INTERNATIONAL MONETARY FUND

The Growth Effects of Natural Disasters

Evidence From A Novel Global Dataset Over 1970-2023

Ha Nguyen, Mehdi Raissi, Bruno Versailles and Alice Tianbo Zhang

WP/26/106

2026
JUN

WORKING PAPER

WP/26/106

IMF Working Paper
Strategy, Policy and Review Department

The Growth Effects of Natural Disasters: Evidence From A Novel Global Dataset Over 1970-2023

Prepared by Ha Nguyen, Mehdi Raissi, Bruno Versailles and Alice Tianbo Zhang

Authorized for distribution by Eugenio Cerutti
June 2026

ABSTRACT: We construct standardized climate anomalies from daily observations and carefully calibrate physical thresholds to identify storms, floods, droughts, heatwaves, and cold snaps across 196 countries over the period 1970–2023. Using a local projections framework, we estimate the contemporaneous and 2-year effects of each disaster type and collectively on real GDP growth. We find that storms, floods, droughts, and heatwaves significantly reduce growth on impact (by roughly 0.1–0.2 percentage points on average), with the largest effects observed in emerging markets and developing economies. Cold spells have no statistically significant impacts. Our estimations also indicate that the initial drop in GDP growth is often not fully offset by a quick rebound, leaving GDP below the pre-disaster trend in the subsequent two years. Severe disasters impose far larger costs. Catastrophic floods can lower growth by up to 3 percentage points (with once-in-100-year storms or heatwaves reducing growth by ~0.5pp and extreme droughts by ~1pp). By combining the estimated global coefficients with each country's own disaster intensity statistics, we translate the aggregate results into localized growth effects and cross-check them against estimates from a dynamic heterogenous panel model. Finally, rolling-window estimates indicate that the contemporaneous growth impact of storms and heatwaves has attenuated in recent decades, whereas droughts have become increasingly damaging, reflecting divergent adaptation and vulnerability trends over time.

RECOMMENDED CITATION: Nguyen, H., Raissi, M., Versailles, B., & Zhang, A. T. (2026). The Growth Effects of Natural Disasters: Evidence From A Novel Global Dataset Over 1970-2023. IMF Working Paper No. WP/26/106. International Monetary Fund

JEL Classification Numbers:	C23, O44, Q54
Keywords:	Local Projections; Natural Disasters; Economic Growth
Author's E-Mail Address:	Hnguyen7@imf.org, mraissi@imf.org, bversailles@imf.org, azhang@imf.org

WORKING PAPERS

The Growth Effects of Natural Disasters:

Evidence From a Novel Global Dataset Over 1970-2023

Prepared by Ha Nguyen, Mehdi Raissi, Bruno Versailles and Alice Tianbo Zhang[1]

---

[1] We are grateful to Bruno Albuquerque, Hasan Dudu, Emanuele Massetti, Gregor Schwerhoff, Dulani Senevirante, Balazs Stadler, and seminar participants at the IMF for helpful comments and suggestions.

Contents

1. Introduction

Natural disasters are increasingly recognized as critical macroeconomic shocks. A substantial body of empirical research has examined their macroeconomic consequences (Mitra et al. 2025), with studies offering mixed conclusions. Skidmore and Toya (2002) suggested that frequent natural disasters might spur long-run growth through capital renewal and institutional reform. Subsequent analyses, including Noy (2009) and Raddatz (2007), documented significant negative short-run growth effects, especially in low-income countries and small island economies. More recent work has emphasized the importance of disaster type, intensity, and country-specific characteristics. Loayza et al. (2012) and Fomby, Ikeda, and Loayza (2013) found that droughts and earthquakes tend to lower growth, while moderate floods may have short-term positive effects. Felbermayr and Gröschl (2014) advanced the literature by introducing physically measured disaster intensity indicators, demonstrating that natural disasters reduce GDP per capita growth, with the magnitude of impact mitigated by institutional quality and trade openness. Felbermayr et al. (2022) used night-light data to reveal how local weather extremes affect spatially disaggregated economic indicators, highlighting effects often overlooked in country-level aggregation. Botzen et al. (2019) provide a comprehensive synthesis of theoretical, computational, and empirical studies, concluding that natural disasters cause substantial direct economic losses (such as property damage in high-income countries and fatalities in low-income ones) and that indirect macroeconomic effects, while generally negative, tend to be more severe in less-diversified, lower-income economies.[2]

Despite these advances, much of the literature continues to rely on the Emergency Events Database (EM-DAT), maintained by the Centre for Research on the Epidemiology of Disasters (e.g., Nguyen et al., 2025). While EM-DAT has been key to cataloging global disaster events, its use in growth regressions presents several limitations. First, EM-DAT relies on reported damages and event declarations, which vary widely across countries and over time. This leads to underreporting smaller-scale or slow-onset disasters, such as heatwaves and droughts, that may not trigger formal emergency declarations but still exert significant macroeconomic costs. Second, damage estimates are often based on insurance claims or government reports, potentially introducing bias: richer countries with better reporting infrastructure may appear more affected than poorer ones with limited data. Third, EM-DAT lacks standardized measures of disaster intensity, making it difficult to assess severity or compare events across countries.

To address these data gaps, several studies use climate anomalies and physical thresholds to construct more comparable measures of non-geological natural disasters. This approach reduces endogeneity concerns in disaster-growth regressions and allows for more precise macroeconomic impact estimates. However, the choice of thresholds— ranging from absolute values (e.g., precipitation exceeding X mm) to percentile-based cutoffs (e.g., temperature anomalies above the 95th percentile or exceeding two standard deviations of the respective weather distributions)— introduces methodological complexity, including whether they should be common across countries. Akyapı, Bellon, and Massetti (2025) construct hundreds of such variables from high-frequency, high-spatial-resolution weather observations and use machine learning (LASSO) to identify a subset of extreme weather variables that drive economic

---

[2] Moreover, Klomp and Valckx (2014) conduct a meta-analysis of the growth effects of natural disasters based on 25 primary studies. They conclude that natural disasters have a significant negative effect on growth, an effect that has intensified over time and is strongest for climatic disasters in developing countries. Moreover, there are significant short-run declines in economic growth for climatic and geological disasters for which long-run effects are insignificant. Hydrometeorological disasters are found to reduce growth in both the short and long run.

outcomes. They estimate that severe heat and drought could reduce annual GDP growth by roughly 0.2pp per standard deviation of extreme weather (while more mild temperatures boost growth). Our approach deliberately avoids the proliferation of disaster indicators that can arise from different threshold choices. Specifically, we rely on a parsimonious set of five disaster types, each defined using standardized, locally calibrated thresholds that reflect country-specific weather distributions.

We contribute to the literature by constructing the Global Standardized Weather Anomalies Dataset (G-SWAD), a novel global panel dataset of standardized weather anomalies from daily observations and using carefully calibrated physical thresholds to identify five major disaster types, namely storms, floods, droughts, heatwaves, and cold spells, spanning 196 countries over the period 1970–2023. By using physical thresholds derived from each country's historical distribution of weather anomalies with time-varying climate norms, we ensure a measure of disaster intensity that is comparable across countries and hazard types (all expressed in standard deviations). Leveraging G-SWAD and a local projections framework, we estimate the contemporaneous and 2-year effects of each disaster type on year-on-year real GDP growth (and cumulative GDP over 2 years), controlling for lagged output growth and fixed/time effects. Our findings reveal that storms, floods, droughts, and heatwaves have economically meaningful short-term effects on GDP growth, both on average and in extreme cases, with the most pronounced effects observed in emerging markets and developing economies (EMDEs). Specifically, storms, droughts, and heatwaves each significantly reduce contemporaneous GDP growth, with average one-year impacts on the order of –0.1 to –0.2 percentage points (pp). Floods and cold snaps, by contrast, exhibit negligible average effects on growth (cold events are statistically insignificant). However, severe disasters impose far larger GDP losses: a once-in-100-year storm or heatwave is associated with roughly a –0.5pp hit to GDP growth, an extreme drought about –1pp, and a catastrophic flood around –3pp. Felbermayr and Gröschl (2014), likewise find natural disasters significantly suppress growth with the worst 5% of disaster events in their data cause about a –0.5pp GDP per capita growth drop.

By combining the estimated homogenous panel coefficients with each country's own disaster intensity statistics, we translate the results into localized growth effects. For example, given a homogenously-estimated storm coefficient of –3.66, a country experiencing an average storm index of 0.05 would be expected to suffer a 0.18pp growth reduction from storms that year. Summing across disaster types yields an annual, country-by-country tally of the total growth drag from extreme weather events, providing policymakers a practical tool to gauge their economy's vulnerability. Importantly, a robustness check using a dynamic heterogeneous panel model (i.e., using the Trimmed Mean Group estimator, allowing each country to have its own disaster coefficient) confirms our baseline results. The similarity between the pooled and heterogeneous estimates suggests that the average short-run growth effect remains relatively robust across various estimation approaches, despite significant differences in mechanisms and vulnerabilities among countries. These results reinforce the conclusions of prior studies such as Felbermayr and Gröschl (2014) and Usman et al. (2025) and extend the literature by incorporating underexplored hazards and providing a unified empirical framework for assessing their consequences.

Our rolling-window estimations reveal that the macroeconomic impact of disasters has evolved over time, reflecting adaptation and changing vulnerabilities. Contemporaneous growth damages from storms and heatwaves have attenuated in recent decades. The immediate effect of storms, initially negative in earlier decades, has become progressively less severe and even turned slightly positive by the early 2000s, while heatwave impacts, though still negative, have also diminished over time. This result is consistent with the findings of Akyapi, Bellon, and Massetti (2025) and is likely explained by (i) higher penetration of air conditioning, and (ii) sectoral shift from agriculture to less heat sensitive sectors. In contrast, droughts have become increasingly damaging: their contemporaneous growth effect has strengthened in recent decades, implying rising vulnerability to water scarcity and limited efficacy of adaptation in agriculture (or even arguably maladaptation) and water-intensive sectors. These heterogeneous time patterns indicate that societies have reduced their sensitivity to some hazards but not others, highlighting the need for hazard-specific resilience strategies.

By exploiting daily weather and climate data and continuous, intensity-based indicators in G-SWAD, we can trace the GDP response to disasters of varying severity within a unified framework over time. This is particularly important for slow-onset and recurrent hazards, such as droughts and heatwaves, that may not trigger formal disaster declarations (and appear in EM-DAT) but can depress economic activity over time. Our results indicate moderately persistent impacts for some disasters, especially in EMDEs, where local projections reveal growth remains below pre-disaster rates for up to two years, a result further corroborated by impulse responses from our dynamic heterogeneous panel estimates over 5 years.

The remainder of the paper is structured as follows. In Section 2, we describe our database and explain the estimation methodology. Section 3 outlines our findings and includes a robustness check with a dynamic heterogeneous panel model. Section 4 focuses on rolling-window estimates and explores how disasters affect agricultural value added. The conclusion is provided in Section 5.

2. Methodology

2.1 Data (G-SWAD)

Our analysis constructs a novel dataset, the Global Standardized Weather Anomalies Dataset (G-SWAD), of daily climate observations from 1940–2023, processed to identify extreme weather events in 196 countries between 1970 and 2023 (see Appendix I. for details). We obtain population weighted daily data on temperature, precipitation, and wind speed from ERA5 (accessed via the *Weighted Climate Data* platform of Gortan et al. 2024 using the 2015 population weights). The panel thus consists of country-day observations of max temperature, precipitation, and maximum wind speed (gust), which are then transformed into country-year natural disasters indicators as described below. The dependent variable in our regressions is winsorized real GDP growth (where top and bottom 1% growth outliers are replaced).[3]

Standardized Climate Anomaly Computation

For each country and each calendar day, we compute a standardized climate anomaly for each variable. This is defined as the deviation of that day's observed value from the preceding 30-year moving average for the same day-of-year (the climatological norm), divided by the 30-year standard deviation. Formally, if $aC_{d,t}$ is the actual value of climate variable C on day d of year t, and $\bar{C}^{(30)}{}_{d}$ *and* $\sigma^{(30)}{}_{d}$ are the mean and standard deviation of that variable over the preceding 30 years for that calendar day, then the standardized weather anomaly is:

---

[3] GDP growth includes substantial outliers in the raw data. Over the period 1970-2023, the minimum and maximum annual growth rates are -64.0 percent and 838.4 percent, respectively, while the 1st and 99th percentiles are -16.8 percent and 23.6 percent. These extreme observations (2 percent of observations) are typically associated with non-climatic events such as post-conflict rebounds, hyperinflation episodes, or major structural breaks. In our specification, we winsorize GDP growth at the 1st and 99th percentiles to prevent a small number of extreme episodes from exerting disproportionate influence on the local projection estimates. Relative to the baseline results in Figure 1, retaining extreme growth realizations materially alters the dynamic profiles for drought and cold and modestly changes the magnitude of the heat response, whereas storms and floods remain broadly similar.

$$sC_{d,t} = \frac{aC_{d,t} - \bar{C}^{(30)}{}_{d}}{\sigma^{(30)}{}_{d}}$$

This transformation expresses all variables in units of standard deviations from the mean, making them *comparable across countries and variables*. We update the 30-year baseline each year (rolling window) so that anomalies reflect information available up to that point (e.g., the anomaly for a day in 1990 is relative to 1960–1989). This is, arguably, an improvement over the current practice of keeping the reference period fixed in the literature (e.g., as in Felbermayr et al, 2022). Our analysis begins in 1970 because a full 30-year history (back to 1940) is required to compute the initial anomalies. By using a moving climatology, we also account for the gradual change in climate, or the "norm". See Kahn et al. (2021), Mohaddes et al. (2023), Mohaddes and Raissi (2025), and Centorrino et al. (2026) for details.

