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Impact of natural disasters: average effects hide heterogeneity across growth regimes and time horizons*

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Abstract

We propose a new approach to measure the sensitivity of economic growth to natural disasters in developing countries at different time horizons (short, medium, and long term). We allow for heterogeneous effects across growth regimes and intensities of disaster shocks using quantile-on-quantile regressions and wavelet decomposition. Our findings yield several insights. First, small disaster shocks boost GDP per capita growth in low-growth countries across all horizons. By contrast, in high-growth countries, such shocks cause sharp short-term growth declines, followed by a rapid recovery in the medium term, albeit without regaining the pre-disaster growth trajectory in the long term. Second, severe disaster shocks lead to long-term growth losses in high-growth countries, despite their initial resilience. Conversely, low-growth countries experience immediate and persistent growth declines that worsen over time. Third, the role of macroeconomic variables in mitigating or amplifying growth losses varies depending on the growth regime, disaster severity, and time horizon.

Keywords: Natural Disasters, growth, developing countries, quantile-on-quantile.
JEL codes: C50, O44, Q54;

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1 Introduction

Natural disasters pose a significant threat to many countries around the world. Over recent decades, these extreme events have become increasingly frequent and intense, resulting in substantial economic losses. For example, the Swiss Re Institute reported that the economic losses from natural disasters reached USD 280 billion in 2023. The short-term impacts of natural disasters have been extensively documented in the literature (see, among others, Raddatz, 2009; Noy, 2009; Strobl, 2012; Loayza et al., 2012; Fomby et al., 2013; Felbermayr and Gröschl, 2014). Recently, research has increasingly focused on analyzing long-term impacts (e.g., Krichene et al., 2021; Berlemann and Wenzel, 2018; Huang et al., 2024; Onuma et al., 2021; Cavallo et al., 2013; McDermott et al., 2014). However, the literature on both short- and long-term effects presents mixed evidence. While some studies report negative effects, others find positive effects, and still others identify no significant impact. These divergent results are often attributed to the nature of disaster indicators commonly used in earlier research, particularly those provided by the EM-DAT database (see Felbermayr and Gröschl, 2014; Strobl, 2012; Hsiang and Jina, 2014).

This paper argues that these inconsistencies stem from two methodological shortcomings in previous studies. The first is the failure to capture the heterogeneous responses to disaster shocks across countries and over time. Most studies rely on standard fixed-effect panel models to estimate the average effect of natural disasters on growth. These models assume a uniform relationship between natural disasters and economic growth, implying that all countries respond similarly to disaster shocks. However, this assumption seems implausible for at least two reasons. First, countries exhibit diverse growth regimes: some experience rapid growth, while others grow more slowly[1]. Rapidly growing economies are likely to have greater resilience to disaster shocks than their slower-growing counterparts. Consequently, it is unreasonable to expect countries with different growth regimes to respond uniformly to natural disaster shocks. Second, the intensity of natural disasters varies considerably across countries. Depending on their geographical location, some countries are more prone to high-intensity natural disasters, while others face moderate-intensity events. For instance, countries in the Pacific Ring of Fire (e.g., the Philippines, Indonesia), the Bay of Bengal (e.g., Bangladesh, India), and the Caribbean region (e.g., Haiti, Cuba) experience particularly violent typhoons and hurricanes. In contrast, countries in sub-Saharan Africa (e.g., Nigeria, Kenya) tend to experience moderate disasters. The impact of natural disasters on growth is, therefore, likely to vary with the severity of the shocks. Standard fixed-effects panel models fail to account for these potential heterogeneous effects. A critical issue arising from this limitation is that in the presence of heterogeneous responses across countries and over time (as is indeed the case), such models yield misleading estimates of average effects (see de Chaisemartin and D'Haultfoeuille, 2020 and Robertson and Symons, 1992). This may explain why previous studies have reached divergent conclusions as mentioned above. Furthermore, by assuming uniform responses, these models obscure the differentiated and complex ways countries react to natural disasters.

Another issue in the literature concerns the distinction between short- and long-term effects on economic growth. The long-term is considered from a specific angle since the question is whether natural disasters have persistent effects over time. If so, they degrade the productive capacity of economies and may explain why steady-state growth is unsustainable. This distinction between short-and long-term horizons offers valuable insights. It helps us to understand why disaster-prone and non-prone coun-

[1] This is shown in Subsection 2.3 of the paper.

tries have unequal outcomes. Moreover, long-term analysis provides a clearer picture of the factors that amplify or mitigate potential losses. For instance, Krichene et al., 2021 investigate the impacts of tropical cyclones and fluvial floods on the determinants of long-term growth. They find that investment spending accentuates the long-term effects of these natural shocks, while consumption and government spending mitigate these effects. Other studies have systematically highlighted the negative long-term effects of tropical cyclones and droughts on growth (e.g., see Berlemann and Wenzel, 2018, Mohan, 2017 Hsiang and Jina, 2014). However, the question of choosing the optimum number of delays in the models to differentiate between the short-, medium-, and long-term remains unresolved. This choice is often ad hoc and is based on statistical criteria (e.g., minimization of information criteria). This issue is not independent of the question of how to reconcile two temporal scales: the infra-annual scales on which natural disasters occur, and the annual scales on which we seek to assess their effects. The issue of mixed frequencies has received little attention but has direct implications for the horizon over which the effects of shocks are assessed.

This paper introduces a new empirical framework to address these two methodological shortcomings (heterogeneity response and time scale). Our empirical framework has four distinct features.

First, we identify the short-, medium-, and long-term components of growth (as well as the same components for the other macroeconomic variables) using frequency-band decomposition based on wavelet analysis. This approach is less ad hoc than selecting delays from autoregressive models (as is typically performed). Moreover, it considerably reduces the risk of multicollinearity associated with the inclusion of different lags in natural disaster variables. An exclusively temporal approach can "overwhelm" the consequences of "local" phenomena, which are easier to detect using frequency analysis.

Second, we introduce heterogeneity in the slope coefficients using a quantile-on-quantile regression approach. This method addresses the limitations of conventional models by allowing the effects of natural disasters on growth to vary across different quantiles of growth and disaster intensity. This enables us to analyze how varying intensities of natural disasters influence growth outcomes at different levels of economic performance.

Third, we analyze the role of growth determinants and structural variables as mitigating or amplifying factors of disaster shocks in a quantile-on-quantile regression framework. Indeed, to identify potential transmission channels, existing studies generally use interaction terms between the transmission channel variable and the disaster variables while maintaining the assumption of homogeneous slope coefficients (see Krichene et al., 2021; Felbermayr and Gröschl, 2014; Noy, 2009; Raddatz, 2009; Skidmore and Toya, 2002). A quantile approach helps account for heterogeneity across countries and over time without the restriction of homogeneous slopes. We hypothesize that the role of a given variable as a mitigating or amplifying factor depends on the magnitude of the shock, the country's growth regime, and the time horizon considered. Thus, we explore how varying disaster intensities influence macroeconomic variables and how these, in turn, affect growth trajectories.

Finally, we exploit the information contained in the infra-annual frequency components of the natural disaster variables. We propose a simple way of dealing with the mixed-data sampling issue (natural disaster variables are measured at a quarterly frequency, while the macroeconomic variables are annual). Our motivation is that by selecting data from natural disasters at the same frequency as macroeconomic variables, we lose information on the intensity of shocks and, in doing so, necessarily introduce aggregation biases. By choosing a higher frequency than the year, the analysis is more parsimonious.

Our analysis focuses exclusively on developing countries[2]. These countries are particularly vulnerable to natural disasters due to their high exposure, limited adaptive capacity, and dependence on climate-sensitive sectors such as agriculture. Moreover, developing countries exhibit significant diversity in their economic structures, institutional frameworks, and growth regimes, providing a rich dataset for analyzing heterogeneity in disaster responses. Despite this diversity, the literature frequently treats them as a homogeneous group, overlooking crucial differences in how they experience and recover from natural disaster shocks. By focusing on developing countries, we aim to highlight these variations and contribute to a more nuanced understanding of their vulnerabilities and resilience.

Our main findings are as follows. On average, natural disasters consistently have a negative impact on growth, and this negative effect compounds over time. Notably, the long-term effect is four times greater than the short-term effect in absolute terms. Moreover, macroeconomic variables play a crucial role in mitigating or exacerbating these impacts. For instance, financial aid and a well-developed financial sector act as shock absorbers, mitigating the negative impacts of disasters across all time horizons. By contrast, investment and imports display dual behavior: they mitigate growth losses in the short and medium term, but amplify these losses in the long term.

However, these average effects mask significant heterogeneities in how countries respond to disaster shocks. When accounting for differences in disaster intensity and growth regimes, a more nuanced picture emerges. First, moderate disaster shocks boost GDP per capita growth in low-growth countries across all time horizons. By contrast, in high-growth countries, such shocks cause sharp short-term growth declines, followed by a rapid recovery in the medium term, albeit without regaining the

[2]In line with the literature, we use the term "developing countries" to refer to low- and middle-income countries, according to the World Bank classification.

pre-disaster growth trajectory in the long term. Second, severe disaster shocks lead to immediate and persistent negative impacts that worsen over time in low-growth countries. In high-growth countries, however, severe shocks initially result in resilience with positive short- and medium-term effects, but their long-term impacts turn negative as growth momentum weakens. Third, the role of macroeconomic variables as mitigating or amplifying factors of growth losses is not uniform across countries; it varies depending on the growth regime, the severity of disaster shocks, and the time horizon.

The rest of the paper is organized as follows. Section 2 outlines our new approach to measuring the impact of natural disasters on growth and the data used. Section 3 discusses our main results. Finally, Section 4 concludes.

2 A new empirical approach to measure the impact of natural disasters on growth

2.1 Econometric methodology

2.1.1 Conventional approach to measuring the growth impact of natural disasters

A conventional way of measuring the sensitivity of growth to natural disasters in the literature is to use a dynamic model relating the growth rate of GDP per capita to the lagged observations of some variables such as tropical hurricanes, storms, extreme temperatures, and floods. A typical regression on panel data is the following

$$g_{i,t} = \alpha_i + \beta_t + \sum_{k=0}^{K} \gamma_k D_{i,t-k} + \epsilon_{i,t}, \tag{1}$$

where the indexes i and t respectively refer to country and years, g is the growth rate of GDP per-capita, D is an exogenous variable of natural disaster, ϵ is an error term. α_i

and β_t are individual and time-fixed effects. The coefficient γ_k measures the dynamic total effects of natural disasters on growth due to both non-economic causes (physical degradation, destruction of infrastructure, power failures, etc.) and the effects passing through some macroeconomic variables. The short-term effects are measured by the coefficients γ_k and medium- to long-term effects are measured by the partial sums of the coefficients:

$$\Omega_L = \sum_{k=0}^{L} \gamma_k, \; L \leq K. \tag{2}$$

To study the transmission channels of natural disaster shocks, a common approach is to define macroeconomic variables that are assumed to influence growth (the degree of openness of the economy, public investment spending, the degree of financialization), and several structural variables such as the inflation rate, the extent of the informal economy, and the share of agriculture and industry in GDP. Then, in an instrumental variable regression, in which the growth rate depends on these variables, the instruments chosen for the latter are natural disaster variables. It is also possible to determine which transmission channels amplify or attenuate the effect of exogenous shocks using a cross-term regression:

$$\begin{aligned} g_{i,t} &= \alpha_i + \beta_t + \sum_{k=0}^{K} \gamma_k D_{i,t-k} + \sum_{j=0}^{J} \delta_j \hat{X}_{i,t-j}, \\ \hat{X}_{i,t} &= \hat{\psi}_i + \hat{\theta}_t + \sum_{m=0}^{M} \hat{\kappa}_m D_{i,t-m}. \end{aligned} \tag{3}$$

The hat symbol indicates estimated variables or coefficients. In the last equation, $\hat{\psi}_i$ and $\hat{\theta}_t$ are individual and time-fixed effects. X is a macroeconomic variable that captures a transmission channel[3]. The coefficient γ_k measures the dynamic direct effects of natural disasters on growth due to non-economic causes (physical degradation, destruction

[3] To avoid problems of collinearity, transmission channels are usually investigated in the literature by studying the role of different macroeconomic variables, one by one, in the regressions.

of infrastructure, power failures, etc.), and the effects passing through some macroeconomic variables are measured by the coefficient δ_j. The interaction of coefficients δ_j and κ_m captures the attenuating or amplifying role of the transmission channels. For instance, the instantaneous effect of a shock is measured by $\gamma_0 + \delta_0\kappa_0$. The cumulative effects over L periods give the short- medium- and long-term effects.

2.1.2 Main differences with our approach

The key differences between our approach and the conventional literature are as follows.

First, short-, medium-, and long-term horizons are apprehended by representing variables in the frequency domain (frequency band analysis) in the long-standing tradition of Burns and Mitchell, 1946, Frisch, 1933, Kuznets, 1930 and Slutzky, 1937. The work of these authors has given rise to abundant literature in economics, notably for cycle analysis (short cycles, but also long waves). Numerous empirical studies filter the short- and long-term components of economic and non-economic variables, using the tools of spectral analysis and wavelets. In this paper, as explained below, we follow this approach.

The second difference concerns the way we account for heterogeneous reactions – between countries and over time – of growth in response to natural disaster shocks. In the standard literature, heterogeneity is assumed to be unobservable (and captured by fixed effects), while slope coefficients are homogeneous across the sample (they depend on neither i nor t). We introduce heterogeneity in the slope coefficients by adopting a quantile-on-quantile regression approach. We do this in two ways. We consider regressions in which the dependent variable is the conditional quantile of growth, without making any assumptions about the conditional distribution. The latter is assumed to depend on the quantile distribution of disaster shocks. Our intuition is that natural disaster shocks do not have the same effect during episodes of fast and slow growth. Similarly, the effects are likely to differ between expansion and recession phases. It is interesting to know whether fast-growing countries are more affected by droughts, floods, and extreme temperatures than slow-growing countries. Moreover, the nature of disaster shocks can influence how they affect growth. For example, if the effect of large positive shocks is different from that of small shocks, the same quantile of growth rate will react asymmetrically to these different shocks. To take such effects into account, it is necessary to consider regressions in which different quantiles of growth rates are regressed on different quantiles of natural disaster shocks.

The third difference lies, as we pointed out in the Introduction, in the different sampling frequencies used for macroeconomic and natural disaster variables.

To the best of our knowledge, these three dimensions have not been considered together in the literature on the effects of natural disaster shocks on growth in developing countries. The following paragraphs provide more details of our empirical framework.

