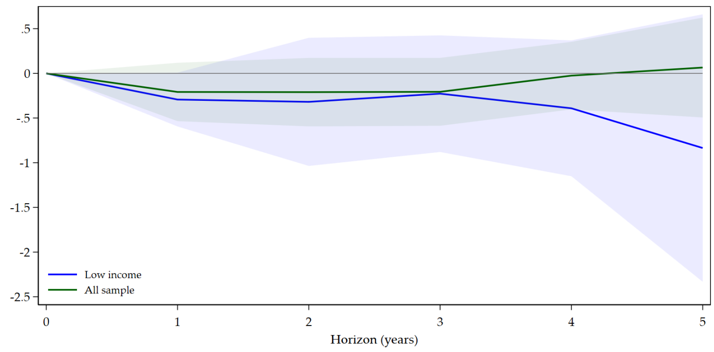
Drought shock at the 90th p.



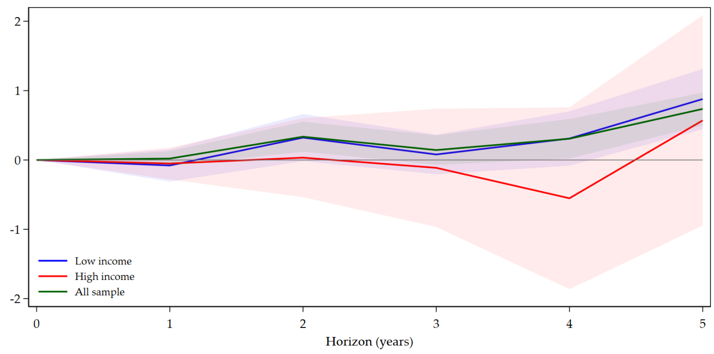
Drought shock at the 10th p.



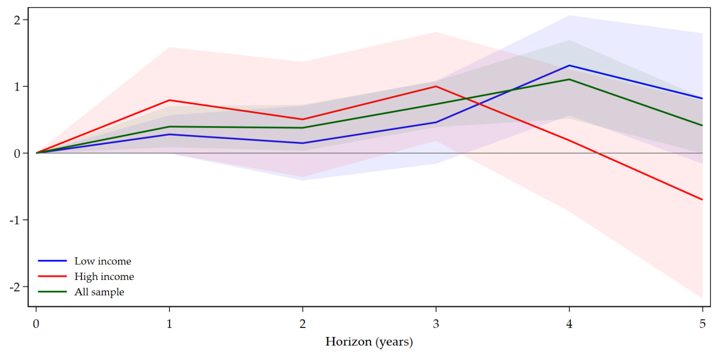
Earthquake shock at the 90th p.



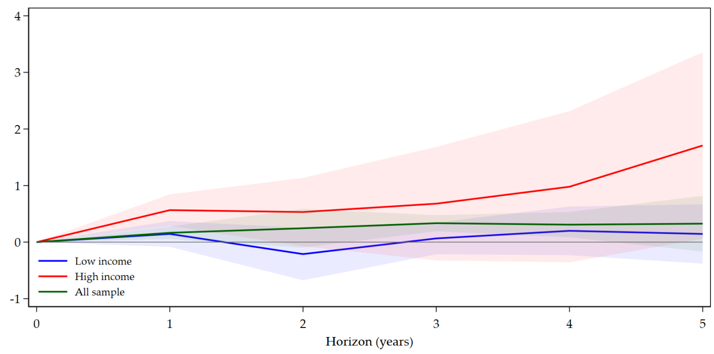
Earthquake shock at the 10th p.



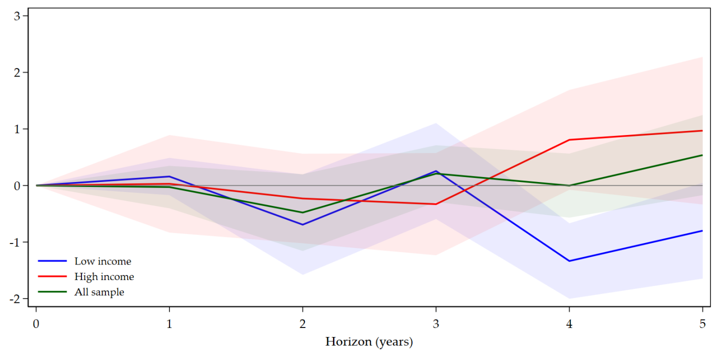
Flood shock at the 90th p.