All climate variables are first aggregated to the country level by averaging daily grid-point data weighted by population (using the 2015 population numbers). This ensures that the weather anomalies are most reflective of conditions experienced in populated areas. The result of the above steps is a country-by-day panel of standardized climate anomalies for each variable (temperature, precipitation, wind speed).

The use of a rolling 30-year climatological baseline is motivated not only by climatological best practice but also by economic considerations. Economic agents such as households, firms, and governments form expectations and make decisions based on recent climatic norms rather than fixed historical benchmarks. Defining extreme events relative to a time-varying baseline therefore captures unexpected shocks to economic activity, rather than predictable seasonal or secular trends. Similarly, population-weighted aggregation ensures that the constructed anomalies reflect weather conditions experienced where economic activity, capital, and labor are concentrated, rather than sparsely populated regions. These choices enhance the economic interpretability of the disaster indicators and reduce measurement errors in linking extreme weather events to macroeconomic outcomes.

Construction of Annual Natural Disaster Indicators

Using the daily standardized climate anomalies, we construct five annual natural disaster indicators — one for each type of extreme weather event considered: storms, floods, droughts, heatwaves, and cold snaps. Each indicator measures the annual-average intensity of extreme anomalous events of that type in a given country-year. Importantly, "extreme" is defined relative to each country's own weather anomalies distribution, and we impose minimum duration criteria for phenomena that unfold over multiple days (e.g., floods, heatwaves, cold snaps) to ensure that we capture sustained events. Below we detail the definition of each disaster indicator and the threshold used to identify an event. The table at the end of this section (Table 1) summarizes these definitions in formula form for reference.

- **Storms (Severe Windstorms):** A "storm" day is defined by a daily maximum wind gust exceeding the mean plus one standard deviation of the Tropical Storm distribution (wind speed 18-32m/s). There is little overlap between the distribution of Tropical Depression and Hurricane (Annex I Figure A2), allowing us to use the cutoff point of 2.12 + 1.36 (μ + σ) based on the Tropical Storm distribution to characterize extreme storms. In terms of standardized anomalies, this threshold corresponds to very large positive wind speed deviations. For each country-year, we compute storm intensity as the average standardized wind speed anomaly on all days where this storm threshold is exceeded. A higher value thus indicates either more frequent storm days or more intense storms (or both) in that year.

- **Floods (Extreme Precipitation Episodes):** We identify extreme rainfall episodes using a high percentile threshold and a persistence criterion. Specifically, a flood episode is recorded if there is a sequence of at least 7 consecutive days in which daily precipitation is extremely high (above the 95th percentile of that day's standardized 30-year precipitation anomalies distribution).[4] This captures prolonged heavy-rain events likely to cause flooding (a one-day downpour is not sufficient to count as a "flood" in our definition). For each country-year, we compute the flood intensity indicator as the average standardized precipitation anomaly across all days in these extreme wet spells. Years with multiple separate flood episodes will have a higher average anomaly (since more days exceed the threshold). This measure effectively combines the frequency and intensity of flood events into one indicator.

- **Droughts (Extremely Dry Conditions):** We identify drought conditions using the lower tail of the standardized precipitation anomalies distribution. Drought days are defined as days when precipitation is below the 5th percentile of the distribution (a severe rainfall deficit). Unlike floods, droughts typically span longer periods by nature; rather than requiring a strict minimum spell length, our indicator effectively captures the cumulative intensity of dry conditions by averaging across all extremely dry days in the year. The drought intensity for a country-year is the average standardized precipitation anomaly on days below the 5th percentile. Note that these anomalies are negative, so a more negative value implies a more severe drought. For ease of interpretation, we flip the sign of the drought indicator, so that a positive value implies a more severe drought. In practice, years with sustained rainfall shortages will have many days with large negative anomalies, yielding a strongly negative average. This construction is analogous to computing a yearly value of the Standardized Precipitation Index (SPI) focused on extreme dryness (SPI ≤ –1.65 corresponds roughly to the lowest 5% of precipitation) – a method recommended by the World Meteorological Organization and widely used in drought studies (Dai 2011).

- **Heatwaves (Extreme Heat Events):** We identify heatwave events as periods of at least 3 consecutive days with abnormally high daytime maximum temperatures. For each day, "abnormally high" is defined as daily maximum-temperature above the 95th percentile of that day's standardized 30-year maximum-temperature anomalies distribution. Thus, a heatwave in our data occurs when a high-temperature anomaly persists for several days in a row, exceeding what is the norm for that location and time of year. For each country-year, we compute heatwave intensity as the average standardized maximum temperature anomaly over all days that are part of any 3+ day heatwave event. A larger value indicates either hotter heatwaves or multiple heatwave episodes within the year. This definition captures both the intensity and occurrence of extreme hot weather episodes, aligning with common definitions in climatology (e.g. WMO and WHO 2015 define heatwaves as periods of extreme day- and night-time temperatures greater than local 95th percentiles with a duration of two days or more. Their excess heat index corresponds to our definition, as does Perkins, S.E., & Alexander, L.V. 2013).

---

[4] Defining extreme precipitation by high-percentile thresholds is standard in climate science. For example, Myhre et al. (2019) use the 95th and 99th percentiles to define extreme daily rain events globally. Multi-day duration criteria are also common. Many studies examine maximum 5-day rainfall totals as an extreme precipitation index (e.g., the "Rx5day" index) when assessing flood risk (Zhang et al. 2011). Because literature has no single consensus on the required duration for a "flood" event, our 7-day criterion is a conservative choice to ensure only very rare, sustained wet spells are counted.

- **Cold Snaps (Extreme Cold Events):** Analogous to heatwaves, we define cold snap events as periods of at least 3 consecutive days with abnormally low temperatures. “Abnormally low” means the daytime maximum temperature is below the 5th percentile of the 30-year standardized temperature distribution for that day. For each country-year, cold snap intensity is calculated as the average standardized maximum temperature anomaly on all days belonging to any 3+ day cold spell.[5] These anomalies will be negative. For ease of interpretation, we flip the sign of the cold indicator, so that a positive value implies a more severe cold. This measure captures prolonged cold spells such as deep winter freezes. This indicator is included for completeness and symmetry with heatwaves.

Table 1 below provides a summary of the disaster indicators, and the precise formulas used.

Table 1: Description of Disaster Indicators[6]

Disaster Type	Definition (Threshold and aggregation)
Storms	Average intensity of days with extreme wind speeds. Threshold: daily max wind gust > mean + 1 standard deviation of the standardized maximum wind speed anomalies distribution for storms. $ND_t^{storm} = \frac{1}{D}\sum_{d=1}^{D}\left(sC_d^{wind}.I\left(sC_d^{wind} > T_{Storm}\right)\right)$ where T_{storm} is the threshold. The indicator variable $I\left(sC_d^{wind} > T_{Storm}\right)$ is equal to 1 if the threshold is exceeded. D=365.
Floods	Average intensity of prolonged heavy-rain days. Threshold: daily standardized precipitation anomaly > 95th percentile, for at least 7 consecutive days. $ND_t^{flood} = \frac{1}{D}\sum_{d=1}^{D}(sC_d^{precip}.I(sC_d^{precip} > T_{95}^{flood}))$ where T_{95}^{flood} is the threshold. The indicator variable $I\left(sC_d^{precip} > T_{95}^{flood}\right)$ is equal to 1 if the threshold is exceeded for at least 7 consecutive days. D=365.
Droughts	Average intensity of extremely dry days. Threshold: daily standardized precipitation anomaly < 5th percentile. $ND_t^{drought} = -\frac{1}{D}\sum_{d=1}^{D}\left(sC_d^{precip}.I\left(sC_d^{precip} < T_5^{drought}\right)\right)$ where $T_5^{drought}$ is the threshold. The indicator variable $I\left(sC_d^{precip} < T_5^{drought}\right)$ is equal to 1 if the threshold is breached. D=365.
Heatwaves	Average intensity of extreme heat days. Threshold: daily standardized max temperature anomaly > 95th percentile, for at least 3 consecutive days. $ND_t^{heat} = \frac{1}{D}\sum_{d=1}^{D}(sC_d^{temp}.I(sC_d^{temp} > T_{95}))$

---

[5] This aligns with definitions in climatological research for cold extremes. For example, the Cold Spell Duration Index (CSDI) used in global climate analyses counts the number of days in spells of at least 5 or 6 consecutive days below the 10th percentile of temperature (Donat et al. 2013). Our criterion is slightly stricter (5th percentile over ≥3 days) but falls within the range of accepted practices.

[6] The full database and codes for all calculations are available upon request.

	where T_{95} is the threshold. The indicator variable $I\left(sC_d^{temp} > T_{95}\right)$ is equal to 1 if the threshold is exceeded for at least 3 consecutive days. D=365.
Cold Snaps	Average intensity of extreme cold days. Threshold: daily standardized max temperature anomaly < 5th percentile, for at least 3 consecutive days. $ND_t^{cold} = -\frac{1}{D}\sum_{d=1}^{D}\left(sC_d^{temp}.I\left(sC_d^{temp} < T_5\right)\right)$ where T_5 is the chosen threshold. The indicator variable $I(sC_d < T_5)$ is equal to 1 if the threshold is breached for at least 3 consecutive days. D=365.

Note that each of the above indicators is a dimensionless index (measured in standard deviations from the mean) that reflects both the frequency and severity of extreme events in a year. A value of zero means no extreme event of that type occurred in that year. Larger positive values indicate more intense or more frequent extreme events (including for droughts and cold snaps, where we flip the signs). For example, a country-year with a storm index of 0.10 experienced on average a standardized max wind gust anomaly of +0.10 (in standard deviations above the chosen threshold) on its storm days – possibly one or two very intense storms. A country-year with a drought index of 0.50 had a significant portion of days with precipitation 0.5 standard deviations below the threshold (indicating a severe, prolonged dry period). These indices allow us to incorporate disaster intensity directly into the regression analysis, rather than just a binary occurrence, and they are less susceptible to reporting bias than damage-based measures from EM-DAT. In Annex II, we show that our dataset captures almost all major climate-related disasters in EM-DAT, but the reverse is not the case (Figure A3 panel D). EM-DAT systematically undercounts and underreports in countries with higher disaster frequency, smaller population, large geography with many localized events, or limited institutional capacity.

2.2 GDP Growth and Other Data

Real GDP growth data are from the Global Macro Database (https://www.globalmacrodata.com) (see Müller et al., 2025). To remove outliers, we winsorize GDP growth observations at the top and bottom 1% of the entire output growth distribution. Concretely, we replace GDP growth for country and year with real annual growth above 23.6 % by 23.6% and replace those below -16.7 % by -16.7%. Many such observations are related to non-climate extreme events (such as major financial crises, domestic macroeconomic recessions, political events, or wars).

For the income groups, we use the latest IMF classification for advanced economies (AEs) and emerging markets and developing economies (EMDEs), and low-income countries (LICs).

2.3 Estimation Strategy

We estimate the following local projections model for each horizon h = 0, 1, 2, with controls for lagged real GDP growth and up to two lags of NDs.[7]

---

[7] We intentionally keep the specification parsimonious. The lagged dependent variable captures the impact of past policy measures and macroeconomic conditions, and country and year fixed effects absorb time invariant country characteristics and structural/institutional and unobserved global factors, respectively. We refrain from adding contemporaneous policy indicators (fiscal or monetary) as controls because these often represent the response to

(continued…)

$$\Delta Y_{i,t+h} = \beta_0 + \sum_{k\in K} \beta_{k,i} \,.\, ND_{k,i,t} + \sum_{k\in K} \alpha_{k,i}\, L^j\left(ND_{k,i,t}\right) + \Delta Y_{i,t-1} + fe_i + fe_t + \epsilon_{i,t}$$

where k indexes disaster types (storm, flood, drought, heat, cold), $\Delta Y_{i,t+h}$ is real GDP growth between year $t+h$ and $t+h-1$, and h goes from 0 to 2—i.e., we investigate the real GDP growth effects of NDs contemporaneously, at time t+1 (one year after shock), and at time t+2 (two years after shock).
We control for

- One lag of GDP growth $\Delta Y_{i,t-1}$
- Country and year fixed effects fe_i, fe_t
- Lags of NDs in years t-1 and t-2, or $\sum_{k\in K} \alpha_{k,i}\, L^j\left(ND_{k,i,t}\right)$ where L^j is the lag operator and j= $1,2$.

To estimate the cumulative growth impact of natural disasters, we rely on a similar local projection method, for each horizon h = 0, 1, 2, with controls for lagged real GDP growth and up to two lags of NDs.

$$Y_{i,t+h} - Y_{i,t-1} = \beta_0 + \sum_{k\in K} \beta_{k,i} \,.\, ND_{k,i,t} + \sum_{k\in K} \alpha_{k,i}\, L^j\left(ND_{k,i,t}\right) + \Delta Y_{i,t-1} + fe_i + fe_t + \epsilon_{i,t}$$

where $Y_{i,t+h} - Y_{i,t-1}$ is real GDP growth between year $t+h$ and $t+h-1$, and h goes from 0 to 2. That is, we investigate the cumulative real GDP growth effects of NDs between year t and year t-1, between year t+1 (one year after shock) and year t-1, and between year t+2 (two years after shock) and year t-1.
We control for

- One lag of GDP growth $\Delta Y_{i,t-1}$
- Country and year fixed effects fe_i, fe_t
- Lags of NDs in years t-1 and t-2, or $\sum_{k\in K} \alpha_{k,i}\, L^j\left(ND_{k,i,t}\right)$ where L^j is the lag operator and j= $1,2$.