We start with the mixed-frequency aspect of our framework. Let us consider the year (denoted by the time index t) as the benchmark frequency and define ${}_{q}x_{i,t}$ as a variable measured at a quarterly frequency with $q \in \{J, A, J, O\}$ where the letters mean respectively January, April, July and October. Then, to explore the "multiresolution" dimension of natural disasters, we consider the growth effects of four different variables denoted ${}_{q}D_{i,t}$. To avoid multicollinearity, each variable is considered individually in the regressions.

Our modified framework is as follows. The following quantile-on-quantile regression can be substituted for Equation 1:

$$\begin{aligned}
g_{i,t}^{\lambda}(\theta,\tau) &= \left(\alpha_0(\theta,\tau)+\gamma(\theta,\tau)[{}_qD_{i,t}-\ {}_qD_{i,t}^{\tau}]\right)\ \left\{K\left(\frac{F_n({}_qD_{i,t})-\tau}{h}\right)\right\}+\epsilon_{i,t}^{\lambda}(\theta,\tau),\\
(\hat{\alpha}_0(\theta,\tau),\hat{\gamma}(\theta,\tau)) &= argmin\left\{\rho_\theta(\epsilon_{i,t}^{\lambda}(\theta,\tau)\right\},\\
\rho_\theta(\epsilon_{i,t}^{\lambda}(\theta,\tau)) &= \sum_{\epsilon_{i,t}^{\lambda}(\theta,\tau)>0}\theta|\epsilon_{i,t}^{\lambda}(\theta,\tau)|+\sum_{\epsilon_{i,t}^{\lambda}(\theta,\tau)<0}(1-\theta)|\epsilon_{i,t}^{\lambda}(\theta,\tau)|,
\end{aligned} \tag{4}$$

where

$$\epsilon_{i,t}^{\lambda}(\theta,\tau)=g_{i,t}^{\lambda}-\alpha_0(\theta,\tau)-\alpha_1(\theta)g_{i,t-1}^{\lambda}-\gamma(\theta,\tau)[{}_qD_{i,t}-\ {}_qD_{i,t}^{\tau}]. \tag{5}$$

$\lambda \in \{s,m,l\}$ indexes three frequency bands corresponding to short-, medium- and long-term horizons. These frequencies are selected from a wavelet analysis (see Appendix A for details). The wavelet transformation is only applied to the growth rate.

θ is the conditional quantile of the growth rate. τ is the quantile of the natural disaster variable. By minimizing the sum of absolute deviation residuals, this estimation is known as a quantile regression ($\rho_\theta(\epsilon_{i,t}^{\lambda}(\theta,\tau))$ is a quantile function). Each quantile of the natural disaster variable affects the conditional quantiles of the growth rate. Therefore, we seek to examine the behavior of the conditional quantile of the independent variable in the neighborhood of a given quantile of the exogenous independent variable. Following the method initially proposed by Sim and Zhou, 2015, the parameter linking the two variables is approximated linearly in the neighborhood of the quantile of ${}_qD_{i,t}$, here denoted ${}_qD_{i,t}^{\tau}$. To ensure that we are in the neighborhood of the τ quantile, we need a weighting function, described here as a Kernel function K, which weights the observations of ${}_qD_{i,t}$ around the τ quantile within bandwidth h (set equal to 0.05). This weighting function, which assigns decreasing weights to the observations as we move away from the quantile, can take various forms. The simplest case is that of a

Gaussian kernel. The function F_n is defined as follows:

$$F_n({}_qD_{i,t}) = \frac{1}{n}\sum_{k=1}^{n} \mathbf{1}({}_qD_k < \ {}_qD_{i,t}), \tag{6}$$

where $\mathbf{1}$ is the indicator function.

To estimate Equation 4 we proceed in two steps. First, macroeconomic variables are transformed into the frequency domain using wavelet decomposition. Second, we perform quantile-on-quantile regressions for each selected frequency.

Following the same principle, to measure the effects that pass through transmission channels, we substitute a new set of equations for the equations defined by (3). Now, we define:

$$\begin{aligned} g^{\lambda}_{i,t}(\theta,\tau) &= \alpha_0(\theta,\tau) + \gamma(\theta,\tau)[{}_qD_{i,t} - \ {}_qD^{\tau}_{i,t}] + \beta(\theta,\tau)\int_{\mu} \hat{X}^{\lambda}_{i,t}(\mu,\tau)d\mu + \epsilon^{\lambda}_{i,t}(\theta,\tau), \\ \hat{X}^{\lambda}_{i,t}(\mu,\tau) &= \hat{a}_0(\mu,\tau) + \hat{\omega}(\mu,\tau)[{}_qD_{i,t} - \ {}_qD^{\tau}_{i,t}] + \nu^{\lambda}_{i,t}(\mu,\tau) \end{aligned} \tag{7}$$

μ is the conditional quantile of the estimated transmission channel variable $\hat{X}^{\lambda}_{i,t}$. The first equation in (7) is our main equation which depends on three quantiles: the quantile of the growth rate θ, the quantile of the natural disaster variable τ, and the quantile of the macroeconomic variable μ, which represent the channel through which the shocks are transmitted to growth. The coefficient $\hat{\gamma}(\theta,\tau)$ measures the direct effects of natural disasters on growth due to non-economic causes (physical degradation, destruction of infrastructure, power failures, etc.), the coefficient $\hat{\omega}(\mu,\tau)$ measures the sensitivity of macroeconomic variables to disaster shocks, while the effects passing through specific macroeconomic variables are captured by $\hat{\beta}(\theta,\tau)$. Note that in our framework, the coefficients are not constant (as in the standard approach) but depend on the growth quantile θ, the disaster quantile τ, or the quantile of macroeconomic variables μ. The analysis includes quantiles from 0.1 to 0.9, allowing us to examine the full range of the distribution, from the lower to the upper quantiles. The procedure for estimating these coefficients is described in Appendix B.

The role of growth determinants in mitigating the impacts of natural disasters is investigated by considering the components of national income identity, as well as other non-economic structural growth determinants. In doing so, we adopt the approach proposed by Krichene et al., 2021. Choosing the variables that come from the GDP accounting identity (consumption, investment, public spending, exports, and imports) can be motivated if we first interpret natural disaster shocks as a large demand shock of high intensity. Natural disasters, by causing loss of income and jobs, destruction of production capacity, and deaths, have an impact on household consumption expenditure, as well as on the activities of companies, which have to modify their investment, import, and export choices. The effect on public spending can be seen either as policymakers reacting to the losses of natural disasters to support the economy, or as government spending adjusting to a drop in tax revenues induced by the loss of activity. The other determinants are chosen because they play a significant role in the growth of developing countries. These include financial conditions, which can act as a shock absorber (aid received from abroad, the volume of liquidity available in the domestic financial system), governance factors (the fight against corruption and the solidity of governance institutions), and the degree of development of informal activities. Finally, shocks from natural disasters can affect the demographic balance.

To estimate Equation 7, we rely on multi-stage regressions.

Stage 1. Quantile-on-quantile regression of each macroeconomic variable X on the natural disaster variables. The regression is expressed as follows:

$$_qX^{\lambda}_{i,t}(\mu,\tau) = a_{0q}(\mu,\tau) + \omega_q(\mu,\tau)[_qD_{i,t} - {}_qD^{\tau}_{i,t}] + {}_q\nu^{\lambda}_{i,t}(\mu,\tau). \tag{8}$$

The index q indicates that the effects are measured at a quarterly frequency (January, April, July, and October). We compute the aggregate impact of natural disasters on each macroeconomic variable:

$$\tilde{\omega} = \sum_{q=J,A,J,O} \left[\frac{1}{N_\mu N_\tau} \int_\mu \int_\tau \hat{\omega}(\mu,\tau) d\tau d\mu \right], \tag{9}$$

N_μ and N_τ are the number of quantiles μ and τ, respectively. The aggregate coefficient $\tilde{\omega}$ measures the average effect of natural disasters on each macroeconomic variable, accounting for heterogeneity in the distribution of disasters and macroeconomic variables.

Stage 2. From the estimated coefficients, we construct an indicator that summarizes the average effect of the influence of natural disasters on $X_{i,t}$, taking into account quantile heterogeneity. We define the following variable:

$$\begin{aligned} {}_q\tilde{X}^{\lambda}_{i,t}(\tau) &= \frac{1}{N_\mu} \int_\mu {}_q\hat{X}^{\lambda}_{i,t}(\mu,\tau) d\mu \\ &= \frac{1}{N_\mu} \int_\mu \hat{a}_{0q}(\mu,\tau) d\mu + \frac{1}{N_\mu} \int_\mu \hat{\omega}_q(\mu,\tau) d\mu \left[{}_qD_{i,t} - {}_qD^{\tau}_{i,t} \right] \end{aligned} \tag{10}$$

N_μ is the number of quantiles μ. We calculate therefore the marginal averages of the estimated coefficients to obtain the average forecasts ${}_q\hat{X}^{\lambda}_{i,t}$ for a given quarter q.

Stage 3. Finally, we estimate the following equation:

$$g^{\lambda}_{i,t}(\theta,\tau) = \alpha_0(\theta,\tau) + \gamma(\theta,\tau)[{}_qD_{i,t} - {}_qD^{\tau}_{i,t}] + \beta(\theta,\tau) {}_q\tilde{X}^{\lambda}_{i,t}(\tau) + \epsilon^{\lambda}_{i,t}(\theta,\tau), \tag{11}$$

${}_q\tilde{X}^{\lambda}_{i,t}(\tau)$ is the variable computed in stage 2. By averaging over τ and θ (i.e., taking into account all quantiles of the shock variable and those of growth), we obtain an aggregate measure of the impact of natural disasters on GDP growth for a given quarter q. We then define the following two measures of the aggregate impact of natural disasters on economic growth:

$$\begin{aligned}\text{Average direct effect: } \hat{\gamma}_{direct} &= \sum_{q=J,A,J,O}\left[\frac{1}{N_\theta N_\tau}\int_\theta\int_\tau \hat{\gamma}(\theta,\tau)d\tau d\theta\right],\\ \text{Average indirect effect: } \hat{\beta}_{indirect} &= \sum_{q=J,A,J,O}\left[\frac{1}{N_\theta N_\tau}\int_\theta\int_\tau \hat{\beta}(\theta,\tau)d\tau d\theta\right]\end{aligned} \tag{12}$$

N_θ and N_τ are the number of quantiles θ and τ, respectively. Hats indicate estimated values. The difference with system 3 is that the coefficients measuring the direct and indirect effects are estimated by exploiting all the information contained in the heterogeneity of the distribution of natural disaster shocks and the macroeconomic variables capturing the transmission channels.

Role of transmission channels: In order to analyze the role of transmission channels in mitigating the impacts of natural disasters, we take the derivative of $g^{\lambda}_{i,t}(\theta,\tau)$ with respect to $Z(D;q,\tau) = [{}_qD_{i,t} - {}_qD^{\tau}_{i,t}]$ in Equation (11). We obtain:

$$\frac{\partial g^{\lambda}_{i,t}(\theta,\tau)}{\partial Z(D;q,\tau)} = \gamma(\theta,\tau) + \beta(\theta,\tau)\eta(\tau), \quad \text{with} \quad \eta(\tau) = \int_\mu \hat{\omega}(\mu,\tau)d\mu \tag{13}$$

$\hat{\gamma}(\theta,\tau)$ indicates the direct effect of natural disasters on growth, $\hat{\beta}(\theta,\tau)$ represents the growth effect of natural disasters that pass through macroeconomic variables (indirect effect). Moreover, the sign of $\hat{\beta}(\theta,\tau)\hat{\eta}(\tau)$ indicates whether a given variable mitigates or amplifies the direct impact of natural disasters. Specifically, $\hat{\beta}(\theta,\tau)\hat{\eta}(\tau) > 0$ indicates a mitigating effect, while $\hat{\beta}(\theta,\tau)\hat{\eta}(\tau) < 0$ indicates an amplifying effect. For example, assume that natural disaster shocks have a negative direct effect on growth (i.e. $\gamma(\theta,\tau) < 0$) and also negatively affect consumption (i.e. $\hat{\eta}(\tau) < 0$), causing the latter to decrease. If $\hat{\beta}(\theta,\tau) > 0$ for consumption, this implies that a drop in consumption (as a result of a natural disaster shock) leads to a variation in the same direction in per capita GDP growth (i.e. losses). In other words, consumption amplifies the direct negative effect of the shock on growth.

2.2 Data description

2.2.1 Natural disasters data

In empirical studies analyzing the impact of natural disasters on economic growth, measuring disaster intensity in a way that mitigates endogeneity concerns remains a critical challenge. Earlier studies often used estimates of human losses and economic damages from the EM-DAT database as proxies for disaster intensity. However, these measures are endogenous because they depend on per capita GDP – the dependent variable in growth regressions (see Felbermayr and Gröschl, 2014). In this study, we follow recent literature that relies on the physical intensity of disasters. Since the physical intensity of natural disasters is exogenous to the socioeconomic conditions of the affected country, the estimated effects are less likely to be affected by endogeneity problems.

We use data from the "Geological and Meteorological Events Database" (GeoMet). This database contains information on the physical intensities of earthquakes, storms, droughts, precipitation, and temperature anomalies, compiled from primary geophysical and meteorological sources. It covers a wide range of countries over the period 1979 – 2010. Below, we briefly describe how these intensity variables are computed in the GeoMet database.

Earthquakes. Earthquake intensity is measured using the Richter scale, with data sourced from the Incorporated Institute for Seismology (IRIS), which records global earthquakes. The GeoMet database provides monthly country-level Richter-scale earthquake data. We aggregate monthly Richter scales into quarterly frequencies for consistency with the study's quarterly focus using the unweighted average.

Extreme Precipitation. Monthly precipitation data are sourced from the Global Precipitation Climatology Project (GPCP), which integrates surface weather station measurements and satellite observations to provide global precipitation in millimeters (mm). The GeoMet database defined extreme precipitation as the proportional deviation of monthly rainfall from the long-term (1979 – 2010) monthly average:

$$\gamma_{m,t}^{prec} = \frac{\mathrm{P}_{m,t} - \overline{\mathrm{P}}_{m,1979-2010}}{\overline{\mathrm{P}}_{m,1979-2010}}, \text{ where m = month, t = year.}$$

This study focuses on positive precipitation deviations ($\gamma_{m,t}^{prec} > 0$), which are more likely to cause significant damage, such as flooding. These monthly measures are aggregated into quarterly indicators using the unweighted average.

