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On the GDP Effects of Severe Physical Hazards *

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Abstract

We assess the impacts from physical hazards (or severe weather events) on economic activity in a panel of 98 countries using local projection methods. Proxying the strength of an event by the monetary damages it caused, we find severe weather events to reduce the level of GDP. For most events in the EM-DAT data set the effects are small. The largest events in our sample (above the 90th percentile of damages) bring down the level of GDP by 0.5 percent for several years without recovery to trend. Smaller events (below the 90th percentile) see a less immediate decrease in initial years (0.1 percent) that progressively widens to become similar to the effect of larger disasters after 10 years. Climatological hazards (droughts and forest fires) appear to have the largest effects. These findings are robust across country groupings by development and alternative measures of the strength of the physical hazard.

Keywords: Climate-related risk, GDP growth, Natural hazards and disasters, Rare disasters, Vulnerability to climate impacts
JEL codes: Q540, O500

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1 Introduction

Each year, extreme weather events take their toll by displacing millions of people and causing tremendous physical damages around the globe.[1] And these costs seem to be on the rise. As a share of global GDP, direct weather-related disaster damages have grown from around 0.03% in the 1970s to nearly 0.16% today (Figure 1). In the United States alone these damages reached $170 billion in 2022, see NOAA National Centers for Environmental Information (2023). However, these numbers only reflect the direct costs associated with the destruction of physical output and capital, and they do not include the indirect macroeconomic effects (e.g., foregone production, lower production efficiency, unavailable/displaced work force) which can reach multiples of the direct damages as the weather-related shocks propagate through various channels to the broader economy.

Many factors have driven up the costs from severe weather events, including increased economic and human activity in economically attractive but hazard-prone and vulnerable areas. But the prospect that severe weather events are very likely to increase both in their physical intensity and frequency in many locations as a result of climate change, raises the risk of even higher economic damages associated with physical hazards.[2]

Against this backdrop we revisit the broader economic costs from severe weather events in a panel of 98 countries using local projection methods. Following Jordà (2005), we run a sequence of regressions of the cumulative change in per-capita-country GDP on the disaster shock variable at each horizon up to 10 years. For information on disaster shocks we turn to the EM-DAT database maintained by the Centre for Research on the Epidemiology of National Disasters (CRED). As we are interested in the effects of all weather-related disasters across types and severity, our preferred measure of disaster are the associated direct dollar damages recorded in EM-DAT.[3] To capture possible nonlinearities in the effects from severe weather, we distinguish between events with damages in the 90th percentile of damages (referred to alternatively as "very costly") and those below ("costly").

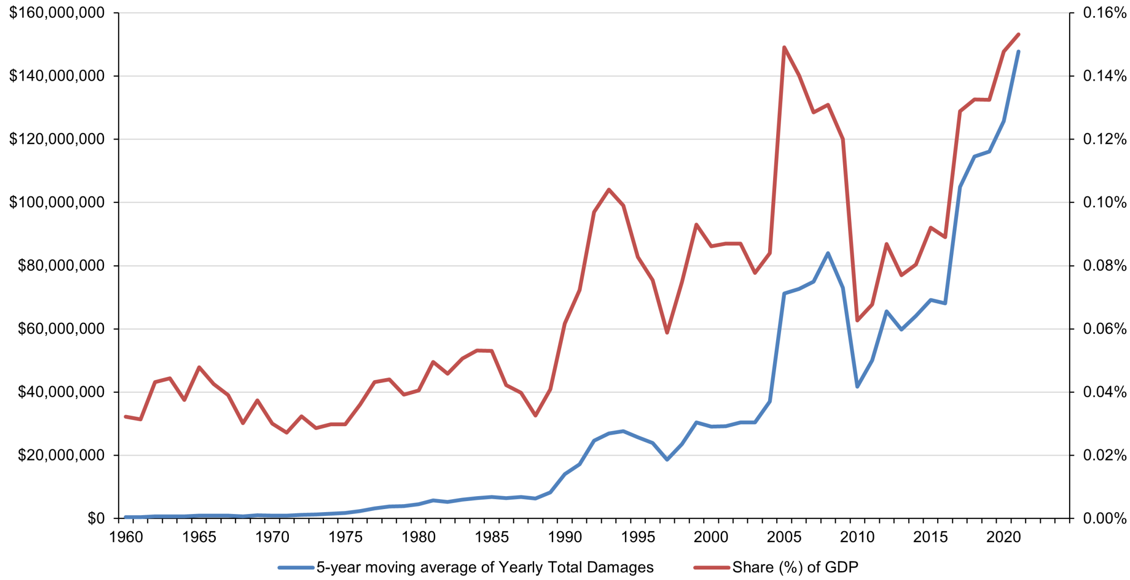
When pooling all weather-related disasters, we find that the average disaster shock in the 90th percentile is associated with a larger year-on-year decrease in GDP (around

[1] The Office Of The United Nations High Commissioner For Refugees (UNHCR) estimates that since 2008 around 20 million people are displaced each year because of severe physical hazards.

[2] According to the IPCC Sixth Assessment Report from 2023, temperature extremes, heavy rainfall, and droughts, and other physical hazards are set to become more frequent and intense compared to the historical norm as global temperatures increase, see Pörtner et al. 2022.

[3] In addition to facilitating comparison across disaster types and aggregation (both across types and time), direct damages also reflect the vulnerability of the affected areas to physical hazards. When using purely geophysical measures (such as wind speeds or precipitation) instead additional data are required to obtain a data on economic implications.

Figure 1: **Cost of all natural disasters as a share of world GDP**



Note: Share (%) of GDP measures direct physical damages in nominal dollars divided by nominal GDP.
Sources: EM-DAT, CRED/UCLouvain, Brussels, Belgium – www.emdat.be; World Bank, World Development Indicators.

-0.5%) than for those below the 90th percentile (less than -0.1%). Nevertheless, the cumulative effect after 10 years is about the same for both groups of disasters, at -0.5%. The timing and shape of the physical effects differ noticeably between the two groups confirming the importance to allow for nonlinearities in the effects.

We repeat our exercise distinguishing disasters by types of physical hazard to account for the fact that the various hazards propagate through different channels.[4] Consider, for example, the likely effects of a cyclone (a meteorological disaster) with those from a drought (a climatological disaster). A cyclone primarily damages and impairs the use of physical capital, public infrastructure, and private and commercial real estate. In addition to the temporary loss of productive capacity, the loss in assets amplifies the effects of the cyclone via the financial sector. By contrast, droughts impact disproportionately the agricultural sector via their effects on water resources (rivers, lakes, and reservoirs). Agricultural output is destroyed, but the physical capital stock is largely unaffected.

Our analysis suggests that climatological disasters (droughts and forest fires) have more pronounced effects on per-capita GDP for very costly and costly events than

[4]We distinguish weather-related disasters into three categories: climatological (droughts, forest fires), meteorological (hurricanes, extreme heatwaves) and hydrological (floods, land slides, wave actions) disasters.

other severe weather events. These types of disasters are associated with a cumulative decrease in per capita growth of 10% (at the 90% confidence level) over 10 years for disasters in the 90th percentile, while those below the 90th percentile experience a 1% drop over the same time frame (at the 68% confidence level).

When we do not separate disasters into very extreme ones (above the 90 percentile of damages) and other extreme events, the shape of the response of the economy resembles the shape of the very extreme ones. However, the average magnitudes of the uncovered effects are smaller. First, by construction the mean (over all observations without distinguishing percentiles) with which we scale the responses is smaller. Second, we show that the marginal effects from severe weather events are smaller for more powerful events. Combining smaller scaling factors and smaller marginal effects lowers the overall impact that we uncover. The changes in the estimated economic impact of severe weather events when distinguishing these events by percentiles of damages reveal the importance of splitting them into two groups in the first place. Without the distinction by intensity, the economic effects from severe weather events are understated.

Having explored differences across types of physical hazards we turn to shedding some light on the role of country characteristics. Disaster damages combine different characteristics of a severe weather event: they reflect the geophysical strength of the physical hazard, the assets exposed to the hazard, and their vulnerability in case of a hazard. Thus, two countries (or locations) that are affected by a hazard of identical geophysical strength may experience very different direct damages. For example, if the first location enjoys greater human and economic activity (exposure) but also features poor infrastructure/protection against the hazard (vulnerability) than the second one, the first location will experience greater direct damages for the same physical hazard treatment. As disaster vulnerability may depend to a large extent on a country's level of development, we split our sample into a high-, middle- and low-income group. To have a sufficient number of observations for each country group, we drop the classification of events into above and below the 90th percentile bins by severity in this part of the analysis.

Qualitatively, the results for each country group are generally in line with the findings derived from the full sample: physical hazards lower economic activity for several years with climatological disasters having more pronounced effects than other types of disasters. The exception are low income countries where meteorological disasters (hurricanes and heatwaves) are worse. Overall, and consistent with our initial expectation, low-income countries also bear larger immediate effects from a mean shock in disaster damages (decreasing 0.5% in the first year). In wealthier countries, technologies like air conditioning, flood barriers or dams that limit the impact from severe weather events are prevalent, whereas the adaptation to physical hazards lacks sufficient funding in low-income countries to prevent larger effects.

The contribution of this paper lies in computing the dynamic economic effects caused by the different types of severe weather events while differentiating by disaster severity. Most existing works either focus on the short-term (Felbermayr and Gröschl 2014) or the long-term impacts (Hsiang and Jina 2014). Regarding the measure of disaster occurrence and strength, two other approaches found in the literature are a simple disaster incidence measure (Raddatz 2009 or Roth Tran and Wilson 2023) and measures of geophysical strength of the hazards (Felbermayr and Gröschl 2014, Hsiang and Jina 2014). We find our approach appealing as direct damages allow comparability across events with regard to their strength and allow for the aggregation of disaster events over the time interval used in the analysis (dictated by the availability of GDP data). In addition, direct damages reflect exposure and vulnerability of the affected areas, data that are hard to obtain for the entire set of countries in our sample. By contrast, geophysical data need to be merged with data on exposure of human and economic activity to the event and with vulnerabilities. Simple disaster incidence measures contain no information about the disaster strength. However, we also conduct our analysis using such a measure and find larger effects than with our original approach.

The study closest to ours is Raddatz (2009). Using slightly different methodology and relying on a disaster incidence measure, Raddatz (2009) argues that severe weather events have a negative impact on GDP growth over a five-year average. Given that the paper uses only the number of disasters in a given year in each country as the shock measure, disasters cannot be differentiated by their strength.