3. Results

3.1 Summary Statistics (Non-zero Events)

The summary statistics describe how frequently and intensely each type of disaster occurred across 196 countries over the period 1970–2023. The table below focuses on non-zero events – i.e. country-years in which a given disaster occurred. It shows the distribution of each disaster index's annual values: the count of event years (N), averages, percentiles (1st, 10th, median, 90th, 99th), and min/max. These indices are measured in standard deviations of climate anomalies (for storms, floods, droughts, heatwaves; and cold spells). A higher value indicates a more severe event year.

- **Storms are common**. They occur in ~75% of all country-years and their intensity is +0.03σ above the storm maximum wind speed threshold. Truly extreme storm years (top 1%) reach ~0.13σ above the chosen threshold. This indicates that while storms (meeting the threshold) are commonplace, the typical storm is only moderately above the threshold, and devastating windstorms are relatively rare.

---

disasters rather than confounding factors. Including them could understate the disaster impact by capturing part of the recovery mechanism (see Cavallo et al., 2013, for a related discussion).

- **Floods are very infrequent.** Only 177 country-year observations (about 1.7% of years) had a “flood” event by our definition (≥7 consecutive days of extreme rainfall in the 95th percentile of the standardized anomalies distribution). But when floods occur, they often involve huge anomalies. The median flood year index is 0.14σ above the chosen threshold, and the distribution has a large upper tail (99th percentile ~9.35σ; maximum 18.10σ above the chosen threshold). While major floods are rare, the dataset captures some extraordinarily intense precipitation episodes.

- **Droughts are the most frequent disaster.** About 86% of years have at least one extended severe dryness episode (days below the 5th percentile of rain). The drought index is negative by construction before flipping its sign for use in Tabel 2 and in our regressions. The median drought year is 0.06σ below threshold (e.g. moderate rainfall deficit). The worst 1% of droughts reach 0.3σ and the maximum severity observed is 0.61σ. This shows that some degrees of drought is almost ubiquitous, though often relatively mild; truly severe nationwide droughts (index > 0.3) are less common but do occur (e.g. at the 99th percentile).

- **Heatwaves are quite frequent.** About 68% of years see at least one heatwave (3+ day extreme heat episode above the 95th percentile of standardized max day-temperature anomalies distribution). Typical annual intensity is moderate (median ~0.05σ). However, at the upper end, 1% of heatwave years exceed 0.50σ above the threshold, and the most extreme heatwave years hit +1.39σ above the threshold.

- **Cold Spells are also quite frequent.** About 69% of years have a cold snap, but generally less severe on the anomaly scale. The median cold-spell year is 0.05σ below the threshold. The cold index rarely drops below 0.30σ (only 1% of events are beyond 0.31σ), and the most extreme cold year is 0.75σ below the threshold. This suggests that in the 1970–2023 data, large-area prolonged cold extremes are relatively limited (which may reflect warming trends over time, or that many countries in tropical regions never experience huge cold deviations).

Table 2. Summary Statistics

Statistics	storm	flood	drought	heat	cold
N	7982	177	9144	7187	7351
Min	0.0095	0.0560	0.0026	0.0052	0.0044
p1	0.0096	0.0577	0.0027	0.0164	0.0140
p10	0.0103	0.0766	0.0057	0.0187	0.0174
p50	0.0300	0.1380	0.0582	0.0526	0.0503
p90	0.0715	0.3678	0.1776	0.1574	0.1348
p99	0.1266	9.3493	0.3259	0.5011	0.3122
Max	0.2564	18.1010	0.6129	1.3853	0.7529
Average	0.0360	0.3575	0.0785	0.0795	0.0675

Notes: All indices are standardized climate anomalies above the chosen thresholds. Storms, floods, droughts, cold snaps, and heatwaves have positive-valued indices (higher = more extreme event). The table excludes zero years to show the distribution of years when an extreme event occurred. A value of 0 indicates no extreme event of that type in that year. For example, a “storm” index of 0.03 means that in that year, on storm days, wind speeds were on average 0.03σ above the extreme wind threshold (i.e., mean+1σ or roughly a modest tropical storm). Large positive values at the 1st or 99th percentile and min or max indicate very rare, catastrophic events (e.g. the maximum flood index suggests an exceptional prolonged rainfall anomaly 18.1σ above the chosen threshold).

Storms and heatwaves are relatively ubiquitous but usually moderate in intensity (with a few outliers like Category 5 Hurricanes). Floods are highly skewed: most countries see no qualifying flood in a given year, but when they do, the rainfall anomalies can be enormous. Droughts and cold spells cover many years across climates, but their anomaly magnitudes tend to be (relatively) bounded.

3.2 Econometric Results: Growth Impacts of Natural Disasters

We estimate the effect of each disaster variable on real GDP growth, both contemporaneously (year *t*) and cumulatively in subsequent two years (*t+1, t+2*). Here we focus on the immediate (same-year) impact and how to interpret the coefficients, as well as the differences across disaster types and country groups. Before discussing individual coefficients, it is useful to emphasize the economic mechanisms underlying the estimated growth responses. Extreme weather events affect output through multiple channels, including the destruction of physical capital (including infrastructure), disruptions to labor supply and productivity, damage to supply chains, and constraints on key inputs such as water and energy. The relative importance of these channels differs by hazard type: storms and floods primarily operate through capital losses, while droughts and heatwaves directly impair agricultural output, energy generation, and labor productivity. The estimated coefficients should therefore be interpreted as reduced-form effects that summarize the combined impact of these channels on aggregate GDP growth.

For each disaster type, the regression estimates a slope coefficient β (for year *t*) which can be interpreted as the percentage-point change in GDP growth caused by a one-unit increase in that disaster's index. Recall that the indices are standardized anomaly measures (in σ units). A "one-unit" increase is a very large shock in many cases (e.g. one full standard deviation anomaly sustained over the threshold days). Thus, it is useful to scale the coefficients by realistic index values (like the average or percentile values from the summary statistics in table 2) to get interpretable growth effects. Appendix III. Table A1 presents the full regression results, while Table 3 shows the coefficients plus the calculated growth effects.

- **Storms:** The coefficient for storms (year *t*) is around –3.66. This means that a one-standard-deviation increase in our storm index (a very large increase in storm intensity) would on average reduce same-year GDP growth by 3.66 percentage points. In practice, most storms are much smaller. The *average* storm index across all observations (including zeros) is only ~0.027. Multiplying: –3.66 * 0.027 ≈ –0.10. In other words, the average storm reduces growth by 0.1 percentage point. For an extreme storm event, say the 99th percentile index (0.127σ), the impact would be larger: –3.66 * 0.127 ≈ –0.47 percentage points (almost a half-point drop in growth).

- **Floods:** The coefficient for floods is small, around –0.34. On face value, a one-unit (1σ) extreme precipitation episode would cut growth by 0.34pp. However, most countries/year combinations have no extreme floods, and the average flood index is a mere 0.006. Thus, the average marginal impact of floods is –0.002 percentage points (–0.34 * 0.006). However, this masks the huge impact of rare catastrophic floods. Because the flood index can be very large (e.g., 9.35σ at the 99 percentile, with the maximum at 18.10σ), multiplying those into the coefficient gives huge effects. For a 99th percentile flood year (index ~9.35σ), the estimates indicate a 3.2 percentage points reduction in growth. Most floods have little macroeconomic effect, but a massive, prolonged flooding disaster can be extremely destructive to output growth. This is consistent with historic flood disasters causing significant infrastructure losses, agricultural collapse, etc.

- **Droughts:** The coefficient on the drought index is -2.95. In other words, when precipitation is far below normal (a large negative anomaly), GDP growth falls. A typical drought year reduces GDP growth by about 0.2pp. For an extreme drought (e.g., index at 0.33σ), the hit would be larger: -2.95 * (0.33) ≈ –0.98 pp (nearly a full percentage point off GDP growth). This underscores that droughts are economically very damaging, likely through agricultural output declines, power/water shortages, etc. Notably, droughts have persistent effects in many cases (discussed later), compounding these losses.

- **Heatwaves:** The coefficient on heatwaves is around –1.14. This implies a 1σ heatwave anomaly would lower growth by ~1.14pp. On average, heatwaves trim GDP growth by ~0.06 percentage points – a smaller effect than storms or droughts, but still negative. More extreme heat years have bigger impacts: at the 99th percentile heat index (~0.501σ), growth drops ~0.57pp. Interestingly, the regression finds heatwaves' impact differs by country type (see below) – advanced economies seem less harmed by or even benefit slightly from heat anomalies, whereas the –1.14 coefficient largely reflects the harm in more vulnerable countries.

- **Cold Spells:** The coefficient for cold spells is 0.17, but is not statistically significant, indicating no clear impact on GDP growth. This could be because cold waves often hit countries that have the means to buffer them. Other potential explanations include that cold snaps occur in already cold climates where an anomaly has less incremental damage, or that such events are relatively rarer in vulnerable regions.

Table 3. The Contemporaneous Growth Impact of Natural Disasters (All Countries)

	Storm	Flood	Drought	Heat	Cold
Coefficient (year t)	-3.663	-0.3433	-2.9529	-1.138	0.1696
Average intensity	0.0271	0.0060	0.0680	0.0540	0.0469
Estimated impact on growth	**-0.0993**	**-0.0021**	**-0.2008**	**-0.0615**	**0.0080**
Intensity at P99 of non-zero distribution	0.1266	9.3493	0.3259	0.5011	0.3122
Estimated impact of p99/p1 (top percentile of extreme events) on growth	**-0.4637**	**-3.2096**	**-0.9624**	**-0.5703**	**0.0529**

Notes: Coefficients report contemporaneous (year t) effects of natural disasters on winsorized GDP growth from the local projection regressions. The full results are reported in Appendix III. Table A1. Mean disaster intensities and percentile numbers are computed from the non-zero distribution. Estimated growth impacts are obtained by multiplying regression coefficients by the corresponding mean or p99 values.

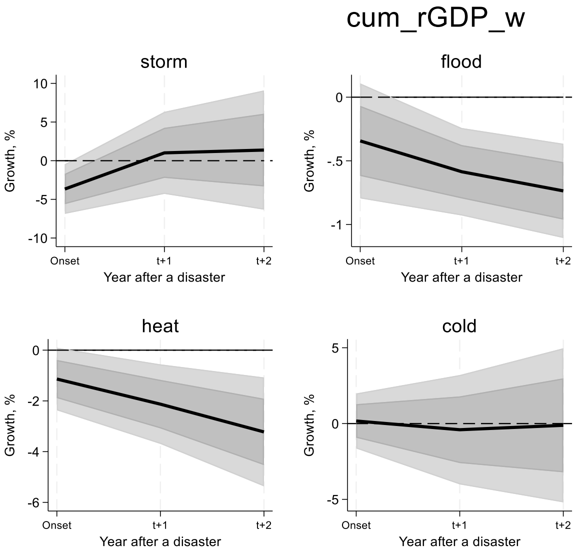
Figure 1 shows the dynamic effects in subsequent years (t+1 and t+2 horizons from the local projections), expressed in cumulative growth terms. The results indicate that some extreme events have moderately persistent and accumulating effects, especially in EMDEs. In these countries, the initial growth losses are not reversed quickly; instead, they compound, leading to increasingly negative cumulative GDP effects over the following two years. This pattern is particularly pronounced for floods and droughts in EMDEs, where cumulative losses deepen steadily from onset to t+2, suggesting lasting damage to capital, infrastructure, and agricultural productivity, as well as slow reconstruction. Heat shocks also show a gradual but persistent accumulation of losses. LICs tend to experience even more persistent losses, especially for heat, although the impact of storms appears more muted, possibly reflecting post-disaster grants and external support (Nguyen et al., 2025).

By contrast, advanced economies exhibit more limited accumulation of losses in the two-year timeframe. For storms, there is some evidence of partial offset, with cumulative effects stabilizing or even slightly improving after t+1, consistent with faster rebuilding and stronger resilience mechanisms. Cold shocks remain relatively small and do not generate meaningful cumulative deviations. Nevertheless, some disasters, particularly floods, still lead to negative cumulative effects, indicating that even in advanced economies, output does not fully return to its pre-disaster path within the subsequent two-year horizon.

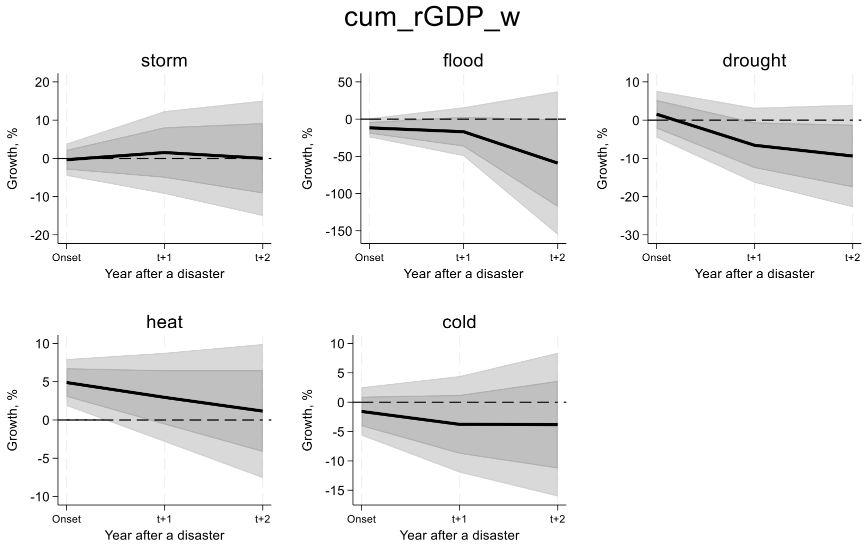
Overall, the widening gap relative to the counterfactual GDP path in EMDEs points to structural constraints, such as limited fiscal space, weaker insurance coverage, and slower capital replacement, that hinder quick recovery. This finding is consistent with Lian et al. (2022), who document large and persistent declines in GDP per capita following extreme weather events. Our local projection results are also in line with the impulse responses from the heterogeneous panel estimates in Figure 3.