Extreme Temperature. Temperature data are obtained from the Global Surface Summary of Day (GSOD, version 7), provided by the National Climatic Data Center (NCDC) from over 9,000 stations worldwide. Extreme temperatures are calculated as the percentage deviation of the maximum monthly temperature from the long-term (1979 – 2010) average:

$$\gamma_{m,t}^{temp} = \frac{\mathrm{T}_{m,t} - \overline{\mathrm{T}}_{m,1979-2010}}{\overline{\mathrm{T}}_{m,1979-2010}}, \text{ where m = month, t = year.}$$

The $\gamma_{m,t}^{temp}$ indicator is positive (heat waves) or negative (cold waves). This study focuses on heat waves ($\gamma_{m,t}^{temp} > 0$). Monthly indicators are aggregated into quarterly averages.

Storms. Storm intensity is measured as the total maximum wind speed in knots. Data are drawn from two sources: the International Best Track Archive for Climate Stewardship (IBTrACS) for hurricane positions and wind speeds and the GSOD database for tornadoes and seasonal storms. Monthly wind speed data are aggregated into quarterly indicators using the unweighted average.

Overall Index. Countries often experience multiple disasters within a year. To quantify the overall impact, we construct an index that combines the intensities of different disasters. Following Felbermayr and Gröschl, 2014, the index is weighted by the inverse of the standard deviation of each disaster type across all years, ensuring that no single disaster dominates the index. To account for differences in country size, the index is scaled by land area. The overall index is calculated at a quarterly frequency for consistency with disaster-specific indicators.

2.2.2 Macroeconomic data

Our annual macroeconomic data cover the period 1990-2010 and are extracted from several sources (see Table Appendix C.1). GDP data and its components (household consumption, investment, public spending, exports, and imports) are taken from the Penn World Table (PWT 10.1; see Feenstra et al., 2015). Data on financial aid and fertility were obtained from World Development Indicators (WDI). As institutional and governance indicators, we use the control of corruption and government effectiveness estimates provided by World Governance Indicators (WGI). For informality, we use estimates based on the dynamic general equilibrium (DGE) model from Elgin et al., 2021. Financial development is proxied by the Financial Development Index provided by the International Monetary Fund (IMF), which captures the depth, access, and efficiency of financial institutions and markets. Our country sample includes 65 developing countries. Table 1 presents descriptive statistics for variables used in the analysis, including the minimum, first quartile (Q1), mean, median, third quartile (Q3), and maximum.

Table 1: Descriptive statistics for macroeconomic variables

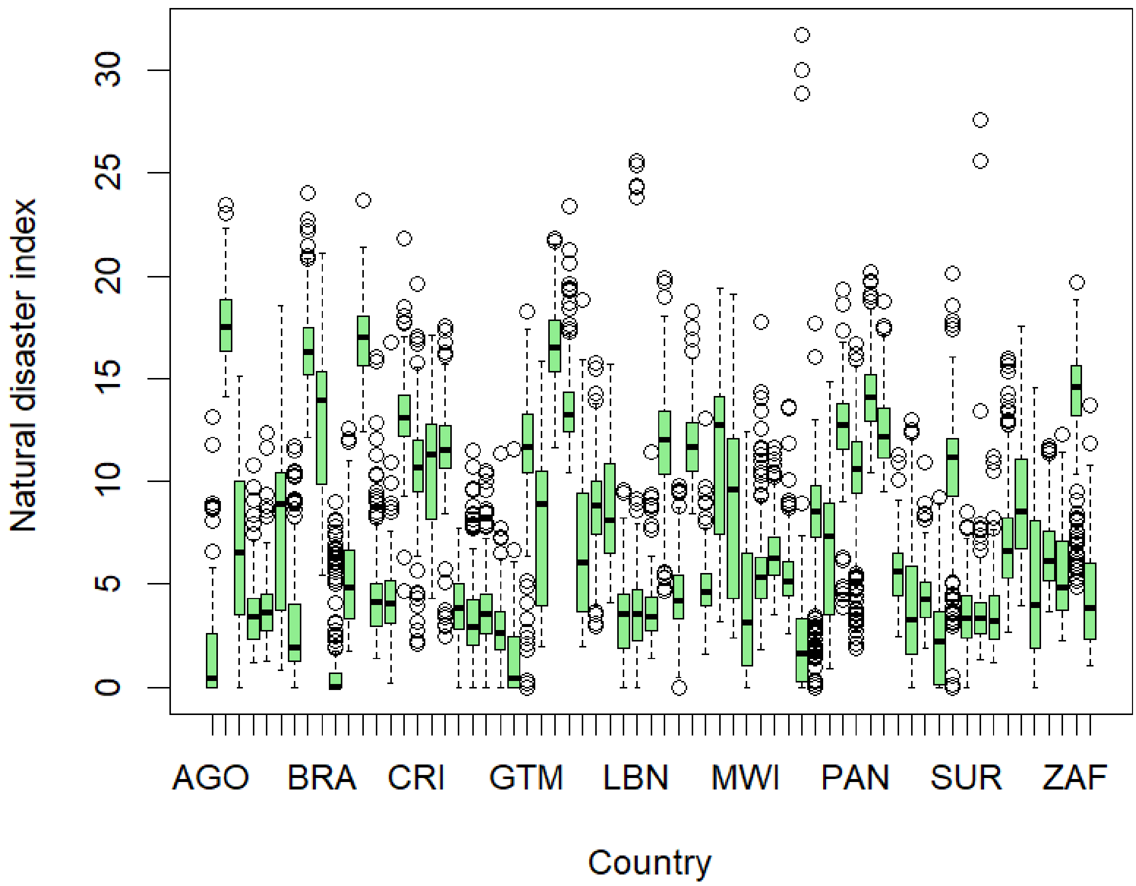
	Min	Q1	Median	Mean	Q3	Max
Economic growth	- 69.94	0.39	2.35	2.10	4.28	65.02
Household consumption	0.19	0.61	0.70	0.69	0.78	1.54
Investment	0.02	0.14	0.19	0.20	0.25	0.74
Government expenditure	0.01	0.11	0.15	0.16	0.19	0.61
Exports	0.002	0.06	0.12	0.16	0.21	0.84
Imports	0.004	0.11	0.17	0.22	0.28	1.27
Fertility	1.34	2.44	3.40	3.83	5.22	7.52
Financial aid	- 0.62	0.49	2.31	5.47	7.72	94.44
Control of corruption	- 1.67	- 0.89	- 0.54	- 0.45	-0.15	1.59
Government effectiveness	- 1.81	- 0.83	- 0.44	- 0.39	0.03	1.34
Financial development	0.00	0.10	0.16	0.21	0.29	0.74
Informal economy	10.96	30.29	37.28	36.92	43.44	71.21

2.3 Natural disasters and growth: evidence of heterogeneity

We present stylized facts on natural disasters and economic growth for our sample of developing countries from 1990 to 2010.

Figure 1 displays a box plot of the disaster intensity index by country. It highlights significant heterogeneity in the disaster intensity across countries. Based on this figure, three groups of countries can be identified. The first group, characterized by a high median index (approximately 15), experiences intense natural disasters. The second group, which can be described as a moderate-risk country, has a median index of approximately 10. The third group includes low-risk countries with a median index below five. Additionally, the presence of numerous outliers among low- and moderate-risk countries suggests that extreme disaster events are not uncommon, even in these groups.

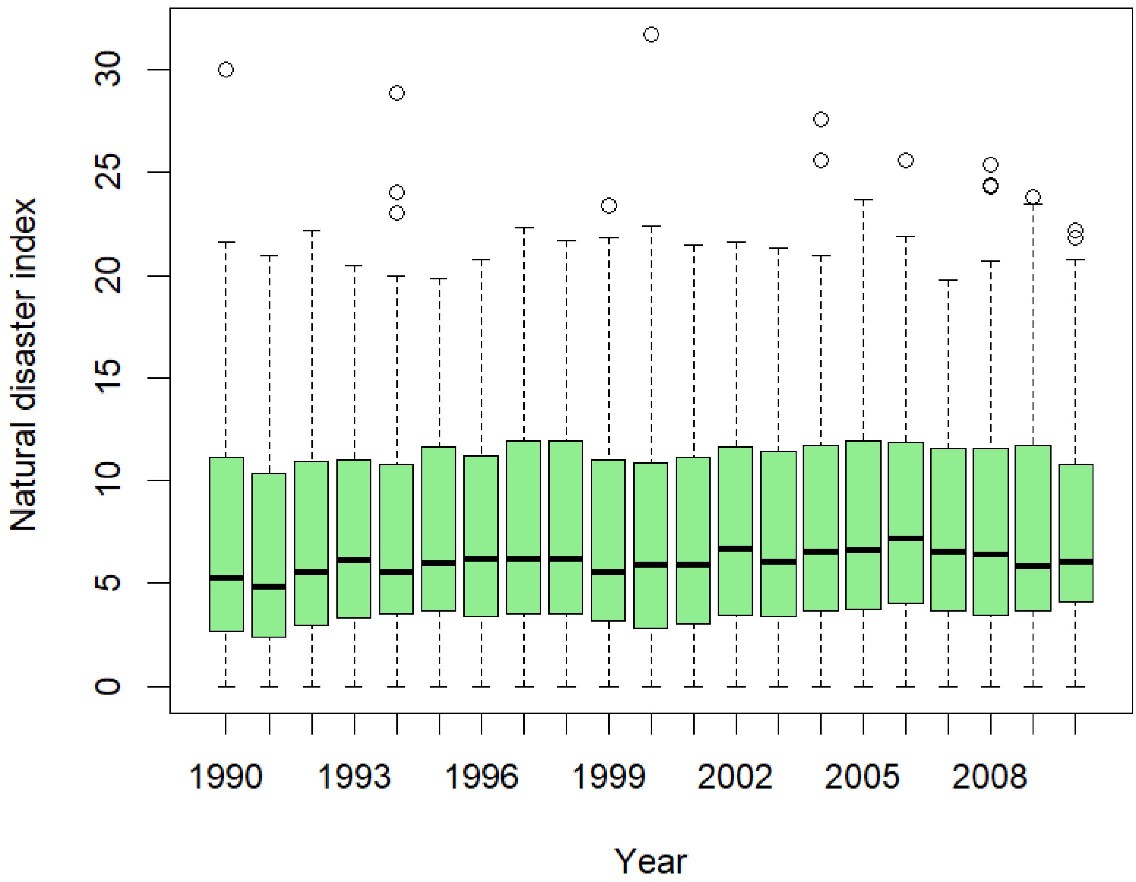
Figure 1: Box plot of the natural disaster Index by country



Source: Author's calculations.
Notes: The solid line in the box represents the median value. The top and bottom horizontal lines in the green box represent the third and first quantiles, respectively. The lower and upper ends of the box plots represent minimum and maximum values, respectively. The empty dots above (and below) the boxes represent the extreme values.

The disaster index also varies significantly over time, as illustrated in Figure 2. While the median index changes slightly, the interquartile range and upper length of the whiskers in each box plot vary across time, indicating fluctuations in the variability of disaster intensity over the years.

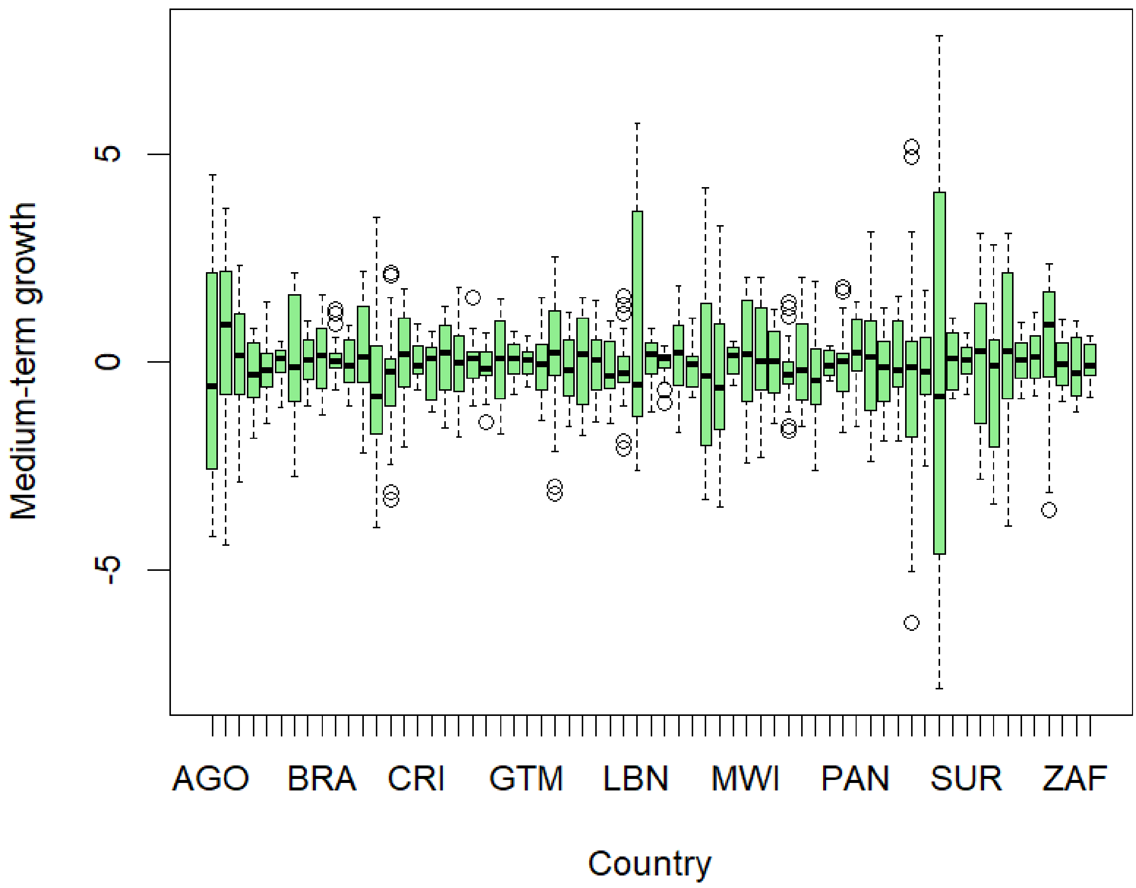
Figure 2: Box plot of disasters index by year (1990-2010)



Source: Author's calculations.
Notes: The solid line in the box represents the median value. The top and bottom horizontal lines in the green box represent the third and first quantiles, respectively. The lower and upper ends of the box plots represent minimum and maximum values, respectively. The empty dots above (and below) the boxes represent the extreme values.