Other authors have investigated the differential effects of extreme disasters. Using data on the geophysical strength of disasters from 1979 to 2010, Felbermayr and Gröschl (2014) establish that the initial output loss from a severe disaster rises nonlinearly with the intensity of the event. The output loss due to a disaster in the top 1-percentile of their disaster intensity measure is about 14 times higher than in the top 5-percentile. Cavallo, Galiani, Noy, and Pantano (2013) find that disasters in the 99th percentile of damages have long-lasting negative effects on GDP, 10% lower on average than it was before the disaster. The effects are far less severe when considering disasters in the 90th or 75th percentile. Hsiang and Jina (2014) use windspeed of global tropical cyclones from 1950-2008 to proxy the strength of the disaster shock and find that GDP growth is lower for years following a cyclone. Disasters in the 90th percentile imply losses of per-capita income of 7.3%. Finally, von Peter, von Dahlen, and Saxena (2012), for their part, also find sustained negative impacts from natural disasters, with annual GDP growth lowered by more than 0.5% for two years. Our paper differs from all these studies by including 10 more years of disaster data and the choice of methodology.

Not all studies find a negative impact from severe weather events on economic activity. Skidmore and Toya (2002) form long-run averages of GDP growth to understand the long-term effects from disasters. They find that disaster occurrence (represented by a dummy variable taking on the value of 1 if a disaster occurred in a given year) boosts long-run GDP growth. However, Noy and Nualsri (2007) and Jaramillo (2009) come to the opposite conclusion, when using data on deaths and damages to proxy the strength of events instead of a simple dummy variable. Other related papers use panel data on at the local level. Roth Tran and Wilson (2023) study the U.S. county-level impact of disaster incidence on income. Barattieri, Borda, Brugnol, Pelli, and Tschopp (2021) estimate the firm- and county-level employment effects following hurricanes in Puerto Rico. Both of these papers interpret their findings as providing partial support for disasters having positive economic effects in the medium to long run.

Section 2 presents the data used in our analysis. Section 3 details our methodology while Section 4 discusses our results. Concluding remarks are offered in Section 5.

2 Data

We assess the effects of severe weather events on aggregate economic activity at the country level across a large set of countries. In addition to information about the occurrence of a weather-related disaster (disaster incidence), we also include information about their strength (disaster severity). The EM-DAT database provides data on the direct damages to physical output and capital (in U.S. dollars) from over 22,000 disasters between 1900 and today.[5] Many papers in the literature have utilized the EM-DAT database to study the effects from natural disasters, amongst others Cavallo et al. (2013), Noy (2009), Skidmore and Toya (2002) and Parker (2018).

Given our interest in assessing the economic implications from severe weather events across the globe, the EM-DAT data on direct damages are appealing. The literature distinguishes three dimensions that determine the physical impact from disasters: physical hazard, exposure, and vulnerability. The first dimension relates to the occurrence, type, and intensity of the event. The exposure dimension reflects the total value of assets and socioeconomic elements. Finally, the vulnerability dimension describes the degree of damage of the exposed assets and socioeconomic elements expected at different hazard intensities. The EM-DAT data on damages combines these three dimensions into

[5] A disaster is included in EM-DAT if at least one of the following criteria is met: 10 or more deaths, 100 or more people affected/injured/homeless, or some declaration by the country of a state of emergency and/or appeal for international aid. The database also records detail on the type of disaster, as well as estimated deaths, damages, and total population affected, amongst other physical and human capital metrics. EM-DAT uses national reporting and insurance claims to estimate the direct monetary damages from natural disasters to the extent possible. Source: EM-DAT, CRED/UCLouvain, Brussels, Belgium – www.emdat.be.

a single measure. Dollar damages tend to be greater for disasters of great intensity, occurring in areas with greater economic and human activity, and in a setting that makes the exposed assets and socioeconomic elements more vulnerable to physical hazards. In addition, exposure and vulnerability can evolve over time. Monetary damages do incorporate such changes. Moreover, dollar damages of disaster occurrences can easily be aggregated across time and type. If the dependent variable of interest is available only at a low frequency—many disaster-prone countries publish GDP data of sufficient quality only annually over large parts of our sample—some countries may experience multiple severe weather events during one unit of time measurement.

One of the shortcomings of the EM-DAT damage data is that estimates can be inaccurate due to faulty government reporting or low insurance penetration. Noy (2009) and Skidmore and Toya (2007) document that economic and social indicators can themselves be correlated with damages, with less developed countries seeing more severe effects in the aftermath of a disaster.

An alternative approach is to gather separate data on hazard intensity, exposure and vulnerability by country and over time. Hsiang and Jina (2014) or Felbermayr and Gröschl (2014) collect geophysical information such as wind speed or precipitation to measure the intensity of physical hazards.[6] The resulting measures are free from the spatial distribution of economic activity and thus some of the events included in their data sets may be of little to no economic consequences when they affect an area without economic activity. As such, these data assess the economic impact from all physical hazards (in the data set) regardless of where they strike, whereas the intensity measures from EM-DAT (deaths, people affected, or direct damages) provide information conditional on the hazard having struck an area of sufficiently significant human and economic activity. Both approaches are of interest. Ideally, spatial data on the geophysical strength of physical hazards is complemented with spatial data on exposure and vulnerability to derive conditional estimates. Microeconomic studies have explored various directions in this regard.

Our analysis uses annual data of constant dollar damages from natural disasters, across a panel of 98 countries and 40 years, from 1980 to 2019. We collect the dependent variable, GDP growth, by taking the logarithm of the World Development Indicators (WDI) GDP series, and generate dummy variables classifying countries into three groups of development.[7] These groupings are a High-Income, Middle-Income and Low-Income country group, classified according to the United Nations cutoffs of GDP per capita in every given year, meaning some countries in our sample switch between

[6] IRI/LDEO Climate Data Library is a collection of numerous databases that contain information on the geophysical strength of severe weather events.

[7] World Development Indicators. Washington D.C. : The World Bank.

groups. Additional series are taken from the Penn World Tables (Feenstra, Inklaar, and Timmer 2015), specifically the population or current account indicators. Our set of countries is similar to that in Noy and Nualsri (2007), likewise with a similar aggregation of damage data, which we found to be a representative mix of size, geographies and varied economies. The complete list can be found in Appendix A.

Each EM-DAT database entry corresponds to a recorded disaster. We normalize the country and year sum of damages by total country GDP to account for a country's economic size. For disasters that last multiple years—such as the droughts in Zimbabwe from 2013 to 2017 or Iran from 1999 to 2001—we allocate the total damages from the disaster evenly over its duration. Furthermore, we sort disasters into the following categories, as defined by EM-DAT:

- Climatological disasters: droughts, wildfires and glacial lake outbursts. These are disasters that are "caused by long-lived, atmospheric processes."
- Meteorological disasters: extreme temperatures, fog, and storms. These disasters are "caused by short-lived, extreme weather and atmospheric conditions."
- Hydrological disasters: floods, landslides and wave actions. These disasters are "caused by the occurrence, movement and distribution of surface and subsurface of bodies of water."

Table 1 summarizes the yearly disaster data, for all years and countries with breakdowns by type of disaster and country income group. Hydrological disasters have the most entries (at 636 in total), while climatological ones have the lowest share (at 228 across all countries and years). Middle-income countries also constitute the largest number of observations (see third column "Obs."). The final column shows the number of observations that are in the 90th percentile of damages as a share of GDP of all disaster events, that fall into the different country income groups and disaster types. Cavallo et al. (2013) group "large" natural disasters in a similar way. We restrict attention to the 90th percentile to make sure to have sufficient observations for each disaster type in our "large" disaster group. As a proportion of the number of overall observations (final column), low-income countries and middle-income countries experience a high share of disasters in the 90th percentile. Conversely, high-income countries have a smaller share of disasters in the 90th percentile, and lower mean values of damages as a share of GDP.

The large share of middle-income countries in both the total population and land area throughout the span of our sample, see also Figure 12 of Appendix A, suggests great exposure to disaster risk by this group of countries. Countries with more land mass and population are more likely to experience a larger number of disasters affecting

Table 1: Summary Statistics

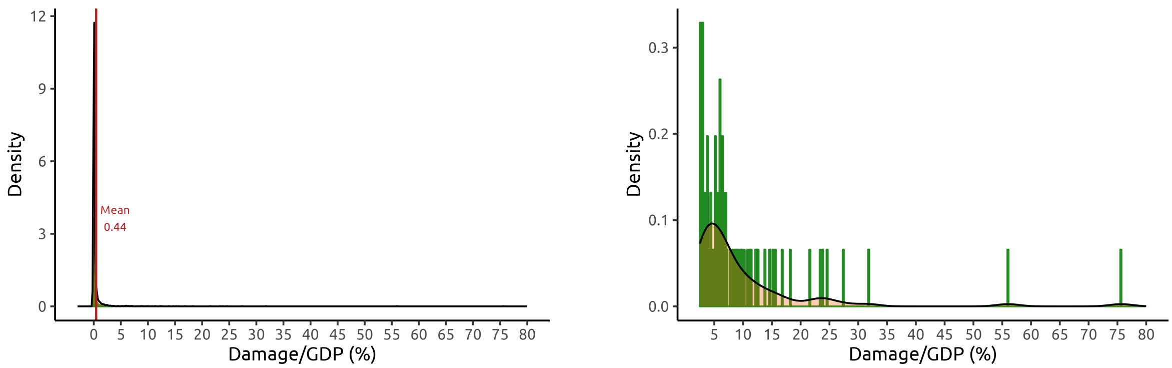
	Damages (% of GDP, only years with disasters)			Years with $D > 90th$ percentile
	Mean	SD	Obs.	Obs.
Total	0.73	2.77	1,030	126 (12.2%)
High-Income	0.20	0.44	351	10 (2.8%)
Middle-Income	0.98	3.51	573	93 (16.2%)
Lower-Income	1.18	2.48	106	23 (21.7%)
Climatological	0.39	1.57	228	14 (6.1%)
High-Income	0.27	0.40	79	4 (5.1%)
Middle-Income	0.48	2.01	134	8 (6.0%)
Lower-Income	0.29	0.59	15	2 (13.3%)
Meteorological	0.79	3.57	461	39 (8.5%)
High-Income	0.14	0.46	212	2 (0.9%)
Middle-Income	1.41	5.06	211	32 (15.2%)
Lower-Income	1.05	2.62	38	5 (13.2%)
Hydrological	0.47	1.50	636	84 (13.2%)
High-Income	0.12	0.23	170	5 (2.9%)
Middle-Income	0.52	1.60	384	62 (16.1%)
Lower-Income	0.99	2.21	82	17 (20.7%)

Higher-income countries are defined as all observations where GDP per capita is above $12,000. Middle-income countries are all countries with GDP per capita between $1,036 and $12,000, while low-income countries are all observations below $1,036. There are 3,920 observations total, split between 1,193 for high-income countries, 1,860 for middle-income countries, and 716 for low-income countries.

