Macroeconomic impact of weather disasters: a global and sectoral analysis*

Torsten Ehlers,† Jon Frost,‡ Carlos Madeira§ and Ilhyock Shim¶

5 November 2025

Abstract

We examine the macro- and sector-level impact of weather disasters on economic activity and inflation for up to 151 countries over 2000-24. Using local projections, we find sizable and long-lived negative effects on GDP: -2%, -1% and -0.4% after average-sized droughts, landslides and wildfires, respectively, over four years. At the sectoral level, several types of weather disaster reduce agriculture-forestry-fishing and mining-construction-water-energy output. By contrast, most types of weather disaster have small and short-lived upward effects on headline inflation, with larger and more persistent increases in food prices. These findings provide guidance on how monetary policy may react to weather disasters.

JEL classification: E31; E32; O13; Q54.

Keywords: climate change; GDP growth; inflation; natural disasters; sectoral production.

*We thank Gaston Gelos, Benoît Mojon, Hyun Song Shin, Frank Smets, Alexandre Tombini, Santiago García-Verdú and participants at Bank for International Settlements (BIS), Bank of Mexico and NGFS Expert Network seminars and the 2025 BEMB International Conference for helpful comments, and Rafael Guerra, Alejandro Parada and Pablo Tomasini for excellent research assistance. The views in this paper are those of the authors and do not necessarily reflect those of the BIS or the Central Bank of Chile.

†Bank for International Settlements, torsten.ehlers@bis.org.

‡Bank for International Settlements, jon.frost@bis.org, and Cambridge Centre for Alternative Finance (CCAF).

§Central Bank of Chile, cmadeira@bcentral.cl.

¶Bank for International Settlements, ilhyock.shim@bis.org.

1 Introduction

Weather disasters can inflict macroeconomically significant damages, on top of their considerable societal costs. Based on the EM-DAT (CRED 2025) database, weather disasters have caused direct economic damages of around 0.14% of GDP, resulted in 27,600 deaths and affected 173 million people per year since 2000.

For monetary policy, these shocks pose fundamental challenges. For one, the occurrence of extreme weather events is naturally hard to predict, as are the type and severity of economic damages (Botzen et al. 2019). More importantly, even after the effect of these shocks can be observed by policy makers, it is a priori not clear how these shocks transmit into relevant macroeconomic effects (Cuaresma et al. 2008, Lee et al. 2021, Cantelmo 2022, Cantelmo et al. 2023, Ehlers et al. 2025). Most extreme weather events reduce production at impact as the workforce and the capital stock are negatively affected. At the same time, recovery and reconstruction efforts may lead to an increase in production in other parts of the economy, generally with a lag. Similarly, demand for certain consumer services or goods (eg discretionary consumer goods) may take a hit, but demand for other type of goods and services (eg construction services, energy) may increase thereafter.

Naturally, the effects on aggregate supply and demand will depend on the type of weather disaster. Droughts, for instance, are likely to affect agricultural production. Storms, landslides and wildfires may lead to a displacement of people and destroy physical capital, triggering a drop in production and demand in other sectors. But they will likely also trigger reconstruction efforts.

In turn, the crucial effects on inflation will depend on the relative impact on supply versus demand for given goods and services, the elasticity of prices and the associated persistence of the impact. If, for instance, agricultural production takes a hit, but demand for food is unchanged, prices will increase. Because demand for food is inelastic, such price increases may be large in the short term. If the effect is persistent enough, it may translate into a meaningful increase in headline inflation. But this effect could also be temporary, if production can recover or if food products can be procured elsewhere, through domestic and international trade. In this case, the effect on

headline inflation is unlikely to be material and monetary policy makers may adopt a ”look-through” approach accepting a short-lived and small increase in inflation. If, on the other hand, a rise in prices triggers higher inflation expectations, then monetary policy may need to tighten.

To shed light on the potential transmission mechanism of extreme weather events, we analyse the effect of weather disasters both at a macroeconomic level and at a more granular level across many countries. In particular, we estimate the impact on GDP and headline inflation, as well as their relevant subcomponents including investments and sectoral components for GDP and key subcomponents of inflation (food, energy, core). Our measure of economic damages from extreme weather events is based on total costs (standardised as a % of national GDP) obtained from EM-DAT (CRED 2025, Delforge et al. 2025). We look at all seven types of extreme weather event covered in EM-DAT, both in aggregate and for each individual type of disasters. This comprises cold waves, droughts, floods, heat waves, landslides, storms and wildfires.

First, we look at the effects of weather disasters on quarterly real GDP growth for 89 countries (OECD and IMF data) and those on different components of monthly inflation for up to 151 countries using data from Ha et al. (2023). Our sample period covers 2000–24. We then study the effects of weather disasters on the output of different economic sectors, including agriculture-forestry-fishing, manufacturing, mining-energy-water-construction and services. Our contribution to the literature is that we examine the sectoral effects using annual data as well as the higher-frequency impact on quarterly GDP growth and monthly inflation, which allows us to better capture the persistence of any potential effects. With the global coverage of our data, we also cover emerging market and developing economies (EMDEs), for which the literature points to a stronger macroeconomic impact of weather disasters (Noy 2009, Acevedo et al. 2020, Cavallo et al. 2022).

We use panel local projections with country and time fixed effects (Jordà 2005) to determine the effects of weather disasters. Our local projection regressions measure the entire cumulative effect on inflation and output from the period in which the disaster hits until the end of the horizon window, which is 12 months for inflation and 16 quarters for GDP. We use a shorter window for inflation, since previous research has shown that the price effects of weather fluctuations and disasters tend to

be small and brief, lasting less than one year (Gagnon and Lopez-Salido 2020, Faccia et al. 2021, Beirne et al. 2024, Ciccarelli et al. 2024, Kotz et al. 2024). The window for GDP growth extends to 4 years since some of the previous research has found longer-lasting effects of weather disasters on output (Raddatz 2009).

We find that the effect on output of several, but not all, types of extreme weather event is economically significant and persistent. Aggregate GDP falls 2%, 1% and 0.4% after the average-size droughts, landslides and wildfires, respectively, over four years. These results are slightly weaker but remain robust after we control for fiscal space proxied by sovereign credit ratings and insurance coverage proxied by insurance premium volume and insurance company assets as a percentage of GDP. After storms, however, real GDP tends to increase rather than decrease.

When we look at the effects of weather disasters on investment, we find that gross capital formation (GCF) increases after all disasters, droughts, floods and storms, while it decreases after heat waves and wildfires. This could be due to reconstruction efforts after some disasters that destroyed physical capital such as floods and storms.

Furthermore, the four main economic sectors react differently to different types of weather events. Agriculture-forestry-fishing decline after droughts and storms. Mining, construction, water and energy decrease after cold waves, heat waves, landslides and wildfires. Manufacturing increases after cold waves and floods, but decreases after storms. Services increase after cold waves and wildfires, possibly as part of repair and rebuilding efforts. Finally, food production (natural and manufactured foods) declines after almost all disasters (except for landslides and storms), a reaction that is consistent with the increase in food inflation.

When we look at more granular sectoral output using annual OECD data, we can confirm the negative impact on output in the food sector. We find that output in various other sectors is affected, including in the construction sector, the real estate sector, and different services sectors (the finance and insurance sector, information and communication sector). We use the granular manufacturing sector data from UNIDO to investigate why the manufacturing sector as a whole is not significantly affected by extreme weather events. Our results suggest that, while some manufacturing sectors

reduce production, others increase output – in particular for rubber and plastics, basic metals as well as tobacco.

The sectoral GDP effects are consistent with the impact on inflation. Food inflation tends to increase after most disasters (all disasters, cold waves, floods, heat waves and storms), which matches the increase in food inflation observed. Another important component of inflation – energy prices – also rises after most disasters (all disasters, cold waves, floods, heat waves, storms and wildfires). The impact on core inflation, which excludes food and energy, is mixed which appears to reflect the limited effect of extreme weather events on manufacturing. Core inflation falls after all disasters and droughts, but rises after heat waves and landslides. The reaction of headline inflation to weather disasters, in turn, is much closer to that of food and energy inflation. Headline inflation increases after all disasters, cold waves, floods, heat waves and storms. Overall, however, our results suggest that the impact on inflation is relatively limited and short-lived. The average-size shock of all types of disaster increases food prices by about 0.5% after 12 months, but has much smaller and less persistent effects on headline inflation at slightly more than 0.1% after five months.

The above results provide some basic guidance to monetary policy makers on whether and how to react to extreme weather shocks. Our results point to two consistent effects: a persistently negative effect on output from a broad range of extreme weather events and a resulting but relatively short-lived effect on inflation – in particular on food and energy inflation. The exact effect on economic activity and inflation will depend on the size of the shock and country-specific circumstances, as well as the sensitivity of inflation expectations to inflation shocks. As such, monetary policy makers would need to assess how the shock affects growth and inflation expectations when deciding whether to "look through" the shock and leave policy unchanged, or not. For example, if a shock has a large and persistently negative impact on growth, a monetary policy maker may consider loosening monetary policy to support economic activity. If a shock pushes up inflation high and affects inflation expectations, a monetary policy maker may consider tightening monetary policy.

Related literature

This study builds on and extends previous research on the inflation and output effects of climate

change. A large body of work has focused on the effects of temperature and precipitation fluctuations (Burke et al. 2015, Colacito et al. 2019, Acevedo et al. 2020, Moessner 2022, Cevik and Jalles 2024, Akyapı et al. 2025). Recent research has also studied the effects of climate commitments, carbon taxes and other environmental policies on prices (Bettarelli et al. 2025) and on firms and financial institutions (Altavilla et al. 2024). Bilal and Stock (2025) summarise the damages estimated from climate change and possible mitigation and adaptation policies. Cavallo et al. (2013) find that natural disasters have small and non-lasting effects on output unless the shocks are followed by political upheaval. Many studies of climate change focus on regional impacts within a country (Gagnon and Lopez-Salido 2020, Bodenstein and Scaramucci 2025) or currency area (Beirne et al. 2024), particularly in advanced economies (AEs) such as the United States and Europe. Relative to the previous work of Ehlers et al. (2025), we extend the analysis to additional disaster categories and to all continents. [1] Furthermore, we present a sectoral analysis across four high-level economic sectors (agriculture, forestry and fishing; mining, construction, water, energy; manufacturing; services), as well as more granular 2-digit manufacturing industries and 2-digit sectors of activity, which is not present in previous work.

Previous research has shown a strong effect of weather disasters on agricultural output (Loayza et al. 2012, Fomby et al. 2013). Our research expands upon these studies by also showing the effects of weather disasters on other economic sectors, especially on services (which comprise the largest share of the economy in many countries) and several manufacturing industries. For OECD economies, our analysis extends the sectorial analysis to 20 sectors that comprise the entire economy, including informal household services.

Our research also matches well with recent findings for the European Union, showing that heat waves, droughts and floods have negative effects on output even after two or four years (Usman et al. 2025). Other studies for the US also show that severe weather shocks have persistent effects up to 20 months (Kim et al. 2025).

[1] The bulletin of Ehlers et al. (2025) only analysed 4 disaster categories (droughts, floods, storms, wildfires), while here we also include cold waves, heat waves and landslides. Furthermore, the bulletin only studied the 8 largest countries of the Americas. The current work studies all continents and we analyze 21 countries (with both GDP and inflation data) in the Americas rather than just 8 countries.

Finally, our study is related to an increased research interest in the effects of macro shocks on risks to growth (Adrian et al. 2025).

This paper is organised as follows. Section 2 summarises the economic losses and mortality from weather disasters across the world. Section 3 details our local projections approach. Section 4 summarises the main results. Section 5 shows robustness checks with an extended set of controls for fiscal space and insurance coverage. Finally, section 6 concludes with a summary of the findings and some policy implications.

2 Data

We start by summarising the available sample of countries for our analysis. Table 1 shows that our analysis for monthly inflation (food, energy, core, headline) covers 151 countries over 2000-24. The country coverage of quarterly GDP is less broad, but still includes 89 countries and a significant number of countries in each continent. Data for the sectoral GDP analysis on the four sectors from the World Bank (agriculture-forestry–fishing, manufacturing, mining-energy-water-construction and services) are available for 118 countries, while data on the 22 manufacturing industries from the United Nations Industrial Development Organization (UNIDO) are available for 131 countries. Manufacturing industries in the UNIDO data only cover around 12.5% of GDP for the median country. Therefore, we also use data on 20 activity sectors comprising the total GDP from the OECD, but these data are available for only 54 countries. Tables in Appendix G provide a detailed list of the countries in each of our exercises and the frequency of disasters across each country and continent.

Table 1: Country coverage for the empirical analysis

Variable	World	Africa	Americas	Asia	Europe	Oceania
Number of countries at monthly and quarterly frequency:						
Inflation (monthly)	151	36	35	38	36	6
GDP (quarterly)	89	12	21	17	36	3
Number of countries at annual frequency:						
World Bank: 4 sectors	118	28	24	25	35	6
OECD activities: 20 sectors	54	7	8	6	31	2
UNIDO: 22 manufacturing industries	131	25	31	33	36	6

We use EM-DAT data for weather disasters from the beginning of 2000 to end-2024. We use the total costs, which are an estimate of economic damages directly related to the occurrence of the disasters, mainly collected from insurance company reports. We refer to these events interchangeably as extreme weather events and weather disasters, as the inclusion criteria for the EM-DAT database are the number of people affected (at least 100), deaths (at least 10), a call for international assistance or a declaration of emergency in a given country.