Flood shock at the 10th p.



Storm shock at the 90th p.



Storm shock at the 10th p.

Notes: Figures show the predictive effects of a 1-SD disaster shock on 90th and 10th percentiles of Services value-added growth estimated by quantile local projections. Shaded areas denote the 90% confidence interval.

7 Concluding Remarks

This paper employs Quantile Local Projections framework to explore whether natural disasters exhibit nonlinear effects on economic growth in developing countries. Building on previous researches on the nonlinear effects of disasters on economic growth, this study reveals significant heterogeneity in the effects of natural disasters based on the type of disaster, economic conditions, and income levels.

Specifically, our study finds that natural disasters exhibit overall nonlinear, state-dependent effects, i.e. floods can have positive effects on GDP growth, particularly during expansions, while droughts and storms tend to exacerbate economic downturns, especially in low-income countries. The analysis reveals that high-income developing economies are more resilient to adverse impacts of disasters, which appear to have insignificant effects on growth. In contrast, low-income economies remain overall vulnerable to natural disasters. Severe droughts and storms are particularly damaging during recessions, leading to persistent declines in GDP growth. The agricultural and industrial sectors, in these mainly agrarian economies, experience prolonged disruptions, underscoring their limited capacity for resilience and recovery.

Thus, the policy implications of our analysis can be summarized as follows. As discussed above, our results depend on business cycles characteristics that can explain the divergent reactions of GDP growth to disasters. For instance, negative responses during recessions in low-income countries underscore the importance of well-designed fiscal and monetary policies that could mitigate the economic consequences of disasters. Counter-cyclical fiscal policies could be very useful as they stimulate demand, support recovery and boost investment in resilient infrastructure, during recessions, when natural disasters exacerbate existing economic challenges. However, limited fiscal space, high debt burdens, and low tax revenue constrain the ability of low-income governments to adopt expansionary fiscal measures. Therefore, international frameworks to assist less developed countries in enhancing their resilience to natural disasters are crucial. 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 than maintaining concentration.

Adaptation is crucial because it enables societies, ecosystems, and economies to respond effectively to the impacts of natural disasters, which are becoming increasingly severe and widespread. Adaptation initiatives rely heavily on limited external funding sources. For instance, low-income countries, where adaptation needs are the highest, suffer from a substantial adaptation finance gap, with financial flows far below the levels required to meet global adaptation goals (UNEP, 2024; IPCC, 2022), which constrains their capacity to invest in proactive and ex-post adaptation measures.

International public funding for adaptation in developing countries is provided by the multilateral development banks (MDBs). MDBs play a pivotal role in providing financial resources, technical assistance, and capacity-building support for adaptation projects. While these projects demonstrate significant benefits in terms of well-being and risk reduction, progress in adaptation encounters obstacles in accessing and allocating funds (IPCC, 2022). To cope with these challenges, countries can explore new funding strategies like blended finance —combining public and private funding— to scale up resources for adaptation projects, emphasizing the fact that proactive adaptation measures, especially cost-effective ones, i.e. nature-based solutions, are less costly than post-disaster recovery and reconstruction (UNEP, 2024).

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 suitable. Examining potential interplays between budgetary and monetary policies in this context becomes particularly appropriate.

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Appendix

Quantile Regressions

Consider we are interested in a random variable Y with a distribution function τ conditional on X defined by $F_{Y|X}(y) = \mathcal{P}(Y \leq y|X)$.[22] 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:

$$Q^{\tau}(Y|X) = X'\beta_{\tau} + \epsilon_{\tau}, \text{ with } Q^{\tau}(\epsilon_{\tau}|X) = 0. \tag{1}$$

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:

$$\hat{Q}^{\tau} = \arg\min_{b} E\left[\rho_{\tau}(Y - b)\right], \tag{2}$$

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

$$\begin{aligned} \rho_{\tau}(y) &= \left[\tau - \mathbb{1}(y < 0)\right] y \\ &= \left[(1-\tau)\mathbb{1}(y \leq 0) + \tau\mathbb{1}(y > 0)\right] |y|. \end{aligned} \tag{3}$$

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

[22] 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 $Q^{\tau}(Y|X) = F^{-1}_{Y|X}(\tau)$.

by $Q^\tau(Y|X)$ and a function $b(X)$. Considering the previous linearity assumption in (1), we have[23]:

$$\beta_\tau = \arg\min_\beta E\left[\rho_\tau(Y - X'\beta)\right]. \tag{4}$$

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.[24] 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 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.[25] 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.