Sources: EM-DAT, CRED / UCLouvain, Brussels, Belgium – www.emdat.be. World Development Indicators. Washington D.C. : The World Bank.

their area and settlements as evidenced by Table 1. Since we define our country income groups by per-capita GDP year by year, the group compositions change over time.[8]

Figure 2: **Distribution of all climate disasters by % of GDP damaged**



(a) All disasters

(b) All disasters above 2.5%

Note: Distribution shows all disasters in EM-DAT. The plot on the right, 2b, excludes disasters below 2.5% to emphasize outliers.

Figure 2 displays the distribution of disaster damages (as share of GDP) in the EM-DAT database. As seen in the left panel, Figure 2a, the distribution is skewed to the right with a mass point of disasters between 0 and 0.1% of GDP damages and a scattering of rare but highly intense damages above 10% of GDP. The panel on the right zooms in on the density function for events that exceed physical damages of 2.5% of GDP.

3 Methodology

To estimate the impact of extreme weather events on GDP, we use a panel fixed-effects regression to compute local projections over different year horizons in line with Jordà (2005). As shown in Li, Plagborg-Møller, and Wolf (2022) and Plagborg-Møller and Wolf (2021), local projections imply the same impulse responses as Vector Autoregressions (VARs) in many circumstances. Since we study the effects of a clearly defined shock (disasters) on a particular variable (cummulative per capita GDP growth), local projections are sufficient for identifying the effects of interest.

[8]Middle-income countries account for a much larger share of population than any other income group towards the end of our sample (more than 70%) as evidenced by Figure 12b in Appendix A, and equally account for around half of the land mass. Meanwhile, low-income countries have a small share of the total land area and population towards the end of our sample (under 10%), due to the progression of China and India into middle-income status in the 1990s and 2000s, respectively. High-income countries are consistently around 20% of the total population, and between 30% and 40% of the land mass.

The main independent variable is direct disaster damages (as a percent of GDP), with the dependent variable being the log difference in GDP per capita between different time periods. Using a panel-data regression allows us to control for unobserved, time-invariant, country-specific quantities.[9] We add time-dummy variables to introduce time fixed-effects which control for any cross-country, time-specific shocks such as global recessions. Finally, we treat the extreme values in our sample of disasters as measured by GDP damages separately as discussed in the previous section. One dummy variable indicates whether a given year contains a "very costly" disaster in the 90th percentile ($\mathbb{1}(> 90\%)$), and another dummy indicates "costly" disasters below the 90th percentile ($\mathbb{1}(< 90\%)$).

Specifically, we estimate the regression over the set of horizons $s \in \{0, 1, 2, ..., 10\}$:

$$\begin{aligned}\log y_{i,t+s} - \log y_{i,t-1} = {} & \beta_1^s D_{i,t} \times \mathbb{1}(< 90\%) + \beta_2^s D_{i,t} \times \mathbb{1}(> 90\%) \\ & + \sum_{\substack{h=-3 \\ h\neq 0}}^{s} \gamma_h^s D_{i,t+h} + \sum_{k=1}^{3} \theta_k^s \Delta \log y_{i,t-k} + \alpha_i + \alpha_t + \varepsilon_{i,t+s} \end{aligned} \tag{1}$$

$y_{i,t}$ denotes GDP per capita in constant prices for country i in year t, $D_{i,t}$ is the (standardized) dollar damage as a share of GDP of country i in year t, and α_i, α_t are country and year-fixed effects, respectively. The first sum, $\sum_{\substack{h=-3 \\ h\neq 0}}^{s} \gamma_h D_{i,t+h}$, represents a series of leads and lags in the value of $D_{i,t}$ to control for disaster damages in the past (or that occur in the future up to horizon s when projecting forward). This approach resembles Roth Tran and Wilson (2023) to prevent the impulse response functions from being subjected to biases from unrelated past or future disasters. Even in the case of related past or future damages (such as droughts), taking this approach allows us to isolate the (estimated) effect of each year's damages.[10]

The final sum in equation (1) brings in lagged values of year-on-year economic growth, $\Delta \log y_{i,t} = \log y_{i,t} - \log y_{i,t-1}$, to control for any pre-disaster growth dynamics that may influence post-disaster growth dynamics in time period s. We include 3 years of past GDP growth, beyond which any additional lagged values do not confer much statistical significance in our linear regression.

The coefficients β_i^s over the 11 readings (with the first year 0 as the contemporaneous effect of disaster damages) summarize the impulse response function for cummulative

[9] This approach may help to reduce certain biases in our regression, such as the level of development, education, or other general variables that are country-specific, correlated with growth, and have broadly remained constant over our observation period. Even so, our findings remain generally robust to inclusion of additional explanatory variables, such as GDP per capita level, openness to trade, or fertility.

[10] The inclusion of these additional variables does not significantly change our results. However, we are able to estimate the effects of individual years more accurately under this approach.

GDP growth in response to a severe weather event. We distinguish between β_1^s and β_2^s for the impulse responses for costly and very costly disasters, respectively. When assessing the effects from each disaster type (climatological, meteorological and hydrological) or for country groupings we only include the relevant data.

4 Results

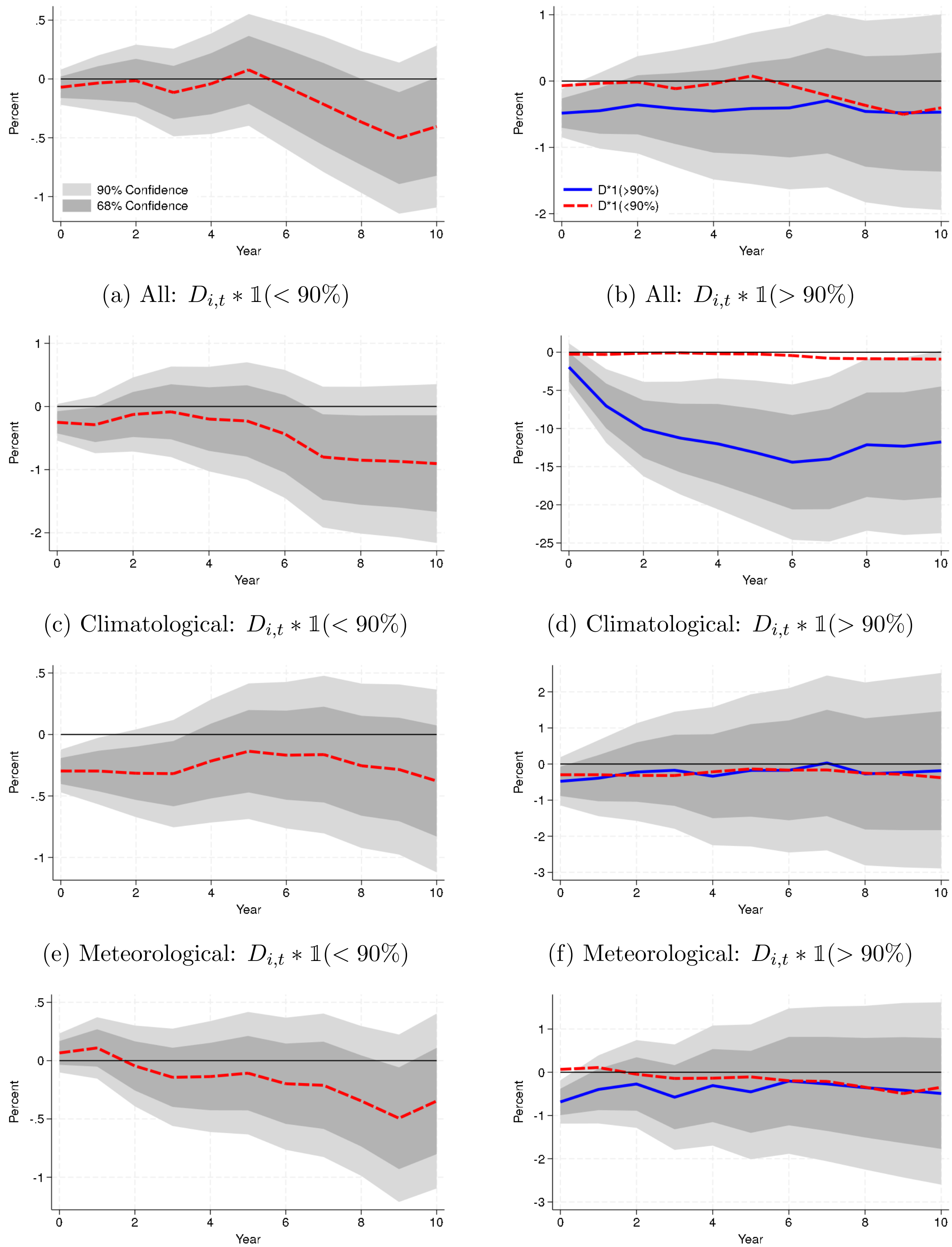
We plot the two impulse response functions (IRFs) of GDP for severe weather events below and above the 90th percentile of damages in Figure 3. The figure shows the results for all extreme weather events and separates by type of disaster, i.e., climatological (droughts, forest fires), meteorological (storms, extreme temperatures), and hydrological (floods, wave actions). We plot the mean IRFs as well as 68% confidence bands (dark gray), and 90% confidence bands (light gray). The responses are scaled by the mean of GDP damages for the respective percentile group. The IRF plots in the left column are for costly disasters (below the 90th percentile group) and those in the right column are for very costly disasters (in the 90th percentile). To facilitate comparisons, we repeat the mean response of the costly disasters in the columns on the right.

The plots in Figure 3 reveal that severe weather events negatively impact GDP per capita for a prolonged period. The effects are of varying statistical significance and magnitudes, but remain negative for almost all time periods of the different disaster groups. Figures 3a and 3b show that costly and very costly severe weather events exhibit a decrease in cumulative GDP per capita growth of around 0.5% after 10 years, but in initial years this decrease is not as immediate for costly disasters (approximately -0.1% in the year of the disaster) as for the very costly ones. These numbers are comparable to Raddatz (2009) who reports that "a climatic disaster affecting at least half a percent of a country's population [...] reduces real GDP per capita by 0.6 percent" 10 years after the initial disaster. The year-on-year results are also corroborated by Felbermayr and Gröschl (2014), who find that year-on-year growth decreases by 0.18% in response to a sample mean shock of a natural disaster.