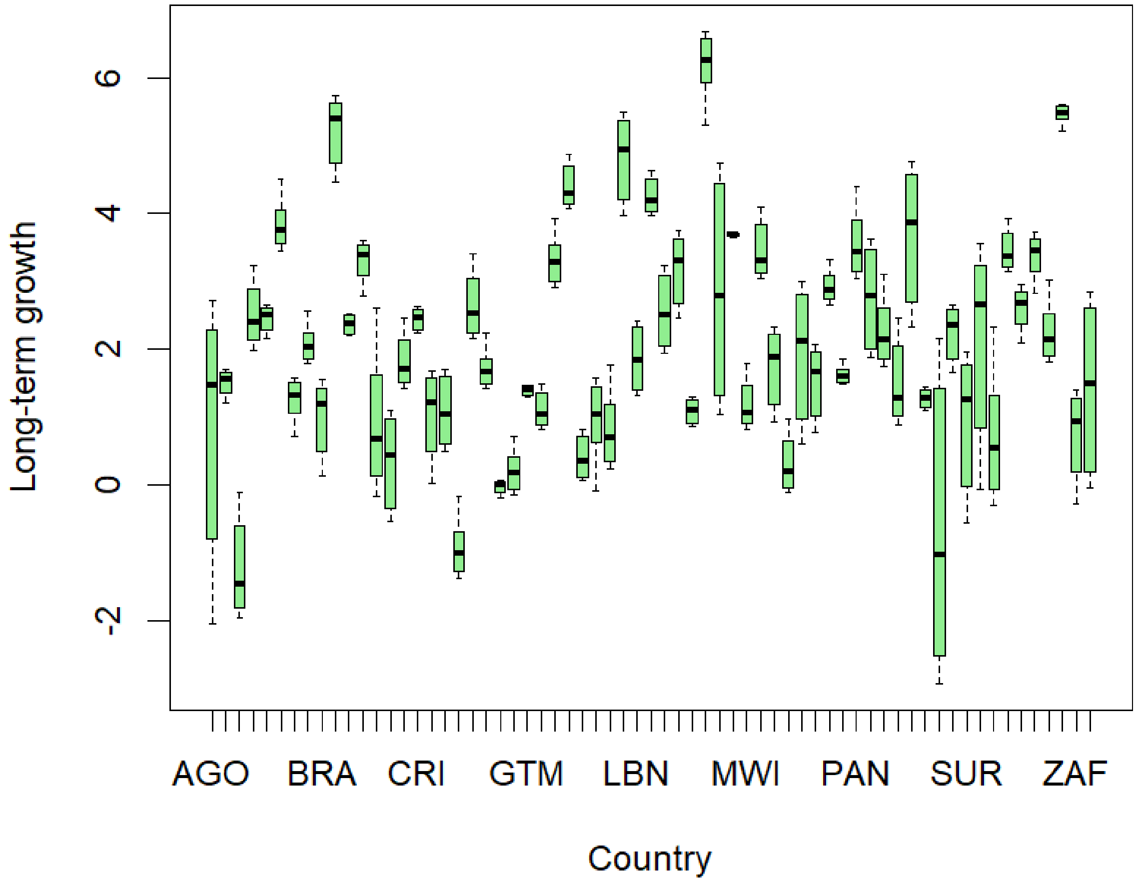
Figures 3 and 4 display box plots of medium- and long-term growth by country, respectively. These figures illustrate the heterogeneity in medium- and long-term growth across countries. Wider boxes indicate greater variability, whereas narrower boxes indicate lesser variability. The median medium-term growth rate for some countries is close to zero (Figure 3), suggesting relative stability (or stagnation) in medium-term growth rate. In contrast, the long-term growth rate is highly volatile (see Figure 4). Some countries exhibit high long-term growth rates (median between 4% and 6%), others show modest growth rates (median between 1% and 3%), while some have negative growth rates.

Figure 3: Box plot of medium-term growth by country



Source: Author's calculations.
Notes: The growth rate is annual. The solid line in the box represents the median value. The top and bottom horizontal lines in the green box represent the third and first quantiles, respectively. The lower and upper ends of the box plots represent minimum and maximum values, respectively. The empty dots above (and below) the boxes represent the extreme values.

Figure 4: Box plot of long-term growth by country

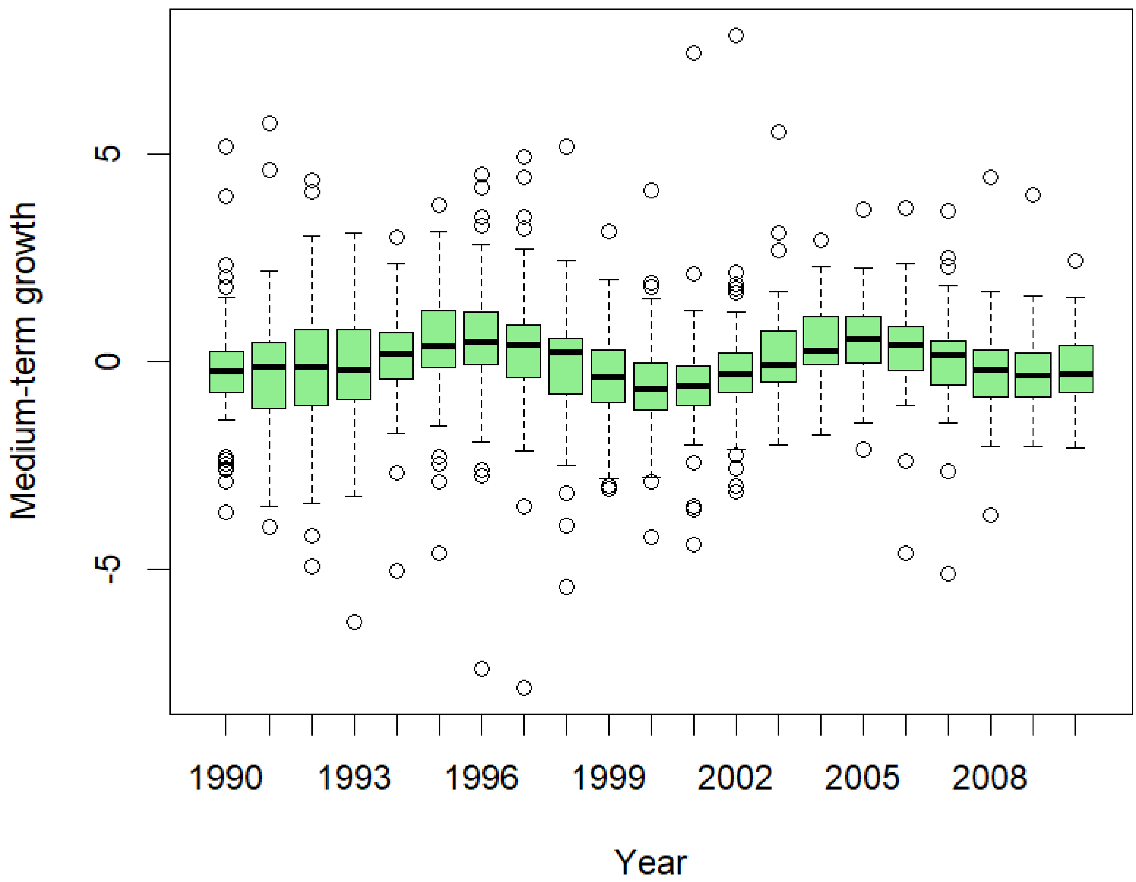


Source: Author's calculations.
Notes: The growth rate is annual. The solid line in the box represents the median value. The top and bottom horizontal lines in the green box represent the third and first quantiles, respectively. The lower and upper ends of the box plots represent minimum and maximum values, respectively. The empty dots above (and below) the boxes represent the extreme values.

Figure 5 presents a box plot of the medium-term growth by year. It highlights considerable variation in medium-term growth rates over time. This variation is evident in the changes in median growth rates, the height of each box plot, and the length of whiskers, which vary annually. Additionally, extreme values are widespread and vary by year, indicating that medium-term growth rates are exceptionally high or low in certain years. A similar trend is observed for long-term growth rates, as shown in figure 6.

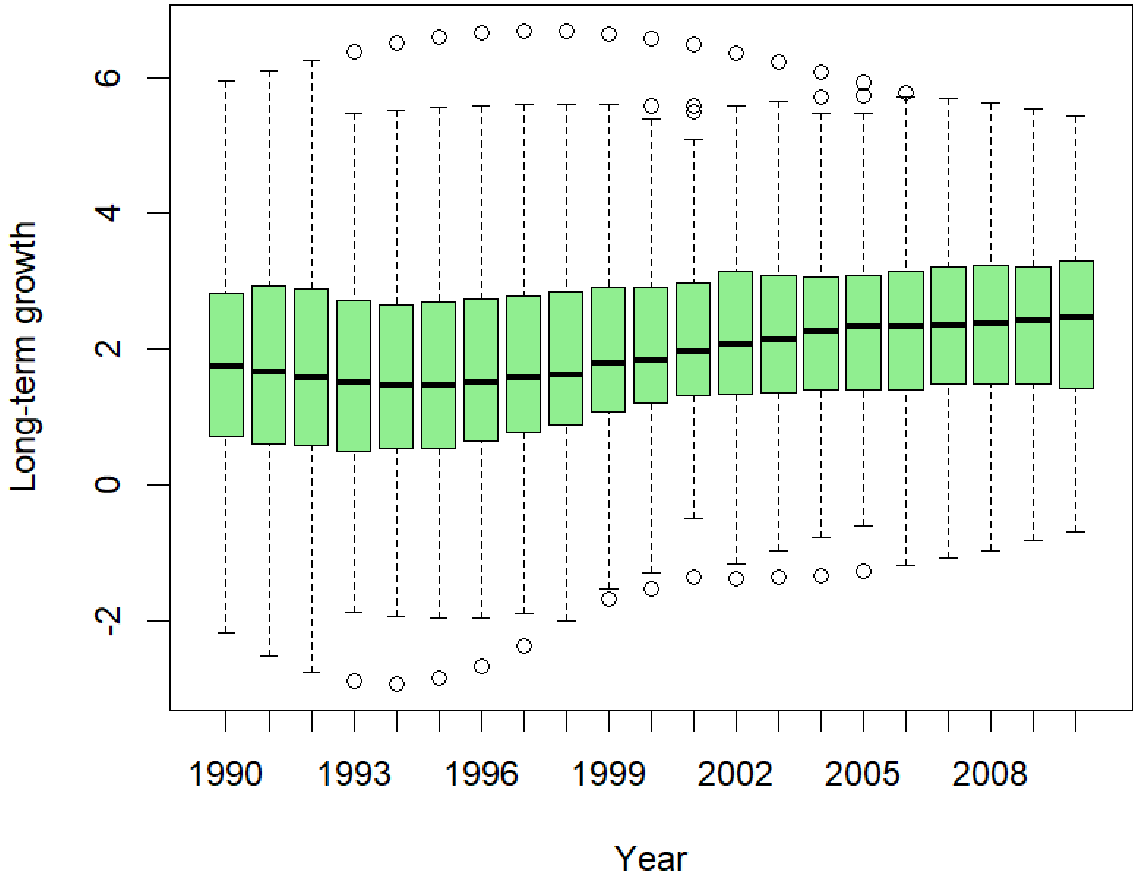
Overall, the key insight from these stylized facts is that natural disaster intensity and growth rates vary significantly across countries and over time, suggesting heterogeneity in the growth response to natural disaster shocks. This observation motivates our use of a quantile-on-quantile regression approach, which captures how responses to disaster shocks differ across countries and over time. Specifically, our empirical framework examines how the impacts of natural disasters vary with shock intensity, growth regimes, and time horizons.

Figure 5: Box-plot of medium-term growth by year (1990-2010)



Source: Author's calculations.
Notes: The growth rate is annual. The solid line in the box represents the median value. The top and bottom horizontal lines in the green box represent the third and first quantiles, respectively. The lower and upper ends of the box plots represent minimum and maximum values, respectively. The empty dots above (and below) the boxes represent the extreme values.

Figure 6: Box-plot of long-term growth by year (1990-2010)



Source: Author's calculations.
Notes: The growth rate is annual. The solid line in the box represents the median value. The top and bottom horizontal lines in the green box represent the third and first quantiles, respectively. The lower and upper ends of the box plots represent minimum and maximum values, respectively. The empty dots above (and below) the boxes represent the extreme values.

3 Results

3.1 Average effects of natural disasters on growth

Table 2 presents the average effect of natural disasters on economic growth, based on the estimates from Equation 4. The effect is often negative for different quarters. Moreover, this negative effect is cumulative over time, as evidenced by increasingly larger negative coefficients for the long term compared to the short term.

Table 2: Growth effects of natural disasters: quantile-on-quantile regression

Dependent variable:	Δ *ln GDP per capita* - Equation 4		
	Short-term	**Medium-term**	**Long-term**
Quarter 1	-0.0909	0.1250	-0.3266
Quarter 2	-0.0432	0.0033	-0.2403
Quarter 3	-0.0720	-0.0829	-0.1787
Quarter 4	-0.0367	-0.0461	-0.2939
Annual effect	$\mathbf{-0.2428}$	$\mathbf{-0.0006}$	$\mathbf{-1.0396}$

Note: This table reports the average effects over all quantiles and for different time horizons. Negative values indicate a reduction in growth following a positive change in the natural disaster index. The reported coefficients are statistically significant at the 10% level. The estimates do not include control variables.

Beyond average effects, a more detailed analysis can be obtained by examining Figures 7 to 9, which display contour plots derived from the estimates of the coefficients $\gamma(\theta, \tau)$[4].

In the short term, natural disasters cause a drop in economic growth in countries that experience high growth rates at the time of the shocks (Figure 7). In these countries, the economy is highly sensitive to small shocks (low-intensity natural disasters). In the medium term, the negative effects are evenly distributed between disasters of different intensities and growth regimes (low, medium, or high).

Figure 9 highlights the importance of considering dual heterogeneity by accounting for both varying growth regimes and differences in shock intensity. Indeed, while the average effect of natural disasters on growth appears negative over the long term in Table 2, Figure 9 tells a different story. Below a certain shock intensity (below 6.5 on the x-axis), long-term effects are positive. This is true regardless of whether we are in a

[4]See the Excel file of "supplementary materials"

regime of low or high growth. The intensity of natural disasters must be high enough for their long-term effects to remain as negative as they are in the short term.