We group certain categories of closely-related disasters. The category of cold waves groups cold waves and severe winter conditions. The category of floods groups coastal, flash, general and riverine floods. The category of landslides groups avalanches, glacial lake outburst floods, landslides, mudslides, rockfall and sudden subsistence. The category of wildfires groups forest fires, land fires (brush, bush, pasture) and wildfires. The category of storms groups blizzards, winter storms, derecho, extra-tropical storms, hail, lightning, thunderstorms, sand or dust storms, severe weather, storms, storm surges, tornadoes and tropical cyclones. Note that all these terms correspond to the same basic concept of storms as a meteorological event, although the name can change according to the continent or hemisphere where the disaster happens. A storm, in meteorological terms, is a disturbed state of the atmosphere characterised by strong winds, precipitation (like rain, snow or hail) and potentially other severe weather phenomena such as thunder, lightning or

tornadoes. Finally, the categories of droughts and heat waves correspond each to only one category of disasters in EM-DAT. [2]

The main explanatory variable in our regressions is the total economic cost divided by the GDP of the country for which the disaster is recorded. We focus on the economic rather than social costs in this paper, as they have a more direct impact on monetary policy. In contrast to other types of disasters, the availability of total costs for weather-related disasters is very high (more than 90% of weather-related disasters). A known issue of the EM-DAT database is the likely under-estimation of economic costs as well as a general under-reporting of disasters. It is not clear whether the costs are consistently underestimated, which could lead to an overestimation of the effects we are trying to measure. The incomplete reporting of disasters, if anything, will make it more difficult to identify the macroeconomic effects of these events.[3]

Table 2 shows that, on average, weather disasters cost the world around 0.14% of GDP, resulted in 27,579 deaths and affected 173 million people per year over the 25 years in our sample. When

[2]Some disasters are correlated and tend to happen together or within the same season. Unfortunately, it is unfeasible to estimate all the possible combinations of seven types of disasters (cold wave, drought, flood, heat wave, landslide, storm, wildfire), especially if some combinations may happen in too few countries. Also, different types of disasters happening in the same period can be highly correlated with the size of the country and be absent in smaller or medium-sized countries. However, we conducted an analysis of the sum of all disasters together, which is shown in all tables and figures of the article. Furthermore, we also estimated results with grouped categories, such as droughts and heat waves together, storms and cold waves together, floods and landslides together. Finally, we also estimated local projection regressions with just two groups of categories, one for cold or precipitation events (cold wave, flood, landslide, storm) and another one for events associated with heat (drought, heat wave, wildfire). The results of the two grouped exercises are qualitatively similar and available upon request. Further, in our regressions we include country-season fixed effects (that is, all countries have a fixed effect for quarter 1, quarter 2, quarter 3 and quarter 4). These country fixed-effects already correct for the weather events that usually occur in a country in a quarter.

[3]Note that several variables in EM-DAT suffer from measurement error, as data sources include news reports. Therefore, some data in EM-DAT should be taken as an approximation, especially for countries at lower levels of development. For instance, if a news article mentions ”hundreds” or ”thousands”, EM-DAT reports values of 200 or 2000, respectively. Furthermore, the number of deaths from a disaster reported in EM-DAT may not accurately reflect the actual number of (excess) deaths caused by the disaster. This is because many countries do not have public health statistics with wide coverage or accurate registries of autopsies. The same can be said of the number of people affected by a disaster. While the number of people affected should in theory be the sum of the number of deaths as well as injured and homeless people, in practice the number reported by EM-DAT can be that of the population of entire regions affected by a disaster. For instance, the top 1% of disasters in EM-DAT show 8 million or more people affected. There is one weather disaster (a drought in India) that is reported to have affected 330 million people. Another drought in India affected 300 million people, and three floods in China affected 150, 134 and 105 million people, respectively. Furthermore, in the case of people affected, the annual numbers shown in this paper may be subject to multiple-counting of the same people. In particular, if the same region in a given year suffers multiple disasters, such as a flood, a wildfire and a drought, then there can be an overestimate of the population affected as some people are counted multiple times for the three different disasters.

we look at different continents, the Americas and Oceania suffered relatively large damages from weather disasters relative to GDP, while Africa and Europe saw smaller damages. Notably, there is substantial variation in economic damages of weather disasters compared to GDP over time. The economic damage in the worst year can be as large as four times that in the average year in many continents.[4]

Figure 1 visualises the total GDP cost due to all types of weather disasters. The most damaging disaster types differ across continents. In the Americas, storms resulted in the largest GDP cost among all types of disasters, followed at some distance by droughts, floods and wildfires. In Asia, Europe and Africa, floods incurred the largest GDP cost, with much smaller damages due to droughts. Finally, in Oceania floods and storms both had a substantial GDP cost, while droughts and wildfires led to more limited damages on average.

Figure 2 shows economic damages from weather disasters as a percentage of GDP over time for each continent. The worst year was experienced by the Americas in 2005, the year of Hurricane Katrina, when damages reached almost 0.9% of GDP. There are also notable spikes in 2010 and 2017. In 2010 Australia was affected by floods and storms, which created damages of 0.65% and 0.24% of GDP, respectively. In the same year, there were storms creating damages of 0.58% and 0.18% of GDP in Fiji and French Polynesia, respectively.[5] In 2017 there were severe storms creating large damages in Antigua and Barbuda, the Bahamas, Colombia, Costa Rica, Cuba, Dominica, Dominican Republic, Saint Kitts and Nevis, Puerto Rico, El Salvador, Sint Maarten, the Turks and Caicos Islands and the United States.[6] The same year saw floods costing 0.79% of GDP of damages in Peru. In 2017 Chile and the United States also suffered wildfires that caused damages of 0.12% and 0.08% of GDP, respectively.

Furthermore, we complement our analysis of the effects of weather disasters on GDP and inflation by considering other variables that can affect the recovery from the damages. In particular, we consider fiscal space variables such as sovereign credit rating (from Kose et al. 2022), the share

[4]In terms of social costs, Asia and Europe had the highest number of deaths on average, while Asia and Africa had the highest number of people affected.

[5]Australia, Fiji and French Polynesia were affected in 2010 by the storms Geraldton, Tomas and Oli, respectively.

[6]The historic 2017 Atlantic hurricane season produced 17 named storms, most notably Harvey, Irma and Maria.

Table 2: GDP cost, deaths and people affected from weather disasters (2000-2024)

Continent	Costs: % GDP*		Deaths		People affected	
	Mean	Max	Mean	Max	Mean	Max
Africa	0.04	0.16	2,871	21,228	15,000,262	33,937,280
Americas	0.24	0.87	1,686	6,830	12,169,956	95,633,912
Asia	0.12	0.18	12,355	144,565	144,882,998	645,882,944
Europe	0.06	0.19	10,615	72,295	644,589	2,873,208
Oceania	0.19	0.87	71	589	291,831	2,892,976
World	0.14	0.36	27,597	147,225	172,989,636	656,310,208

* Country values weighted by GDP in USD.

of hydro-electric and non-hydroelectric renewables in national electricity production (from the World Bank) and insurance market variables such as the total assets of insurance companies and the value of life and non-life insurance premia as a percentage of GDP (from the World Bank). All these variables are available at a yearly frequency from the World Bank and Kose et al. (2022).

Figure 3 summarises World Bank data on life and non-life (property and casualty) insurance premia as a percentage of GDP, as well as on insurance company assets as a percentage of GDP. Europe has the highest levels of life insurance premium volume and insurance company assets compared to GDP. By contrast, the Americas and Oceania make a stronger use of property insurance than other continents, with the annual non-life insurance premia corresponding to 2.6% and 2.2% of GDP, respectively.

Figure 1: Average annual damages from weather disasters by continent (weights by country GDP) over the period from 2000 to 2024

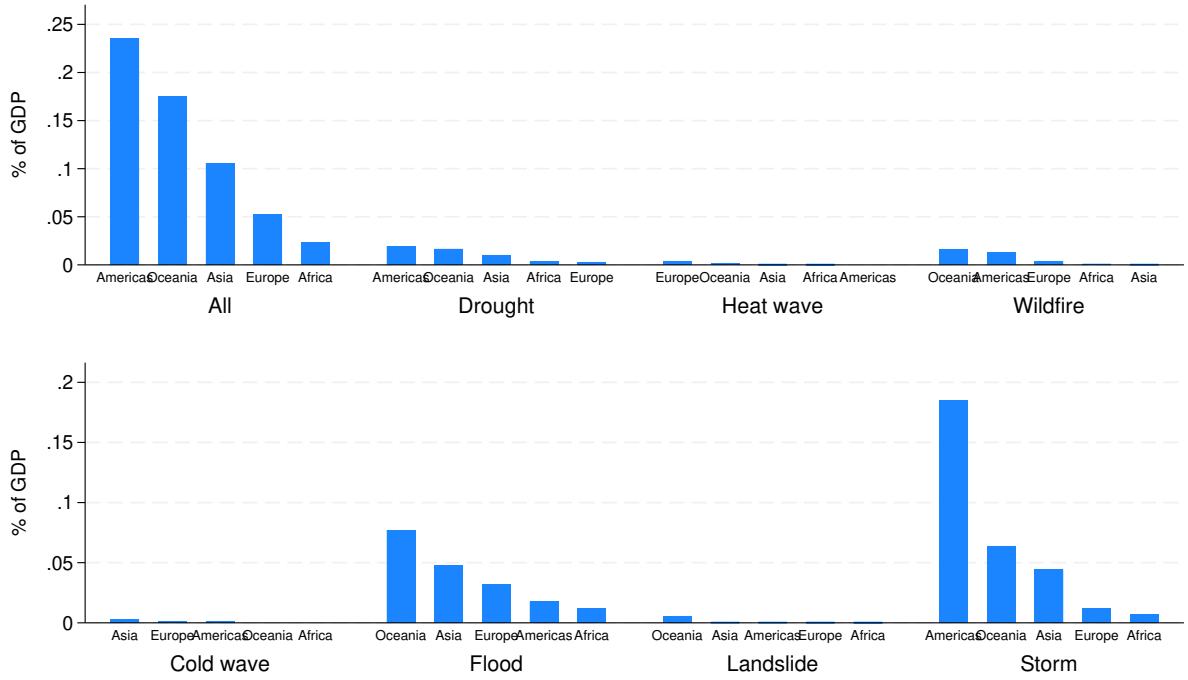


Figure 2: Annual damages from weather disasters across continents (% of GDP) over time

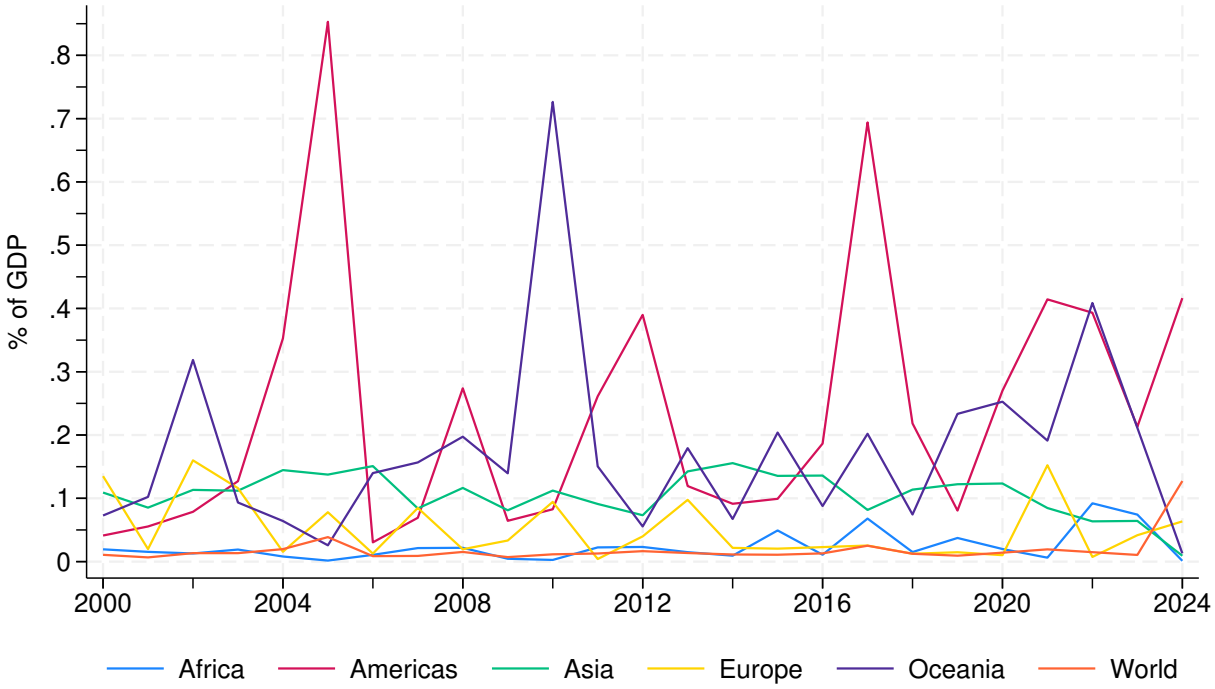
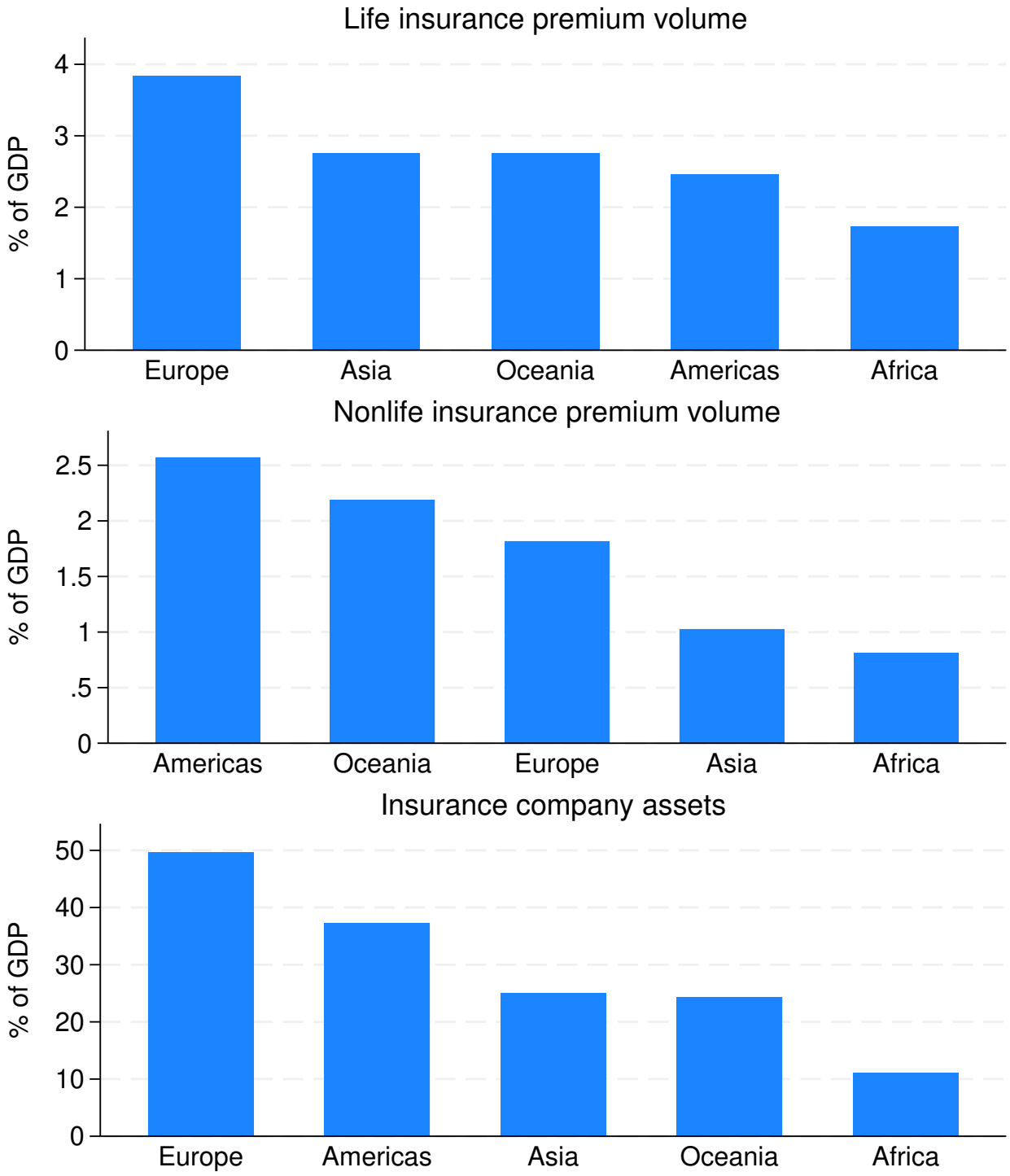