Figure 1. Cumulated Impacts of Extreme Weather Events on Real Output

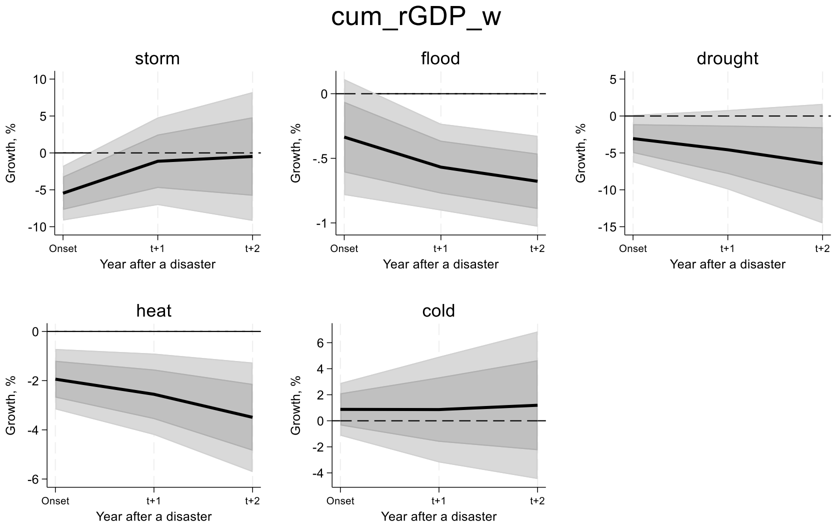
All Countries (196 countries)



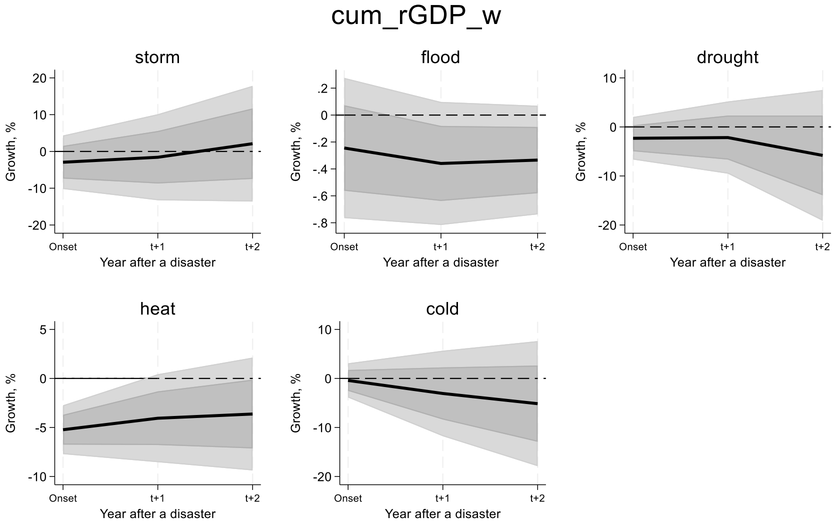
Advanced Economies (39 countries)



Emerging Markets & Developing Economies (157 countries)



Low-income Countries (59 countries)



Notes: The panels report the cumulative impact of each disaster type on real GDP growth over the two years following the event. The estimated responses measure the accumulated percentage change in real GDP relative to the pre-disaster baseline. Specifically, each point in the figure plots the cumulative growth effect computed as [rGDP(t + h) − rGDP(t − 1)] / rGDP(t − 1) × 100, where t denotes the onset year of the disaster and h ∈ {0, 1, 2} is the number of years after the event. This transformation captures the total deviation of output from the level immediately before the disaster, allowing the interpretation of results as cumulative losses or gains in percentage. Shaded areas denote 90% confidence intervals (light grey) and 68% confidence intervals (dark grey) around the estimated responses.

3.3 Econometric Results: Country-Specific Growth Impacts of Natural Disasters

To obtain country-specific growth effects of each disaster type using the estimated coefficients in Table 2 (which are homogenous across all countries), we multiply the slope coefficient β for each disaster type by the corresponding country's annual summary statistic for that disaster (average or P99). For example, if the homogenous slope coefficient for storms is –3.66 (interpreted as the percentage-point change in GDP growth per one-unit increase in the storm intensity index), and a given country's average storm index for a particular year is 0.05, the estimated growth effect of storms for that country-year would be –3.66 × 0.05 =

–0.183 percentage points. This approach can be applied to other disaster types as well—floods, droughts, heatwaves, and cold snaps. By doing so, we translate the average global relationship into a country-specific impact that reflects both the intensity and frequency of disasters experienced by each country. These country-specific results are available upon request in an excel spreadsheet format.

To estimate the total impact of all natural disasters on a country's growth in a given year, we sum the individual effects across all disaster types. That is, for each country-year, we calculate the growth effect for storms, floods, droughts, heatwaves, and cold snaps (using the method above), and then add these effects together. The result is a country-specific estimate of the total macroeconomic impact of natural disasters for that year. This additive approach assumes that the effects of different disaster types are independent and can be linearly combined, which is consistent with the regression framework used in the study. This method provides policymakers and researchers with a practical tool to assess the annual growth drag from extreme weather events at the country level, identify which hazards are most damaging in each context, and prioritize adaptation and resilience investments accordingly.

For robustness, we also estimated a heterogeneous panel model in which the slope coefficients on natural disasters are allowed to vary across countries, rather than being common/homogeneous. In this approach, a composite index of natural disasters was used as the main regressor, and the model was estimated using the Trimmed Mean Group (TMG) estimator. The TMG estimator is particularly useful in this context because it calculates the average effect of natural disasters across countries after removing outliers, thus providing a reliable estimate of the central tendency while still allowing for cross-country heterogeneity. Specifically, we estimate the following dynamic heterogenous panel model:

$$\Delta Y_{it} = \alpha_i + \phi_i \Delta y_{i,\mathrm{t}-1} + \sum_{\ell=0}^{p} \beta_{\mathrm{i}\ell}\, ND_{comp,i,t-\ell} + \sum_{\ell=0}^{p} \gamma_{i\ell}\, \Delta\bar{y}_{w,t-\ell} + \varepsilon_{i,s}, \text{ for } i = 1, \dots, n, \text{ and t } = 1, \dots, T,$$

where ΔY_{it} is real GDP growth for country i in year t. $ND_{comp,i,t}$ is the sum of the 5 disaster indicators for each country-year. $\Delta\bar{y}_{wt}$ is the cross-sectional average of ΔY_{it} (a measure of global growth). Accounting for global growth and its lag helps address issues from correlated shocks across countries. Without a global term, the residuals across countries would be highly correlated (a "common factor" problem). Including world growth makes the errors "weakly, rather than strongly, correlated" across countries.

Unlike pooled estimation techniques such as fixed effects where only intercept heterogeneity is considered, the above specification allows for slope coefficients to vary across countries. Under this more general specification, short-term and long-term country-specific effects can be estimated by running least squares regressions for each country separately and then considering averages of the estimated short-term and long-term coefficients across countries. Pesaran and Smith (1995) show that simple averages of the estimated coefficients (known as mean group, MG, estimates) result in consistent estimates of the underlying population means of the parameters when the time-series dimension of the data is sufficiently large. Setting $p = 1$, the estimated long-run effect of natural disasters on growth in country i is given by

$$\hat{\theta}_i = \frac{\hat{\beta}_{i,0} + \hat{\beta}_{i,1}}{1 - \hat{\phi}_i},$$

and the Mean-Group (MG) estimator is the sample average of $\hat{\theta}_i$. That is

$$\hat{\theta}_{MG} = \frac{1}{n}\sum_{i=1}^{n} \hat{\theta}_i.$$

We then exclude outliers from the average long-run effects by relying on the TMG estimator.

The results from the heterogeneous panel model estimations are reported in Table 4. The contemporaneous growth impact of natural disasters ($\hat{\beta}_0$) can then be compared to the average of the country-specific growth effects obtained using the homogeneous coefficients applied to each country's disaster summary statistics (as described previously). The latter estimates are visually summarized using a box plot of the distribution of disaster impacts across countries where the average value (marked by "X") in the left-hand chart of Figure 2 is very close to the TMG estimate of –0.543 in Table 4. The close alignment between these two approaches reinforces the robustness of the main results: whether one uses a global average estimated coefficient or allows for country-specific slopes, the estimated macroeconomic impact of natural disasters on growth remains comparable. This strengthens confidence in the empirical strategy and demonstrates that the findings are not driven by outliers or by the assumption of homogeneity in disaster impacts. Moreover, even when accounting for country-specific factors and their influence on disaster impacts (including institutional quality, economic structure, etc.), the central estimate of disasters' effect on growth remains effectively unchanged. This is evidence that omitted country-level variables are not materially biasing the main pooled estimates. If such omitted variables were driving the results, one would expect the fully heterogeneous model to produce a significantly different average effect than the pooled model (because of the heterogeneity bias; cf. Pesaran & Smith, 1995).

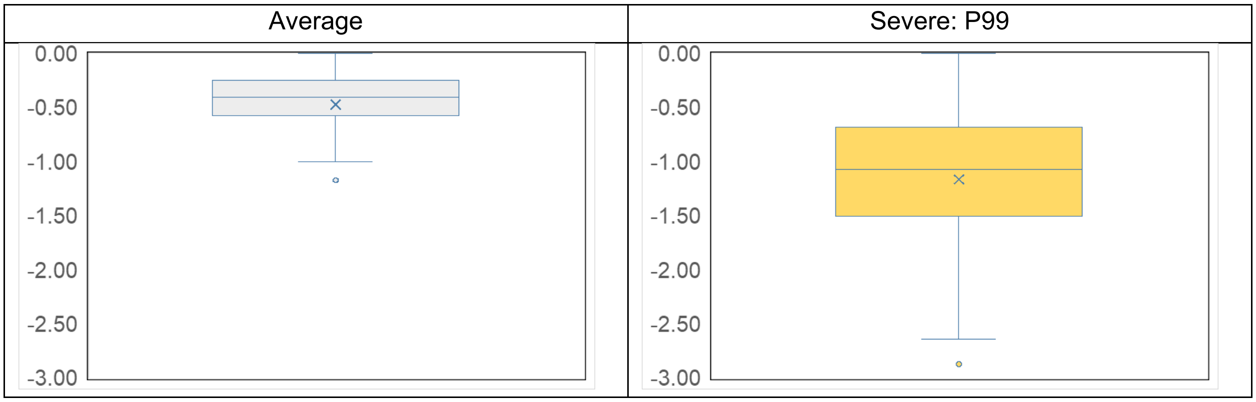
Note also that $\hat{\beta}_1$ and $\hat{\theta}$ in Table 4 are not statistically significant. This means the initial decline in GDP growth after a disaster is only partly offset the next year, and there is no lasting change from the pre-disaster trend in the long-term. Figure 3 reports the impulse response of real GDP growth to a one-unit shock in the composite natural-disaster index, based on the Trimmed Mean Group (TMG) dynamic heterogeneous panel estimates in Table 4. The results indicate a sizable contemporaneous contraction in real GDP growth: a one-unit disaster shock reduces growth on impact by about 0.54 percentage points. The following year, growth partially rebounds, consistent with short-run normalization and reconstruction-related activity after the initial disruption. Thereafter, the growth response quickly converges back toward zero, reflecting limited persistence in growth dynamics (with $\hat{\phi} \approx 0.32$), so that disaster shocks primarily affect growth over a short horizon rather than permanently shifting growth rates.

Table 4. Short-term and long-run TMG estimates of the growth impact of natural disasters

Short-term Coefficients		Long-term Coefficients	
$\hat{\phi}$	0.3208***	$\hat{\theta}$	-0.1873
	(0.0188)		(0.6566)
$\hat{\beta}_0$	-0.5431*		
	(0.3187)		
$\hat{\beta}_1$	0.4278		
	(0.3219)		
N*T	10357		

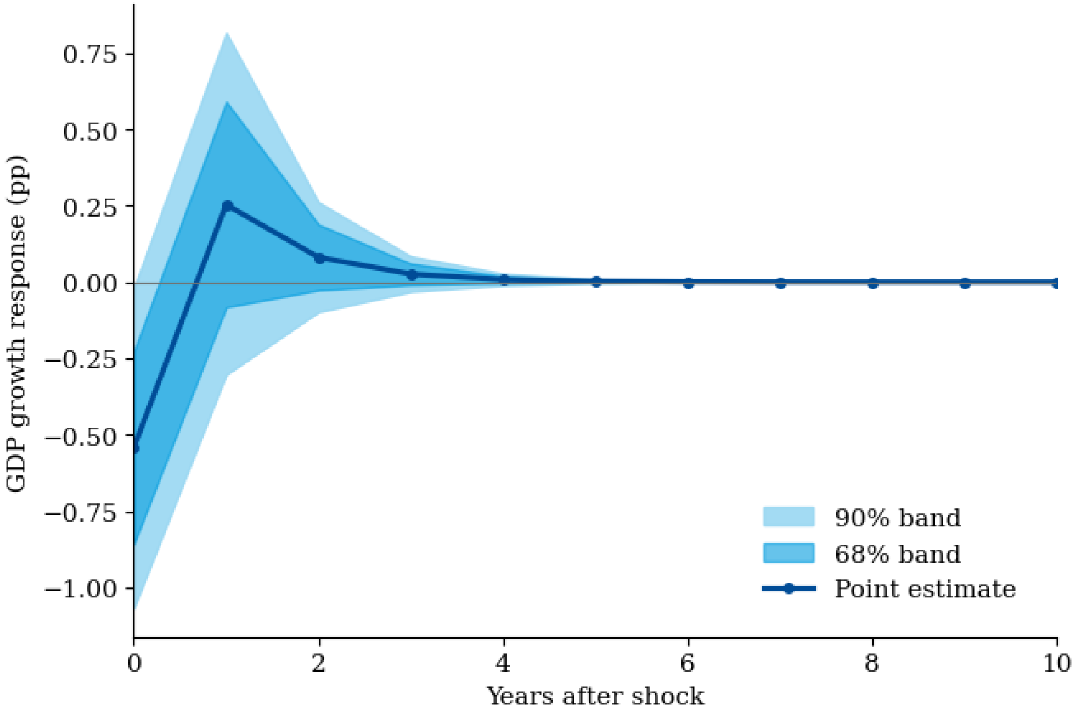
Notes: The table reports Trimmed Mean Group (TMG) estimates of the short-run and long-run effects of natural disasters on real GDP growth. The disaster variable is a composite index aggregating storms, floods, droughts, heatwaves, and cold snaps. The TMG estimator averages the heterogeneous slope coefficients across countries and accounts for cross-sectional dependence by controlling for lagged global GDP growth. Standard errors are in parentheses. N×T denotes total observations. *, **, and *** indicate significance at the 10, 5, and 1 percent levels.