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

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

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

[25]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 Koenker (2005).

Table A1: *Data description*

Variable	Description	Source
dlrgdpc	Real GDP per capita annual growth rate in logarithmic form.	WDI[1]
dlagrpc	Real agricultural value-added per capita growth rate in logarithmic form.	WDI
dlindpc	Real industrial value-added per capita annual growth rate in logarithmic form.	WDI
dlserpc	Real services value-added per capita annual growth rate in logarithmic form.	WDI
dlcpi	Log difference of the CPI.	WDI
dlcrd	Log difference of the domestic credits to GDP ratio.	WDI
dlneer	Log difference of the nominal effective exchange rate.	WDI
temp_g	Log difference of the annual surface temperature change.	IMF Climate Change Dashboard
dhc	Log difference of the human capital measure.	PWT[2]
kaopen	Chinn-Ito index measuring a country's degree of capital account openness.	Chinn and Ito (2008)
DS	Number of people affected by natural disasters.	EM-DAT

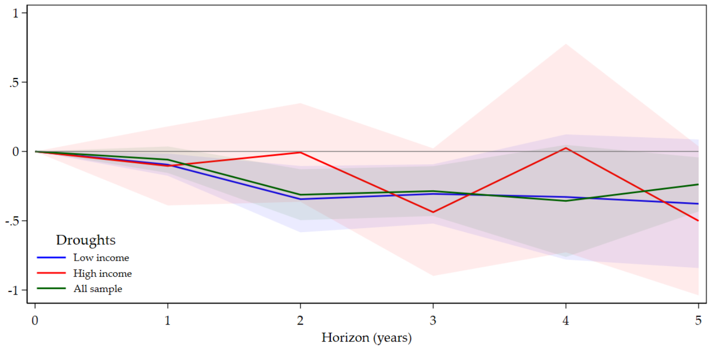
[1] World development indicators.

[2] Penn World Table 10.1

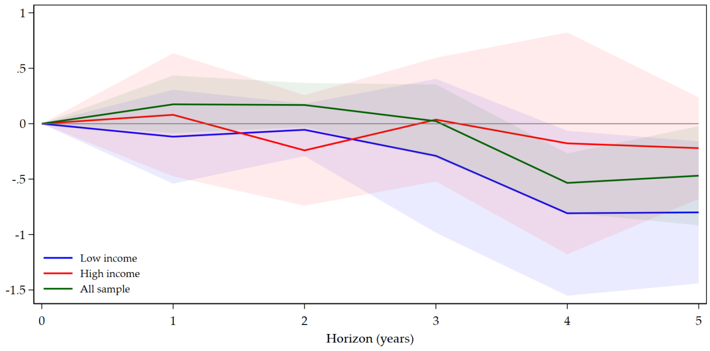
Table A2: *Country list*

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, Niger, Rwanda, Sudan, Togo, Uganda	Benin, Cameroon, Côte d'Ivoire, Eswatini, Kenya, Lesotho, Nigeria, Republic of the Congo, Senegal, Tanzania,	Botswana, Gabon, Mauritius, South Africa
Asia	Hong Kong, Seychelles	Syria	Bangladesh, Bhutan, Cambodia, India, Iran, Kyrgyzstan, Lao PDR, Mongolia, Nepal, Pakistan, Philippines, Sri Lanka,	China, Jordan, Malaysia, Turkey
Central America	Barbados, The Bahamas		Belize, El Salvador	Costa Rica, Dominican Republic, Guatemala, Jamaica, Mexico
Europe				Georgia
North Africa			Algeria, Egypt, Mauritania, Tunisia	
Oceania				Fiji
South America	Chile, Uruguay		Bolivia	Brazil, Colombia, Ecuador, Panama, Paraguay, Peru