Figure 3: Insurance premia and assets as a share of GDP: average for the period 2000–2021



3 Empirical approach

3.1 Baseline local projections

We test whether weather disasters overall, and specific types of weather disasters (cold waves, droughts, floods, heat waves, landslides, storms, wildfires) affect macroeconomic outcomes. We then estimate the cumulative impact after h periods of each disaster type (D) across countries c and over time t:

$$(1)\ Y_{c,t+h} - Y_{c,t-1} = \beta_h^D(WD_{c,t}^D, \Delta Y_{c,t-1}) + \alpha_{c,s(t),h}^D + \alpha_{t,h}^D$$

with $Y_{c,t}$ being the logarithm of the consumer price index (CPI) or gross domestic product (GDP) level (multiplied by 100). The Y variables are winsorised at the bottom 1st percentile and the top 99th percentile. In this analysis, winsorising the Y variables gives qualitatively similar coefficients and statistical significance levels to those without winsorisation, but somewhat smaller confidence bands. We use monthly inflation data from Ha et al. (2023), and quarterly GDP data from the OECD and the IMF.

The weather disaster variables $WD_{c,t}^D$ are analogously winsorised at the top 99th percentile. Other controls include the lagged inflation or GDP growth ($\Delta Y_{c,t-1}$) plus fixed-effects for country-season pairs ($\alpha_{c,s(t),h}^D$), with $s(t)$ being month or quarter of the year, and time fixed effects ($\alpha_{t,h}^D$).

The impulse response functions for the effect of the natural disaster at time $t+h$ are given by the estimated local projection parameters and the mean weather disaster as a percentage of GDP:

$$(2)\ Shock(Y_{t+h}) = \beta_h^D \theta^D, \text{ with } \theta^D = \frac{\sum_{c,t} WD_{c,t}}{\sum_{c,t} 1(WD_{c,t} > 0)}.$$

For the regressions of each type D of weather disasters, we exclude countries that had zero costs associated with such disasters over the entire period (2000-24). These countries likely suffer from the under-reporting of total economic costs in the EM-DAT database.[7]

[7] If we consider all countries with disaster data in EM-DAT and either inflation or GDP information available,

3.2 Sectoral local projections

We estimate the cumulative impact after h periods of each disaster type (D) across sectors i of countries c when disasters occur at time t.

$$(3)\ Y_{c,i,t+h} - Y_{c,i,t-1} = \beta^D_{i,h} WD^D_{c,t} + \alpha^D_{c,i,h} + \alpha^D_{i,t,h} + \phi_h ShVA_{c,i,t-1},$$

with $Y_{c,i,t}$ being the logarithm of the sectoral GDP level (with the difference being multiplied by 100). $ShVA_{c,i,t}$ is the share of sector i in the total value-added of national manufacturing or GDP at time t. Controls include country-sector ($\alpha^D_{c,i,h}$) and time fixed-effects ($\alpha^D_{i,t,h}$). The lagged endogenous variable is omitted to avoid Nickell bias (Nickell 1981, Blundell and Bond 2023), as annual frequency data imply at most 25 years of data and for many countries substantially less. These exercises are estimated 20 sectors available across the OECD economies and for the 22 manufacturing industries from UNIDO data.

In the case of the four large economic sectors (agriculture-forestry-fishing, manufacturing, mining-construction-energy-water, services) and the investment (gross fixed capital formation and gross capital formation) measured by the World Bank, we instead estimate the effect of natural disasters on their ratio as a percentage of GDP. Therefore, the regression is made in level:

$$(4)\ Y_{c,i,t+h} - Y_{c,i,t-1} = \beta^D_{i,h} ND^D_{c,t} + \alpha^D_{c,i,h} + \alpha^D_{i,t,h}.$$

Finally, we estimate the following regression for the food production index (which includes natural and manufactured foods) published by the World Bank:

$$(5)\ Y_{c,i,t+h} - Y_{c,i,t-1} = \beta^D_{i,h} ND^D_{c,t} + \alpha^D_{c,i,h} + \alpha^D_{i,t,h},$$

where $Y_{c,i,t}$ is the logarithm of the food production index and the difference is multiplied by 100.

then our analysis includes 165 countries for all disaster types. The exclusion of countries with zero disasters leads to an analysis with 163 countries for all disasters. For each disaster type, the exclusion of countries with zero reported damages from disasters leads to an analysis with 19, 49, 129, 17, 22, 121 and 24 countries for cold waves, droughts, floods, heat waves, landslides, storms and wildfires, respectively. Note that some countries may have zero reported economic damages in EM-DAT, although such countries were severely affected by weather disasters. This is because some countries report large numbers of deaths or people affected, but have no statistics for the economic damages of the disasters.

3.3 Controls for fiscal space and insurance coverage

Natural disasters are exogenous to economic outcomes. However, the reaction of economic outcomes may suffer from relevant missing covariates (such as fiscal expansion or repairs after insurance payouts). The channels or mechanisms of weather disasters affecting inflation and GDP are therefore difficult to interpret: disasters can be both a supply and a demand shock. Inflation or deflation can happen simultaneously with GDP expansions or reductions. Previous research has shown that both fiscal support and insurance payouts attenuate the effects of disasters on output (Melecky and Raddatz 2015, von Peter et al. 2024).

We again estimate the cumulative impact after h periods of each disaster type (D) across countries c and time t:

$$(6)\ Y_{c,t+h} - Y_{c,t-1} = \beta_h^D(WD_{c,t}^D, \Delta Y_{c,t-1}, x_{c,t-1}, x_{c,t-1} \times WD_{c,t}^D) + \alpha_{c,s(t),h}^D + \alpha_{t,h}^D.$$

where $x_{c,t-1}$ includes the long-term sovereign credit rating (scale of 0 to 21) and property (nonlife) insurance premia (as a percentage of GDP). Again, the shock feeding the impulse response functions is the average disaster size as a percentage of GDP.[8]

4 Baseline empirical results

Our baseline regressions (Equation (1)) first cover aggregate GDP. Then, we show the regression results for sectoral output (Equation (3)). In the next section, we show the robustness results when we consider fiscal support capacity and insurance coverage (Equation (6)).

[8]We do not account for foreign aid in our controls because previous research shows a small and insignificant effect of international aid during and after weather disasters (Raddatz 2009, Cantelmo et al. 2023). In the absence of consistent and reliable data across our sample, we can thus abstract from aid.

4.1 Impact on aggregate GDP

Figure 4 shows our estimation results based on quarterly GDP data for 89 countries. Aggregate GDP falls after droughts, landslides and wildfires. In particular, we find that aggregate GDP falls by 2%, 1% and 0.4% after average-size droughts, landslides and wildfires, respectively, over the next four years.

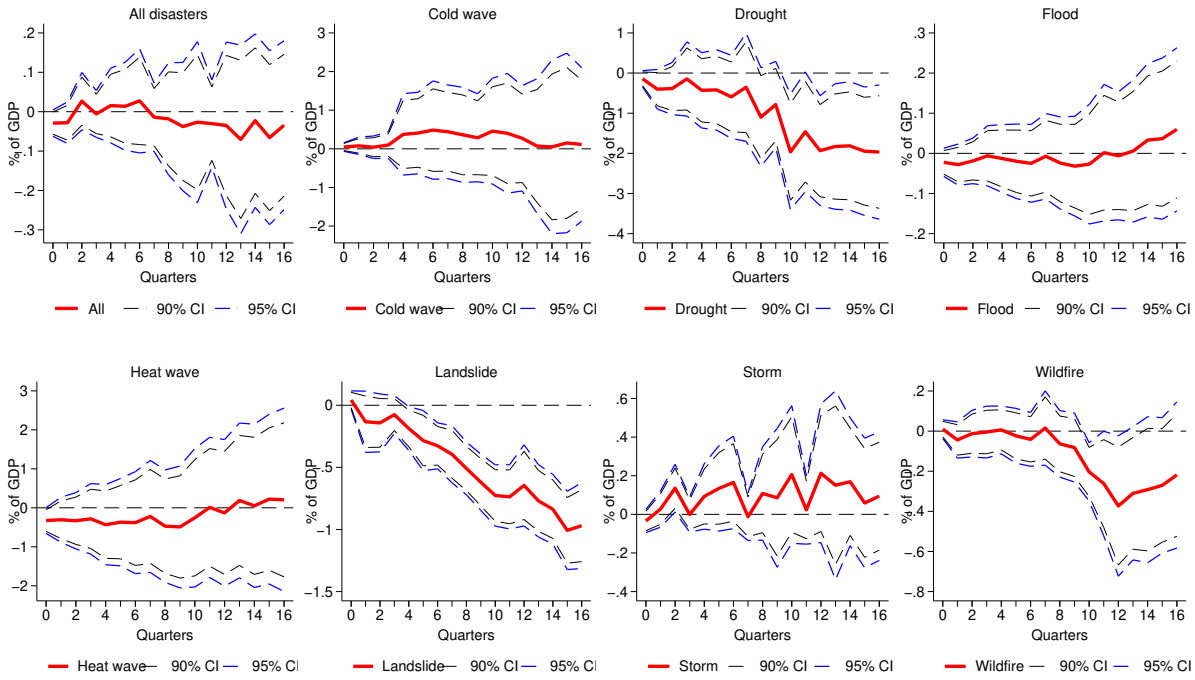
The increase in GDP after storms is due in part to fiscal support and insurance payouts. We can compare the impact of storms on GDP over the next two years in Figure 4 (1.5%, which does not control for fiscal support capacity or insurance coverage) with that in Figure 9 (0.8% which controls for fiscal support capacity) and that in Figure 14 (0.5% which controls for both fiscal support capacity and insurance coverage). We see that the positive impact on GDP after storms is substantially smaller after controlling for these mitigants.

We look at the reaction of investment (as a % of GDP) by the same set of countries over the next four years after weather disasters.[9] Table 3 shows that gross capital formation (GCF) significantly increase in the same year and two years after storms. GCF also increases after all disasters, droughts and floods. These results may reflect reconstruction or idiosyncratic factors. GCF also increases, albeit marginally significantly, after all disasters, droughts and floods. By contrast, both gross fixed capital formation (GFCF) and GCF decrease after cold waves, heat waves and wildfires over the next four years.[10]

[9]Note that since the analysis for investment is in annual frequency, then it is normal to expect that some effects may materialize only one year later, since disasters may happen at the end of year zero. This is especially relevant for investment, since it is an economic activity that takes time to build.

[10]GFCF measures gross investment in fixed capital assets. GCF measures GFCF, changes in inventories and the net acquisition of valuables.