When comparing the magnitudes of the indirect macroeconomic effects to the initial direct damages it is key to keep the following in mind. The direct damages are concentrated on the physical capital stock (private and public). While some (stored) output might be directly destroyed by the disaster, the output loss both in the year of the severe weather event and thereafter stems from the loss in productive capacity and the associated drops in productive efficiency and work force availability. These supply side effects are amplified through financial and demand channels.

Moving on to the sub-categories of disasters, cumulative GDP per-capita growth is about 0.5% lower for meteorological and hydrological disasters after a period of 10 years

Figure 3: **Cumulative growth responses to shock from damage and 90th percentile**



(a) All: $D_{i,t} * \mathbb{1}(< 90\%)$

(b) All: $D_{i,t} * \mathbb{1}(> 90\%)$

(c) Climatological: $D_{i,t} * \mathbb{1}(< 90\%)$

(d) Climatological: $D_{i,t} * \mathbb{1}(> 90\%)$

(e) Meteorological: $D_{i,t} * \mathbb{1}(< 90\%)$

(f) Meteorological: $D_{i,t} * \mathbb{1}(> 90\%)$

(g) Hydrological: $D_{i,t} * \mathbb{1}(< 90\%)$

(h) Hydrological: $D_{i,t} * \mathbb{1}(> 90\%)$

Note: The shock is scaled by the average value of the interaction term.

for both costly and very costly disasters, as in Figures 3e, 3f, 3g and 3h. Hydrological disasters seem to drive the shape of the IRFs when using the full sample of observations which is not too surprising given the large share of hydrological events in the EM-DAT database. In contrast to the other disaster types, the effects from climatological costly and very costly disasters differ markedly from each other: cumulative GDP per capita decreases by 1% after 10 years for disasters below the 90th percentile, whereas it drops by around 12% for disasters in the 90th percentile. Both of these impacts cumulate over time, with the initial years registering a 0.2% decrease and 2% decrease, respectively.

One possible explanation for the particularly damaging impact of climatological disasters may be their sustained impact. Raddatz (2009) also finds that "among climatic disasters, droughts have the largest average impact, with cumulative losses of 1% of GDP per capita" in response to their occurrence. Unlike other disasters such as storms or floods, droughts can last months or years, while forest fires and droughts both have long-run consequences on land resources due to soil deterioration.

Given the size differences between costly and very costly direct damages, one would generally expect the response of cumulative GDP per-capita growth to be noticeably larger for disasters in the 90th percentile than those below the 90th percentile. Although true for climatological disasters, and for meteorological and hydrological disasters in the first few years, this does not hold for meteorological and hydrological disasters further out.

To shed some light on the differences between percentiles, we perform auxiliary regressions in (2)-(4). These regressions re-obtain the coefficients of the year-on-year growth effects on the groups of costly and very costly GDP damages. This approach provides a robustness check and helps distinguishing the marginal from the overall effects. As a bi-product, we are able to visualize the data distribution of each GDP damage percentile group separately, by plotting the residuals. Consider the regressions identifying the effect of costly disasters below the 90th percentile:

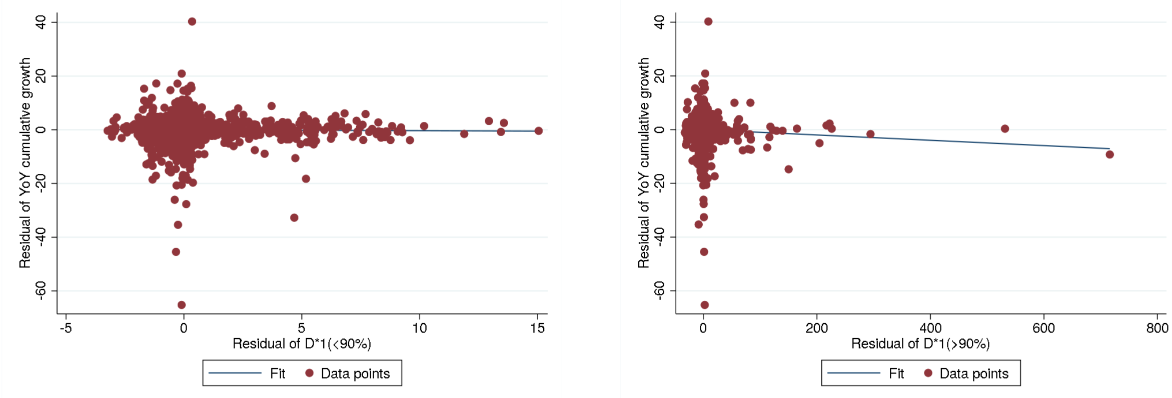
$$\log(y_{i,t}) - \log(y_{i,t-1}) = \beta_2' D_{i,t} \times \mathbb{1}(> 90\%) + \lambda_2' C + \varepsilon_{i,t}' \tag{2}$$

$$D_{i,t} \times \mathbb{1}(< 90\%) = \beta_2^* D_{i,t} \times \mathbb{1}(> 90\%) + \lambda_2^* C + \nu_{i,t} \tag{3}$$

$$\varepsilon_{i,t}' = \beta_1^s \nu_{i,t} + \epsilon_{i,t} \tag{4}$$

First, we regress the one-period ahead GDP per-capita growth on our control variables (regression 2), then we regress our interaction term of interest on the controls (regression 3), where $C = \sum_{h=1}^{3} (D_{i,t-h} + \Delta \log y_{i,t-h}) + \alpha_i + \alpha_t$ is the vector of control variables and λ is the corresponding coefficient estimate vector. The residuals from the first regression $\varepsilon_{i,t}'$ are the variation in GDP growth unexplained by very costly disasters (disasters above the 90th percentile) and remaining controls. The residuals from the second regression $\nu_{i,t}$ are the variations in the damages from costly disasters (below the 90th percentile) unexplained by the very costly disasters and the controls. Regressing the residuals of the former regression on those of the latter (as in 4) gives us the same coefficients of the interaction term as our baseline regression, β_1^s. We also run the regression with the roles of the percentile groups reversed to obtain β_2^s.

Figure 4: **Scatter plots of residual regressions to all disasters**



(a) All: below 90th percentile

(b) All: above 90th percentile

Note: Fitted lines for the residual regression from $D_{i,t} * \mathbb{1}(> 90\%)$ and $D_{i,t} * \mathbb{1}(< 90\%)$.

Figure 4 plots the slope β_1^s and β_2^s and the residuals from the regressions concerning all disasters, for each interaction term of GDP damages with 90th percentile splits. While the average effect one year ahead is worse for very costly disasters (-0.48 versus -0.070 for disasters below the 90th percentile) as is consistent with the early years of Figures 3a and 3b, the marginal effect (which corresponds to the unscaled slope β in response to 0.1% additional GDP damages) is more negative for costly disasters: the coefficient in Figure 4a is -0.04, whereas that in 4b is -0.01.[11] A key concern of our analysis is how outliers may inflate our estimates, in particular for β_2^s. The residual scatter plot in Figure 4b reveals the existence of some outlier events in the very costly disaster damages with residual values above 300. However, these outliers reduce the slope estimate; when removing them, the slope estimate almost doubles in absolute value.[12] Hsiang and Jina (2014) report a similar finding. They find that the marginal effect of smaller disasters on growth (defined as cyclones with wind speeds below 10 meters per second) is more negative than the marginal effect of larger disasters (wind

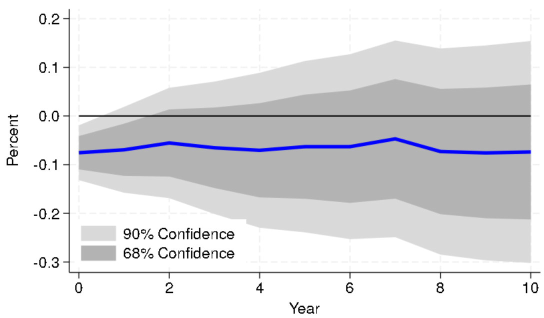
[11] A breakdown by type of disaster can be found in Appendix B, summarized in scatter plot shown in Figure 14.

[12] This observation reaffirms our finding that the marginal effects of disasters are declining in the magnitude of the disaster, as evidenced by the slope comparisons between costly and very costly disasters.

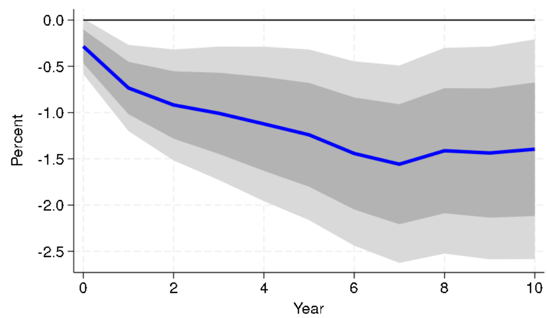
speeds above 20 meters per second).

This larger "marginal" effect for costly direct damages (below the 90th percentile) could reflect larger upfront costs (or a threshold effect) to severe weather events. For instance, a flood of 60 cm likely incurs more damage than a flood of 30 cm, but both will have upfront costs that will close roads, erode river banks, or cause displacement. An additional 10 cm on the 60 cm flood will likely not be as significant as an additional 10 cm on a 10 cm flood.

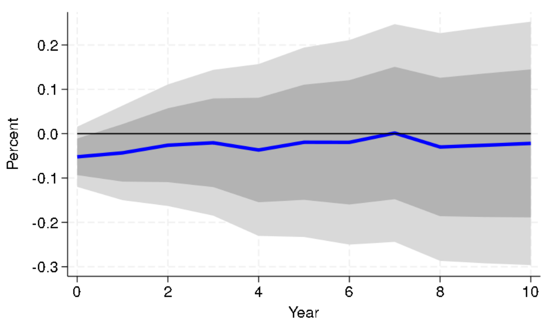
Figure 5: **Response of GDP (percent deviation) to a mean shock to physical damages, all countries**



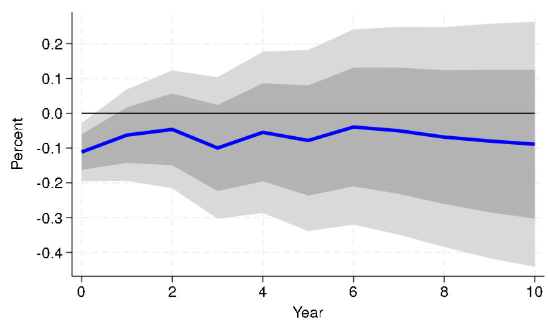
(a) All disasters



(b) Climatological disaters



(c) Meteorological disasters



(d) Hydrological disasters

When we remove the interaction dummy corresponding to percentiles in Figure 5, the shape of the IRFs resembles the ones for very costly disasters across disaster groupings. However, the magnitudes of the effects differ importantly between Figure 5 and Figure 3. First, the mean with which we scale the IRFs is smaller in Figure 5. Second, as just discussed, the marginal effects from severe weather events are smaller for more powerful events. Combining smaller scaling factors and smaller marginal effects lowers the overall impact that we uncover. The changes in the estimated economic impact of severe weather events when distinguishing percentiles of damages reveal the importance of classifying disasters by their intensity.