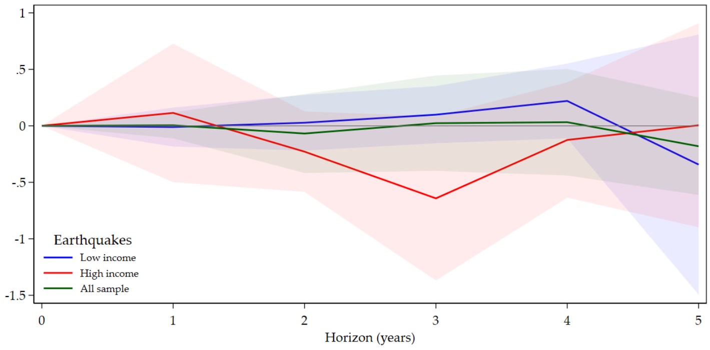
Figure A1: *Severe Natural disasters, 90th and 10th percentiles responses of real GDP per capita growth.*



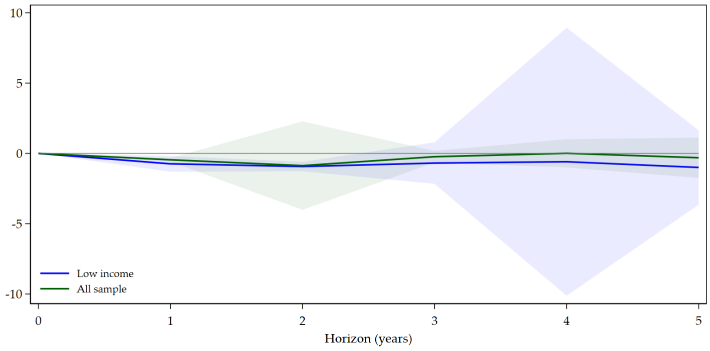
(a) Drought shock at the 90th p.



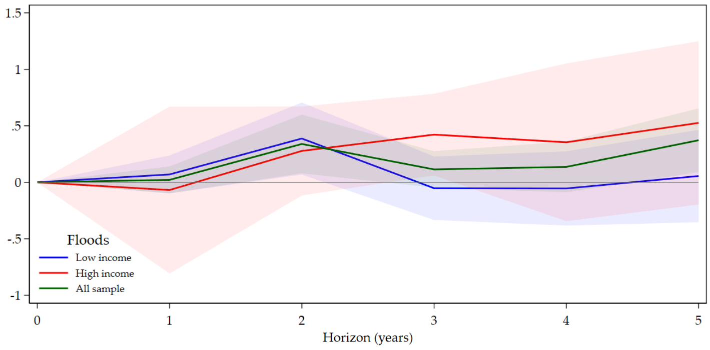
(b) Drought shock at the 10th p.



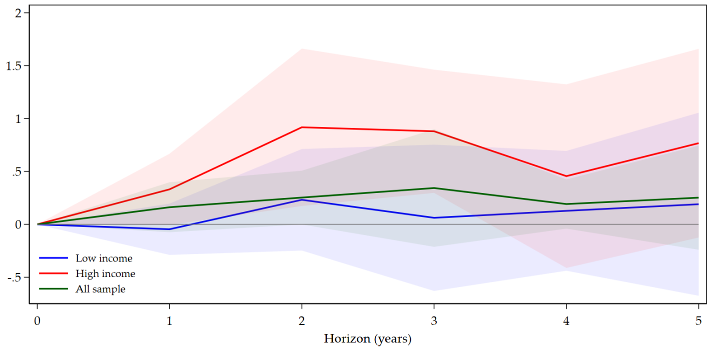
(c) Earthquake shock at the 90th p.



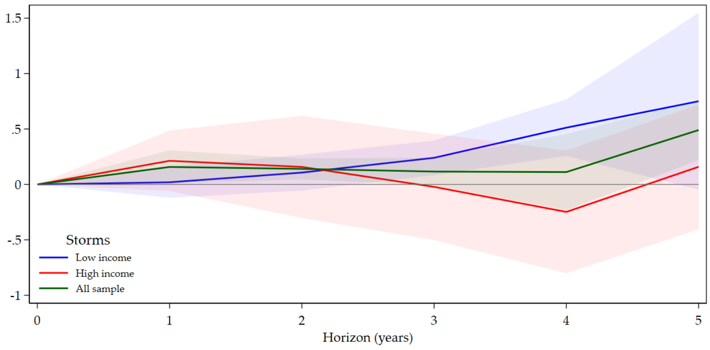
(d) Earthquake shock at the 10th p.