Figure 2. Distribution of Country-Specific Growth Effects



Notes: The figure displays the distribution of country-specific growth impacts of disasters, using the homogenous coefficients on disasters from the local projection regressions and each country's disaster intensity. The left panel reports country-specific average growth effects based on mean disaster intensity, while the right panel reports growth effects associated with catastrophic events, measured using the p99 of the country-specific disaster intensity distribution. The "X" in the left panel denotes the cross-country mean, which closely aligns with the Trimmed Mean Group (TMG) estimate reported in Table 4. Negative values indicate reductions in real GDP growth.

Figure 3. Impulse Response of Cumulative GDP to a Natural Disaster Shock (TMG)



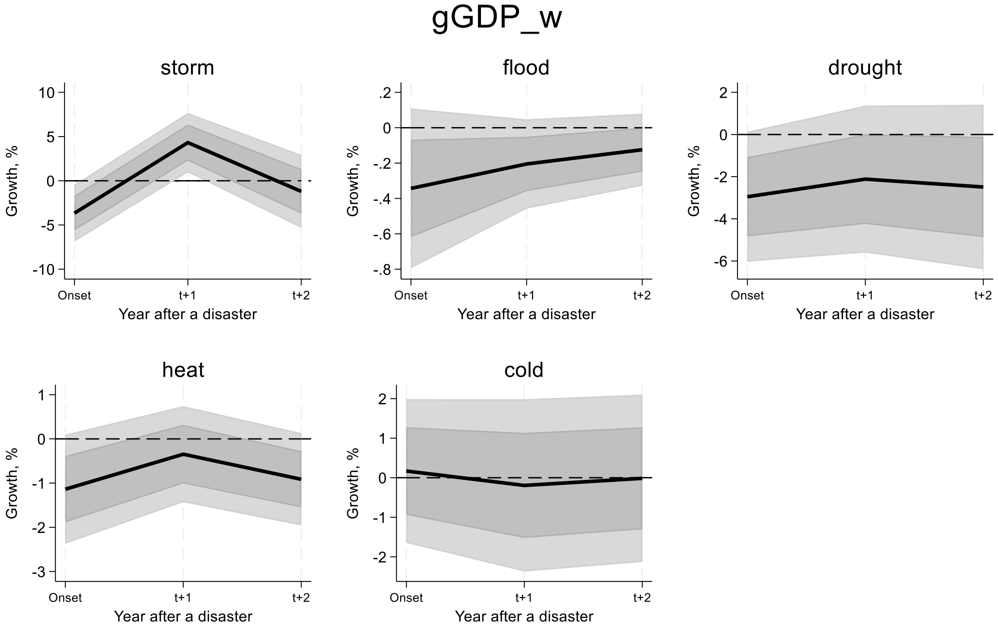
Notes: The figure reports the impulse response of real GDP growth to a unit shock in the composite natural-disaster (ND) index, based on the dynamic heterogeneous panel estimates in Table 4.

3.4 Econometric Results: Year-on-year Growth Impacts of Natural Disasters

Figure 4 shows the annual growth impact of NDs on all countries, AEs, and EMDEs. The full sets of estimated coefficients for AEs and EMDEs are presented in Appendix III. Table A1. A key finding of the paper is that the contemporaneous growth impact of natural disasters is much larger in emerging markets and developing economies (EMDEs) than in advanced economies (AEs).[8] The difference between AEs and EMDEs arises from both exposure and resilience. EMDEs not only tend to experience some hazards more intensely (for instance, the deadliest tropical cyclones mostly hit developing countries in the tropics), but they also have weaker capacity to mitigate and recover. This typically transpires through EMDEs having relatively poorer infrastructure implying that storms and floods cause greater destruction relative to GDP. EMDEs are also typically more agrarian economies which means droughts translate more significantly into reduced output. And EMDEs have also more limited healthcare and worker protections implying that heat and other stresses reduce labor productivity more sharply. AEs typically have better infrastructure (so even if a hurricane hits, rebuilding is faster and insured), more diversified economies (so a hit to agriculture or a region doesn't affect the whole GDP significantly), and policy buffers (government relief, insurance, etc.). Prior studies (e.g., Nguyen et al., 2025) find government spending rises immediately in AEs after disasters, offsetting private sector losses. In contrast, EMDEs face falling investment and (for small islands) export revenue after disasters, leading to net output declines. Moreover, some weather shocks (like moderate heat) may even be beneficial in cooler rich countries, whereas in an already hot, irrigation-limited poor country, extra heat would be more detrimental. This aligns with findings in prior research that institutions and income level mitigate disaster impacts. For example, Felbermayr and Gröschl (2014) found the negative impact of disasters on income was smaller in countries with better institutions and more trade openness.

Figure 4. Impacts of Extreme Weather Events on YoY Output Growth

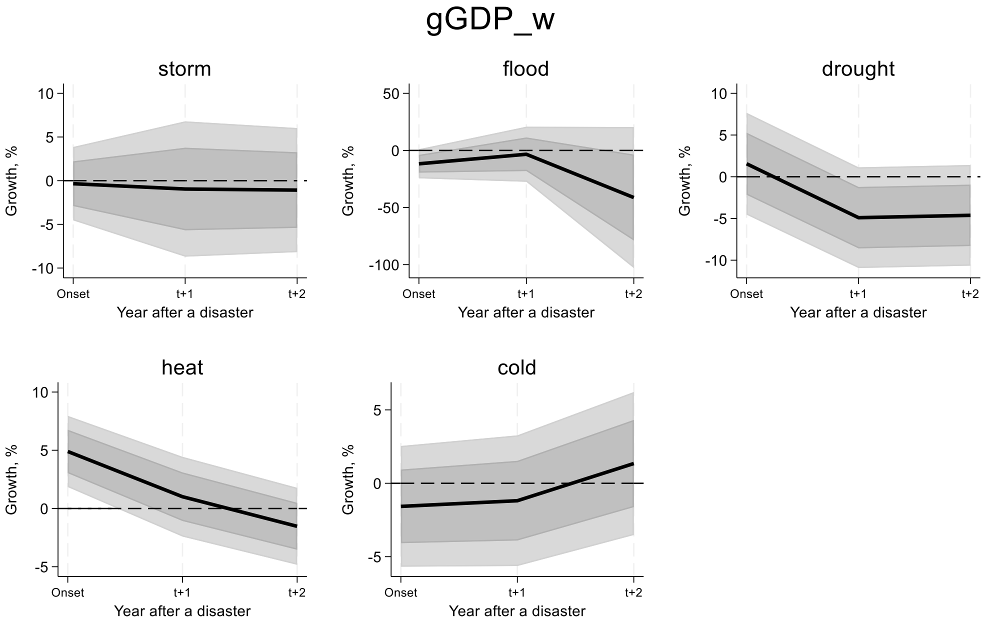
All countries



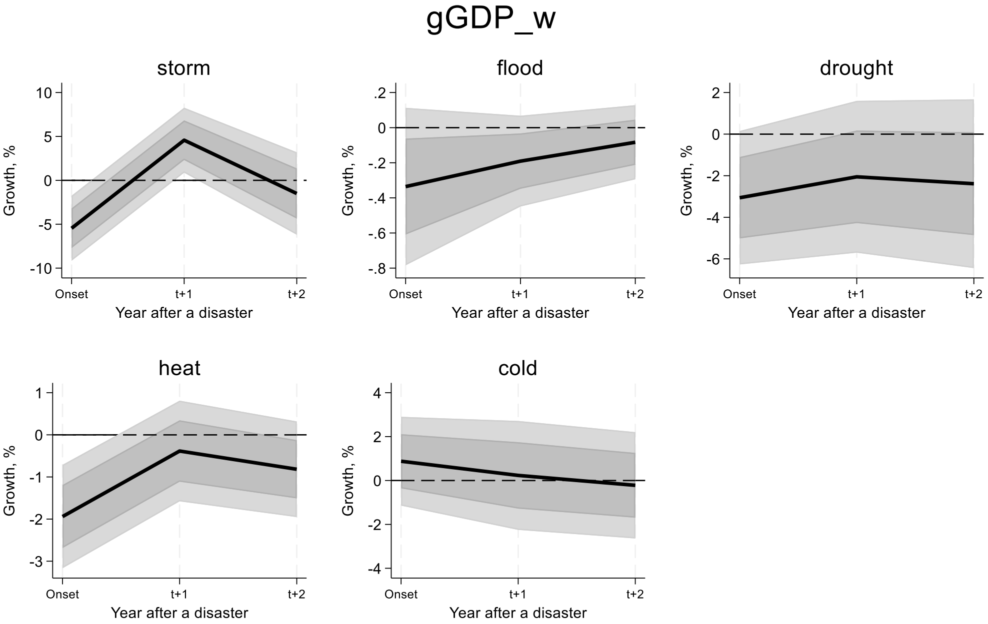
---

[8] Year-on-year growth responses illustrate the immediate drop and any rebound in growth. The lack of significance in year 1 or 2 does not necessarily mean no impact. It can mean a quick recovery or simply wide confidence intervals. Because our analysis is conducted at annual frequency, very short-term output fluctuations immediately following disasters may be averaged out; for instance, a sharp drop and rebound within the same year would appear as a small net annual effect. High-frequency analyses (e.g., using quarterly GDP or night-light data) could usefully complement our results by tracing the intra-year adjustment dynamics. We leave this to future research.

Advanced Economies (39 countries)



Emerging Markets & Developing Economies (157 countries)



Notes: The panels report the impact of each disaster type on year-on-year real GDP growth. The estimated responses trace the deviation of annual real GDP growth from its pre-disaster trend. GDP growth is winsorized at p1 and p99 levels. Unlike the cumulative specification, the year-on-year metric captures the contemporaneous and subsequent annual percentage-change effects of a disaster. Formally, each point in the figure corresponds to the estimated response of [rGDP(t + h) − rGDP(t + h − 1)] / rGDP(t + h − 1) × 100, where t denotes the onset year of the disaster and h ∈ {0, 1, 2}. This transformation shows how disasters affect GDP growth rate. Shaded areas denote 90 percent confidence intervals (light grey) and 68 percent confidence intervals (dark grey) around the estimated annual effects. Appendix III. Table A1 presents the full set of coefficients for all countries.

4. Extensions

4.1. Rolling window estimates

Estimating rolling-window effects is important because the macroeconomic impact of climate shocks is not structural or time-invariant. Countries adapt, economic structures evolve, and exposure to climate risks changes over time. A single full-sample estimate implicitly assumes that the effect of a drought, heatwave, or storm in the 1970s is comparable to the effect of the same shock in the 2010s, despite profound changes in technology, infrastructure, sectoral composition, and policy responses. The rolling-window approach relaxes this assumption and allows the data to reveal how vulnerability and resilience evolve. In doing so, it helps distinguish between shocks for which adaptation has been effective, such as heat, providing a more policy-relevant assessment of climate risks than static average effects.

The rolling-window estimates reveal substantial time variation in the contemporaneous (h = 0) macroeconomic effects of natural disasters on GDP growth (see Figure 5). For storms, the estimated impact is negative or close to zero in the earlier windows but becomes progressively less negative and turns mildly positive in windows centered in the late 1990s and early 2000s. This pattern suggests that the short-run growth effects of storms has weakened over time, consistent with improved resilience, faster reconstruction, and more effective disaster response mechanisms in recent decades.

For droughts, the estimated coefficients rise markedly over time. The estimates imply that the contemporaneous negative impact of droughts on GDP growth has intensified in more recent decades. The increase is pronounced in windows centered after the early 2000s, where estimates become large and statistically significant. This pattern suggests growing macroeconomic vulnerability to water scarcity, likely reflecting increased dependence on water-intensive activities, agricultural stress interacting with higher temperatures, and limited scope for short-run adaptation to prolonged precipitation shortfalls.

The contemporaneous effect of heat shocks is consistently negative throughout the sample, but its magnitude declines over time. Early windows show relatively large negative effects of extreme heat on GDP growth, while more recent windows display smaller (though still negative) impacts. This attenuation is consistent with adaptation mechanisms such as increased air-conditioning penetration, changes in labor utilization, technological adaptation, and sectoral shifts away from heat-exposed activities.

Cold shocks display an inverse U-shaped pattern. The estimates imply negative effects in earlier decades, a moderation in the late 1990s and early 2000s, and a partial re-emergence of adverse effects in the most recent windows. This may reflect improved insulation, heating technologies, and infrastructure resilience offset by greater exposure through energy systems or supply chains in recent decades.