4.1 Country income blocks

The economic effects of severe weather events differ by country characteristics. The level of development is commonly viewed as a major determinant of weather-related disasters. Richer countries (in terms of per-capita GDP) have a different capacity to absorb the damages associated with severe weather events as they have better access to financial markets and can mobilize domestic resources more easily. They also have the financial means to build greater resilience through adaptation. In addition, many rich countries rarely experience disastrous weather events by virtue of their geography (Western Europe) or, if they do, the events are localized given the size of the country (United States and Canada) and affect only a small share of economic activity.[13] For middle income countries, some authors have raised the possibility that severe weather events may have a positive effect on economic activity if the event leads to subsequent upgrading of the physical capital stock and infrastructure. While such a relationship may be observed in the data, assigning meaningful causality to it appears questionable. The severe weather event may only determine the timing of the upgrading but not the fact that eventually such upgrading would have happened anyways.

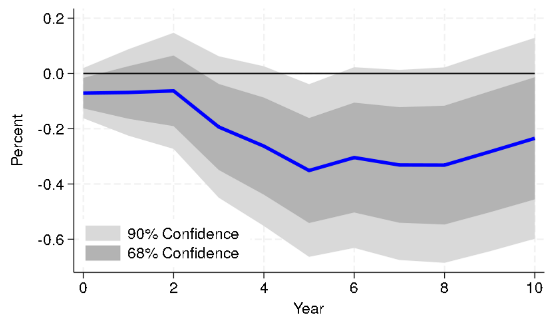
Given the sparsity of very costly events in our data set we refrain from differentiating between events above and below the 90th percentile when analyzing country groups. In light of the earlier discussion of Figure 5, comparisons across the country groups may not be meaningful. Therefore, we focus on the comparisons between types of disasters for each group. We define the group of high-income countries for a given year as including those countries for which real GDP per capita is above $\$12,000$ in that year, in accordance with the United Nations' most recent definition. Middle-income countries are defined as countries with per-capita income between $\$1,035$ and $\$12,000$. Low-income countries feature per-capita income below $\$1,035$.

Figure 6 isolates the effect of GDP damages on high-income countries. In response to all severe weather events, per-capita GDP declines on impact in high-income countries and accumulated over 10-years stays negative. This result is driven by the effects of climatological disasters (-1% over 10 years) and meteorological disasters (-0.2% over 10 years), both of which are significant at the 68% level. Only hydrological disasters buck this trend, with an initial decrease that turns positive after 4 years and grows to a 1% expansion after 10 years.

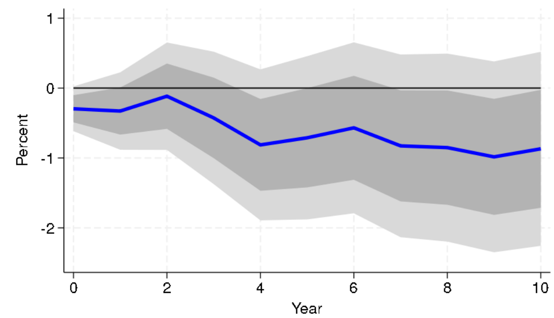
Figure 7 shows the results for middle-income countries. This is the group with the most observations for all categories of disasters. When pooling disasters, the impact of a mean shock is negative for the initial year at about -0.1%, but over the duration of 10

[13] For large countries, given the joint historic geographic distribution over severe weather events and economic activity most physical hazards are small from a national perspective.

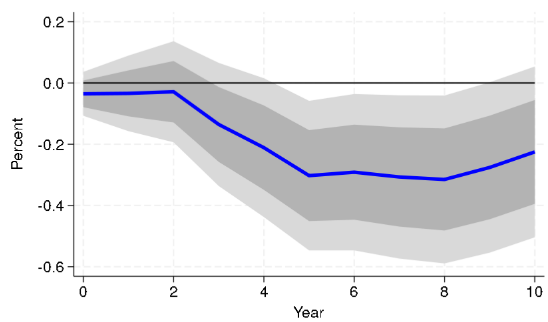
Figure 6: **High-income countries: response of GDP (percent deviation) to a mean shock to physical damages**



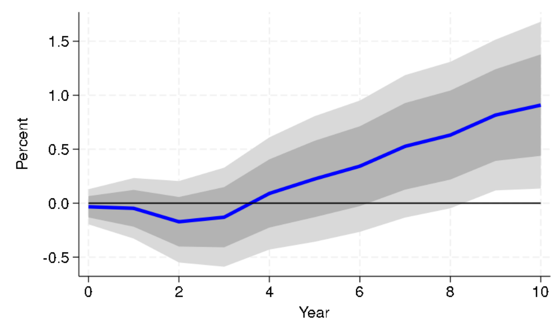
(a) All disasters



(b) Climatological disaters



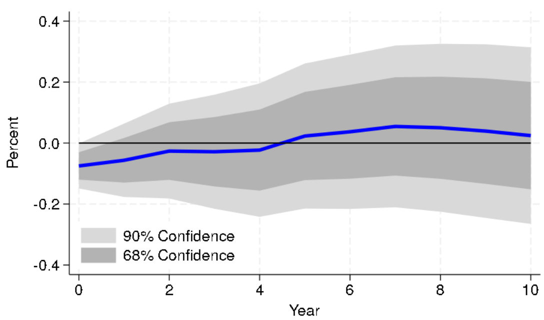
(c) Meteorological disasters



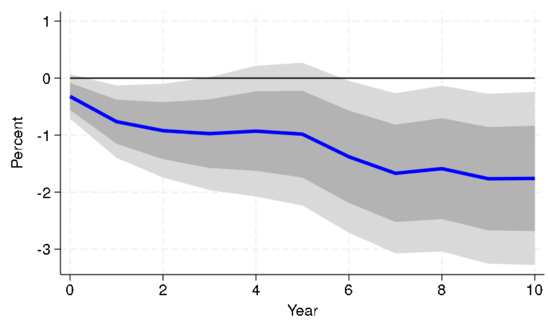
(d) Hydrological disasters

Note: The figure represents the response of GDP, in percent deviation from year preceding the shock year (year 0), to a mean shock of GDP disaster damages. All disasters are classified as climatological, meteorological, and hydrological. High-income countries are all observations where GDP per capita is above $12,000.

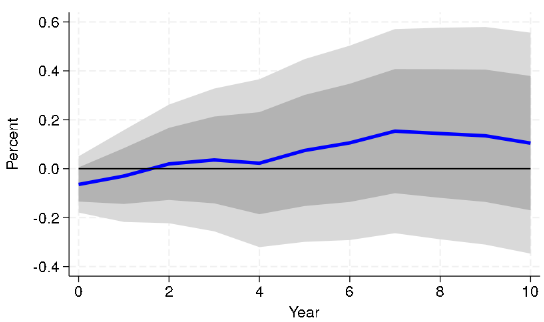
Figure 7: **Middle-income countries: response of GDP (percent deviation) to a mean shock to physical damages**



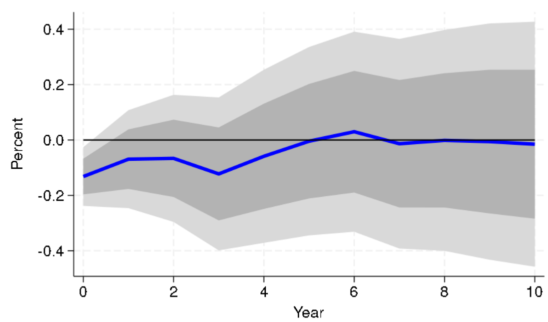
(a) All disasters



(b) Climatological disaters



(c) Meteorological disasters

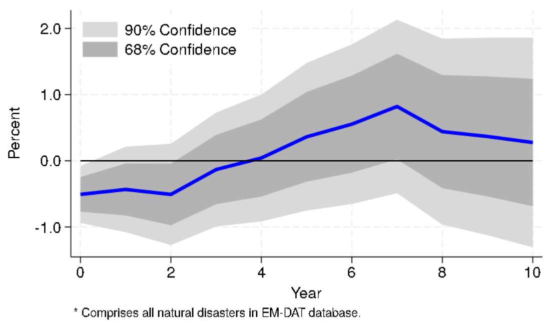


(d) Hydrological disasters

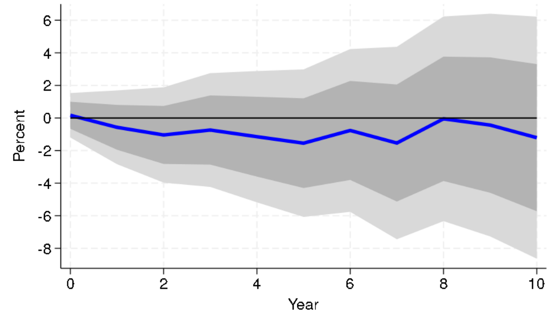
Note: The figure represents the response of GDP, in percent deviation from year preceding the shock year (year 0), to a mean shock GDP destroyed by disasters. All disasters are classified as climatological, meteorological, and hydrological. Middle-income countries are between \$1,035 and \$12,000.

years, seems to hover around no change (0%) compared to there not being a shock. This result is broadly in line with the hydrological category. While meteorological disasters see an initial drop as well, the 10-year cumulative GDP growth trends slightly positive. Climatological events cause the largest drop with about -2% of GDP per-capita growth spread out over 10 years and significant at the 90% confidence level.