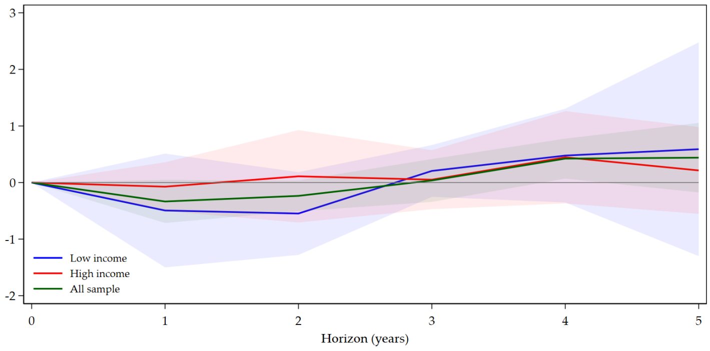
(e) Flood shock at the 90th p.



(f) Flood shock at the 10th p.



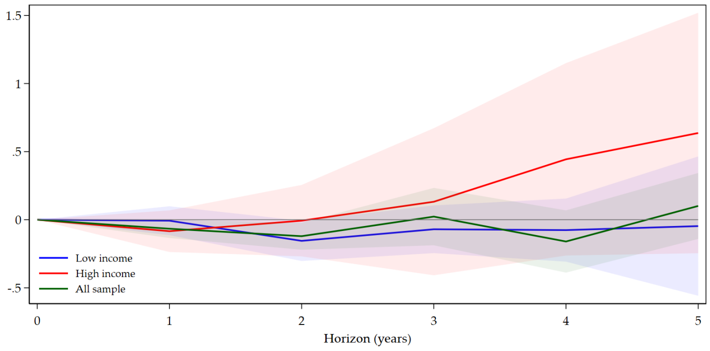
(g) Storm shock at the 90th p.



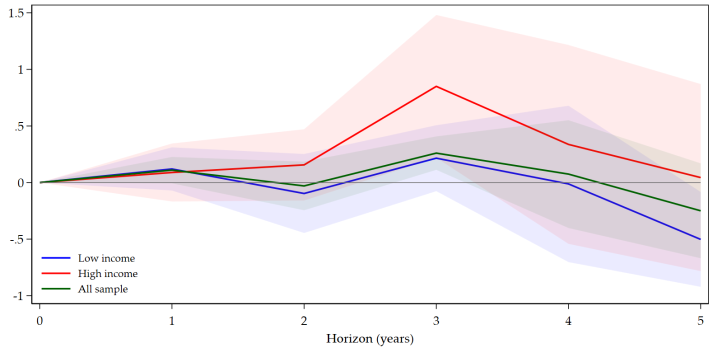
(h) Storm shock at the 10th p.

Notes: Figures show the predictive effects of a 1-SD severe disaster shock on 90th and 10th percentiles of GDP growth estimated by quantile local projections. Shaded areas denote the 90% confidence interval.

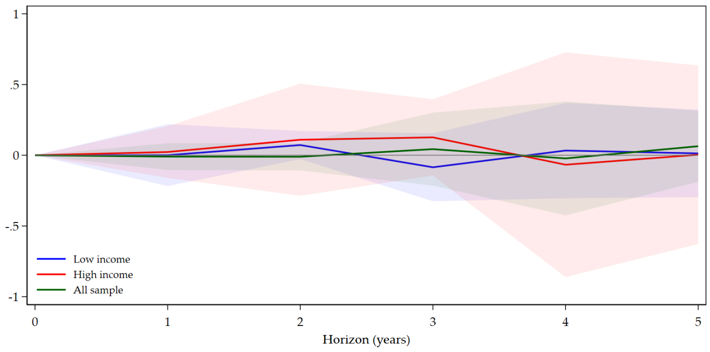
Figure A2: *Natural disasters, 80th and 20th percentiles responses of real GDP per capita growth.*



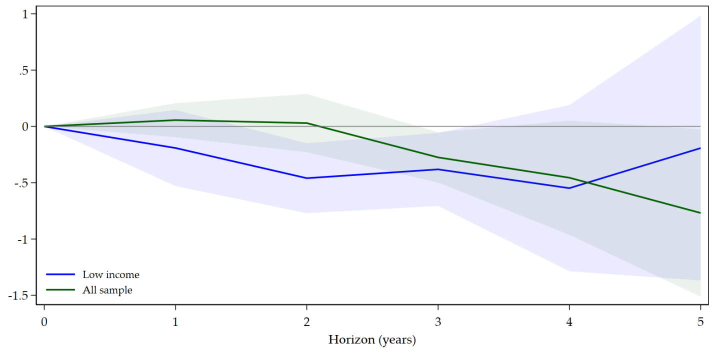
(a) Drought shock at the 80th p.