Given the low number of flood observations, rolling estimates for floods are not precisely estimated.

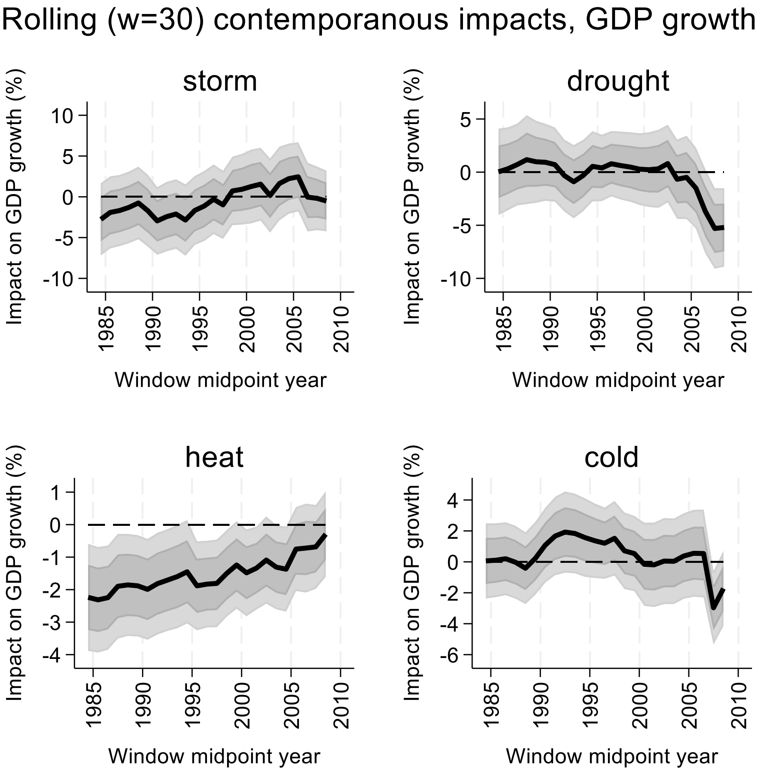
Three broad implications emerge from these results. First, the heterogeneous time patterns across disaster types underscore the importance of distinguishing among natural disasters rather than relying on aggregate temperature or disaster indices. Policies aimed at climate resilience need to be shock-specific: measures effective against heat may not reduce vulnerability to droughts, and vice versa.

Second, adaptation appears to matter for temperature-related shocks, particularly heat: economies seem to have reduced their short-run sensitivity to extreme heat over time. This suggests that investments in infrastructure, technology, and institutional responses can substantially mitigate macroeconomic risks from climate-related natural disasters.

Third, not all disasters exhibit declining impacts. The strengthening effect of droughts points to limits of adaptation when shocks involve persistent resource constraints, such as water scarcity or at times maladaptation. Unlike heat, which can often be mitigated through technological or behavioral adjustments, drought directly constrains agricultural output, hydropower generation, and water-dependent industrial activity, with limited short-run substitutes.

Overall, the rolling estimates highlight that climate vulnerability is not static. While adaptation has reduced the contemporaneous costs of some extreme weather events, rising exposure and structural constraints, particularly related to water availability, have amplified the economic consequences of others.

Figure 5. Rolling Impacts of Extreme Weather Events on Real Output



Notes: The panels report rolling-window (window length = 30 years) estimates of the contemporaneous impact of each disaster type on year-on-year real GDP growth. Each point corresponds to the estimated coefficient from a regression estimated over a 30-year subsample, plotted at the midpoint year of the window. The estimates trace how the immediate growth impact of storms, droughts, heat, and cold has evolved over time, capturing changes in exposure, vulnerability, and adaptation. The dependent variable is annual real GDP growth, defined as [rGDP(t) − rGDP(t − 1)] / rGDP(t − 1) × 100, where t denotes the disaster year. Shaded areas denote 90 percent confidence intervals (light grey) and 68 percent confidence intervals (dark grey) around the rolling estimates.

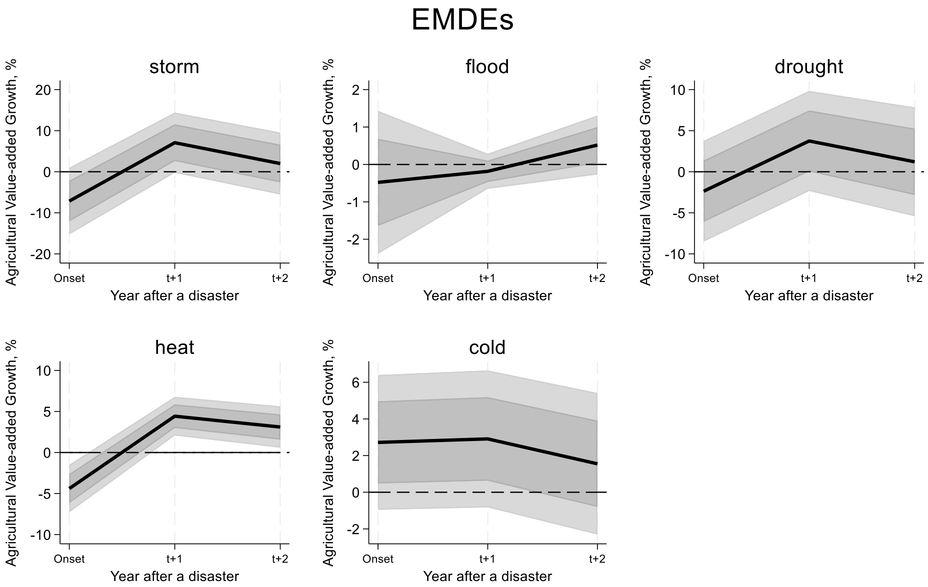
4.2. On the mechanisms: agricultural value-added growth

Understanding the aggregate GDP effects of natural disasters requires identifying the sectoral channels through which these shocks operate. Agriculture is a natural starting point, particularly in EMDEs, because it is directly exposed to climates and extreme weather events and remains an important source of employment, income, and input supply for the rest of the economy. Shocks to agricultural production can propagate to aggregate GDP through multiple mechanisms, including food price effects, reductions in rural income and consumption, supply-chain disruptions, and spillovers to agro-processing and trade. By examining agricultural value-added growth alongside aggregate GDP growth, we can better assess whether climate-related natural disasters primarily operate through direct production losses in agriculture or whether their macroeconomic effects are driven by broader economy-wide channels. This sectoral perspective helps clarify why some disasters generate large agricultural losses but relatively muted GDP responses, while others propagate more strongly to aggregate economic activity, providing a more nuanced understanding of the mechanisms underlying climate-related GDP impacts.

We examine the impact of extreme weather events on value-added growth of agriculture. Data are from the World Development Indicators database of the World Bank. Note that data are not as complete as GDP growth. Coverage varies between full year coverage to less than 10 years for some countries.

With that caveat, we find that natural disasters have large and heterogeneous effects on agricultural value-added growth in EMDEs, with magnitudes that are substantially larger than those observed for aggregate GDP growth. Across all disaster types, agriculture emerges as a more exposed sector, absorbing the bulk of the short-run economic damage from natural disasters (Figure 6).

Figure 6. Impacts of Extreme Weather Events on Agriculture Value-Added Growth



Notes: The panels report the impact of different disaster types on year-on-year agricultural value-added growth in EMDEs over the disaster year and the subsequent two years. The estimated responses trace the deviation of annual agricultural value-added growth from its pre-disaster trend, capturing both contemporaneous and short-term dynamic effects on the agricultural sector. The dependent variable is defined as [AgrVA(t + h) − AgrVA(t + h − 1)] / AgrVA(t + h − 1) × 100, where AgrVA denotes real agricultural value added, t is the year of disaster onset, and h ∈ {0, 1, 2}. Shaded areas denote 90 percent confidence intervals (light grey) and 68 percent confidence intervals (dark grey) around the estimated responses.

Storms generate a sharp contraction in agricultural value-added growth at the onset of the disaster, followed by a strong rebound in the subsequent year. The initial decline reflects direct crop damage, losses of livestock, and destruction of rural infrastructure, while the rebound is consistent with replanting, reconstruction, and catch-up production. Although storms affect aggregate GDP growth, the magnitude of the GDP effect is smaller, indicating that non-agricultural sectors are less exposed in EMDEs.

Heat stress also produces large effects on agricultural value-added growth, with a sizable contraction at onset followed by a partial recovery. Heat directly affects crop yields and agricultural labor productivity, leading to stronger sectoral responses than those observed at the aggregate level. GDP growth, by comparison, shows much smaller and smoother responses to heat stress, reflecting lower exposure of non-agricultural sectors and the presence of adaptation mechanisms.

By contrast, the impacts of floods, droughts, and cold on agricultural value-added growth are generally less precisely estimated. While the point estimates often suggest adverse effects, the confidence intervals are wider and frequently include zero. The weaker statistical significance of these shocks likely reflects substantial heterogeneity across countries and regions. The impacts of droughts and cold depend critically on irrigation coverage, crop composition, and adaptive capacity.

Overall, the contrast between agriculture and GDP growth indicates that agriculture remains highly vulnerable to extreme weather events. These findings underscore the importance of sector-specific adaptation policies, especially in agriculture, to mitigate the economic consequences of climate change.

4.3. On the role of debt

To assess whether fiscal space shapes the macroeconomic impact of natural disasters, we interact $ND_{k,i,t}$ with lagged public debt (as a percentage of GDP). The motivation is that higher debt levels may constrain governments' ability to respond through reconstruction spending, transfers, and support to affected sectors, thereby amplifying the economic costs of shocks. Conversely, countries with lower debt levels may have greater room to smooth the impact through countercyclical fiscal policy and faster rebuilding. This interaction therefore provides a simple way to capture how initial fiscal conditions mediate the transmission of disaster shocks to output.

Table 5: The role of debt in extreme events' impacts

	(1) h=0	(2) h=1	(3) h=2
storm # L.central gov debt, %GDP	0.0844	0.0617	0.0353
	(0.103)	(0.137)	(0.0994)
flood # L.central gov debt, %GDP	-0.0656**	-0.0880**	0.0767*
	(0.0312)	(0.0440)	(0.0448)
drought # L.central gov debt, %GDP	-0.0493	-0.0130	-0.0289
	(0.0299)	(0.0482)	(0.0410)
heat # L.central gov debt, %GDP	-0.0859**	-0.0163	-0.00904
	(0.0384)	(0.0344)	(0.0286)
cold # L.central gov debt, %GDP	-0.0352	-0.0719	-0.00262
	(0.0688)	(0.0493)	(0.0486)
Observations	1564	1564	1524

Notes: The table reports local projection estimates of the interaction between disaster shocks and lagged central government debt (percent of GDP) on cumulative real GDP growth at horizons h = 0, 1, and 2. Coefficients capture how the impact of each disaster varies with initial debt levels (t-1). A negative coefficient implies that higher public debt amplifies the adverse effect of the shock on output, while a positive coefficient suggests mitigation. All specifications include country fixed effects, year fixed effects, and controls for contemporaneous and lagged disaster shocks. Standard errors clustered at the country level are reported in parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively.

The results suggest that fiscal space matters for certain types of disasters. In particular, the interaction terms for floods and heat are negative and statistically significant at some horizons, indicating that higher initial debt amplifies the adverse cumulative impact of these shocks on growth. For storms and droughts, the interaction effects are generally not statistically significant, suggesting more limited heterogeneity along this dimension. Overall, the findings are consistent with the view that constrained fiscal space can hinder recovery and lead to more persistent output losses following some extreme events, although the strength of this channel varies across disaster types.

5. Conclusions

This paper provides new evidence on the cross-country growth effects of natural disasters using high-frequency climate anomalies and carefully calibrated physical thresholds to identify disasters for a global panel of 196 countries spanning over five decades. We find that storms, floods, droughts, and heatwaves significantly reduce GDP growth contemporaneously by approximately 0.1–0.2 percentage points on average, with the largest effects observed in EMDEs. Cold spells, by contrast, have no statistically significant impact. Severe disasters impose far larger costs. For example, a catastrophic flood can lower growth by up to 3 percentage points, while once-in-100-year storms or heatwaves reduce growth by around 0.5pp and extreme droughts by about 1pp. We also translate these aggregate results into localized growth effects by combining the estimated global coefficients with each country’s own disaster intensity and we validate these findings using estimates from a heterogenous panel model. Rolling-window estimates further reveal that the short-run growth impact of storms and heatwaves has declined in recent decades, whereas droughts have become increasingly damaging, reflecting divergent adaptation and vulnerability trends. Finally, the pronounced heterogeneity in impacts between advanced economies and EMDEs underscores the critical role of resilience and adaptation capacity in determining whether extreme weather events results in temporary growth slowdowns or persistent GDP losses.

References

Akyapı, Berkay, Matthieu Bellon, and Emanuele Massetti. 2025. "Estimating Macrofiscal Effects of Climate Shocks from Billions of Geospatial Weather Observations." *American Economic Journal: Macroeconomics* 17 (3): 114–59**.**

Botzen, W.J., O. Deschenes, and M. Sanders. 2019. “The Economic Impacts of Natural Disasters: A Review of Models and Empirical Studies.” *Review of Environmental Economics and Policy*, Volume 13, Issue 2, Summer 2019, pp. 167-188.

Cavallo, Eduardo, Sebastian Galiani, Ilan Noy, and Juan Pantano Martinez. 2013. “Catastrophic Natural Disasters and Economic Growth.” *Review of Economics and Statistics* 95(5): 1549–1561.