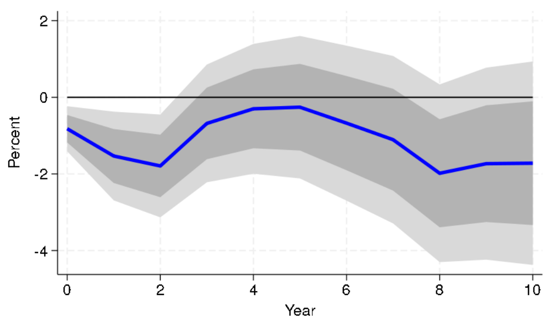
Figure 8: **Low-income countries: response of GDP (percent deviation) to a mean shock to physical damages**



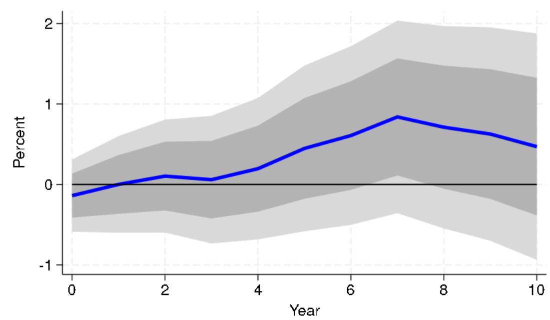
(a) All disasters



(b) Climatological disaters



(c) Meteorological disasters



(d) Hydrological disasters

Note: The figure represents the response of GDP, in percent deviation from year preceding the shock year (year 0), to a mean shock GDP destroyed by disasters. All disasters are classified as climatological, meteorological, and hydrological. Low-income countries are those below $1,035.

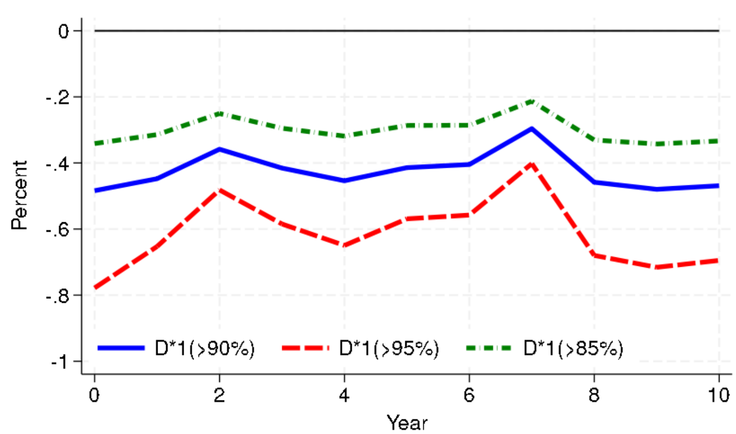
The under-performance of middle-income countries for climatological disasters compared to other categories shows the heterogeneity with which different disasters affects this income group. Benson and Clay (2004) theorize that economic development may not reduce the negative effects of disasters in a linear fashion, and they specifically single out middle-income countries as being most susceptible to climatological disasters. This is because these countries tend to be more integrated than low-income countries, which can "increase the multiplier effects of adverse performance." Furthermore, developed countries may not have as large a proportion of their economies exposed to sectors prone to damages from droughts or forest fires, such as the agricultural, livestock, or manufacturing sectors dependent on agro-processing (more common in developing countries). Other factors hypothesized by Benson et al. include the degree of openness, lower investment in risk reduction, higher levels of poverty, all of which are typically worse in middle-income countries as opposed to developed countries.

Finally, Figure 8 plots the local projection IRFs for low-income countries. This is the country group with the least observations in our data set and probably the lowest data quality. The effects of all disasters are mainly driven by hydrological disasters, the bulk of disaster damage observations for low-income countries. Meteorological disasters deliver a sustained negative impact, stabilising around -2% of cumulative GDP per capita growth at the 10-year mark. Meanwhile, climatological disasters have a slight negative effect.

4.2 Sensitivity of results

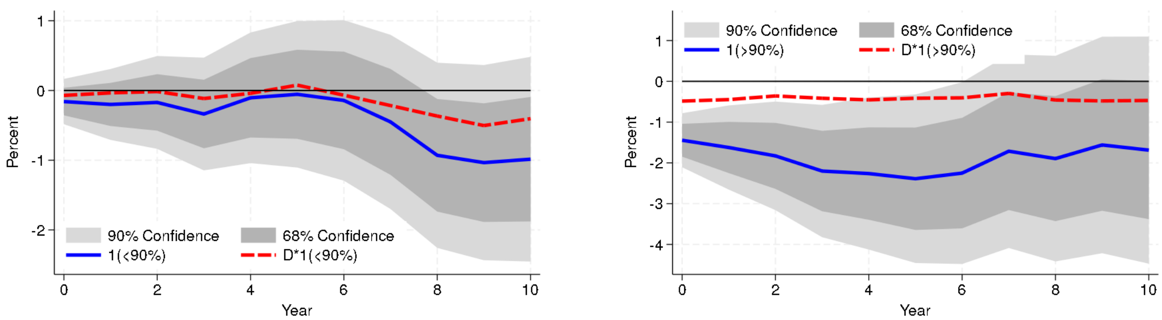
We set the 90th percentile as a cutoff in our baseline specification because it isolates those disasters that are in the group of outliers while maintaining a large enough subgroup size. The average damage as a percent of GDP is 4.7% for disasters in this percentile bracket, whereas disasters between the 80th and 90th percentile feature on average only direct physical damages of 0.9% of GDP. When going to the 95th percentile, the number of observations in the "very costly" disaster group is cut to 57. The impulse responses in Figure 9 show the effects under alternative cutoffs of the 85th, 90th, and 95th percentiles, respectively. Qualitatively, the responses are similar across cutoff levels. The magnitude of the effects increases strongly with the cutoff level.

Figure 9: **Cumulative growth responses to shock from damage and different percentiles**



We also experiment with alternative measures to test the robustness of our results. While we still group disasters into costly and very costly groups of direct damages (90th percentile splits), we do not make use of the direct damage data in the regression to distinguish disasters by their intensity. Within the percentile-split groups, individual disasters are no longer differentiated by their strength. It is only the number of disaster occurrences in each percentile that matters.

Figure 10: **Cumulative GDP growth responses to shock from alternative disaster physical damage measure and 90th percentile**



(a) All: $\mathbb{1}(< 90\%)$

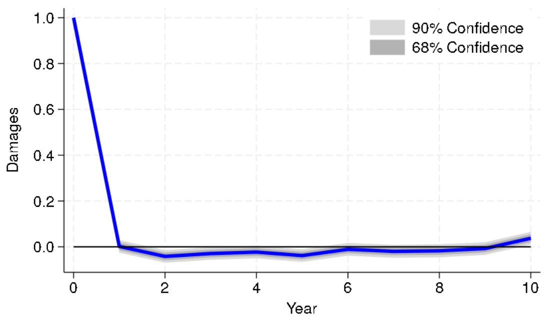
(b) All: $\mathbb{1}(> 90\%)$

Note: The two disaster measures are dummy variables.

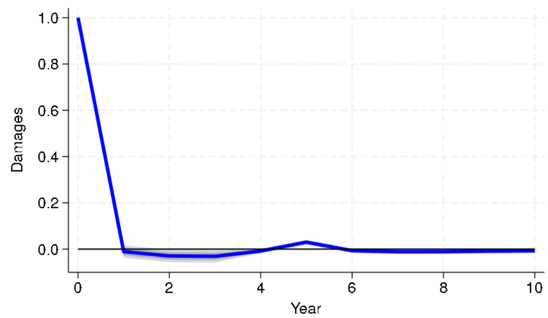
Figures 10a and 10b show our findings (solid blue line) and compare them with our earlier approach in which we use the detailed direct physical damages. The effects under the alternative approach appear to be somewhat larger for both costly and very costly disasters, but qualitatively similar. Also when using disaster occurrence, we find that very costly disasters in the 90th percentile of damages do, overall, have a more negative effect on cumulative GDP per capita growth than costly disasters below the 90th percentile.

Additional sensitivity analysis examines the correlation of direct physical damages with future realisations of damages. Figure 11 shows that across types of disasters direct physical damages do not predict future damages. Hence, there is no indication of inter-year correlation.

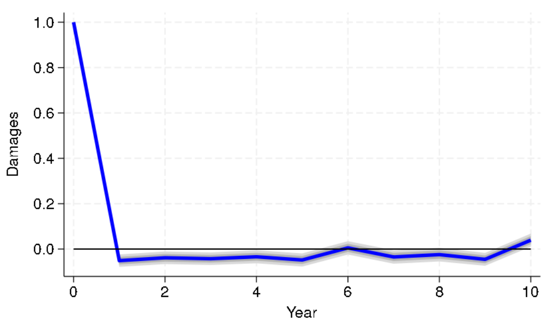
Figure 11: **Response of GDP (percent deviation) to an increase in disaster physical damages by 0.1% of GDP**



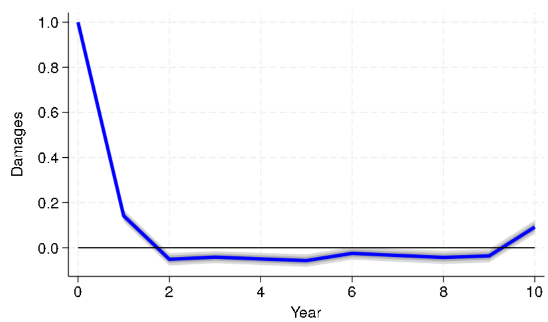
(a) All disasters



(b) Climatological



(c) Meteorological



(d) Hydrological

Note: The figure plots the response of GDP damages in future periods, in percent deviation from year preceding the shock year (year 0), to an increase in disaster damages by 0.1% of GDP. The grey shaded ribbons correspond to confidence bands, with the darker one representing the 68% confidence interval while the lighter one is the 90% confidence interval.

5 Conclusion

We use local projections to estimate the impacts severe weather events (measured by direct disaster damages) on cumulative per-capita GDP growth over a 10-year period. For very costly disasters in the 90th percentile of direct weather-related damages, the negative effects are more immediate than for costly disasters below the 90th percentile.

The most severe effects are seen following climatological disasters (comprising droughts and forest fires), although both meteorological (storms and extreme temperatures) and hydrological (floods and wave actions) disasters also affect cumulative GDP per-capita growth negatively. For all disaster types, the marginal effect of direct weather-related damages from physical hazards (i.e., the decrease of GDP when direct physical damages increase by 1% of GDP) are larger for costly disasters. However given that the average (mean) disaster size in the 90th percentile is larger, the GDP effects from very costly disasters are more negative than for only costly disasters in the years following the event. Not splitting disasters into two groups lowers yields significantly smaller estimates of the effects of severe weather events.