Figure 4: GDP reaction after weather disasters



4.2 GDP analysis on four large economic sectors

To better understand where the impact on GDP growth comes from, we look at the output by four main economic sectors in the same and the next three years. Table 4 shows that facing all disasters, no economic sector changes significantly its output as a share in GDP. However, sectors react differently to each type of disaster. Agriculture, forestry and fishing decline after droughts and storms, an effect which persists for three and two years, respectively. Mining, construction, water and energy decrease after cold waves, heat waves, landslides and wildfires. Manufacturing increases after cold waves and floods, but decreases after storms. Services increase after cold waves and wildfires, possibly due to repair and rebuilding efforts. In addition, Table 5 show that food production is negatively affected by almost all types of disaster (except landslides and storms).

Table 3: Effects of weather disasters on investment as a % of GDP

t+h:	+0	+1	+2	+3	+4
Gross fixed capital formation					
All disasters	0.123	0.164	0.246	0.0384	-0.0449
	(0.0959)	(0.138)	(0.175)	(0.169)	(0.231)
Cold waves	-0.0770	0.507**	0.0214	0.179	-1.524***
	(0.143)	(0.176)	(0.270)	(0.194)	(0.200)
Droughts	0.428	1.190	0.0485	-0.150	0.388
	(1.076)	(1.194)	(1.420)	(1.511)	(1.453)
Floods	-0.117	0.612	0.121	0.0936	0.625
	(0.410)	(0.486)	(0.608)	(0.674)	(0.774)
Heat waves	-3.530***	-4.340***	-0.103	3.180	1.588
	(0.886)	(1.423)	(1.482)	(2.323)	(3.241)
Landslides	1.981	0.585	0.0142	3.522	7.082
	(1.948)	(3.014)	(2.969)	(3.177)	(6.349)
Storms	0.0965*	0.0309	0.157*	0.000728	-0.0139
	(0.0535)	(0.0770)	(0.0854)	(0.0857)	(0.127)
Wildfires	-0.210	-1.398	-1.645	-2.934**	-3.999*
	(1.493)	(1.461)	(1.336)	(1.389)	(2.266)
Gross capital formation					
All disasters	0.150	0.285*	0.219	0.128	-0.122
	(0.0927)	(0.158)	(0.165)	(0.205)	(0.232)
Cold waves	-0.0474	0.130	-0.509	-0.0245	-1.357***
	(0.206)	(0.182)	(0.293)	(0.222)	(0.243)
Droughts	0.234	1.212*	0.489	-0.114	0.677
	(0.759)	(0.666)	(1.030)	(1.496)	(1.418)
Floods	-0.199	1.088*	0.553	0.426	0.810
	(0.407)	(0.556)	(0.619)	(0.743)	(0.771)
Heat waves	-4.662**	-4.068*	2.219	4.711	2.311
	(1.692)	(1.942)	(2.051)	(3.347)	(4.205)
Landslides	0.0861	-0.679	-2.385	3.513	6.168
	(1.596)	(2.653)	(3.373)	(2.392)	(5.002)
Storms	0.104**	0.113	0.148**	0.106	-0.0531
	(0.0460)	(0.0909)	(0.0701)	(0.124)	(0.115)
Wildfires	-1.733	-2.303**	-2.991*	-3.681*	-4.602
	(1.171)	(0.972)	(1.471)	(1.944)	(3.710)

Robust standard errors in (). Clusters by country.
***,**,* denote 1%, 5%, 10% statistical significance.
All regressions include fixed effects by country and year (omitted).

Table 4: Effects on the output of four large economic sectors

t+h:	+0	+1	+2	+3	+0	+1	+2	+3
	Agriculture, Forestry and Fishing				Mining, construction, water, energy			
All disasters	-0.0762	-0.0716	-0.0174	-0.0134	0.0232	0.0769	-0.00225	-0.0805
	(0.0490)	(0.0565)	(0.0580)	(0.0850)	(0.0529)	(0.0888)	(0.104)	(0.122)
Cold waves	0.134*	-0.248**	0.0271	0.931***	0.0478	1.837	-4.997	-8.290*
	(0.0745)	(0.107)	(0.105)	(0.104)	(2.441)	(3.925)	(4.179)	(4.260)
Droughts	-1.107***	-0.592*	-0.864*	-0.675	0.0422	0.311	0.315	0.325
	(0.356)	(0.348)	(0.437)	(0.509)	(0.341)	(0.652)	(0.729)	(1.074)
Floods	-0.118	0.155	-0.00287	0.0159	-0.131	-0.0277	0.306	0.126
	(0.226)	(0.445)	(0.471)	(0.527)	(0.208)	(0.253)	(0.300)	(0.349)
Heat waves	-0.0868	-0.500	0.378	-0.509	-0.509	-1.503	-1.416**	-0.268
	(0.372)	(1.122)	(0.975)	(1.216)	(0.605)	(0.890)	(0.620)	(1.171)
Landslides	2.053	-0.738	0.827	1.671	-2.793	-3.520	-4.262	-4.609*
	(1.294)	(2.398)	(0.962)	(1.111)	(1.754)	(3.188)	(2.888)	(2.329)
Storms	-0.0351*	-0.0510**	-0.0381	-0.0375	0.0213	0.0527	0.00923	-0.0326
	(0.0184)	(0.0246)	(0.0293)	(0.0316)	(0.0268)	(0.0452)	(0.0545)	(0.0634)
Wildfires	-0.0315	0.317	0.0740	0.371	-1.537*	-3.051**	-2.490**	-1.931
	(0.329)	(0.583)	(0.597)	(0.505)	(0.843)	(1.226)	(0.926)	(1.171)
	Manufacturing				Services			
All disasters	-0.0130	-0.0385	-0.0291	-0.0500	0.0884	0.0308	-0.0203	0.0994
	(0.0330)	(0.0480)	(0.0685)	(0.0838)	(0.0536)	(0.0936)	(0.112)	(0.127)
Cold waves	1.442	2.840**	3.724***	4.764**	0.0551	0.424***	0.143	-0.320*
	(1.345)	(1.091)	(1.066)	(1.684)	(0.0963)	(0.114)	(0.157)	(0.176)
Droughts	-0.114	-0.185	0.135	0.0310	1.030	0.260	0.177	0.533
	(0.229)	(0.400)	(0.541)	(0.652)	(0.985)	(1.196)	(1.123)	(1.372)
Floods	0.430**	0.357	0.305	0.281	0.208	-0.160	-0.406	-0.195
	(0.200)	(0.331)	(0.369)	(0.418)	(0.320)	(0.481)	(0.508)	(0.507)
Heat waves	1.281	1.454	-0.0958	-0.0296	-1.177	-0.228	0.322	1.688
	(0.852)	(1.044)	(1.085)	(1.324)	(1.225)	(1.471)	(1.979)	(1.702)
Landslides	-0.533	-0.325	2.221*	-4.746	2.101	9.169	11.52	13.53*
	(0.629)	(0.955)	(1.220)	(3.030)	(1.337)	(5.366)	(6.917)	(6.773)
Storms	-0.0176	-0.0307**	-0.0359*	-0.0454*	0.0266	0.0250	0.0138	0.0458
	(0.0141)	(0.0142)	(0.0199)	(0.0235)	(0.0278)	(0.0464)	(0.0555)	(0.0537)
Wildfires	-0.453	-0.406	-0.925	-0.846	1.984*	3.219**	3.850**	2.977***
	(0.515)	(0.708)	(0.928)	(1.016)	(1.082)	(1.366)	(1.379)	(0.943)

Robust standard errors in (). Clusters by country.
***,**,* denote 1%, 5%, 10% statistical significance.
All regressions include fixed effects by country and year (omitted).

Table 5: Effects of weather disasters on the accumulated growth of the food production index (including natural and manufactured foods)

t+h:	+0	+1	+2	+3
All disasters	-.249**	-.283**	-.374**	-.332*
	(.124)	(.135)	(.16)	(.183)
Cold waves	-.109	.041	.056	-.261***
	(.102)	(.124)	(.038)	(.098)
Droughts	-1.662***	-1.136**	-1.331***	-.629
	(.49)	(.467)	(.477)	(.472)
Floods	-.423***	-.47***	-.427**	-.37**
	(.12)	(.167)	(.185)	(.169)
Heat waves	-3.446***	-1.088	-.597	-4.403**
	(.77)	(1.314)	(1.062)	(1.926)
Landslides	-.23	-.018	-.206	-.23
	(.195)	(.359)	(.408)	(.254)
Storms	-.033	-.173	-.377	-.279
	(.114)	(.21)	(.24)	(.238)
Wildfires	-.332	-.292	-.648*	-.4
	(.25)	(.242)	(.364)	(.498)

Robust standard errors in (). Clusters by country.

***,**,* denote 1%, 5%, 10% statistical significance.

All regressions include fixed effects by country and year (omitted).

4.3 Detailed sectoral GDP analysis

Going more granular, we now consider 20 sectors from OECD data for 54 countries. Table 6 shows that weather disasters significantly reduce output by the accommodation and food sector, confirming the earlier result of a negative effect on food production. In addition, various other housing-related sectors are also negatively affected such as the real estate and construction sector.

But the more granular sectoral analysis also shows a reduction in output in several service sectors, such as the finance and insurance sector and information and communication sector. By contrast, activity in the household services sector (which includes domestic care and informal work) increases three years after weather disasters. (Coefficients are positive but insignificant in years 0, 2 and 4). The household sector as a whole therefore mitigates the negative growth impact from other sectors. This could reflect greater domestic child care and elder care responsibilities after a disaster. It may also relate to greater informal employment after a weather disaster.[11]

To better understand the lack of a significant impact on the manufacturing sector, we use the granular manufacturing sector data from UNIDO. Table 7 shows that extreme weather events (all disasters) do reduce output in some parts of the manufacturing sector, but increase it in others. The production of coke, fuel, non-metallic mineral, electrical machinery and other transport tends to decline after weather disasters. But the production of rubber and plastics, basic metals and tobacco actually increases. These results intuitively correspond to different effects of natural disasters across different types of businesses. In particular, certain manufacturing goods (eg basic metals) are likely to be in higher demand after a disaster strikes. The opposing effects across different sub-sectors explain the non-significant effects of weather disasters on overall manufacturing output. Tables in the appendix show the results for individual extreme weather event types.

[11]The OECD concept of household services in the Supply and Use Tables (SUT) encompasses activities of households as employers, undifferentiated goods and services-producing activities of households for own use. This includes unpaid work within the home, such as care for other members. This activity sector is imputed from time use surveys, surveys of the household economy and household expenditure surveys. Note that several countries do not implement these surveys at a yearly frequency and frequencies of 3 or 5 years can be common. This may explain why the household services reacts to the weather disasters only after a lag of a few years.

Table 6: effects of weather disasters on the output of 2 digit sectors of activity (OECD data)

All disasters / t+h:	+0	+1	+2	+3	+4
Accommodation & food	-.405*	-.28	-.608**	-.953	-.799
	(.228)	(.323)	(.264)	(.584)	(.494)
Administrative services	.259	-.002	.215	-.184	-.913
	(.272)	(.499)	(.433)	(.572)	(.706)
Agriculture-forestry-fishing	-.052	-.581	-.234	-.61	-.567*
	(.238)	(.399)	(.431)	(.394)	(.315)
Arts & recreation	.084	.355	.087	-.761	-.695
	(.331)	(.57)	(.554)	(.557)	(.685)
Construction	-.306	-.201	-.774**	-.966***	-.724***
	(.286)	(.295)	(.348)	(.248)	(.202)
Education	.09	-.041	-.09	-.15	-.31
	(.169)	(.291)	(.26)	(.264)	(.341)
Electricity, gas, steam, AC	.013	.127	.559	.113	-.386
	(.45)	(.517)	(.484)	(.541)	(.709)
Finance & insurance	-.406**	-.205	-.064	-.26	-.693***
	(.188)	(.319)	(.28)	(.228)	(.059)
Health & social work	.075	-.262	-.483	-.59	-.483
	(.179)	(.354)	(.332)	(.365)	(.328)
Household services	.742	-.315	.015	1.906***	.854
	(.824)	(1.067)	(.675)	(.547)	(.597)
Information & communica.	-.213*	-.42**	-.595**	-.637*	-.564
	(.118)	(.201)	(.258)	(.337)	(.413)
Manufacturing	-.427*	-.446	-.55	-1.017	-1.425*
	(.239)	(.402)	(.583)	(.781)	(.833)
Mining & quarrying	.438	.618	.866	-.245	-1.586*
	(.747)	(.758)	(1.101)	(.728)	(.922)
Other services	.312	.173	-.12	-.932	-1.152
	(.277)	(.33)	(.376)	(.665)	(.756)
Profession., scient., tech.	-.33	-.446	-.411	-.514	-.607*
	(.237)	(.464)	(.529)	(.419)	(.337)
Public adminis. & defence	.04	-.148	-.358	-.323	.002
	(.195)	(.458)	(.523)	(.447)	(.435)
Real estate	-.109	-.326	-.493***	-.861***	-1.145***
	(.189)	(.248)	(.154)	(.027)	(.167)
Trade & repair	-.088	-.169	-.275	-.472	-.4
	(.215)	(.315)	(.395)	(.297)	(.267)
Transport & storage	0	-.029	-.08	-.311	-.528**
	(.139)	(.326)	(.323)	(.49)	(.266)
Water supply & managem.	.119	.12	.557	.376	-.01
	(.232)	(.4)	(.475)	(.394)	(.446)

Robust standard errors in (). Clusters by country.
***,**,* denote 1%, 5%, 10% statistical significance.
All regressions include fixed effects by country and year (omitted) and control for the share of each sector i in the total national GDP (%, lagged by one year).