Figure 7: 3D representation of the effects of natural disasters on short-term growth

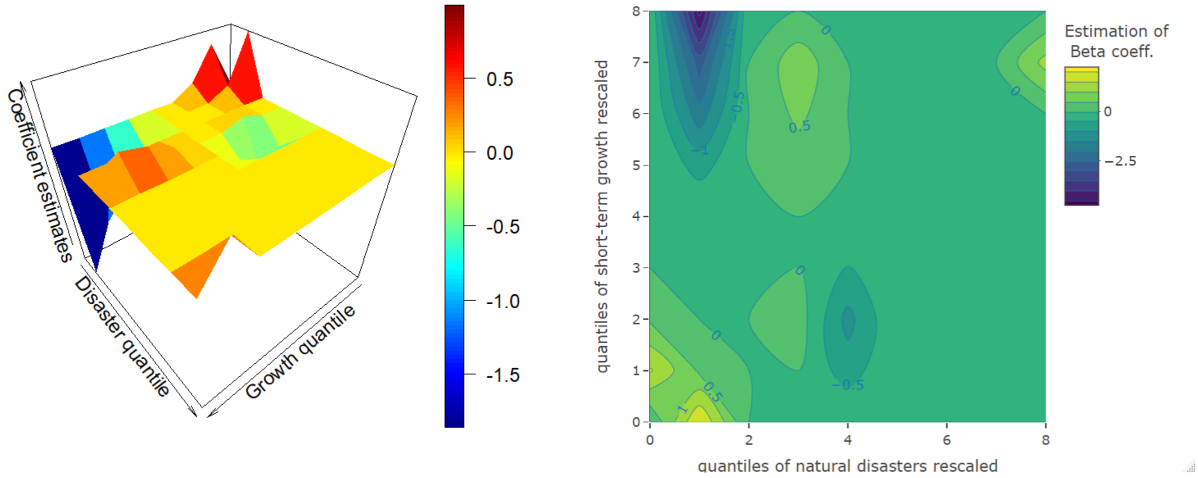


Figure 8: 3D representation of the effects of natural disasters on medium-term growth

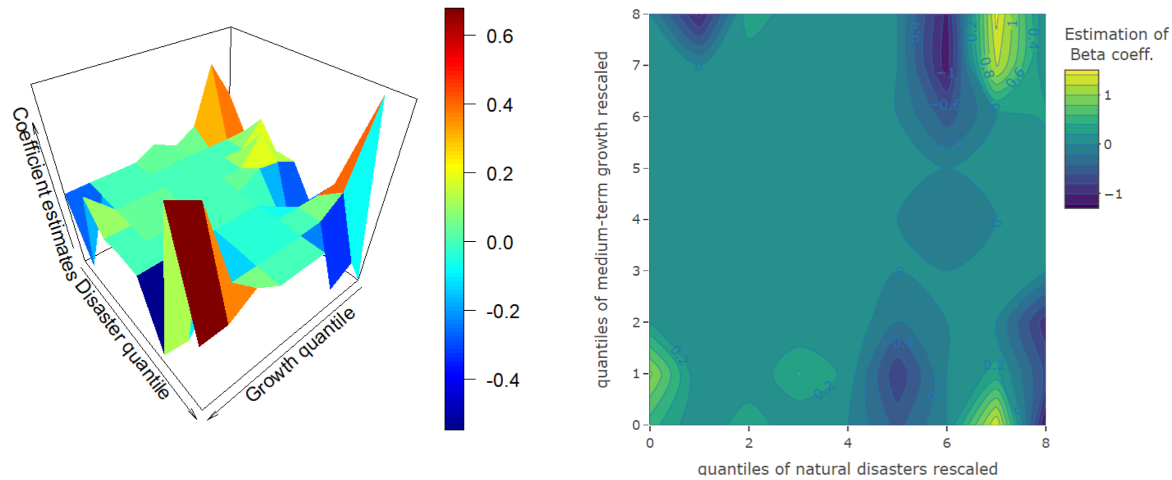
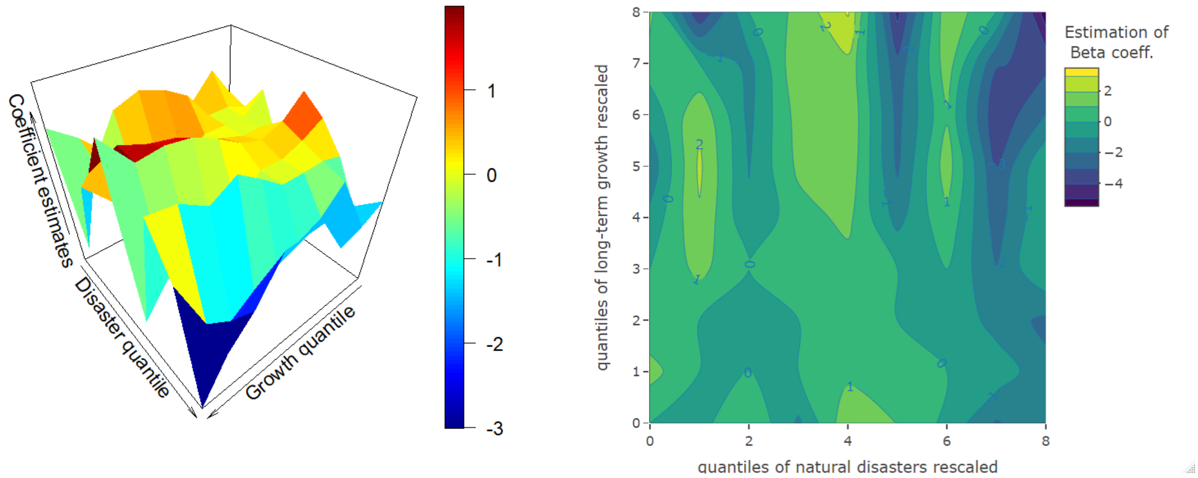


Figure 9: 3D representation of the effects of natural disasters on long-term growth



3.2 Sensitivity of growth determinants to natural disasters

Before analyzing the effects of natural disasters that pass through different transmission channels, we must first examine how these channels respond to disaster shocks.

Table 3 shows the effects of natural disasters on the demand components of GDP as well as on other structural variables. The reported coefficients are the averaged effects after summing over the quantiles μ and τ as in Equation 9. Comparing the magnitude of the coefficients with those in Table 2, we notice that the short- and medium-term effects are small and that most of the impact of the shocks occurs in the long term. Substantial negative effects are observed for demography and the informal sector, which can be explained by the fact that natural disasters cause a high cumulative number of deaths and destroy economic activities when the informal sector is large. The irreversible destruction of production capacity also explains the negative sign of the investment.

Table 3: Sensitivity of growth determinants to natural disasters.

	Equation 9		
	Short-term	**Medium-term**	**Long-term**
Demand-side determinants			
Consumption	-0.0003	0.0077	$0,1976$
Investment	0.0010	$0,0042$	$-0,0688$
Government expenditures	0.0004	$-0,0027$	$0,0451$
Exports	$0,0017$	$-0,0039$	$0,0401$
Imports	$-0,0018$	$0,0051$	$0,2785$
Other determinants			
Fertility	$-0,0047$	$-0,0096$	$-1,7014$
Financial aid	$0,0986$	$0,0851$	$1,4498$
Control of corruption	$0,0013$	$0,0094$	$0,5697$
Government effectiveness	$-0,0012$	$0,0136$	$0,6490$
Financial development	-0.0000	$0,0020$	$-0,0385$
Informality	$0,0247$	$0,0444$	$-3,4655$

This table reports the average effects over all quantiles and for different time horizons. Negative values indicate a reduction in growth following a positive change in the natural disaster index. The reported coefficients are statistically significant at the 10% level.

As expected, in the long term, natural disasters increase variables that are resilience factors for economies in the face of the losses and damage they cause: public spending increases moderately, but international financial aid increases more sharply. Governments also need to improve their governance (in our case, through better control of corruption and efficiency of government decision-making) to attenuate the potential negative effects of natural disasters. We see that the destruction of domestic production capacity leads to an increase in imports.

In addition to average effects, the contour plots obtained from the coefficient estimates provide valuable information. Figures 10 to 13 illustrate the substantial heterogeneity in the responses of macroeconomic variables to disaster shocks. Furthermore, these figures suggest the existence of threshold effects in the reactions of some macroeconomic variables. For example, the greater the intensity of disasters, the greater the positive response of public spending (see Figure 11). However, there seems to be a substitution effect between public spending and financial aid in the case of severe shocks. Comparing Figures 11 and 12, we observe that, for the highest values of disaster intensity, the reaction of public spending is positive, while that of financial aid is negative. In the case of the latter variable, we observe nonlinear effects. Countries with very high growth regimes receive less financial aid if shocks are of low intensity, or conversely of very high intensity. One possible interpretation is that such countries generally have more internal factors than lower-growth countries to mitigate the effect of shocks. When the intensity of natural disaster shocks is neither too low nor too high, financial aid increases with the shock intensity.

Figure 10: 3D representation of the long-term response of investment in the aftermath of natural disasters.

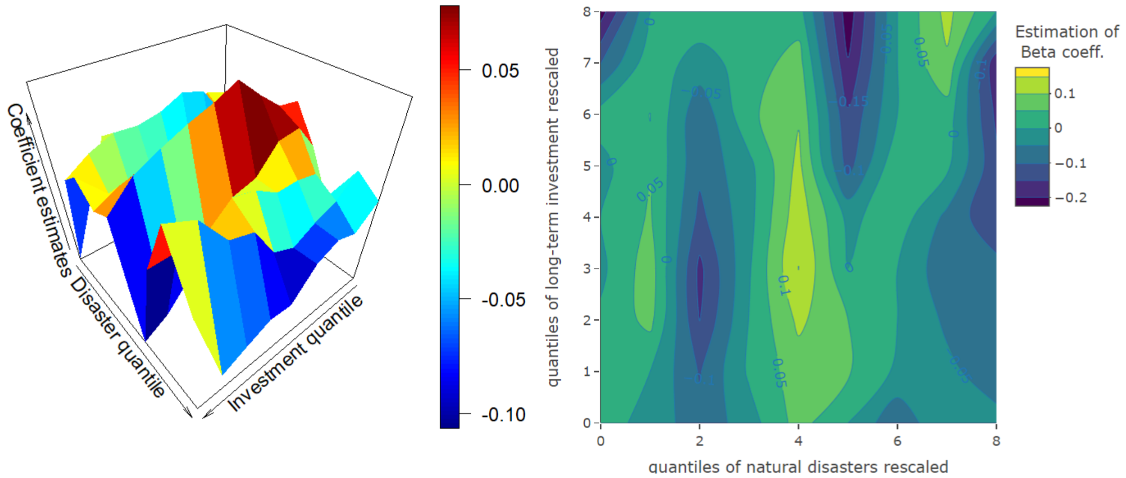


Figure 11: 3D representation of the long-term response of public expenditures in the aftermath of natural disasters.

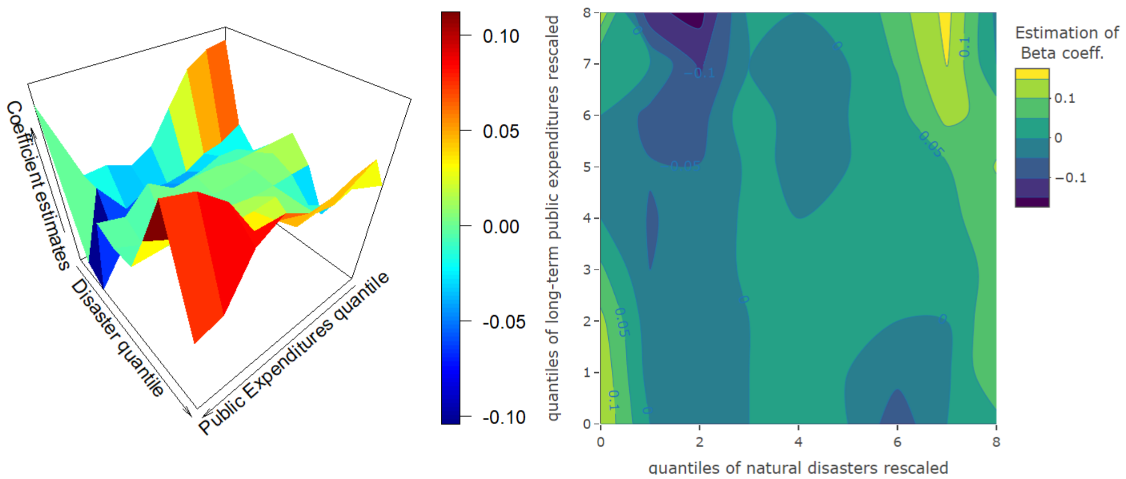


Figure 12: 3D representation of the long-term response of financial aid in the aftermath of natural disasters.

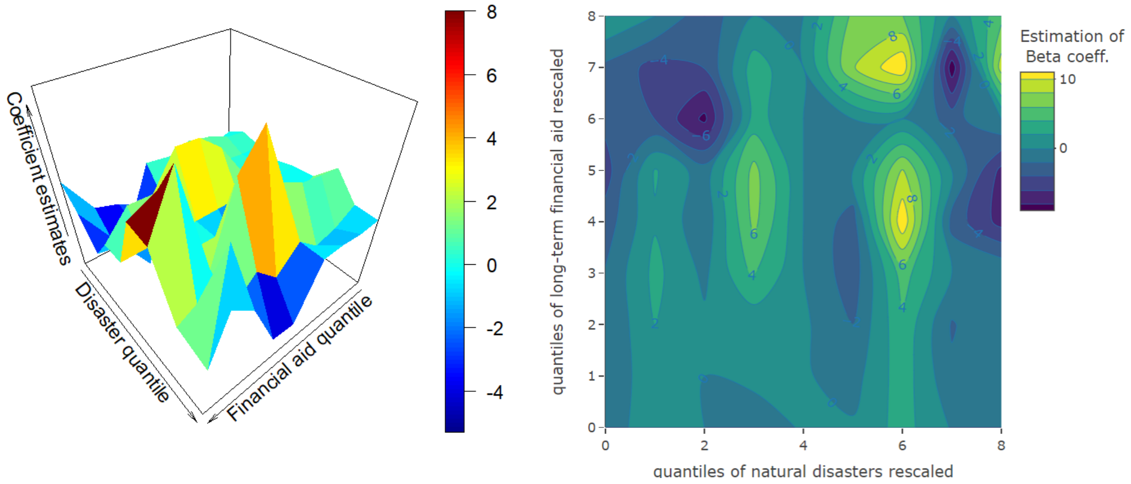
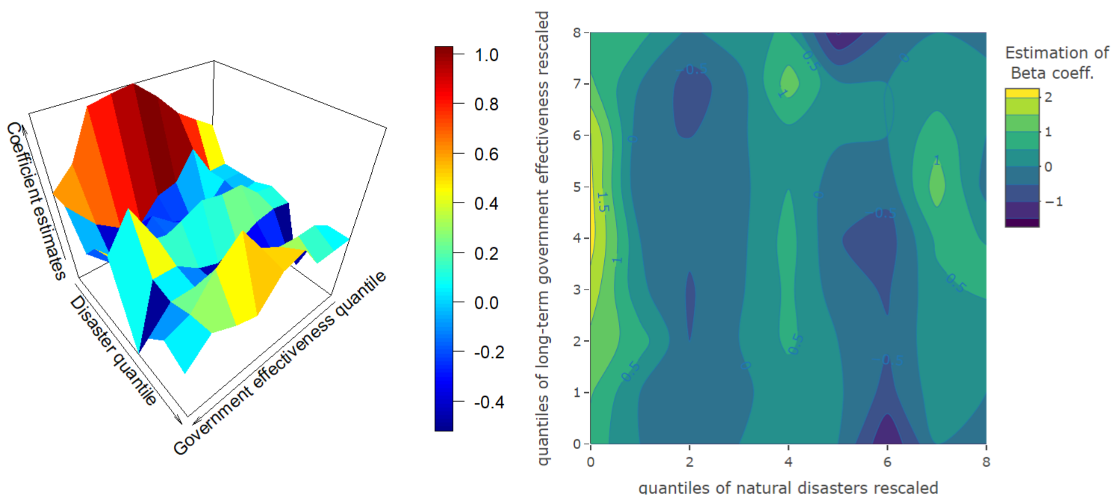


Figure 13: 3D representation of the long-term response of government effectiveness in the aftermath of natural disasters.