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A Country list

Here is a list of the countries used for analysis:

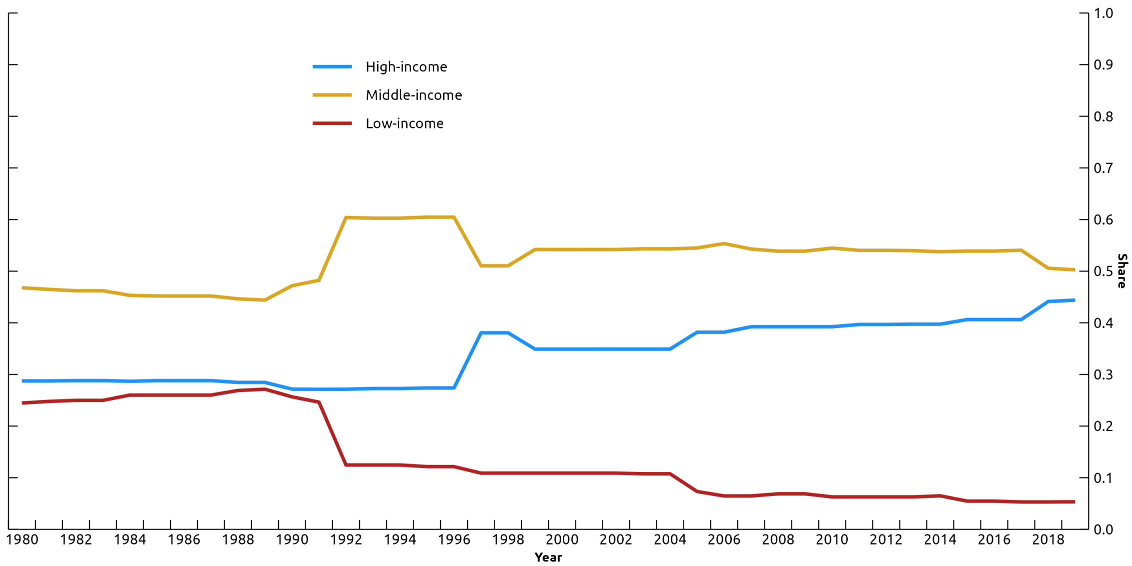
Table 2: List of countries by income group

High-Income Countries	Middle-Income Countries		Low-Income Countries
Australia	Algeria	Jordan	Bangladesh†
Austria	Argentina*	Kazakhstan*	Benin†
Barbados	Bolivia	Kenya	Burundi
Belgium	Botswana	Malaysia*	Central African Republic
Canada	Brazil	Mauritania	Gambia
Hong Kong	Cameroon	Mauritius	Guinea-Bissau
Cyprus*	Chile*	Mexico	India†
Denmark	China†	Nicaragua	Lesotho†
Finland	Colombia	Pakistan†	Malawi
France	Congo	Panama*	Mali
Germany	Costa Rica*	Paraguay	Mozambique
Greece	Dominican Republic	Peru	Nepal†
Hungary*	Ecuador	Philippines	Niger
Iceland	Egypt	Poland*	Rwanda
Ireland	El Salvador	Senegal	Sierra Leone
Israel	Fiji	South Africa	Togo
Italy	Ghana†	Syria†	Tanzania†
Japan	Guatemala	Thailand	Uganda
Kuwait	Guyana	Trinidad and Tobago*	Venezuela†
Netherlands	Haiti	Tunisia	Zambia†
New Zealand	Honduras	Turkey*	
Norway	Indonesia	Uruguay*	
Portugal*	Iran	Yemen	
Republic of Korea*	Jamaica	Zimbabwe†	
Singapore			
Spain			
Sweden			
Switzerland			
United Kingdom			
United States			

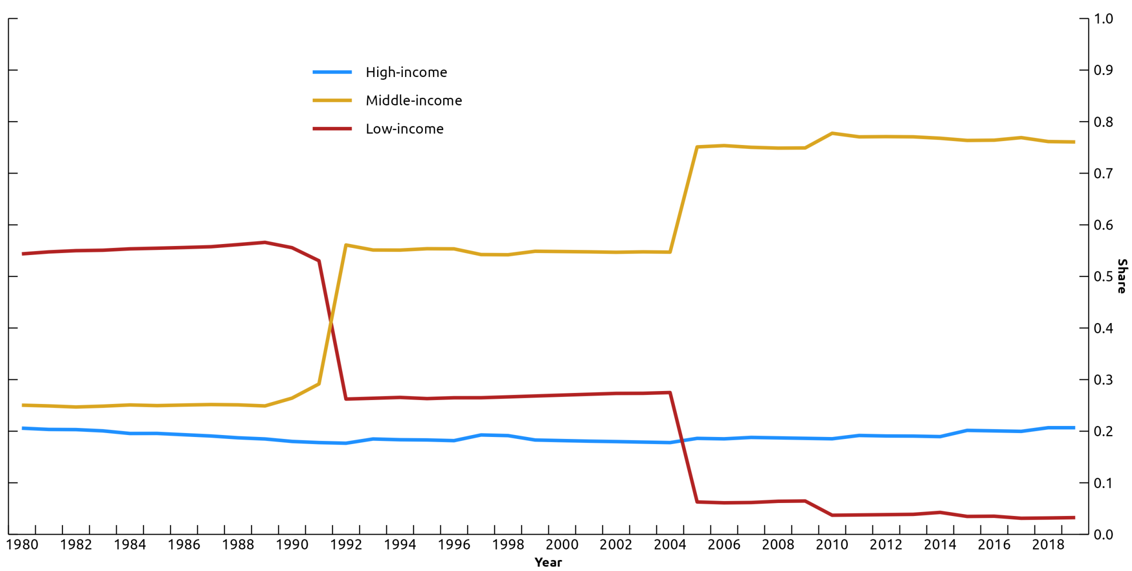
*: country that switches between middle and high income.

†: country that switches between low and middle income.

Figure 12: **Share of country income groups**



(a) By land area

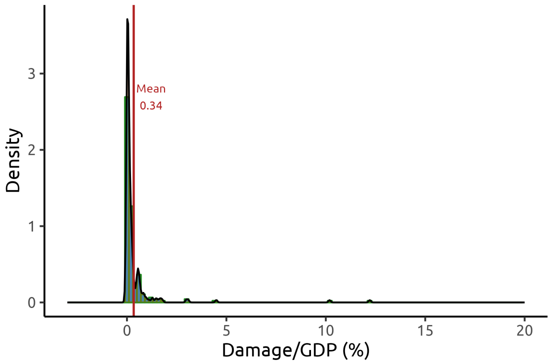


(b) By population

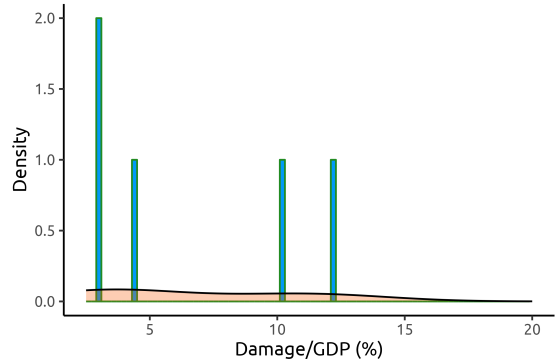
*: Source: World Development Indicators (WDI). Washington, D.C. : World Bank.

B Distribution of extreme events

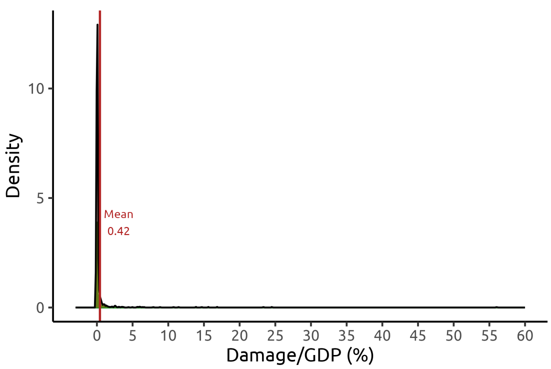
Figure 13: **Distribution of disasters by intensity (% of GDP damaged) and by type of disaster**



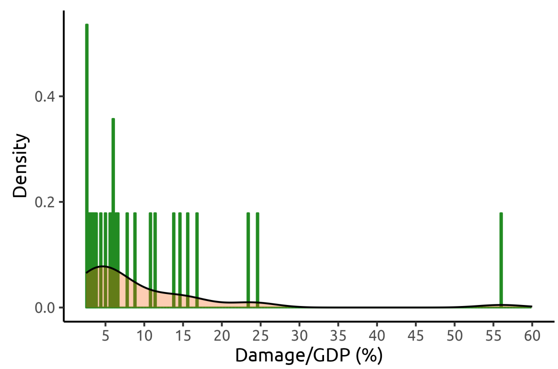
(a) Climatological, above 0.1%



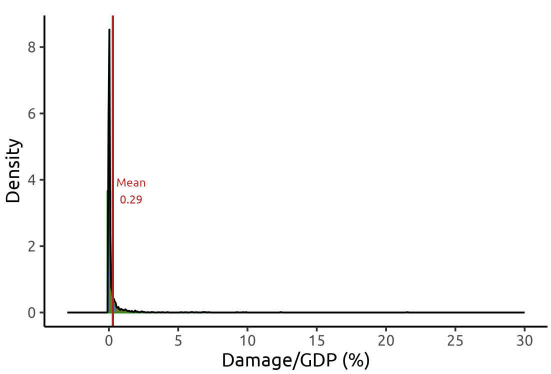
(b) Climatological, above 2.5%



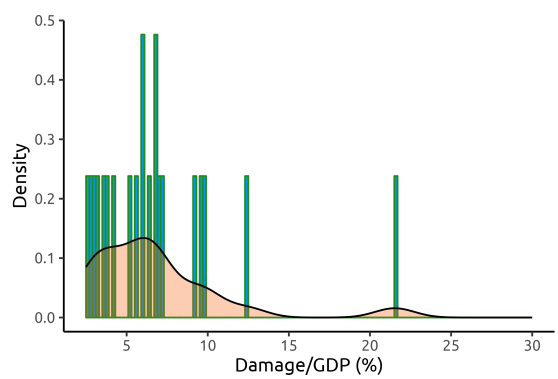
(c) Meteorological, above 0.1%



(d) Meteorological, above 2.5%



(e) Hydrological, above 0.1%



(f) Hydrological, above 2.5%

Note: Distribution shows all disasters in EM-DAT. We plot one set of bar charts on a linear scale (bin width is 0.2% of GDP). Plot 2b excludes disasters below 2.5% to emphasize outliers.