Table 7: effect of weather disasters on the output of 22 manufacturing industries (UNIDO data)

All disasters / t+h:	+0	+1	+2	+3	+4
Food and beverages	.064	.236	.292	.194	.058
	(.107)	(.199)	(.253)	(.405)	(.567)
Tobacco products	1.095	3.48**	4.766**	4.9	4.172
	(.758)	(1.426)	(2.424)	(3.259)	(3.57)
Textiles	-.799	-.171	-.195	-.486	-1.448
	(.619)	(.802)	(.954)	(1.073)	(1.178)
Wearing apparel, fur	-.33	.393	.113	.158	-.354
	(.365)	(.751)	(.876)	(.781)	(.899)
Leather, footwear	.145	-.013	.27	-1.025	-.947
	(.449)	(.696)	(.993)	(.982)	(1.169)
Wood (excl. furniture)	-.344	-.114	-.9*	-.893*	-1.209
	(.274)	(.522)	(.499)	(.526)	(.763)
Paper	-.14	-.364	-.559	-.816	-.875
	(.322)	(.349)	(.42)	(.504)	(.642)
Printing & publishing	.147	2.274	2.558	1.958	2.396
	(.461)	(1.584)	(2.262)	(2.827)	(3.368)
Coke, fuel	-1.366***	.303	.881	-.537	.256
	(.495)	(.733)	(.651)	(.392)	(.896)
Chemicals	.273	.674	.79	.657	-.265
	(.573)	(.913)	(.996)	(1.198)	(.696)
Rubber and plastics	.216	.732***	.668*	.599	-.271
	(.174)	(.265)	(.357)	(.703)	(.97)
Non-metallic mineral	-.122	-.41	-.175	-.707*	-1.485*
	(.276)	(.307)	(.277)	(.373)	(.782)
Basic metals	.444	.846	2.009**	2.465*	3.493*
	(.62)	(.669)	(.901)	(1.261)	(1.813)
Fabricated metal	-.291	-.025	.127	-.23	.105
	(.51)	(.502)	(.489)	(.618)	(.708)
Machinery & equipment	.153	1.377	1.684	3.221	3.701
	(.854)	(1.705)	(1.737)	(2.432)	(2.861)
Office, computing	-.333	-1.841	-3.669*	-2.435	-3.74
	(1.277)	(1.644)	(2.109)	(2.376)	(3)
Electrical machinery	-.852**	-.79	-1.188	-1.381	-1.81
	(.339)	(.758)	(1.347)	(1.542)	(1.644)
Communication	-1.657	-2.924	-3.715	-3.092	-3.84
	(2.005)	(2.424)	(3.039)	(3.07)	(3.323)
Medical, optical	.318	-1.298	-2.057	-.915	-1.443
	(1.368)	(1.808)	(2.592)	(2.493)	(2.735)
Motor vehicles	-.595	-.303	-.653	-.766	-1.117
	(.496)	(.828)	(.873)	(.997)	(.98)
Other transport	-.448	-.582	-1.699**	-2.76*	-1.399
	(.701)	(1.075)	(.683)	(1.453)	(1.675)
Furniture	-.2	-.299	-.683	-1.4	-1.693*
	(.676)	(.549)	(.779)	(.911)	(.886)

Robust standard errors in (). Clusters by country.
***,**,* denote 1%, 5%, 10% statistical significance.
All regressions include fixed effects by country and year (omitted) and control for the share of each industry i in the total national manufacturing value added (%, lagged by one year).

4.4 Impact on inflation

Given the impact on aggregate GDP as well as its sectoral components, including manufacturing, the next logical question for monetary policy makers is whether there is any resulting impact on inflation – and if so, how persistent it is.

To better capture the impact on energy inflation, which in turn is an important component of headline inflation, we also control for the share of hydro-electric energy production in each country. Hydro-electric energy production can in principle react very differently to weather disaster shocks than other types of energy production, including other types of renewable energy such as wind or solar energy (Opperman et al. 2022). Droughts, for instance, often limit hydro-electric energy production as water levels decrease. In Brazil, for instance,electricity prices for consumers have often increased in recent years in response to droughts as hydro-electric energy production fell.

For this, we run similar regressions as for sovereign credit rating and property insurance, but instead we use the additional controls and interaction with natural disasters for the production of hydro-electric power (as a percentage of national electricity production). Data on the hydro-electric energy share in total national power production are available from the World Bank at a yearly frequency.

The effect on food inflation of extreme weather events appears to be the potentially strongest and most persistent (Figure 5). This is in line with the previous findings that output in food-related sectors typically takes a hit after extreme weather events. As the demand for food is highly inelastic, food prices are likely to go up. The summary effect of all disasters and the effect of storms on food prices are economically meaningful at about a 0.5% and 1% increase, respectively, after 12 months. While the effect of droughts and floods on food inflation is also positive and persistent, it is not statistically significant.

The effect on energy prices after controlling for the share of hydro-electric production, is less strong and less persistent than that on food prices as shown in Figure 6. For all disasters, there seems to be a significantly positive effect of around 0.2% after 8 months. Storms also seems to have

a strong and lasting effect at about 0.6% after 10 months.

Core inflation appears to be less affected. Overall, the results reported in Figure 7 suggest that compared to the impacts on food and energy prices, most types of weather disaster do not significantly affect core inflation.

Both food inflation and energy price inflation appear to feed into headline inflation, as suggested by Figure 8. Headline inflation increases after all disasters, but moderately so. Also, the effect is only significant for 5 months. Similar to food and energy inflation, the effect of storms is fairly strong at about a 0.6% increase in headline CPI after 12 months.

Appendix graphs show that the increase in food inflation after different types of disasters is robust across many geographic areas (continents or countries sorted by size).

Figure 5: Food inflation reaction after weather disasters, with controls for hydroelectric energy production as a share of total power production

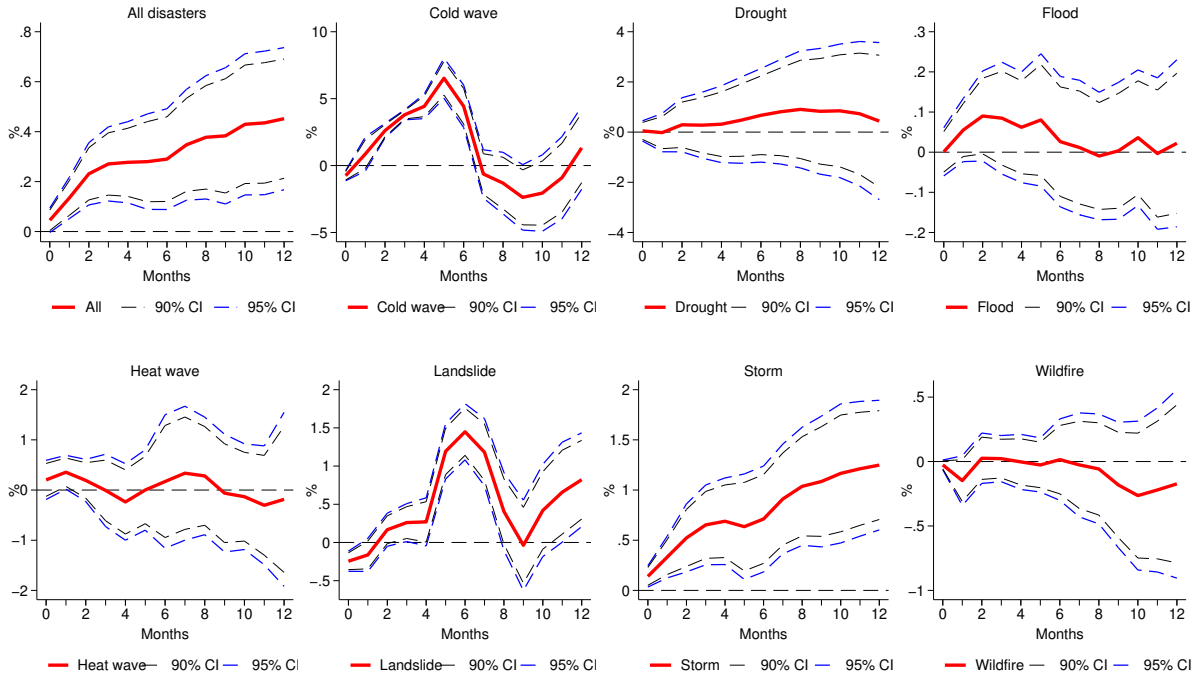


Figure 6: Energy inflation reaction after weather disasters, with controls for hydroelectric energy production as a share of total power production

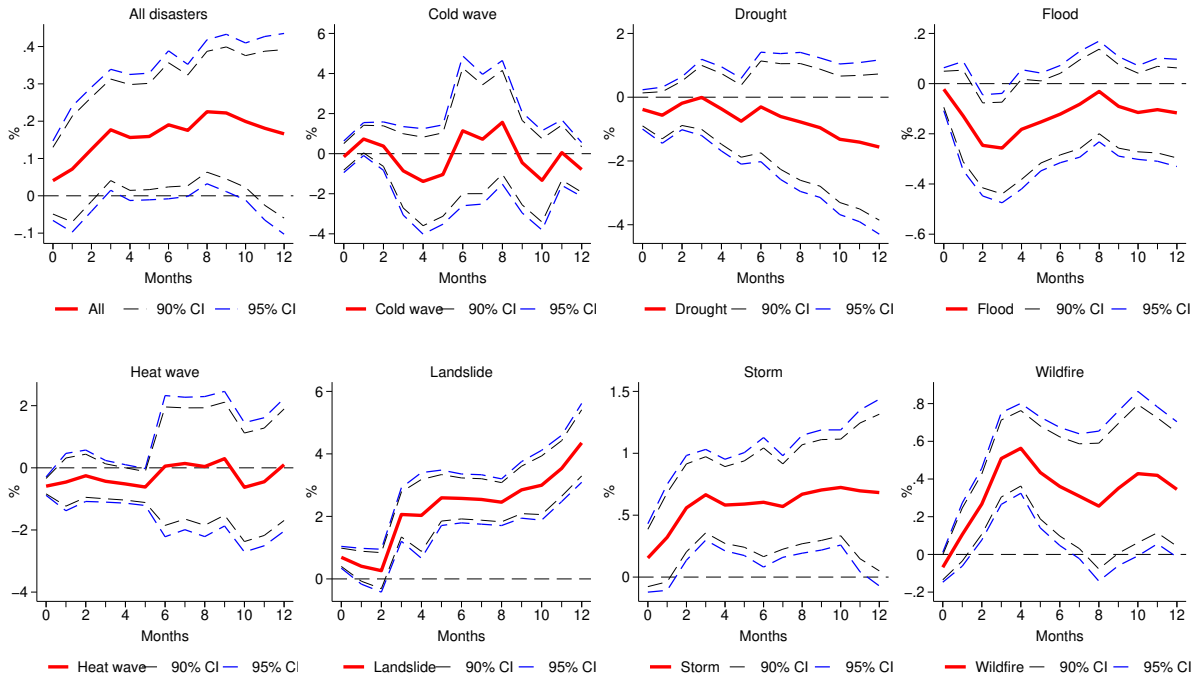


Figure 7: Core inflation reaction after weather disasters, with controls for hydroelectric energy production as a share of total power production

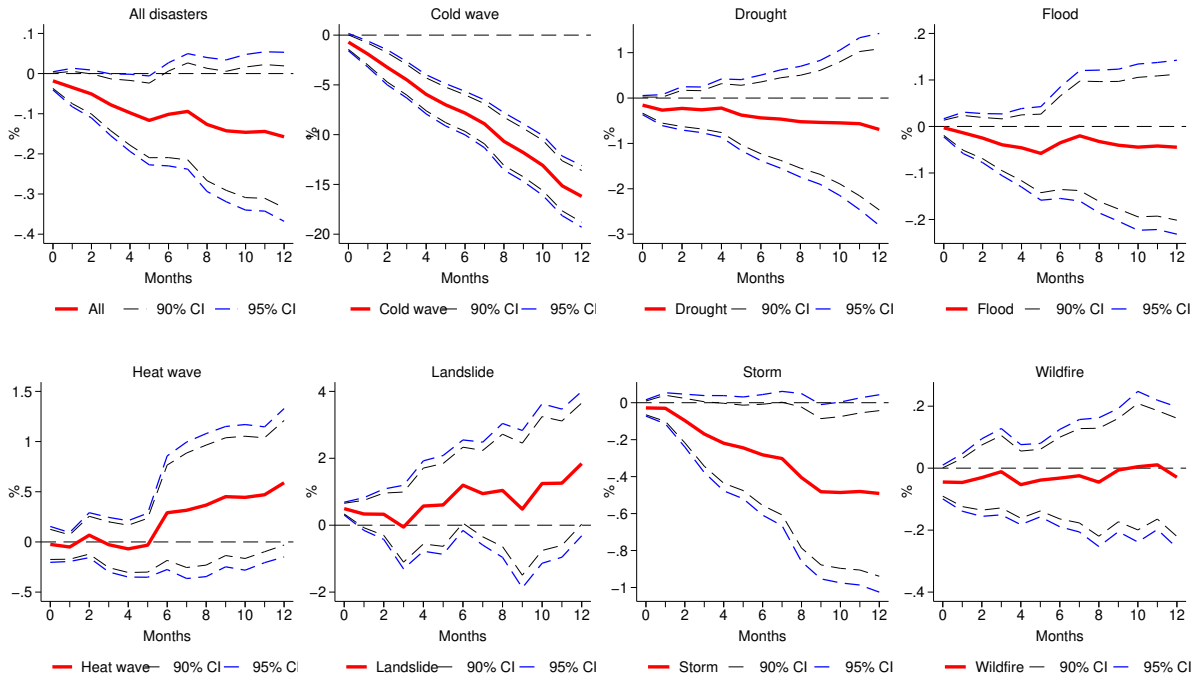
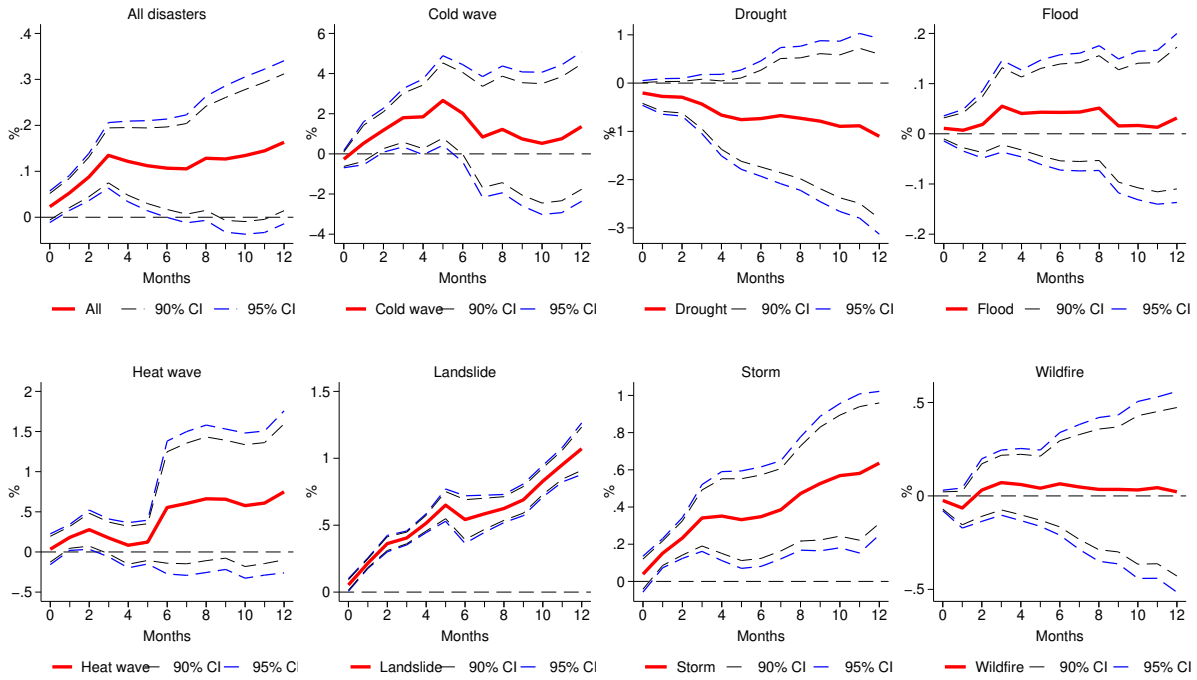