Centorrino, S., Massetti, E., Mohaddes, K., Raissi, M. and Yang, J.C., 2026. Macroeconomic Consequences of Sustained Warming: A Bias-Corrected Dynamic Heterogeneous Panel Approach. Cambridge Working Papers in Economics, 2617. Faculty of Economics, University of Cambridge.

Dai, A., 2011. “Drought Under Global Warming: A Review.” Wiley Interdisciplinary Reviews: Climate Change, 2(1), 45–65.

Donat, M. G., Alexander, L. V., Yang, H., Durre, I., Vose, R., Dunn, R. J., ... & Kitching, S., 2013. Updated Analyses of Temperature and Precipitation Extreme Indices Since The Beginning of The Twentieth Century: The HadEX2 dataset. *Journal of Geophysical Research: Atmospheres*, *118*(5), 2098-2118.

Felbermayr, Gabriel J., & Gröschl, Jasmin K., 2014. “Naturally Negative: The Growth Effects of Natural Disasters.” *Journal of Development Economics*, 111(C), 92–106.

Felbermayr, G., J. Gröschl, M. Sanders, V. Schippers, and T. Steinwachs. 2022. “The Economic Impact of Weather Anomalies.” *World Development* 151 (2022) 105745.

Fomby, Thomas, Yuki Ikeda and Norman Loayza. 2013. “The Growth Aftermath of Natural Disasters”, *Journal of Applied Econometrics*, Vol. 28, No. 3 (April-May 2013), pp. 412-434.

Gortan, M., Testa, L., Fagiolo, G., Lamperti, F., 2024. A Unified Dataset for Pre-processed Climate Indicators Weighted by Gridded Economic Activity, *Scientific Data* 11, 533 (2024)

Jordà, Oscar. 2005. “Estimation and Inference of Impulse Responses by Local Projections.” *American Economic Review* 95(1): 161–182.

Kahn, M. E., Mohaddes, K., Ng, R. N., Pesaran, M. H., Raissi, M., & Yang, J. C., 2021. “Long-term Macroeconomic Effects of Climate Change: A Cross-country Analysis.” *Energy Economics*, *104*, 105624.

Klomp, J., and K. Valckx. 2014. “Natural Disasters and Economic Growth: A Meta-Analysis.” *Global Environmental Change* 26:183–95.

Loayza, Norman V., Olaberría, Eduardo, Rigolini, Jamele, & Christiaensen, Luc., 2012. “Natural Disasters and Growth: Going Beyond the Averages.” *World Development* 40(7): 1317–1336.

Lian, Weicheng, Nami Hagiwara, Alan Timofeev, Benjamin Carton, and Florence Jaumotte. 2022. “Aftermath of Natural Disasters: Economic Growth, Inequality, and Poverty.” *IMF Working Paper* No. 2022/169, International Monetary Fund.

Mitra, P., M. Raissi, B. Versailles, S. Centorrino, M. Ivanyna, K. Kirabaeva, E. Massetti, and others. 2025. “Integrating Climate Change into Macroeconomic Analysis: A Review of Data, Models, and Scenarios.” IMF Working Paper 2025/170, International Monetary Fund, Washington, DC.

Mohaddes, Kamiar, Ryan NC Ng, M. Hashem Pesaran, Mehdi Raissi, and Jui-Chung Yang. 2023. "Climate Change and Economic Activity: Evidence from US States." *Oxford Open Economics* 2: odac010.

Mohaddes, K., & Raissi, M., 2025. “Rising Temperatures, Melting Incomes: Country-specific Macroeconomic Effects of Climate Scenarios.” *PLOS Climate*, *4*(9), e0000621.

Myhre, G. *et al.,* 2019. “Frequency of Extreme Precipitation Increases Extensively With Event Rareness Under Global Warming.” *Scientific Reports, 9*, 16063.

Nguyen, Ha Minh, Alan Feng, and Mercedes Garcia-Escribano. 2025. "Understanding the macroeconomic effects of natural disasters." *IMF Economic Review*: 1-38.

Noy, Ilan. 2009. “The Macroeconomic Consequences of Disasters.” *Journal of Development Economics* 88(2): 221–231

Müller, Karsten, Chenzi Xu, Mohamed Lehbib & Ziliang Chen. 2025. “The Global Macro Database: A New International Macroeconomic Dataset”. *NBER Working Paper No. 33714*

Pesaran, M.H. and Smith, R., 1995. Estimating Long-run Relationships From Dynamic Heterogeneous Panels. *Journal of econometrics*, *68*(1), pp.79-113.

Perkins, S.E., & Alexander, L.V., 2013. “On the Measurement of Heat Waves.” *Journal of Climate, 26*(13), 4500–4517.

Raddatz, Claudio. 2007. “Are External Shocks Responsible for the Instability of Output in Low-Income Countries?” *Journal of Development Economics* 84(1): 155–187.

Skidmore, Mark, & Toya, Hideki. 2002. “Do Natural Disasters Promote Long-Run Growth?” *Economic Inquiry* 40(4): 664–687.

Usman, S., Fernández, G. G. T., & Parker, M. (2025). Going NUTS: The Regional Impact of Extreme Climate Events Over the Medium term. *European Economic Review*, *178*, 105081.

WMO and WHO 2015 “Heatwaves and Health: Guidance on Warning System Development”, WMO-No. 1142.

Zhang, X., Alexander, L., Hegerl, G. C., Jones, P., Tank, A. K., Peterson, T. C., ... & Zwiers, F. W., 2011. “Indices for Monitoring Changes in Extremes Based on Daily Temperature and Precipitation Data.” *Wiley Interdisciplinary Reviews: Climate Change*, *2*(6), 851-870.

Appendix I. Data and Code Availability

All data and codes used in constructing the above indicators are available upon request. They include:

- **Daily standardized climate anomalies dataset (country-day):** gadm0_weighted_climateVar_1940-2023.dta – this Stata data file contains the population-weighted daily values for each climate variable, and their 30-year baseline means and standard deviations, from which standardized anomalies are computed.
- **Annual extreme weather dataset (country-year):** gadm0_year_extremeWeather_1940-2023.dta – this Stata file contains the derived annual indicators for storms, floods, droughts, heatwaves, and cold snaps for each country-year. Our analysis focuses on 1970–2023.
- **Codebooks:** Detailed variable descriptions are provided in accompanying Excel files gadm0_weighted_climateVar_1940-2023_varlist.xlsx and gadm0_year_extremeWeather_1940-2023_varlist.xlsx. These spreadsheets list all variables in the above datasets, their units, and definitions (for example, explaining naming conventions like _p95 for 95th percentile thresholds, _sa30yr for standardized anomaly with 30-year baseline, etc.).
- **Replication code:** The Stata do-file NRVZ_01_cleanData.do contains the data processing code that takes raw ERA5 daily data and produces the two datasets and indicators described above. This code performs the steps of computing 30-year rolling climatologies, standardizing anomalies, applying thresholds, and aggregating to annual frequency. Researchers can run this code to replicate our disaster indicators. Additional analysis code for the regressions, tables, and figures is provided in the same online repository (see README for file listings).

Raw data sources are publicly available. The ERA5 population weighted climate data were accessed via the *WeightedClimateData* interface.[9] The macroeconomic series (real GDP growth) were obtained from the IMF's World Economic Outlook and World Bank's World Development Indicators.

Between 1970 and 2023, there are substantial interannual variations in the average intensity of natural disasters in G-SWAT. In Figure A1, we observe a clear downward trend in the average intensity of cold snaps, coupled with an upward trend in the average intensity of heatwaves and standardized temperature anomalies. The effects of El Niño are clearly visible with notable peaks of average standardized temperature anomalies in 1997-1998, 2009-2010, 2015-2016, 2023. The year 2005 stood out as one of the hottest years on record with significant and widespread heatwaves globally even in the absence of an El Niño event. Changes in drought intensity tend to track the variability in temperature, but no clear trend is observed. Storms and floods show considerable interannual variation without apparent trends.

Figure A2 shows the distribution of daily standardized weather anomalies from the 30-year rolling averages for storm, flood, drought, heatwaves and cold snaps. For storms, panel A shows the maximum wind speed separately for Tropical Depression (9-17m/s), Tropical Storm (18-32m/s), and Hurricanes (33m/s or higher). There is little overlap between the distribution of Tropical Depression and Hurricane, allowing us to use the cutoff point of 2.12 + 1.36 (mean plus one standard deviation based on the Tropical Storm distribution) to characterize extreme storms. Panels B and C show the full distribution for daily

---

[9] Available from Gortan et al. (2024) here: shttps://weightedclimatedata.streamlit.app/

precipitation and maximum temperature standardized anomalies overlaid with the distributions for flood, drought, heatwave and cold snaps based on intensity thresholds discussed in the methodology section.

Figure A1. Time Series of Average Standardized Anomalies

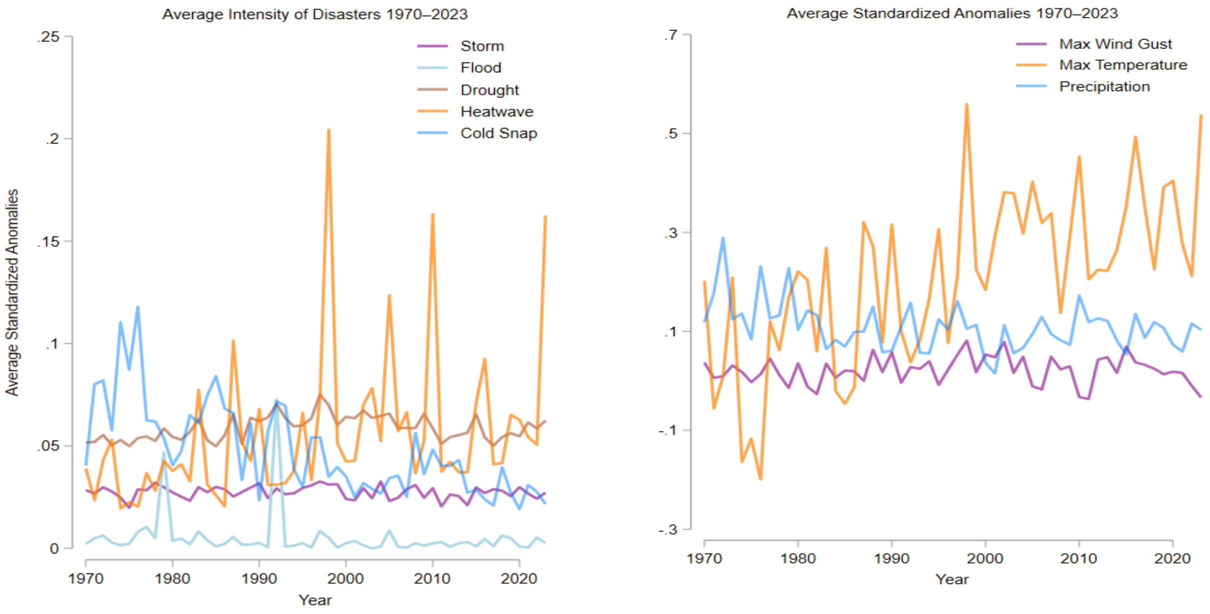
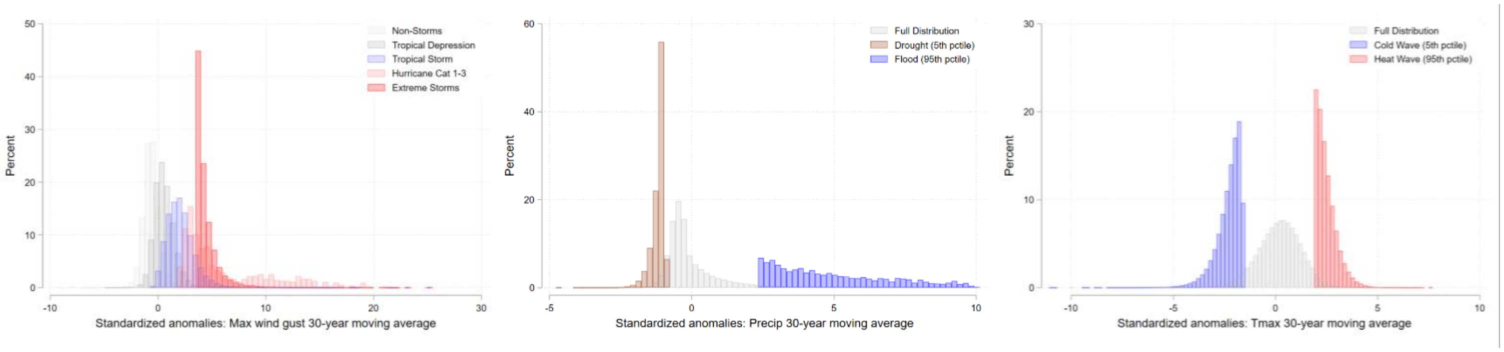


Figure A2. Distribution of Standardized Weather Anomalies

A. Storm

B. Flood and Drought

C. Heatwave and Cold Snap



Appendix II. Comparison with EM-DAT

We compare G-SWAD with EM-DAT, one of the most widely used global disaster databases. EM-DAT is originally reported at the event occurrence level, but information on disaster start day is sparse. We therefore aggregate the data to country-month level to maintain the granularity of our comparison while ensuring data availability. Disasters in EM-DAT are classified into six main groups: Geophysical, Hydrological, Meteorological, Climatological, Biological, and Extra-Terrestrial. We select disasters that are classified as “Storm,” “Flood”, "Drought" and "Extreme Temperature"[10] under the Hydrological, Meteorological and Climatological groups. Due to known data quality issues pre-2000 in EM-DAT, we restrict the comparison to the period 2000-2023. During this period, EM-DAT reported 7407 climate-related disasters, 99% of which (n=7330) are matched to our data.