3.3 Role of transmission channels

We now examine the role of macroeconomic transmission channels in either mitigating or amplifying the direct negative impacts of natural disasters. To do this, we combine the results of the indirect effects of natural disasters on growth, derived from Equation 12 (see Table Appendix B.1), with the estimates presented in Table 3. Table 4 reports the average direct effects of natural disasters on growth and identifies the variables that attenuate or amplify these negative effects.

The signs of the coefficients in the column "Direct" provide information about how a natural disaster shock affects the growth rate of GDP per capita. They highlight the existence of negative first-round (short-term) effects. Then, after a certain time (medium term), some direct second-round effects may appear, mitigating the initial damage. In the table, the coefficients in the columns "Direct" corresponding to medium-term effects, are indeed smaller in absolute value (but still negative) than those for short-term effects. However, we can see that these improvements are temporary. Indeed, the direct rebound effect on growth disappears in the longer term since the long-term direct effects are even more negative than in the short term. Thus, disaster shocks have a permanent negative direct effect on GDP per capita growth.

The sign of the coefficients in the "Indirect" column indicates which channels mitigate or amplify losses due to natural disasters. Furthermore, the red upward arrows indicate that a given variable amplifies the negative effects of disaster shocks on growth. Conversely, the blue downward arrows indicate the attenuating effect.

We find that government spending, investment, and imports mitigate the impact of shocks over the short to medium term, even if they amplify the negative effects on growth in the long term.

Table 4: Transmission channels as mitigating and amplifying factors after natural disasters

	Short-term		**Medium-term**		**Long-term**	
	Direct	Indirect	Direct	Indirect	Direct	Indirect
Demand-side determinants						
Consumption	−0.131	−0.0001↑	−0.064	0.0005↓	−0.342	0.9985↓
Investment	−0.280	0.0008↓	−0.084	0.0056↓	−0.314	−0.1686↑
Government expenditures	−0.175	0.0003↓	−0.108	0.0166↓	−0.342	−3.4438↑
Exports	−0.227	0.0092↓	−0.083	−0.0008↑	−0.312	−0.1558↑
Imports	−0.267	0.0011↓	−0.053	0.0017↓	−0.309	−1.0714↑
Other determinants						
Fertility	−0.136	0.0003↓	−0.054	−0.0035↑	−0.337	−0.3131↑
Financial aid	−0.213	0.0012↓	−0.096	0.0082↓	−0.320	0.0377↓
Control of corruption	−0.217	0.0005↓	−0.0006	0.0028↓	−0.315	−0.1430↑
Government effectiveness	−0.141	−0.0003↑	−0.117	−0.0096↑	−0.329	−0.2752↑
Financial development	−0.276	0.0000↓	−0.048	0.0014↓	−0.314	0.0817↓
Informality	−0.137	0.0008↓	−0.040	0.0037↓	−0.312	−0.6550↑

Note: This table reports the average effects over all quantiles and for different time horizons. The column "direct" measures the direct effects of natural disasters, while the column "indirect" shows the estimated coefficients of the indirect effects that pass through the control variables. The reported coefficients are statistically significant at the 10% level. Red upward arrows indicate that a given variable amplifies the negative effect of disaster shocks on growth. Conversely, blue downward arrows indicate an attenuating effect.

By contrast, consumption has a stabilizing effect on medium- and long-term growth. However, it amplifies the negative effects of disaster shocks in the short term. An interesting result emerges regarding fertility. In the short term, lower fertility has a positive demand effect. Fewer resources devoted to feeding people increase per capita GDP growth. However, in the medium and long term, changes in this variable affect growth via the supply channel. A drop in the number of workers reduces the economy's productive capacity and causes growth to fall (amplifying the negative effects of shocks). Financial aid and the development of the financial sector have a shock-absorbing effect regardless of the time horizon considered. The effect of the informal economy is twofold. In the short and medium term, its development attenuates the negative impact of shocks on growth but amplifies them in the long term.

3.4 Heterogeneous responses to natural disasters

The results discussed so far focus mainly on the average effects. However, Figures 7 to 9 suggest substantial heterogeneity in growth responses to disaster shocks, depending on the intensity of the shock and the growth regimes of the affected countries. Similarly, Figures 10 to 13 demonstrate significant variation in the responses of macroeconomic and structural variables to disaster shocks. To highlight the heterogeneity of reactions according to the magnitude of shocks and growth regimes, Tables 6 and 7 show estimates of $\hat{\gamma}_{direct}$ and $\hat{\beta}(\theta,\tau)\hat{\eta}(\tau)$ for pairs of (θ,τ) such that $\theta \leq 20\%$ (low growth), $\theta \geq 80\%$ (high growth) and $\tau \leq 20\%$ (small disaster shocks), $\tau \geq 80\%$ (large disaster shocks). In these tables, we indicate which variables have attenuating effects (blue downward arrows) and which have amplifying effects (red upward arrows). To determine whether a variable has an attenuating or amplifying role, we rely on Equation 13. Specifically, we cross the sign of the coefficient $\hat{\beta}(\theta,\tau)$ (reported in the "indirect" column of Tables Appendix B.2 and Appendix B.3) with the sign of the coefficients $\hat{\eta}(\tau)$ (reported in the Tables 5), which captures how growth determinants themselves are influenced by natural disasters. Tables 6 and 7 present several interesting results.

1.-Small-scale natural disasters, in low growth regimes, have a little destabilizing effect on growth when positive resilience effects are sufficiently strong.

When shocks are small in the slow-growth regime (Area I), countries do not experience any negative direct effects on the growth rate of GDP per capita (positive coefficients in the columns capturing direct effects). Therefore, some resilience effects appear almost instantaneously following a disaster and remain so all the time (in the medium and long term). Nonetheless, these beneficial effects diminish over time (the coefficients remain positive but are smaller for the medium and long term than for the short term). When disaster shocks are small, any indirect effects of control variables take time to appear. Indeed, short-term indirect effects are nonexistent (the coefficients are nearly zero).

Looking at indirect effects, when the shocks are of low magnitude and the growth regime is slow (Area I), public spending and consumption in response to shocks reinforce the resilience of growth in the long run. The explanation for this is as follows. Concerning public spending, we see in Table 5 that it is pro-cyclical in the long term in the case of small shocks, in the sense that governments increase their spending in response to natural disasters to reinforce the positive direct resilience effects of growth. Such positive reactions from public authorities are progressive. Indeed, in the table, the response of public spending is almost ten times greater in the long term (the coefficient is 0.037 for small disaster shocks in the long term and 0.004 in the short term). In the case of consumption, although its reaction is counter-cyclical in the long term (see the negative coefficient of -0.104 in Table 5). This counter-effect is small enough not to reverse the positive direct reaction of growth to disasters. Structural variables have virtually no indirect effects in the short and medium term, but they systematically amplify the negative effect of shocks on economic growth (see the last column of Table 7). However, such effects are offset by the positive direct resilience effects of growth.

Thus, as a first conclusion, economies experiencing weak growth episodes are slightly negatively affected by small shocks from natural disasters. These countries bounce back quickly and permanently.

Table 5: Sensitivity of growth determinants to natural disasters by the size of disaster shocks

	Short-term		**Medium-term**		**Long-term**	
	Small	Large	Small	Large	Small	Large
Demand-side determinants						
Consumption	0.001	−0.004	0.019	0.021	−0.104	0.621
Investment	0.003	0.000	0.009	0.017	0.008	−0.196
Government expenditures	0.004	−0.003	−0.004	−0.009	0.037	0.235
Exports	0.009	0.005	−0.010	0.001	0.049	0.420
Imports	0.003	−0.007	−0.006	0.022	0.330	0.915
Other determinants						
Fertility	0.001	−0.012	0.017	0.062	−8.744	1.907
Financial aid	0.302	0.016	0.328	0.084	−3.487	−4.069
Control of corruption	−0.023	−0.007	0.003	0.000	2.643	0.881
Government effectiveness	−0.003	−0.007	−0.011	−0.034	3.072	1.044
Financial development	−0.001	−0.000	0.000	0.005	0.300	0.104
Informality	0.095	−0.017	0.209	0.032	−53.937	−17.359

Note: This table reports the average effect of small ($\tau \leq 20\%$) and large ($\tau \geq 80\%$) disaster shocks on each control variable for different time horizons. The reported coefficients are statistically significant at the 10% level.

2.- Large-amplitude shocks always cause irrecoverable long-term growth losses

Large shocks have persistent negative direct effects over the long term regardless of the growth regime. Economies experiencing rapid growth at the time of a natural disaster are more affected than those experiencing slow growth (see the negative coefficients in the column "direct" of Areas II and IV in Tables 6 and 7).

When we look at indirect effects, few variables have the capacity to mitigate these negative long-term effects. Fertility rates, financial development, and control of corruption are hardly the only variables with downward-oriented arrows in the tables. Moreover, large shocks create volatility in the growth response when the growth is initially rapid. For example, if we look at the direct effects in Area IV of Tables 6 and 7, we can see that the direct effects initially show the resilience of economies in the short and medium terms (positive coefficients), before this effect is offset by very negative effects (negative coefficients). This implies that rapid growth creates a cushioning effect that delays the inevitable negative impact of shocks on growth. When growth is slow, the growth-absorbing effect lasts less long, since the negative reaction of growth is already apparent in the medium-term. In the face of large shocks, demand variables (except for foreign trade variables) moderate the negative effects on medium-term growth. In conclusion, in the face of large-scale natural disasters, growth inevitably slows down (gradually eliminating resilience effects), and these disasters generate major losses over the long term.

Figure 14 shows the following. To benefit from direct short- and medium-term resilience effects when disasters occur, either a low-growth country must be hit by a low-amplitude shock or a country must grow rapidly if a high-amplitude natural disaster occurs. The figure shows that there is no symmetry in the sense that a high-growth country hit by small shocks does not benefit from resilience effects. Moreover, if a small shock initially causes growth in a high-growth country to fall sharply, the country recovers quickly (growth losses are rapidly reduced). But there is a sensitivity to initial conditions, because these losses, which are gradually reduced, never turn into positive factors in the long-term. So, in the end, the somewhat paradoxical result is that countries that benefit from positive effects all the time are slow-growth countries, provided that shocks are of low amplitude. Apart from this, natural disasters always lead to irrecoverable long-term growth losses.

Table 6: Heterogeneous effects across growth regimes and the size of disaster shocks. Control variables: demand components.

	Short-term		**Medium-term**		**Long-term**	
	Direct	Indirect	Direct	Indirect	Direct	Indirect
Area I: ***Small shock in slow growth regime***						
Consumption	3.96	0.00	1.54	$-0.01\uparrow$	1.32	$0.04\downarrow$
Investment	3.96	0.00	1.54	$0.04\downarrow$	1.32	$-0.04\uparrow$
Government expenditures	4.09	0.00	1.55	$-0.01\uparrow$	1.32	$0.02\downarrow$
Exports	3.96	0.00	1.54	$-0.01\uparrow$	1.32	$-0.99\uparrow$
Imports	4.01	0.00	1.53	0.00	1.32	$-1.20\uparrow$
Area II: ***Large shock in slow growth regime***						
Consumption	-0.43	$0.01\downarrow$	-0.62	$0.02\downarrow$	-5.83	$-1.60\uparrow$
Investment	0.00	0.00	-0.60	$0.01\downarrow$	-5.74	$-0.53\uparrow$
Government expenditures	0.00	$0.01\downarrow$	-0.62	$0.03\downarrow$	-5.74	$-0.28\uparrow$
Exports	0.00	$0.08\downarrow$	-1.03	$-0.00\uparrow$	-5.74	$-0.42\uparrow$
Imports	-0.43	$0.00\downarrow$	-0.77	$-0.01\uparrow$	-5.74	$-0.23\uparrow$
Area III: ***Small shock in fast growth regime***						
Consumption	-7.43	0.00	-1.07	$0.03\downarrow$	-1.84	$0.20\downarrow$
Investment	-7.43	0.00	-1.11	$-0.15\uparrow$	-1.84	$-0.09\uparrow$
Government expenditures	-7.42	0.00	-1.49	$0.16\downarrow$	-1.84	$0.13\downarrow$
Exports	-7.43	0.00	-1.06	$0.05\downarrow$	-1.84	$-1.79\uparrow$
Imports	-7.41	0.00	-1.06	$0.00\downarrow$	-1.84	$-2.66\uparrow$
Area IV: ***Large shock in fast growth regime***						
Consumption	1.81	$-0.06\uparrow$	2.67	$0.13\downarrow$	-6.85	$-4.66\uparrow$
Investment	0.59	0.00	1.71	$0.31\downarrow$	-6.77	$-2.01\uparrow$
Government expenditures	1.71	$-0.02\uparrow$	1.98	$0.13\downarrow$	-6.77	$-1.15\uparrow$
Exports	0.65	$0.01\downarrow$	1.71	$0.00\downarrow$	-6.77	$-1.54\uparrow$
Imports	0.63	$-0.00\uparrow$	1.71	$0.03\downarrow$	-6.77	$-1.08\uparrow$