Figure 8: Headline inflation reaction after weather disasters, with controls for hydroelectric energy production as a share of total power production



5 Robustness checks

5.1 Controls for sovereign credit rating

As mentioned in the previous sections, when we gauge the impact of weather disasters, it is crucial to consider the availability of government support for disaster-hit regions and of insurance payouts which helps repairing damaged properties. In this section, we conduct two exercises: first by only considering sovereign credit rating as a proxy for the room for fiscal support, and second by considering both the credit rating and protection provided by insurance coverage. Overall we find similar results for inflation and GDP to those in the baseline regressions.

Figure 9 shows that when controlling for sovereign credit rating, GDP still falls after droughts, landslides and wildfires. The effect, however, is not as pronounced or even positive after all disasters, cold waves, floods, heat waves and storms. This shows that the availability of fiscal space is crucial for how disasters affect economic growth.

Turning to the effects on inflation, after controlling for sovereign credit rating, Figure 10 shows that food prices still increase after most disasters (all disasters, cold waves, floods, heat waves and wildfires). The results for energy prices are less consistent, as shown in Figure 11. As before, the effect on core inflation is mixed. Figure 12 shows that core inflation falls after droughts, landslides and storms, but increases after heat waves. The effect on headline inflation, in turn, remains consistent. Figure 13 shows that headline inflation increases after all disasters, cold waves, floods, heat waves, storms and wildfires.

Intuitively, the effects on inflation cannot be reversed with the availability of fiscal space. Fiscal support typically help to sustain demand right after a disaster hits and therefore contribute to price increases. But it may also help to restore productive capacity and therefore supply more speedily, which is in line with the generally short-lived effects on inflation that we find.

Figure 9: GDP reaction after weather disasters, with controls for sovereign credit rating

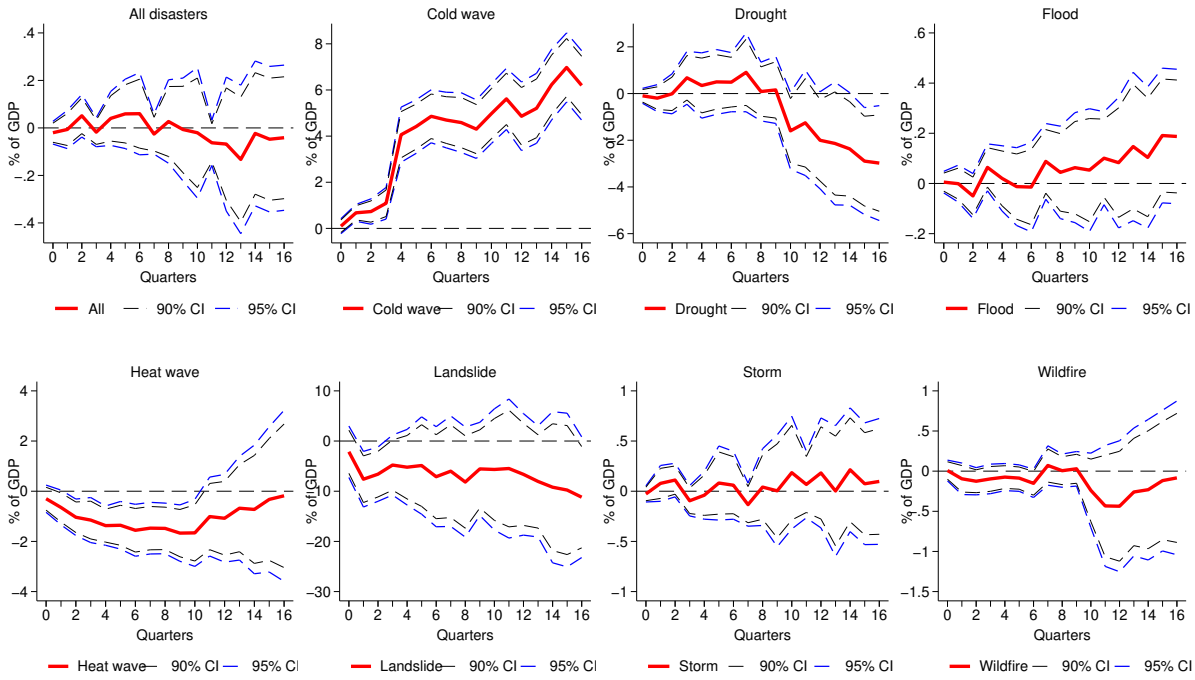


Figure 10: Food inflation reaction after weather disasters, with controls for sovereign credit rating

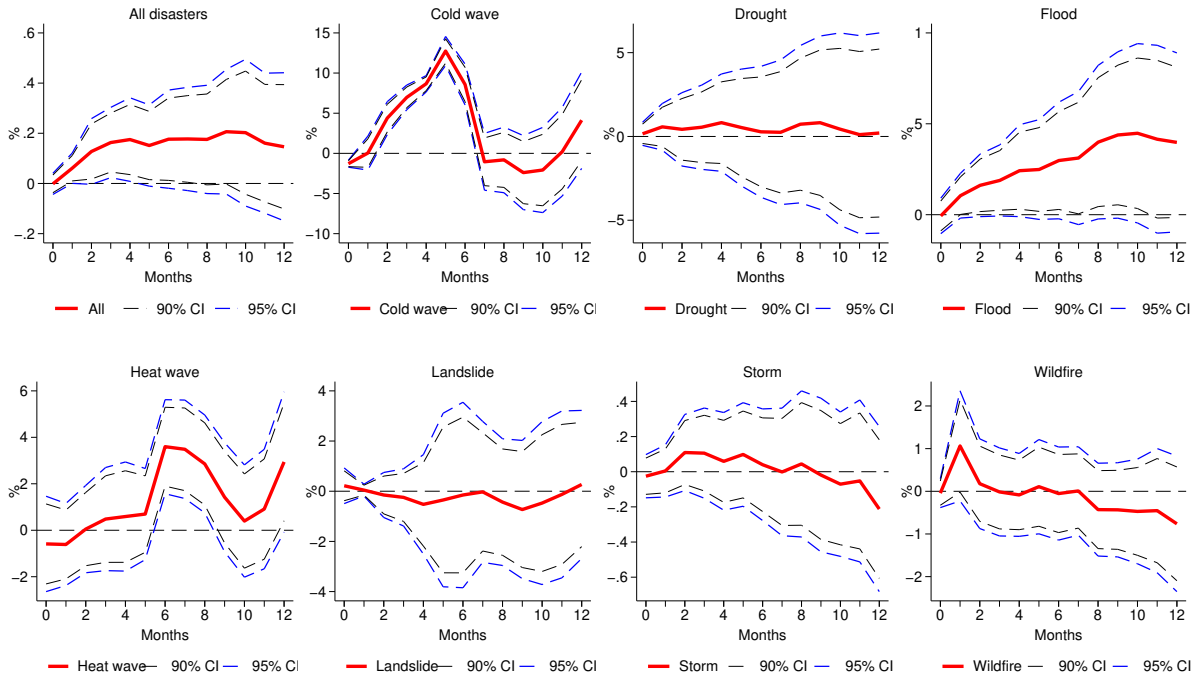


Figure 11: Energy inflation reaction after weather disasters, with controls for sovereign credit rating

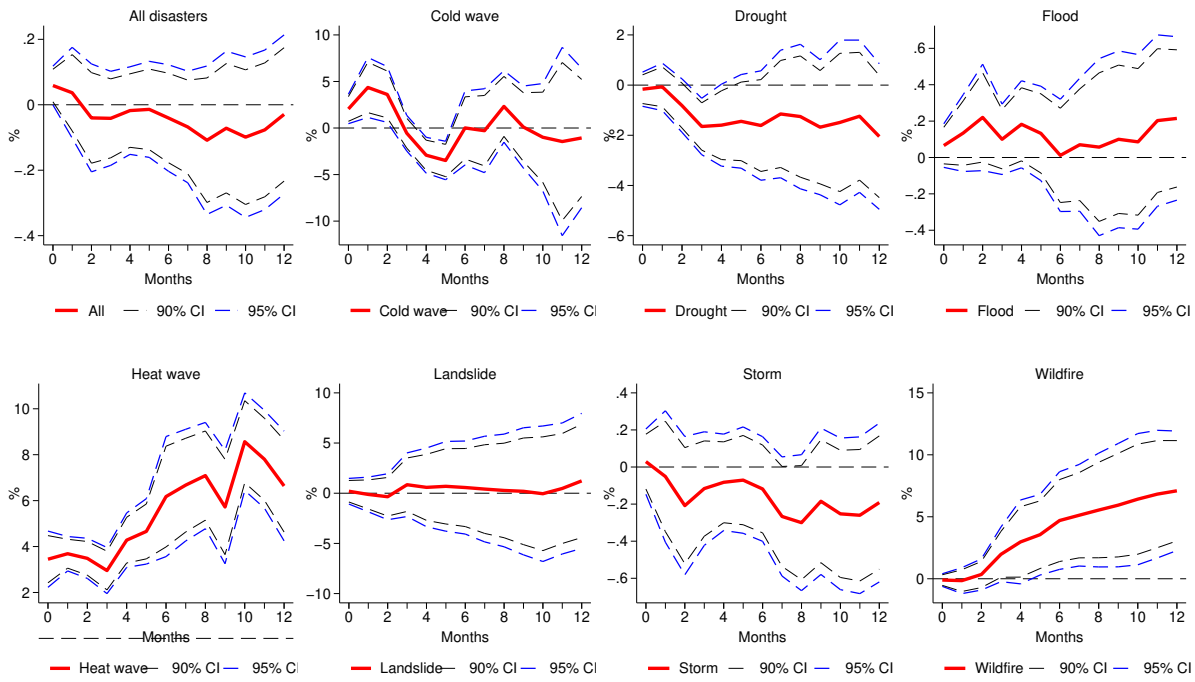


Figure 12: Core inflation reaction after weather disasters, with controls for sovereign credit rating