Table 3: Dummy interaction with 90th percentile cuttoff of disasters: all disasters

	Dependent variable:	
	Year on year per capita GDP growth	
	(1)	(2)
damage*$\mathbb{1}$(< 90th Percentile) - 0.1% Shock	-0.0401	
	(0.0522)	
damage*$\mathbb{1}$(> 90th Percentile) - 0.1% Shock	-0.0102^{***}	
	(0.00467)	
damage*$\mathbb{1}$(< 90th Percentile) - mean shock		-0.0702
		(0.0912)
damage*$\mathbb{1}$(> 90th Percentile) - mean shock		-0.4839^{***}
		(0.2215)
lag(damage)	0.0024	0.0024
	(0.0045)	(0.0045)
lag(damage,2)	-0.000094	-0.000094
	(0.0044)	(0.0044)
lag(damage,3)	-0.0017	0.0017
	(0.0031)	(0.0031)
lag(per capita growth)	0.1770^{***}	0.1770^{***}
	(0.0172)	(0.0172)
lag(per capita growth,2)	0.0273	0.0273
	(0.0172)	(0.0172)
lag(per capita growth,3)	0.0376^{**}	0.0376^{**}
	(0.0164)	(0.0164)
Constant	1.3240^{***}	1.3240^{***}
	(0.0815)	(0.0815)
R-squared	0.21	0.21
Number of individuals	97	97
Number of observations	3,381	3,381

Note: the ”mean shock” is the independent variable normalised by the mean disaster value from all periods where we observe a disaster.

Table 4: Dummy interaction with 90th percentile cuttoff of disasters: climatological disasters

	Dependent variable:	
	Year on year per capita GDP growth	
	(1)	(2)
damage*$\mathbb{1}$($<$ 90th Percentile) - 0.1% Shock	-0.1373	
	(0.0963)	
damage*$\mathbb{1}$($>$ 90th Percentile) - 0.1% Shock	-0.0536	
	(0.0521)	
damage*$\mathbb{1}$($<$ 90th Percentile) - mean shock		-0.2507
		(0.1760)
damage*$\mathbb{1}$($>$ 90th Percentile) - mean shock		-1.9495
		(1.8938)
lag(damage)	-0.0163	-0.0163
	(0.0161)	(0.0161)
lag(damage,2)	-0.0246	-0.0246
	(0.0160)	(0.0160)
lag(damage,3)	-0.0143	-0.0143
	(0.0159)	(0.0159)
lag(per capita growth)	0.1752^{***}	0.1752^{***}
	(0.0172)	(0.0172)
lag(per capita growth,2)	0.0273	0.0273
	(0.0171)	(0.0171)
lag(per capita growth,3)	0.0374^{**}	0.0374^{**}
	(0.0164)	(0.0164)
Constant	1.3258^{***}	1.3258^{***}
	(0.0771)	(0.0771)
R-squared	0.21	0.21
Number of individuals	97	97
Number of observations	3,381	3,381

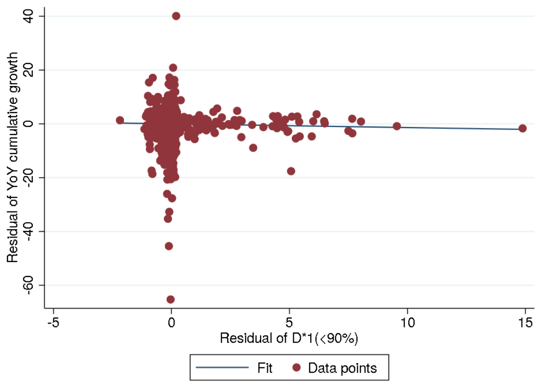
Table 5: Dummy interaction with 90th percentile cuttoff of disasters: meteorological disasters

	Dependent variable:	
	Year on year per capita GDP growth	
	(1)	(2)
damage*$\mathbb{1}$(< 90th Percentile) - 0.1% Shock	-0.2070^{***}	
	(0.0736)	
damage*$\mathbb{1}$(> 90th Percentile) - 0.1% Shock	-0.0061	
	(0.0052)	
damage*$\mathbb{1}$(< 90th Percentile) - mean shock		-0.2969^{***}
		(0.1056)
damage*$\mathbb{1}$(> 90th Percentile) - mean shock		-0.4784
		(0.4060)
lag(damage)	0.0018	0.0018
	(0.0053)	(0.0053)
lag(damage,2)	0.0009	0.0009
	(0.0052)	(0.0052)
lag(damage,3)	-0.0002	-0.0002
	(0.0052)	(0.0052)
lag(per capita growth)	0.1762^{***}	0.1762^{***}
	(0.0172)	(0.0172)
lag(per capita growth,2)	0.0282^{*}	0.0282^{*}
	(0.0171)	(0.0171)
lag(per capita growth,3)	0.0368^{**}	0.0368^{**}
	(0.0164)	(0.0164)
Constant	1.3298^{***}	1.3298^{***}
	(0.0779)	(0.0779)
R-squared	0.21	0.21
Number of individuals	97	97
Number of observations	3,381	3,381

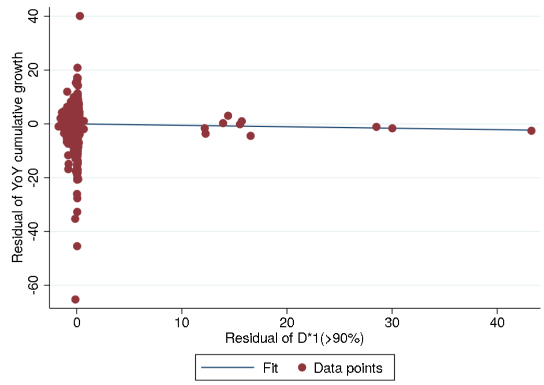
Table 6: Dummy interaction with 90th percentile cuttoff of disasters: hydrological disasters

	Dependent variable:	
	Year on year per capita GDP growth	
	(1)	(2)
damage*$\mathbb{1}$(< 90th Percentile) - 0.1% Shock	0.0578	
	(0.0890)	
damage*$\mathbb{1}$(> 90th Percentile) - 0.1% Shock	-0.0243^{**}	
	(0.0108)	
damage*$\mathbb{1}$(< 90th Percentile) - mean shock		0.0661
		(0.1017)
damage*$\mathbb{1}$(> 90th Percentile) - mean shock		-0.6866^{**}
		(0.3051)
lag(damage)	0.0150	0.0150
	(0.0108)	(0.0108)
lag(damage,2)	0.0011	0.0011
	(0.0103)	(0.0103)
lag(damage,3)	-0.0043	-0.0043
	(0.0102)	(0.0102)
lag(per capita growth)	0.1767^{***}	0.1767^{***}
	(0.0172)	(0.0172)
lag(per capita growth,2)	0.0277	0.0277
	(0.0172)	(0.0172)
lag(per capita growth,3)	0.0375^{**}	0.0375^{**}
	(0.0164)	(0.0164)
Constant	1.2862^{***}	1.2862^{***}
	(0.0793)	(0.0793)
R-squared	0.21	0.21
Number of individuals	97	97
Number of observations	3,381	3,381

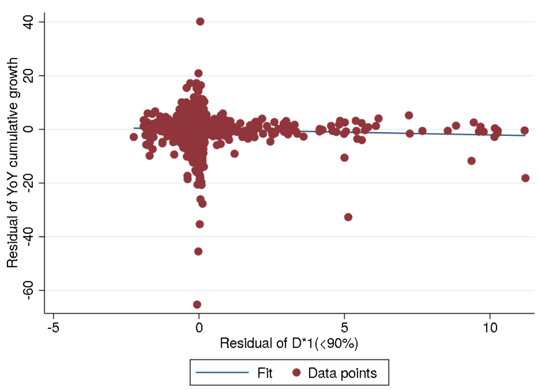
Figure 14: **Scatter plots of residual regressions to different disaster types**



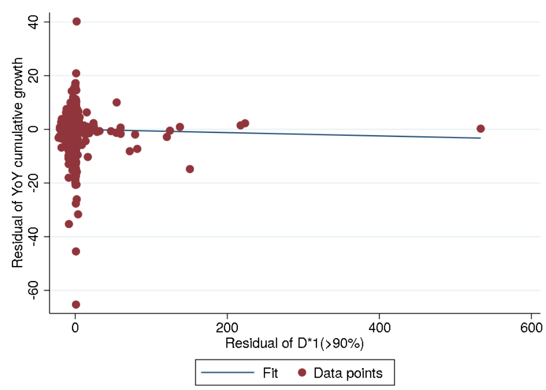
(a) Climatological: below 90th percentile



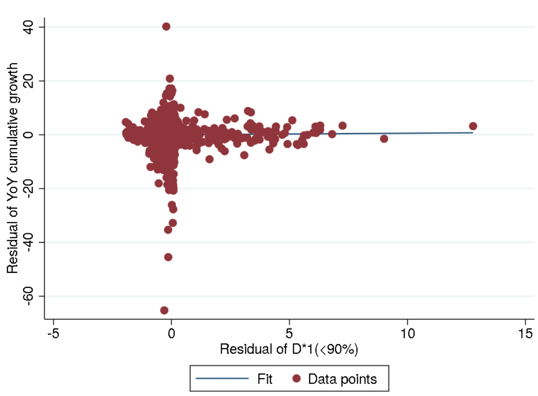
(b) Climatological: above 90th percentile



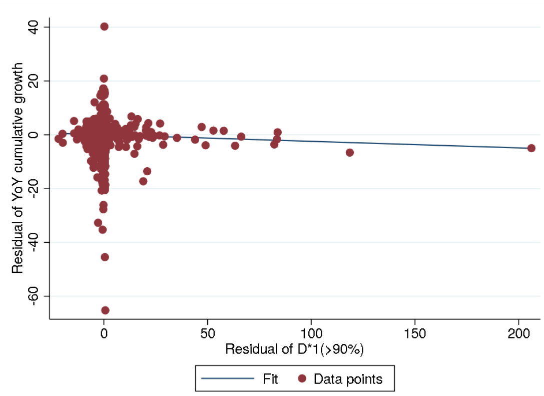
(c) Meteorological: below 90th percentile



(d) Meteorological: above 90th percentile



(e) Hydrological: below 90th percentile



(f) Hydrological: above 90th percentile

Note: Although the fit lines for the residual regression from $damage * \mathbb{1}(> 90\%)$ seems to be more negative than the residual from $damage * \mathbb{1}(< 90\%)$, the scale is much larger on the x-axis, more than compensating for this seemingly more negative effect and netting out to a less negative one for a marginal shock as illustrated in tables (3) - (6).