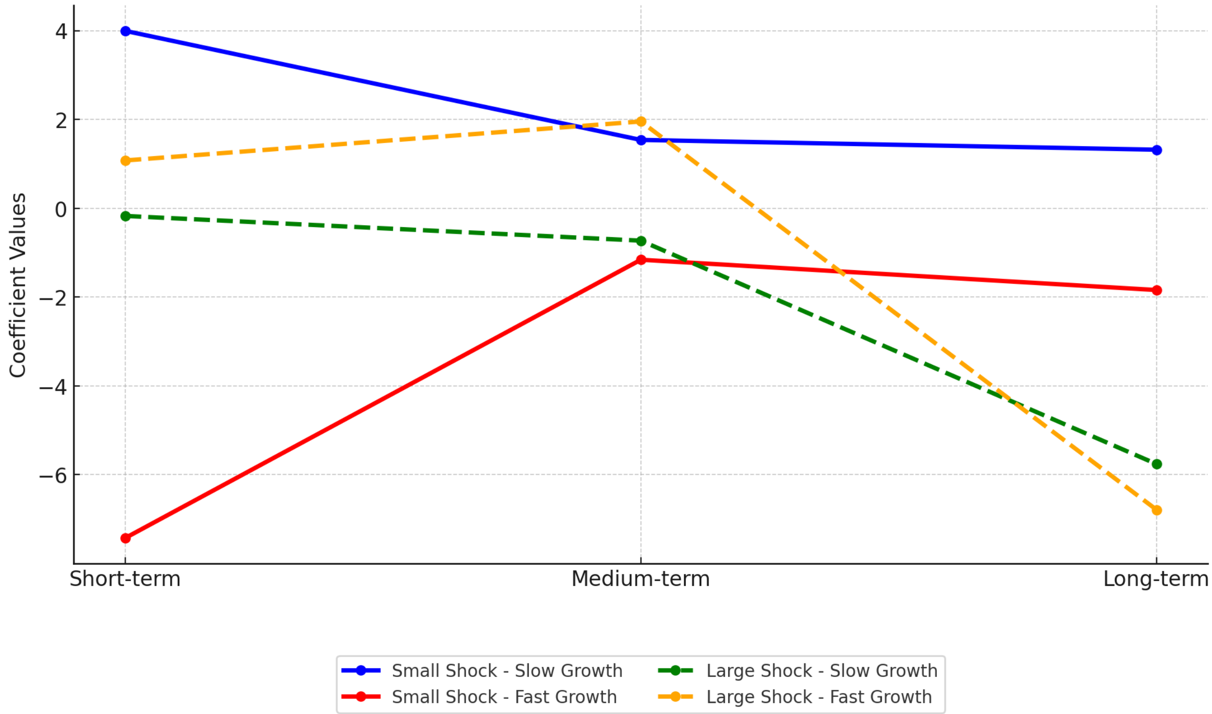
Note: This table reports the average effect over all quantiles and for different time horizons. The reported coefficients are statistically significant at the 10% level. We consider pairs of (θ, τ) such that $\theta \leq 20\%$ (low growth), $\theta \geq 80\%$ (high growth) and $\tau \leq 20\%$ (small disaster shocks), $\tau \geq 80\%$ (large disaster shocks). Red upward arrows indicate that a given variable amplifies the negative effect of disasters shocks on growth. Conversely, blue downward arrows indicate an attenuating effect.

Table 7: Heterogeneous effects across growth regimes and the size of disaster shocks. Control variables : structural variables.

	Short-term		**Medium-term**		**Long-term**	
	Direct	Indirect	Direct	Indirect	Direct	Indirect
Area I: ***Small shock in slow growth regime***						
Fertility	4.01	0.00	1.54	0.00	1.32	$-0.87\uparrow$
Financial aid	4.14	0.00	1.54	$-0.02\uparrow$	1.32	$-0.14\uparrow$
Control of corruption	4.08	0.00	1.54	0.00	1.32	$-0.98\uparrow$
Government effectiveness	3.97	0.00	1.54	0.00	1.32	$-5.59\uparrow$
Financial development	4.01	0.00	1.54	0.00	1.32	$-1.59\uparrow$
Informality	4.01	0.00	1.54	$-0.01\uparrow$	1.32	$1.08\downarrow$
Area II: ***Large shock in slow growth regime***						
Fertility	0.00	0.00	-0.62	$0.01\downarrow$	-5.74	$-0.02\uparrow$
Financial aid	-0.43	0.00	-0.86	$0.01\downarrow$	-5.74	$-0.37\uparrow$
Control of corruption	-0.43	0.00	-0.53	0.00	-5.74	$0.04\downarrow$
Government effectiveness	0.00	0.00	-0.86	$0.02\downarrow$	-5.74	$-0.08\uparrow$
Financial development	0.00	$-0.00\uparrow$	-0.77	$-0.01\uparrow$	-5.74	$-0.02\uparrow$
Informality	0.00	0.00	-0.96	$0.00\downarrow$	-5.74	$-0.35\uparrow$
Area III: ***Small shock in fast growth regime***						
Fertility	-7.41	0.00	-1.12	$0.01\downarrow$	-1.84	$-2.19\uparrow$
Financial aid	-7.39	0.00	-1.49	$0.10\downarrow$	-1.84	$-0.31\uparrow$
Control of corruption	-7.42	0.00	-1.11	$0.00\downarrow$	-1.84	$-2.38\uparrow$
Government effectiveness	-7.43	0.00	-1.45	$0.09\downarrow$	-1.84	$-15.14\uparrow$
Financial development	-7.41	0.00	-1.06	$0.00\downarrow$	-1.84	$-4.03\uparrow$
Informality	-7.41	0.00	-1.06	$0.03\downarrow$	-1.84	$2.70\downarrow$
Area IV: ***Large shock in fast growth regime***						
Fertility	1.76	$-0.02\uparrow$	2.81	$0.11\downarrow$	-6.77	$0.51\downarrow$
Financial aid	0.63	0.00	2.52	$0.00\downarrow$	-6.77	$-1.38\uparrow$
Control of corruption	0.63	0.00	2.81	$0.00\downarrow$	-6.77	$-0.33\uparrow$
Government effectiveness	1.71	$-0.01\uparrow$	1.85	$0.01\downarrow$	-6.77	$-0.46\uparrow$
Financial development	0.59	0.00	1.71	$0.04\downarrow$	-6.77	$0.01\downarrow$
Informality	1.78	$-0.05\uparrow$	2.81	$0.04\downarrow$	-6.77	$-1.22\uparrow$

Note: See note Table 6.

Figure 14: Dynamics of Direct Effects from Short to Long-term by growth regimes



Source: Author's calculations.
Notes: This graph shows the dynamics of the direct effects (coefficients of column "Direct" of tables 6 and 7) from the short term to the long term for each growth regime-shock size combination.

4 Conclusion

The main lesson to be learned from this paper is that we need to be cautious about drawing conclusions from research that studies the consequences of natural disaster shocks based on average effects, and on an exclusively temporal approach to capture short-, medium- and long-term effects. Low-growth and high-growth countries do not react in the same way to shocks. Nor do high and low-intensity natural disasters have the same effects. Averaging these heterogeneous reactions likely contributes to the inconsistent conclusions (found in previous studies) on the overall impact of natural disasters on growth, and obscures the differentiated and complex ways countries react to natural disasters.

Measuring the long term in the time domain, for example, using models with staggered lags on the shock variables, implies by construction, a gradual attenuation of the effects of disasters, since growth is a stationary process. However, by doing this, we run the risk of minimizing the effects of the persistence of shocks and overestimating the effects of resilience. Wavelet decomposition allows us to avoid making restrictive assumptions about mean-reverting growth phenomena. An interesting result is that, when we do not impose a particular shape on the dynamic response of growth to disasters, these can induce irreversible effects in the long term.

The important message of our paper is that, when we are interested in measuring the effect of disasters on growth, it is interesting to have an approach based on the joint distribution of growth and disaster shocks, or of control variables and these same shocks. This means that the impact coefficients vary and depend on the location of the observations in the joint distribution. This is the whole point of using double quantiles. Our paper has shown that the results are not the same depending on whether we are at the extremes or more at the center of the distributions (around the mean), but especially all the extreme counts (those of the disaster shocks and those of the growth variable).

This paper could be extended in several ways.

First, the results obtained here concern developing countries, which are particularly affected by natural disasters. More detailed information than the GDP growth rate could be used to take greater account of the spatial dimension of the problem. Natural disasters affect specific territories (and rarely an entire country), which means that the information of interest is to understand how these shocks affect the activities of certain territories. We could, for example, use satellite data measuring the degree of luminosity of human activities, instead of the GDP growth rate.

Second, it would be interesting to take the wavelet approach further. The different components (short-, medium- and long-term) of the same shock capture phenomena, some of which are temporary in nature, while others have structural causes. For example, the temporary factors that trigger a short-term cyclone are linked to meteorological phenomena between the topics and the equator (warming of ocean water and strong humidification of the air, and condensation that occurs as the air rises in altitude). The long-term components capture weather phenomena that occur over longer time scales (increased frequency of cyclonic winds and lasting changes to the ocean water cycle). An interesting question is therefore to identify the instruments that could be used to mimic the different components.

Third, it would be interesting to decompose the panel of country GDPs into a global component, which is common to all countries, and an idiosyncratic component. In this way, we could find out whether the heterogeneity captured by the quantiles reflects different growth responses to natural disasters from one country to another or differences over different years.

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Appendix A Short-, medium- and long-term : identification through wavelet analysis

This appendix provides a short description of the way we filter out the short, medium and long(term components in growth and macroeconomic variables series.

We perform a multi-resolution decomposition by applying J-level wavelet filters to growth and macroeconomic time series (for each country). For a detailed presentation of wavelet analysis, we refer the reader to Percival and Walden, 2006. Here, we simply sketch the main principles of the approach with an illustration of one country of our sample.

Define $\mathbf{y} = \{y_t\}_{t=1}^{T}$, i.e. a time series of lenght T with the assumption that $T = 2^M$ (the series is dyadic). The principle of wavelet decomposition is to go beyond the standard Fourier decomposition, which only gives indications of the frequency content of a series. The aim is to exploit both the temporal and frequency properties of observations in the $\mathbf{y}$ series. Assume that the dgp (data-generating process) of the observations is continuous, and let us denote it $\mathbf{Y} = \{Y(t)\}_{t\in\mathbb{R}}$.

As we are only observing discrete realizations of the dgp of the variable Y, we are interested here in the discrete wavelet transform of $Y(t)$. It is written as the sum of two components $Y(t) = Y^1(t) + Y^2(t)$, where

$$\begin{aligned} Y^1(t) &= \sum_{k=-\infty}^{\infty} \alpha_j(k) 2^{-j/2} \phi(t2^{-j} - k), \\ \alpha_j(k) &= \langle Y(t), \phi_k(t) \rangle = \int Y(t)\phi(t-k)dt, \end{aligned} \tag{B1}$$

$$\begin{aligned} Y^2(t) &= \sum_{k=-\infty}^{\infty} \beta_j(k) 2^{-j/2} \psi(t2^{-j} - k), \\ \beta_j(k) &= \langle Y(t), \psi_k(t) \rangle = \int Y(t)2^{j/2}\psi(2^{j/2}t - k)dt. \end{aligned} \tag{B2}$$

In a multi-resolution analysis, j represents different scales. Here we assume $j = 1, ..., M$. The functions ϕ and ψ are called father and mother wavelets respectively (there are many in the literature. see for example Ngui et al., 2013, for a presentation of wavelet selection). For $j = 1$, one splits the frequencies into two parts: low frequencies on the interval $[0, \pi]$ and high frequencies on the interval $[\pi, 2\pi]$. The amount of information returned by the first sub-interval is provided by the father wavelet (i.e. by $Y_1(t)$ and the scaling coefficient $\alpha_j(k)$). That returned by the second sub-interval is given by the wavelet coefficient $\beta_j(k)$. For $j = 2$, we repeat the same operation, splitting the first sub-interval into two ($[0, \pi/2]$ and $[\pi/2, \pi]$). On each sub-interval, we calculate the scaling and wavelet coefficients. The same procedure is followed for the interval $[\pi, 2\pi]$. And so forth by increasing the value of j.

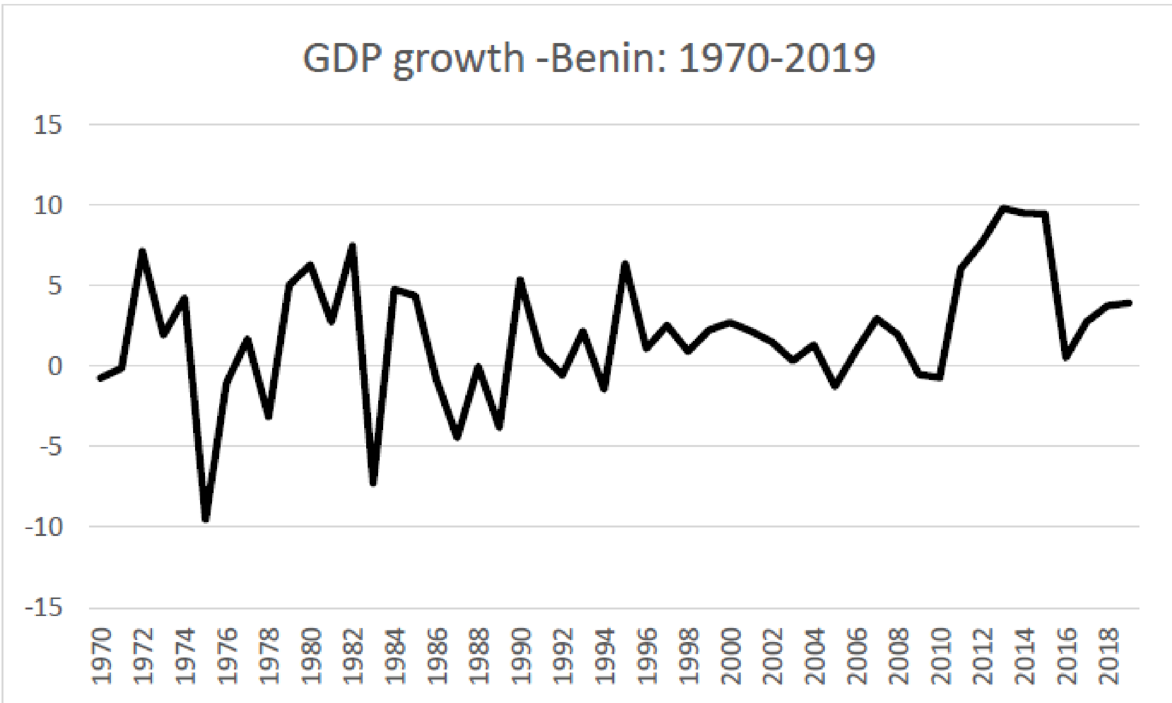
Our aim is to filter out the various components of the growth rate series and the macroeconomic variables corresponding to different time horizons (short, medium, long). For the decomposition, we use the so-called Mallat algorithm, which allows us to decompose the time series, then reconstruct them from the estimated wavelet and scaling coefficients. We now illustrate the method using growth rate data for one of our sample countries, Benin.