A key difference between EM-DAT and G-SWAD is that the former is event-based and reported by administrative and third-party sources, including governmental and non-governmental agencies, insurance companies, research institutes, and the press, whereas the latter comes from geophysical and meteorological observations with intensity measurements. As a result, our comparison focuses on disaster count and occurrence, rather than intensity. We calculate the total[11] number of climate-related disasters, including storms, floods, droughts, heatwaves and cold snaps, for each country-month across these two datasets. More than 81% of EM-DAT climate-related disasters (n=6013) are captured by our data. Most of the unmatched observations (n=1083) are tropical depressions[12] that do not meet our intensity threshold for storms.

Figure A3 panel A shows a scatterplot of country-month observations for G-SWAD and EM-DAT. Our dataset consistently shows a higher number of disasters compared to EM-DAT. Close to 50% of the country-month observations in our sample have 2 more disaster occurrences than EM-DAT, and 22% of observations have 5 more disasters (Figure A3 panel B). To check if the underreporting in EM-DAT varies systematically across countries and relative to the mean of the two datasets, we show in panel C the difference in average monthly disaster counts against the mean of the two sources in a Bland-Altman type plot. There is a clear negative linear relationship, indicating the two sources diverge systemically as disaster frequency increases. For countries with low disaster occurrence, the two datasets are in alignment and differences are close to zero. However, EM-DAT systematically reports fewer disasters than G-SWAD for disaster-prone.

The divergence is concentrated among two groups of countries. The first consists of small island developing states in the Caribbean and the Pacific, such as Trinidad and Tobago (TTO), Niue (NIU), Grenada (GRD), Antigua and Barbuda (ATG). For these countries, G-SWAD's daily geophysical- and meteorological-based methodology captures frequent extreme weather events that rarely meet EM-DAT's casualty or damage reporting thresholds[13] given their smaller population. The second group includes low-income countries in Sub-Saharan Africa with limited statistical and institutional capacity, such as the Democratic Republic of the Congo (COD), the Central African Republic (CAF), and Uganda (UGA), where disasters occur but are systematically underreported to international databases. Russia (RUS), with its vast geography spanning multiple climate zones, emerges as a distinct case. G-SWAD could be capturing high frequency regional and localized extreme weather events, many of which would be consolidated or unreported in EM-DAT.

Overall, these comparisons reveal that G-SWAD captures almost all major climate-related disaster events in EM-DAT, but the reverse is not the case (panel D). EM-DAT systematically undercounts and underreports in countries with higher disaster frequency, smaller population, large geography with many localized events, or limited institutional capacity. These distinctions have important implications for empirical applications and disaster risk management. EM-DAT data contains systematic measurement errors that are correlated with country characteristics, such as income, population size, and institutional capacity, thereby raising endogeneity concerns. G-SWAD, by deriving disaster frequency and intensity from geophysical and meteorological

---

[10] Within the "extreme temperature" disaster type in EM-DAT, we create separate variables for heat wave and cold snap to correspond to our analysis.

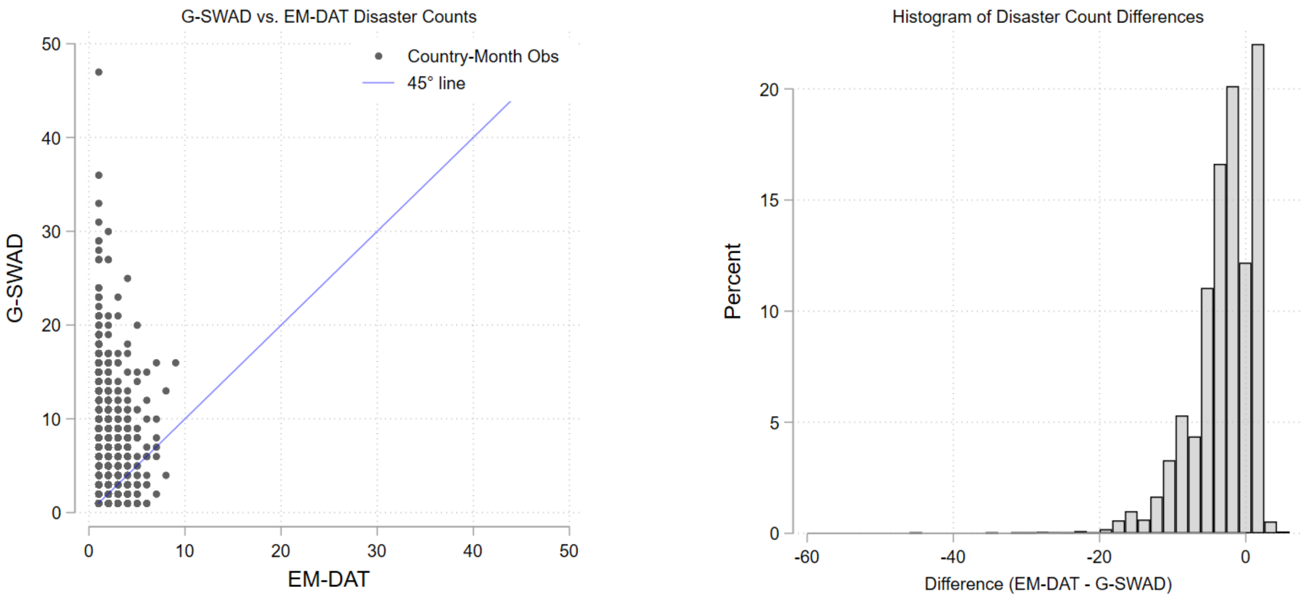
[11] We do not compare disaster occurrence for each type of disasters individually to minimize attribution and classification errors in EM-DAT data. For instance, a disaster classified as storm by EM-DAT could in fact correspond to a flood in our data due to exceeding the threshold for precipitation anomalies.

[12] NASA defines tropical depression as "a low-pressure area is accompanied by thunderstorms that produce a circular wind flow with maximum sustained winds below 39 mph (17m/s)."

[13] EM-DAT focuses on major disasters and inclusion in the database requires at least one of the following criteria: 10 fatalities; 100 affected people; a declaration of state of emergency; a call for international assistance.

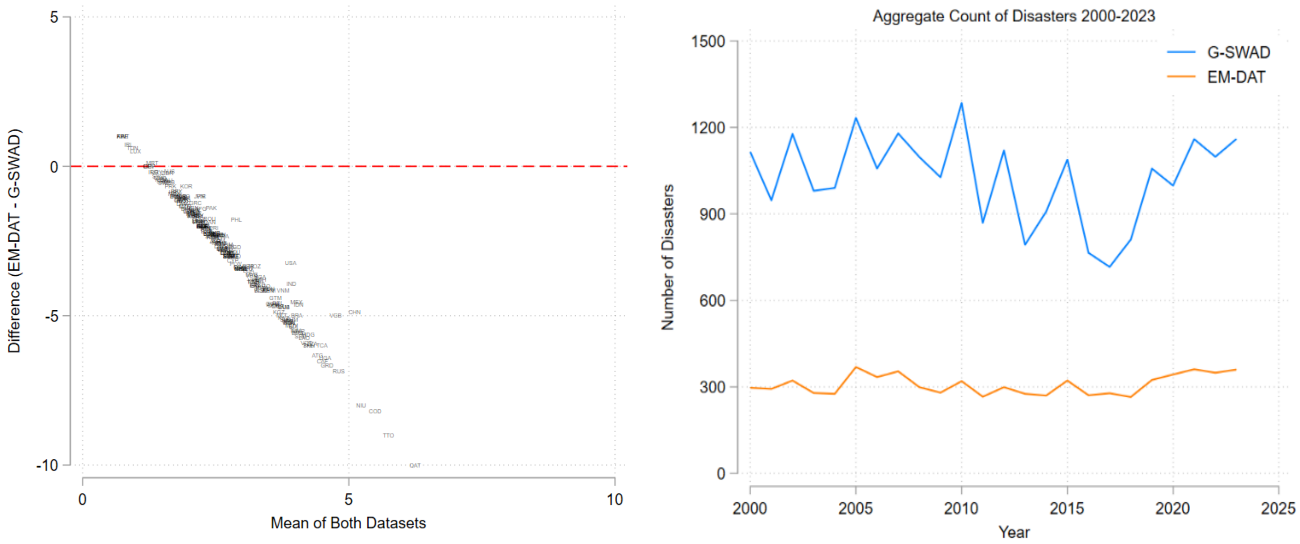
observations rather than administrative and third-party reporting, offers a comprehensive set of extreme weather variables that are more reliable for causal inference and cross-country comparison.

Figure A3. Comparison of Weighted Climate Data and EM-DAT



A. Scatterplot of Country-Month Observations

B. Histogram of Disaster Count Differences



C. Bland-Altman Plot of Differences

D. Time Series of Aggregate Disaster Counts

Appendix III. Impact of Extreme Weather Events on GDP Growth

Table A1: Impact of Extreme Weather Events on GDP Growth

	All Countries			AEs			EMDEs		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Storm	-3.663*	4.316**	-1.199	-0.344	-0.953	-1.076	-5.460**	4.573**	-1.499
	(1.959)	(2.046)	(2.515)	(2.560)	(4.724)	(4.330)	(2.260)	(2.258)	(2.865)
Flood	-0.343	-0.205	-0.124	-11.690	-3.347	-41.255	-0.336	-0.191	-0.083
	(0.275)	(0.154)	(0.124)	(7.760)	(14.706)	(37.637)	(0.274)	(0.158)	(0.129)
Drought	-2.953	-2.116	-2.490	+1.561	-4.905	-4.623	-3.059	-2.052	-2.385
	(1.878)	(2.125)	(2.377)	(3.721)	(3.680)	(3.678)	(1.957)	(2.226)	(2.475)
Heat	-1.138	-0.346	-0.914	4.897**	1.014	-1.529	-1.941**	-0.384	-0.817
	(0.752)	(0.662)	(0.636)	(1.863)	(2.088)	(2.015)	(0.749)	(0.729)	(0.692)
Cold	+0.170	-0.194	-0.015	-1.574	-1.187	+1.346	+0.878	+0.232	-0.219
	(1.107)	(1.327)	(1.289)	(2.508)	(2.713)	(2.970)	(1.234)	(1.513)	(1.478)
L.gGDP_w	0.418***	0.274***	0.234***	0.601***	0.423***	0.368***	0.395***	0.256***	0.218***
	(0.032)	(0.035)	(0.033)	(0.075)	(0.086)	(0.071)	(0.033)	(0.037)	(0.035)
L.storm	6.138***	0.641	-0.537	-1.477	-0.250	-2.970	7.089***	0.513	-0.585
	(2.099)	(2.559)	(2.317)	(4.018)	(4.245)	(5.036)	(2.347)	(2.918)	(2.505)
L2.storm	-1.976	-1.219	3.022	0.681	-1.301	-2.003	-2.517	-1.520	2.745
	(2.370)	(2.251)	(2.090)	(3.552)	(4.640)	(4.209)	(2.743)	(2.482)	(2.372)
L.flood	-0.044	0.011	0.195	6.247	-22.684	-28.841	-0.040	0.043	0.219
	(0.282)	(0.219)	(0.350)	(12.201)	(31.520)	(27.649)	(0.280)	(0.223)	(0.355)
L2.flood	-0.008	0.175	0.131	3.620	8.142	12.987*	0.025	0.195	0.131
	(0.100)	(0.434)	(0.100)	(2.858)	(6.746)	(7.585)	(0.108)	(0.433)	(0.098)
L.drought	+0.538	-0.392	-0.056	+0.774	+2.602	+1.401	+0.605	-0.264	+0.093
	(2.015)	(1.937)	(1.883)	(1.595)	(1.923)	(0.971)	(2.102)	(2.013)	(1.950)
L2.drought	+0.232	+0.258	+1.227	+2.062	+0.625	-1.334	+0.463	+0.479	+1.500
	(1.731)	(2.324)	(1.927)	(1.356)	(1.371)	(1.387)	(1.800)	(2.391)	(1.967)
L.heat	0.114	-0.783	-0.461	-0.472	-2.130	1.144	0.350	-0.557	-0.502
	(0.750)	(0.658)	(0.662)	(1.466)	(2.050)	(1.716)	(0.831)	(0.713)	(0.757)
L2.heat	-1.103*	-0.864	-0.402	-1.648	1.468	1.148	-1.075	-1.109	-0.931
	(0.616)	(0.702)	(0.731)	(2.042)	(1.881)	(1.565)	(0.683)	(0.799)	(0.827)
L.cold	-0.700	-0.292	-0.656	-3.620	-8.142	-12.987*	-0.823	-0.801	-0.696
	(1.076)	(1.148)	(1.238)	(2.858)	(6.746)	(7.585)	(1.257)	(1.356)	(1.481)
L2.cold	-0.112	-0.604	+0.836	+0.774	+2.602	+1.401	-0.547	-0.544	+1.013
	(1.161)	(1.286)	(1.040)	(1.595)	(1.923)	(0.971)	(1.380)	(1.541)	(1.233)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Countries	196	196	196	39	39	39	157	157	157
Observations	10161	9966	9771	2028	1989	1950	8133	7977	7821
Within R-squared	0.259	0.167	0.148	0.524	0.377	0.347	0.237	0.153	0.137

Notes: Columns (1)–(3) report local projection estimates of the effect of natural disasters on winsorized GDP growth at horizons t through t+2. Regressions include country and year fixed effects, lagged GDP growth, and two lags of each disaster indicator. Standard errors are clustered at the country level and reported in parentheses. *, **, and *** indicate significance at the 10, 5, and 1 percent level.

PUBLICATIONS

The Growth Effects of Natural Disasters: Evidence From A Novel Global Dataset Over 1970-2023
Working Paper No. WP/2026/106