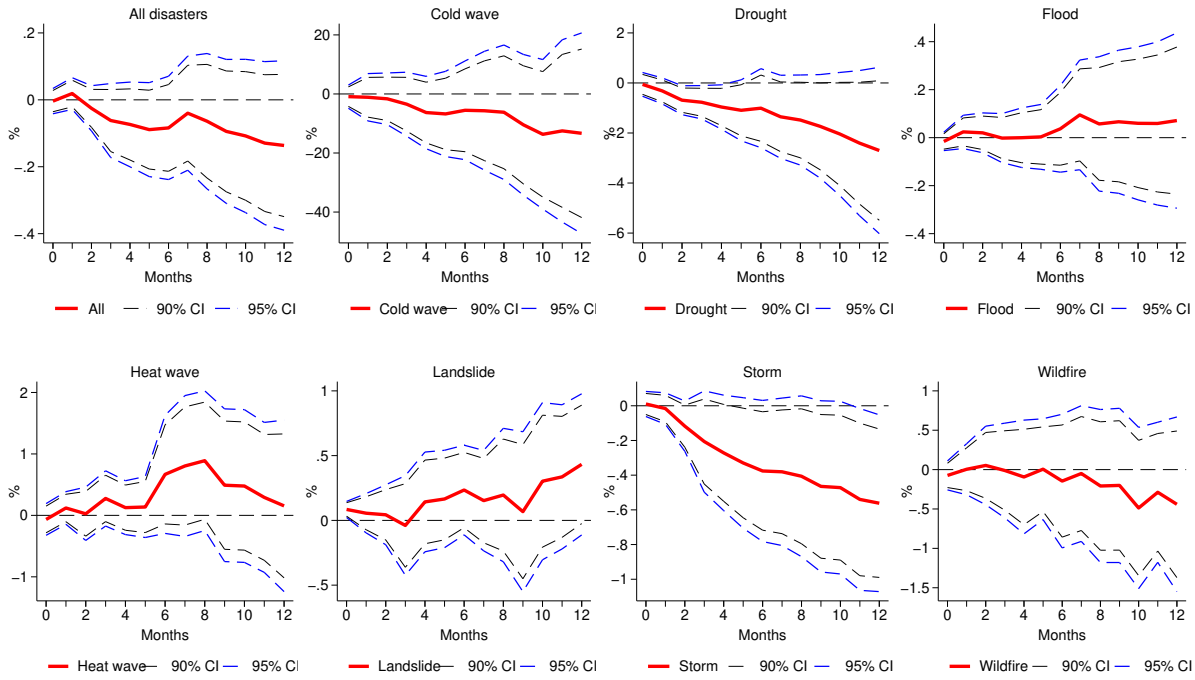
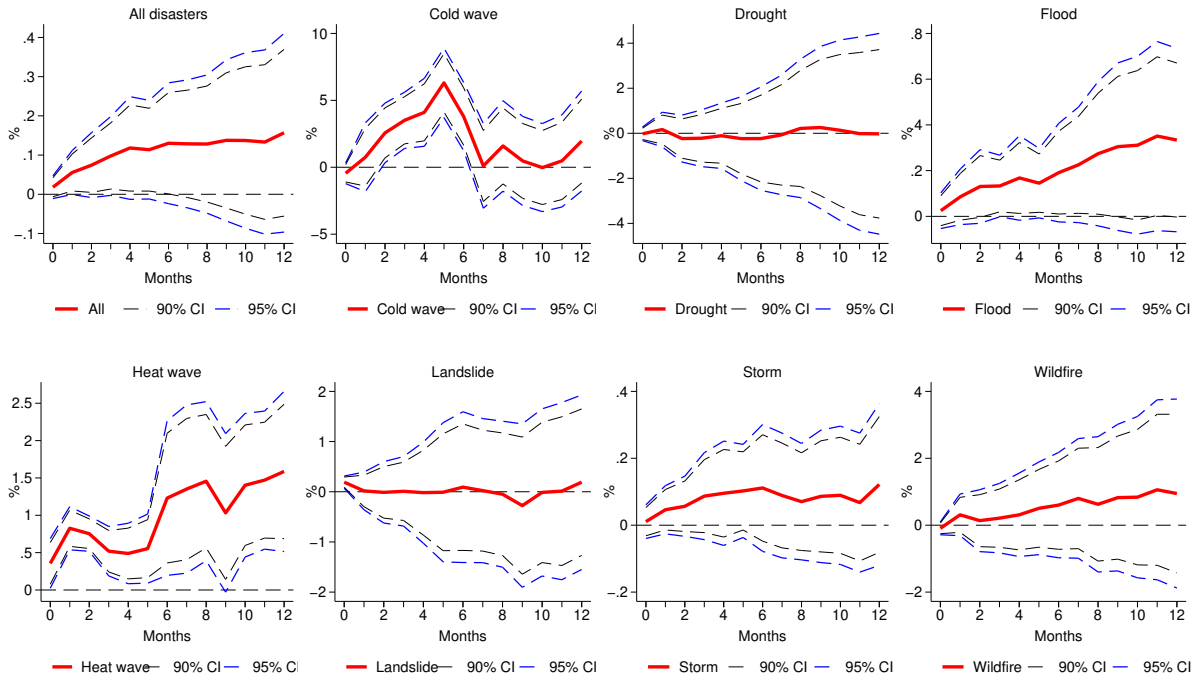


Figure 13: Headline inflation reaction after weather disasters, with controls for sovereign credit rating



5.2 Controls for sovereign credit rating and insurance coverage

Controlling for both sovereign credit rating and insurance coverage yields similar results for GDP growth to those presented above. Figure 14 shows that GDP falls after some disasters, but that the effect is dampened or even reversed for all disasters, cold waves, floods, heat waves and storms.

The effect on food inflation remains very consistent. Figure 15 shows that food inflation increases after almost all types of disaster (all disasters, cold waves, floods, heat waves, landslides, storms and wildfires). The results for energy price inflation are slight less consistent, as shown in Figure 16. As before, the impact on core inflation is mixed. Figure 17 depicts that core inflation falls after droughts, heat waves, landslides and storms, but increases after floods. The impact on headline inflation, however, remains very consistent as shown in Figure 18. Headline inflation increases after all disasters, cold waves, floods, storms and wildfires.

Figure 14: GDP reaction after weather disasters, with controls for sovereign credit rating and property insurance premium

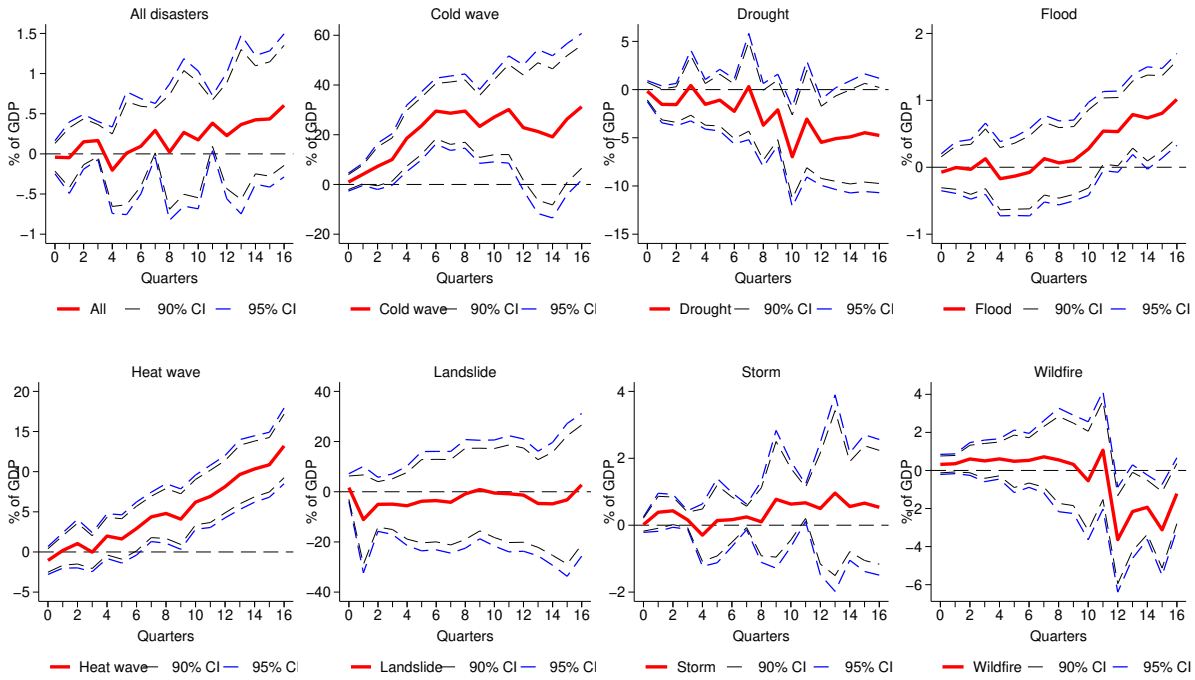


Figure 15: Food inflation reaction after weather disasters, with controls for sovereign credit rating and property insurance premium

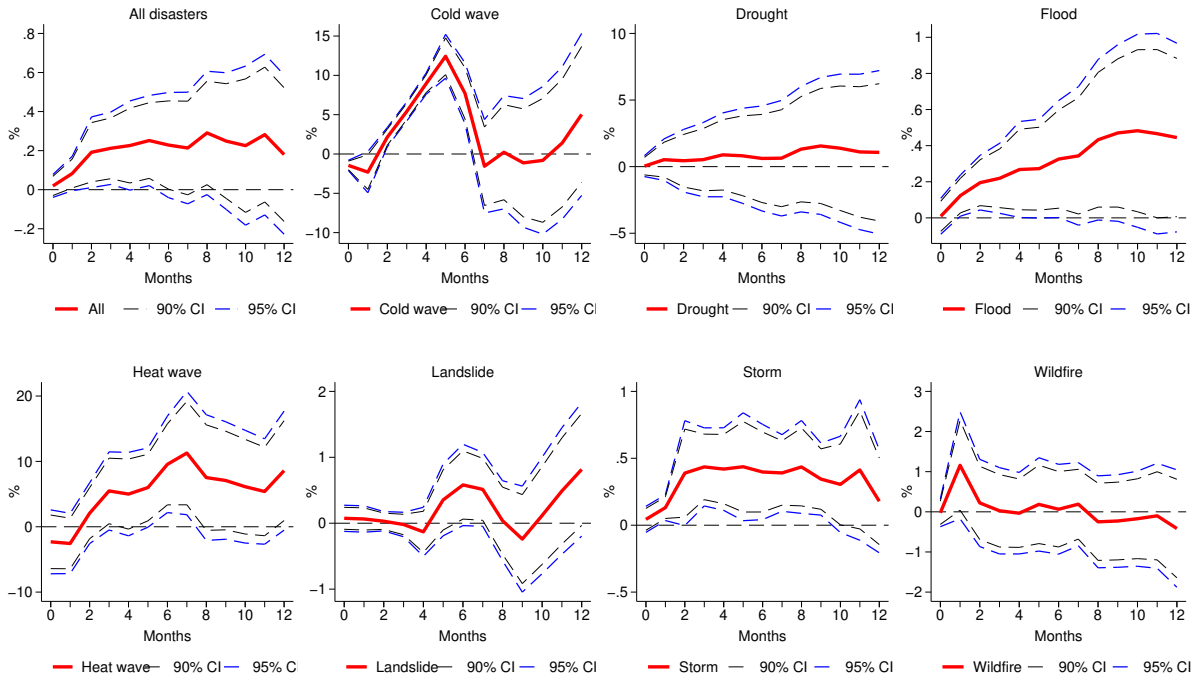


Figure 16: Energy inflation reaction after weather disasters, with controls for sovereign credit rating and property insurance premium

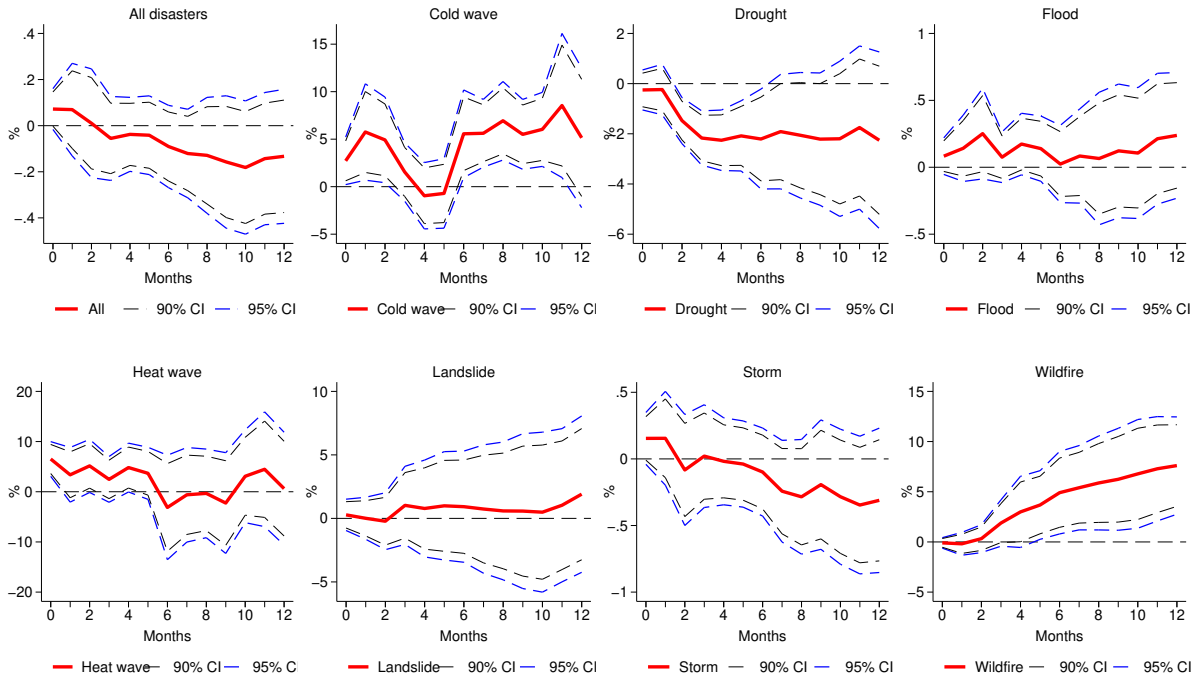


Figure 17: Core inflation reaction after weather disasters, with controls for sovereign credit rating and property insurance premium