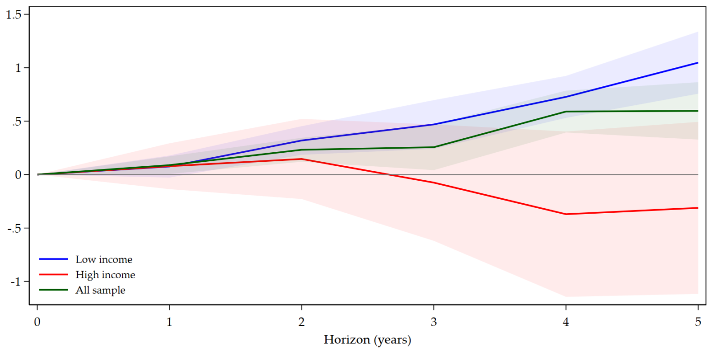
(b) Drought shock at the 20th p.



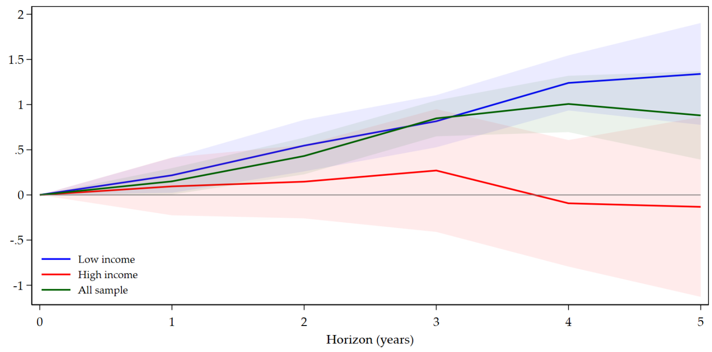
(c) Earthquake shock at the 80th p.



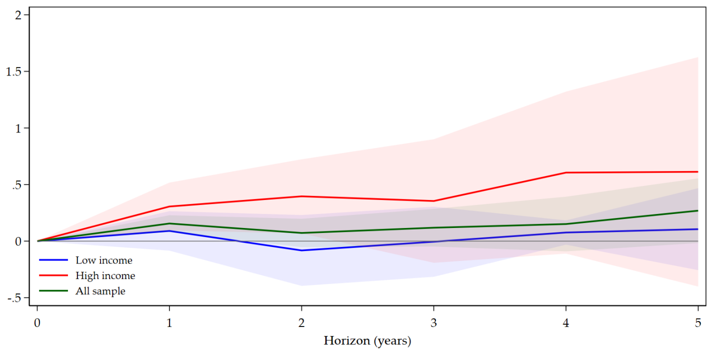
(d) Earthquake shock at the 20th p.



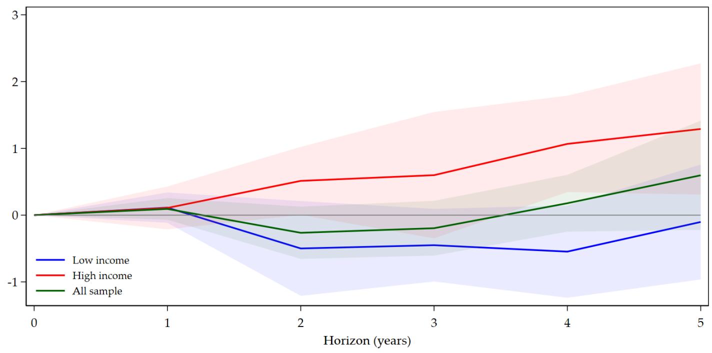
(e) Flood shock at the 80th p.



(f) Flood shock at the 20th p.



(g) Storm shock at the 80th p.



(h) Storm shock at the 20th p.

Notes: Figures show the predictive effects of a 1-SD disaster shock on 80th and 20th percentiles of GDP growth estimated by quantile local projections. Shaded areas denote the 90% confidence interval.