We consider the growth rate of per-capita real GDP. We take the GDP in constant price of 2017 national prices from Penn World Tables database (rgdpna from PWT 10.1). we consider the size of population in millions from the same data base. The growth rate is defined as the first difference of log of real GDP over population (in percent), from 1970 to 2019. The frequency of data is annual.

Figure Appendix A.1 shows the evolution of the growth rate since 1970. The series shows fluctuations, irregular in both amplitude and periodicity. Figure Appendix A.2 shows the various components extracted using Daubechies wavelet basis functions and

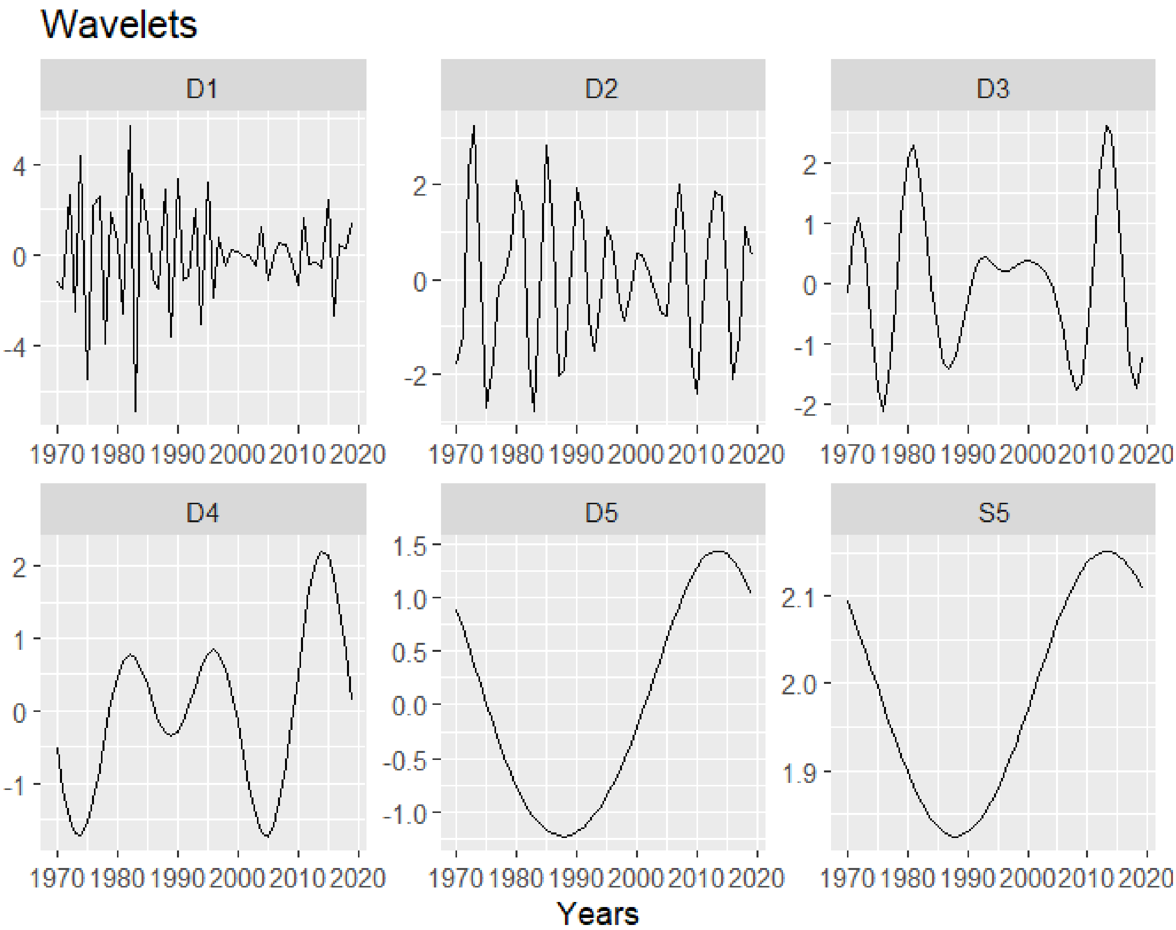
MODWT with $j = 1, ..., 5$. For $j = 1$ ($D1$), the component corresponds to very short-term fluctuations, which can be considered here as noise. For $j = 2$ ($D2$), variations of varying amplitude are repeated every 5 years or so. For $D3$ and $D4$, cycles of between 5 years and 10 years are observed. For $D5$, the periodicity is around twenty years. The smoothest component of the original series is detected for $j = 5$ and has the same periodicity as the long cycle of 20 years. We measure the short-, medium- and long-term components respectively by the $D2$ component (quasi-periodic variations of 5 years), the $D4$ component (fluctuations whose periodicity varies between 5 and 10 years) and the $D5$ component (20-year cycle). A similar analysis of the other countries in the sample leads to similar conclusions regarding the identification of the various components.

Figure Appendix A.1: Original time series



Source: Author’s estimates.

Figure Appendix A.2: Main components of the growth series for Benin



Source: Author's estimates.

Appendix B Quantile-on-quantile approach

Appendix B.1 Estimation of equation 7

$$
\begin{aligned}
g_{i,t}^{\lambda}(\theta,\tau) &= \alpha_0(\theta,\tau) + \gamma(\theta,\tau)[{}_qD_{i,t} - {}_qD_{i,t}^{\tau}] + \beta(\theta,\tau)\int_{\mu}\hat{X}_{i,t}^{\lambda}(\mu,\tau)d\mu + \epsilon_{i,t}^{\lambda}(\theta,\tau),\\
\hat{X}_{i,t}^{\lambda}(\mu,\tau) &= \hat{a}_0(\mu,\tau) + \hat{\omega}(\mu,\tau)[{}_qD_{i,t} - {}_qD_{i,t}^{\tau}] + \nu_{i,t}^{\lambda}(\mu,\tau),\\
(\hat{\alpha}_0(\theta,\tau),\hat{\gamma}(\theta,\tau),\hat{\beta}(\theta,\tau)) &= argmin\left\{\rho_\theta(\epsilon_{i,t}^{\lambda}(\theta,\tau)\right\}\left\{K\left(\frac{F_n({}_qD_{i,t})-\tau}{h}\right)\right\},\\
\rho_\theta(\epsilon_{i,t}^{\lambda}(\theta,\tau)) &= \sum_{\epsilon_{i,t}^{\lambda}(\theta,\tau)>0}\theta|\epsilon_{i,t}^{\lambda}(\theta,\tau)| + \sum_{\epsilon_{i,t}^{\lambda}(\theta,\tau)<0}(1-\theta)|\epsilon_{i,t}^{\lambda}(\theta,\tau)|,\\
(\hat{a}_0(\mu,\tau),\hat{\omega}(\mu,\tau)) &= argmin\left\{\rho_\mu(\nu_{i,t}^{\lambda}(\mu,\tau)\right\}\left\{K\left(\frac{F_n({}_qD_{i,t})-\tau}{h}\right)\right\},\\
\rho_\mu(\nu_{i,t}^{\lambda}(\mu,\tau)) &= \sum_{\nu_{i,t}^{\lambda}(\mu,\tau)>0}\mu|\nu_{i,t}^{\lambda}(\mu,\tau)| + \sum_{\nu_{i,t}^{\lambda}(\mu,\tau)<0}(1-\mu)|\nu_{i,t}^{\lambda}(\nu,\tau)|,
\end{aligned}
\tag{B3}
$$

where

$$
\nu_{i,t}^{\lambda}(\mu,\tau) = \hat{X}_{i,t}^{\lambda} - \hat{a}_0(\mu,\tau) - \hat{\omega}(\mu,\tau)[{}_qD_{i,t} - {}_qD_{i,t}^{\tau}]. \tag{B4}
$$

Appendix B.2 Direct and indirect average effects of natural disasters on economic growth

Table Appendix B.1: Direct and indirect average effects of natural disasters on economic growth

	Short-term		**Medium-term**		**Long-term**	
	Direct	Indirect	Direct	Indirect	Direct	Indirect
Demand-side determinants						
Consumption	−0.131	0.326	−0.064	0.065	−0.342	5.053
Investment	−0.280	0.756	−0.084	1.326	−0.314	2.451
Government expenditures	−0.175	0.679	−0.108	−6.132	−0.342	−76.36
Exports	−0.227	5.429	−0.083	0.215	−0.312	−3.884
Imports	−0.267	−0.605	−0.053	0.337	−0.309	−3.847
Other determinants						
Fertility	−0.136	−0.055	−0.054	0.367	−0.337	0.184
Financial aid	−0.213	0.012	−0.096	0.096	−0.320	0.026
Control of corruption	−0.217	0.382	−0.0006	0.302	−0.315	−0.251
Government effectiveness	−0.141	0.226	−0.117	−0.707	−0.329	−0.424
Financial development	−0.276	−0.949	−0.048	0.715	−0.314	−2.122
Informality	−0.137	0.031	−0.040	0.084	−0.312	0.189

Note: This table reports the average effect over all quantiles and for different time horizons. The column "direct" measures the direct effects of natural disasters, while the column "indirect" shows the estimated coefficients of the indirect effects that pass through the control variables. The reported coefficients are statistically significant at the 10% level

Table Appendix B.2: Heterogeneous effects across growth regimes and the size of disaster shocks.

	Short-term		**Medium-term**		**Long-term**	
	Direct	Indirect	Direct	Indirect	Direct	Indirect
Area I: ***Small shock in slow growth regime***						
Consumption	1.16	−4.48	0.63	−0.12	0.87	4.84
Investment	1.16	−0.88	0.63	1.20	0.87	−2.46
Government expenditures	1.19	3.81	0.63	0.41	0.87	−3.31
Exports	1.16	−1.59	0.63	0.20	0.87	−10.52
Imports	1.17	−6.23	0.62	0.05	0.88	−6.74
Area II: ***Large shock in slow growth regime***						
Consumption	−0.72	0.28	−0.53	0.24	−1.52	2.97
Investment	−0.64	3.12	−0.53	0.08	−1.48	4.73
Government expenditures	−0.64	−0.86	−0.53	−0.77	−1.48	−114.39
Exports	−0.64	4.99	−0.56	−0.22	−1.37	1.60
Imports	−0.72	−0.87	−0.46	−0.08	−1.48	0.73
Area III: ***Small shock in fast growth regime***						
Consumption	−1.66	1.85	−0.10	4.84	0.52	9.01
Investment	−1.66	0.20	−0.08	−0.39	0.52	−3.07
Government expenditures	−1.61	0.73	−0.18	−5.91	0.52	−5.57
Exports	−1.66	0.18	−0.06	−1.17	0.52	−11.67
Imports	−1.66	2.99	−0.07	1.52	0.54	−11.21
Area IV: ***Large shock in fast growth regime***						
Consumption	0.74	2.22	−0.10	−3.78	−0.87	3.68
Investment	0.19	0.36	−0.19	3.78	−0.81	8.19
Government expenditures	0.47	−0.13	−0.18	−14.78	−0.90	−149.32
Exports	0.36	14.47	−0.17	1.68	−0.89	2.20
Imports	0.29	0.32	−0.14	−0.09	−0.81	0.23

Note: This table reports the average effect over all quantiles and for different time horizons. The coefficients reported are significant at least at the 10% level of significance. Low shocks are defined as disaster intensities below the median intensity and large shocks as disaster intensities equal to and above the median intensity, respectively. Slow growth regimes are defined as growth rates below the median growth rate, and fast growth regimes are defined as growth rates equal to or above the median growth rates.

Table Appendix B.3: Heterogeneous effects across growth regimes and the size of disaster shocks.

	Short-term		**Medium-term**		**Long-term**	
	Direct	Indirect	Direct	Indirect	Direct	Indirect
Area I: ***Small shock in slow growth regime***						
Fertility	1.17	0.34	0.63	−0.01	0.87	0.08
Financial aid	1.20	−0.03	0.63	−0.01	0.87	−0.05
Control of corruption	1.19	2.45	0.63	−0.03	0.87	−0.72
Government effectiveness	1.16	1.11	0.63	0.01	0.86	−0.79
Financial development	1.17	−2.64	0.63	0.08	0.87	−3.12
Informality	1.17	−0.10	0.63	−0.02	0.87	0.26
Area II: ***Large shock in slow growth regime***						
Fertility	−0.64	0.00	−0.53	0.03	−1.52	0.16
Financial aid	−0.57	0.07	−0.59	0.02	−1.47	0.07
Control of corruption	−0.57	−0.16	−0.41	0.00	−1.48	0.40
Government effectiveness	−0.49	−0.10	−0.59	−0.10	−1.48	0.02
Financial development	−0.64	−1.07	−0.46	−0.54	−1.48	−0.67
Informality	−0.64	−0.36	−0.53	0.02	−1.47	0.03
Area III: ***Small shock in fast growth regime***						
Fertility	−1.66	−1.04	−0.11	0.30	0.52	0.11
Financial aid	−1.61	−0.01	−0.18	0.07	0.52	−0.09
Control of corruption	−1.62	−0.25	−0.08	−0.86	0.52	−1.18
Government effectiveness	−1.66	−0.05	−0.18	−2.48	0.48	−1.06
Financial development	−1.66	−1.05	−0.07	0.68	0.52	−4.59
Informality	−1.66	0.05	−0.06	0.01	0.52	0.47
Area IV: ***Large shock in fast growth regime***						
Fertility	0.64	0.43	−0.06	0.94	−0.85	0.33
Financial aid	0.29	0.01	−0.10	0.25	−0.83	0.14
Control of corruption	0.29	0.00	−0.02	1.69	−0.81	0.27
Government effectiveness	0.52	0.14	−0.17	−0.24	−0.81	−0.04
Financial development	0.19	0.31	−0.13	2.16	−0.81	−0.68
Informality	0.64	0.41	−0.06	0.26	−0.81	0.05

Note: See note in Table Appendix B.2

Appendix C Data Appendix

Table Appendix C.1: Variable, description and data source

Variable	Description	Source
Economic growth	Growth of the log of real GDP per capita (in %)	PWT 10.01
Household consumption	Share of household consumption at current PPPs	PWT 10.01
Investment	Share of gross capital formation at current PPPs	PWT 10.01
Government expenditure	Share of government consumption at current PPPs	PWT 10.01
Exports	Share of merchandise exports at current PPPs	PWT 10.01
Imports	Share of merchandise imports at current PPPs	PWT 10.01
Fertility	Total fertility rate adjusted for under-5 mortality rate	WDI
Financial Aid	Net official development assistance and official aid received (% GDP)	WDI
Corruption	Control of Corruption	WGI
Governance	Government Effectiveness	WGI
Financial development	Financial Development Index	IMF
Informal economy	DGE model-based estimates of informal output (% of official GDP)	Elgin et al. (2019)