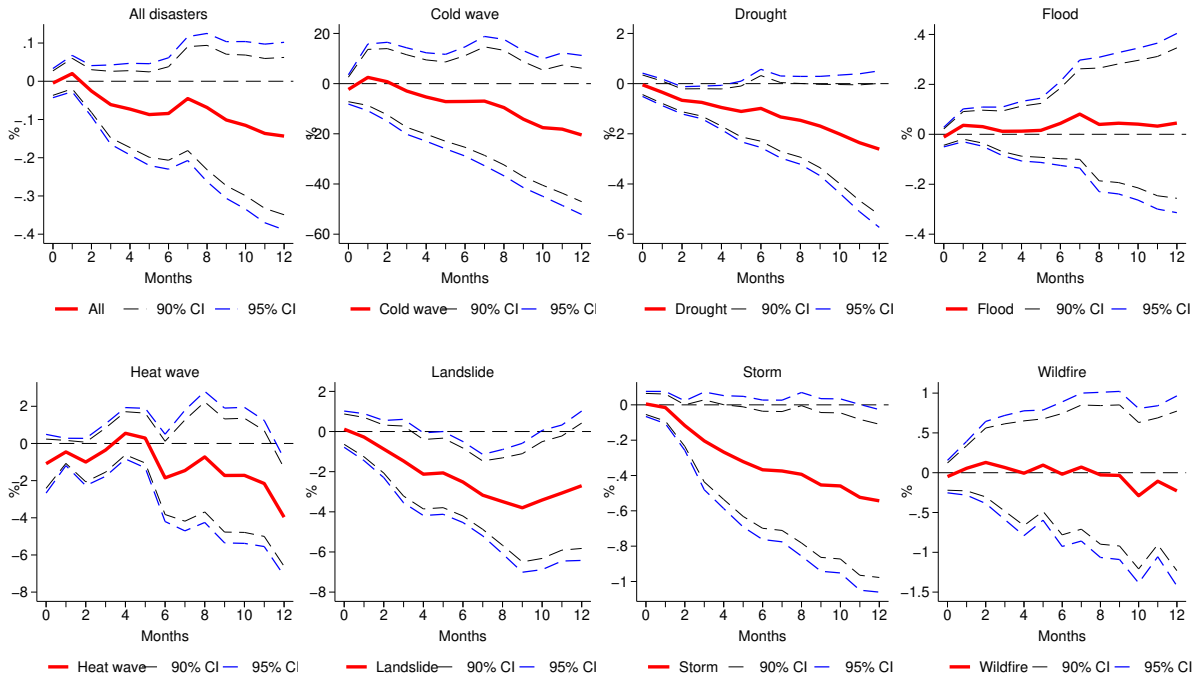
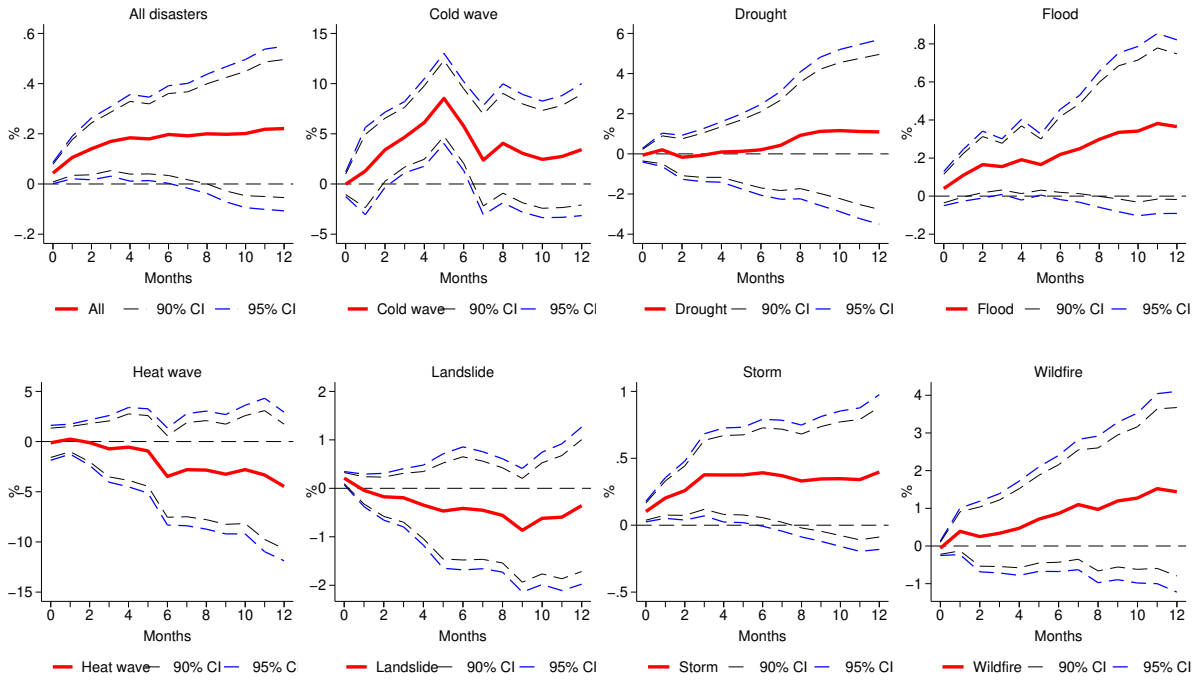


Figure 18: Headline inflation reaction after weather disasters, with controls for sovereign credit rating and property insurance premium



6 Conclusion and policy implications

Using local projections, we find that GDP falls after most extreme weather events. The effect is both economically meaningful and persistent. The negative effect is driven mainly by the agriculture-forestry-fishing sector and the mining-construction-water-energy sector. However, there are opposite effects of extreme weather events on different industries within the manufacturing sector. In general, the household sector serves as a buffer against the negative growth impact of weather disasters.

The results on the impact of weather disasters on sectoral GDP help us understand their impact on inflation. We find that food prices rise fairly significantly and persistently, by 0.5% after 12

months, for all types of disaster. We do not find notable effects on core inflation, but food inflation seems to pass through to a relatively small and short-lived effect on headline inflation. Agriculture-forestry-fishing declines persistently after droughts, which matches the results on food production and food inflation.

Naturally, the macroeconomic effects of a given weather disaster will depend on the nature of the shock and country circumstances – in particular the existing fiscal space and the insurance coverage of affected firms and individuals. Nevertheless, our results do suggest that in many cases, "looking through" the temporary increase in inflation may be an appropriate response. At the same time, an easing of policy could be warranted given the typically negative effect of weather disasters on growth.

Yet, our results also indicate that policy makers need to tread carefully. The consistent effects on food inflation suggest that economies where food-related items represent a large share of the consumption basket are more likely to experience significant inflation pressures.

Our results for an average disaster, while relevant to describe identified patterns in the data, may not be representative of a truly extreme event. A highly extreme shock could push up inflation high enough such that second round effects become more prominent. Such effects, however, cannot be estimated with sufficient precision as, by nature, the observations for such events are extremely rare.

Last but not least, the persistence of the effect on inflation depends on whether and how temporary increases in food or energy inflation feed into inflation expectations. A temporary but sharp increase in inflation implies a permanent impact on the price level and consumers may have become more sensitive to price level increases as we witnessed after the COVID pandemic. While observations for weather disasters are too scarce to estimate a recent potential increase in the persistence of inflationary effects, monetary policy response may well change with more intense and frequent extreme weather shocks.

References

[1] Acevedo, S., M. Mrkaic, N. Novta, E. Pugacheva and P. Topalova (2020), "The effects of weather shocks on economic activity: what are the channels of impact?", *Journal of Macroeconomics*, 65, 103207.

[2] Adrian, T., F. Grinberg, N. Liang, S. Malik and J. Yu (2022), "The Term Structure of Growth-at-Risk," *American Economic Journal: Macroeconomics*, 14(3), 283-323.

[3] Akyapı, B., M. Bellon and E. Massetti (2025), "Estimating macrofiscal effects of climate shocks from billions of geospatial weather observations", *American Economic Journal: Macroeconomics*, 17(3), 114–59.

[4] Altavilla C., M. Boucinha, M. Pagano and A. Polo (2024), "Climate risk, bank lending and monetary policy", ECB Working Papers 2969.

[5] Beirne, J., Y. Dafermos, A. Kriwoluzky, N. Renzhi, U. Volz and J. Wittich (2024), "Weather-related disasters and inflation in the euro area", *Journal of Banking and Finance*, 169, 107298.

[6] Bettarelli, L., D. Furceri, L. Pisano and P. Pizzuto (2025), "Greenflation: Empirical evidence using macro, regional and sectoral data", *European Economic Review*, 174, 104983.

[7] Bilal, A. and J. Stock (2025), "Macroeconomics and climate change", NBER Working Papers 33567.

[8] Bodenstein, M. and M, Scaramucci (2025), "On the GDP effects of severe physical hazards", *European Economic Review*, 175, 105019.

[9] Botzen, W., 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*, 107, 333–346.

[10] Burke, M., S. Hsiang and E. Miguel (2015), "Global non-linear effect of temperature on economic production", *Nature*, 527, 235–239.

[11] Cantelmo, A. (2022), "Rare disasters, the natural interest rate and monetary policy", *Oxford Bulletin of Economics and Statistics*, 84(3), 473–496.

[12] Cantelmo, A., M. Giovanni and C. Papageorgiou (2023), "Macroeconomic outcomes in disaster prone countries", *Journal of Development Economics*, 161, 103037.

[13] Cavallo, E., S. Galiani, I. Noy and J. Pantano (2013), "Catastrophic natural disasters and economic growth", *Review of Economics and Statistics*, 95(5), 1549–1561.

[14] Cavallo, E., O. Becerra and L. Acevedo (2022), "The impact of natural disasters on economic growth", in *Handbook on the economics of disasters*, Edward Elgar Publishing, pp. 150–192.

[15] Cevik, S. and J. Jalles (2024), "Eye of the storm: The impact of climate shocks on inflation and growth", *Review of Economics*, 75(2), 109–138.

[16] Ciccarelli, M., F. Kuik and C. Martínez Hernández (2024), "The asymmetric effects of temperature shocks on inflation in the largest euro area countries", *European Economic Review*, 168, 104805.

[17] Colacito, R., B. Hoffmann and T. Phan (2019): "Temperature and growth: a panel analysis of the United States", *Journal of Money, Credit and Banking*, 51(2–3), 313–368.

[18] CRED (Centre for Research on the Epidemiology of Disasters) (2025), *EM-DAT – The International Disaster Database*, Institute Health and Society UClouvain, Belgium. https://www.emdat.be.

[19] Cuaresma, J., J. Hlouskova and M. Obersteiner (2008), "Natural disasters as creative destruction? Evidence from developing countries", *Economic Inquiry*, 46(2), 214–226.

[20] Delforge, D., V. Wathelet, R. Below, C. L. Sofia, M. Tonnelier, J. A. van Loenhout and N. Speybroeck (2025), "EM-DAT: the emergency events database", *International Journal of Disaster Risk Reduction*, 105509.

[21] Ehlers, T., J. Frost, C. Madeira and I. Shim (2025), "Macroeconomic impact of extreme weather events", *BIS Bulletin*, 98.

[22] Faccia, D., M. Parker and L. Stracca (2021), "Feeling the heat: extreme temperatures and price stability", ECB Working Papers 2626.

[23] Fomby, T., Y. Ikeda and N. Loayza (2013), "The Growth Aftermath Of Natural Disasters", *Journal of Applied Econometrics*, 28(3), 412–434.

[24] Gagnon, E. and D. López-Salido (2020), "Small Price Responses to Large Demand Shocks", *Journal of the European Economic Association*, 18(2), 792–828.

[25] Ha, J., M. Kose and F. Ohnsorge (2023), "One-stop source: A global database of inflation", *Journal of International Money and Finance*, 137, 102896.

[26] Jorda, O. (2005), "Estimation and inference of impulse responses by local projections", *American Economic Review* 95, 161–182.

[27] Kim, H., C. Matthes and T. Phan (2025), "Severe Weather and the Macroeconomy", *American Economic Journal: Macroeconomics*, 17(2), 315–341.

[28] Kose, M., S. Kurlat, F. Ohnsorge and N. Sugawara (2022), "A cross-country database of fiscal space," *Journal of International Money and Finance*, 128, 102682.

[29] Kotz, M., F. Kuik, E. Lis and C. Nickel (2024), "Global warming and heat extremes to enhance inflationary pressures", *Communications Earth & Environment*, 5, 116.

[30] Lee, C., C. Wang, S. Ho and T. Wu (2021), "The impact of natural disaster on energy consumption: International evidence", *Energy Economics*, 97, 105021.

[31] Loayza, N., E. Olaberría, J. Rigolini and L. Christiaensen (2012), "Natural disasters and growth: Going beyond the averages", *World Development*, 40(7), 1317–1336.

[32] Melecky, M. and C. Raddatz (2015), "Fiscal responses after catastrophes and the enabling role of financial development", *World Bank Economic Review*, 29(1), 129–149.

[33] Moessner, R. (2022), "Effects of precipitation on food consumer price inflation", CESifo Working Paper 9961.

[34] Noy, I. (2009), "The macroeconomic consequences of disasters", *Journal of Development Economics*, 88(2), 221–231.

[35] Opperman, J., R. Camargo, A. Laporte-Bisquit, C. Zarfl and A. Morgan (2022), "Using the WWF water risk filter to screen existing and projected hydropower projects for climate and biodiversity risks", *Water*, 14(5), 721.

[36] Raddatz, C. (2009), "The wrath of God: macroeconomic costs of natural disasters", World Bank Policy Research Working Papers 5039.

[37] Usman, S., G. Fernández and M. Parker (2025), "Going NUTS: The regional impact of extreme climate events over the medium term," *European Economic Review*, 178, 105081.

[38] von Peter, G., S. von Dahlen and S. Saxena (2024), "Unmitigated disasters? Risk sharing and macroeconomic recovery in a large international panel", *Journal of International Economics*, 149, 103920.