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Sectoral Impact and Propagation of Weather Shocks

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Sectoral Impact and Propagation of Weather Shocks
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ABSTRACT: Local weather shocks have been shown to affect local economic output, however, little is known about their propagation through production networks. Using a six-sector global dataset over the past fifty years, this paper examines the effect of weather fluctuations and extreme weather events on sectoral economic production and the transmission of weather shocks across sectors, countries and over time. I document that agriculture is the most harmed sector by heat shocks, droughts and cyclones. Using input-output interlinkages, I find that sectors at later stages of the supply chain suffer from substantial and persistent losses over time due to domestic and foreign heat shocks in other sectors. A counterfactual analysis of the average annual output loss accounting for heat shocks across trade partners shows a substantial underestimation of the economic cost of temperature increases since 2000.

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Keywords:	Climate change; sectoral shocks; spillovers; weather shocks
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WORKING PAPERS

Sectoral impact and propagation of weather shocks

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Sectoral impact and propagation of weather shocks

Guglielmo Zappalà*

Abstract

Local weather shocks have been shown to affect local economic output, however, little is known about their propagation through production networks. Using a six-sector global dataset over the past fifty years, this paper examines the effect of weather fluctuations and extreme weather events on sectoral economic production and the transmission of weather shocks across sectors, countries and over time. I document that agriculture is the most harmed sector by heat shocks, droughts and cyclones. Using input-output interlinkages, I find that sectors at later stages of the supply chain suffer from substantial and persistent losses over time due to domestic and foreign heat shocks in other sectors. A counterfactual analysis of the average annual output loss accounting for heat shocks across trade partners shows a substantial underestimation of the economic cost of temperature increases since 2000.

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1 Introduction

There is a large and urgent demand for data-driven estimates of climate damages by policymakers to properly account for the benefits and costs of additional climate change mitigation efforts (Newell et al., 2021). A growing interest in understanding the nexus between climatic conditions and economic outcomes has led to a plethora of studies that analyze this relationship (see Kolstad and Moore (2020) for a recent review). Despite recent advancements employing panel econometric methods to estimate the response of economic outcomes to weather fluctuations (Auffhammer, 2018; Hsiang, 2016), previous articles focus on the responses of local aggregate measures of economic activity to local shocks. The potential transmission of non-local weather shocks within sectoral production networks has so far received little attention and can provide a more accurate quantification of climate damages.

This paper uses cross-country sector-level data combined with weather information and input-output interlinkages to examine how weather shocks heterogeneously affect sectoral production across the world and then traces the propagation of such shocks in production networks through the economy, across countries and over time. Production data come from the United Nations Statistics Division (UNSD, 2022), which contains information on gross value added for six sectors[1], across 184 countries from 1970 through 2020. To identify sector-specific weather shocks, I exploit plausibly exogenous variations in temperature, precipitation, dryness conditions and wind speed, aggregating grid-cell weather information at the country level using the grid-cell fraction of cropped area for the agricultural sector and population for the other sectors.

In line with previous findings (Acevedo et al., 2020; Dell et al., 2012), I document that agriculture is the most harmed sector by various weather shocks. In particular, using a measure of abnormal weather realizations with respect to the country-specific daily distribution, I find that an additional day above the 95$^{\text{th}}$ percentile of the daily temperature distribution reduces agricultural growth rate by 11% of its sample mean. Using a measure of dryness from the Standardized Precipitation Evapotranspiration Index (SPEI)

[1] Agriculture, hunting, forestry, and fishing; Mining, manufacturing and utilities; Construction; Wholesale, retail trade, restaurants, and hotels; Transport, storage, and communication; Other activities.

(Vicente-Serrano et al., 2010), I document a negative and substantial effect of droughts and dryness conditions on agricultural production. Conversely, drier conditions marginally benefit production in the construction and in the transport, storage and communication sectors, in which tasks in outdoor "interface" areas (Cachon et al., 2012) are sensitive to abundance in precipitation. Lastly, using a measure of wind speed by Kunze (2021), I document that tropical cyclones harm not only agriculture, but also have destructive power in the other activities sector, comprising government and financial sector.

Sectoral output can incur losses from climate change through different channels (Carleton & Hsiang, 2016). For instance, weather is an input in crop production and can directly harm agriculture (Acevedo et al., 2020; Hultgren et al., 2022; Schlenker & Roberts, 2009). Other sectors can experience losses due to reductions in labor supply and productivity (Graff Zivin et al., 2018; Graff Zivin & Neidell, 2014; Rode et al., 2022), total factor productivity (Letta & Tol, 2019; Zhang et al., 2018), or damages to assets and infrastructure (Bakkensen & Barrage, 2018; Fankhauser & Tol, 2005; Hsiang & Jina, 2014). In the second part of the paper, I investigate whether sectors suffer indirectly from shocks on trade partners due to the transmission of weather shocks happening elsewhere. I trace the propagation of shocks in production networks using sectoral interlinkages from EORA26 (Kanemoto et al., 2011; Lenzen et al., 2012) and consider shocks originating in upstream and downstream sectors, both domestic and foreign.

Using abnormally hot temperatures, I document that domestic shocks, accounting for weather shocks within the same country weighted by the relative importance of intersectoral linkages, have a strong negative effect on several sectors' output, notably construction; transport, storage and communication; wholesale, retail trade, restaurants and hotel. The magnitude of the effect is substantial and comparable to the effect of weather shocks on agricultural production. Using local projections (Jordà, 2005), I find that the effect of domestic shocks is persistent over time, dampening sectoral growth up to ten periods after the shock. By distinguishing between the origin of the shocks coming from customer or supplier sectors, I find that agriculture, a sector in the early stage of the supply chain, besides being harmed by local shocks, is negatively affected by shocks in customer sectors, which propagate upstream and can be interpreted as demand shocks. Conversely, sectors at later stages of the supply chain, such as wholesale, retail trade, restaurants and hotel, and other activities, are negatively affected by shocks that hit supplier sectors and that propagate downstream, as a result of supply-side productivity shocks, creating powerful downstream propagation. When I compute the economic cost of recent warming from 2000 onwards accounting for trade interlinkages, I show that heat shocks are responsible for an average annual output loss of 0.3%, highlighting a substantial underestimation of estimates that omit sectoral linkages and underlining the importance of this channel as a component of the total economic impact of climate change.

The contributions of this article relate to two main strands of literature. First, this paper contributes to the climate economics literature by providing sector-specific evidence on climate impacts across the world. Several cross-country studies have employed aggregate measures of economic activity such as national or regional GDP per capita (Acevedo et al., 2020; Akyapi et al., 2022; Burke et al., 2015; Burke & Tanutama, 2019; Dell et al., 2012; Kahn et al., 2021; Kalkuhl & Wenz, 2020; Kotz et al., 2021) to measure the impact of temperature fluctuations on economic production (see Newell et al. (2021) for a review). Previous articles often use a coarse sectoral tripartition of the economy into agricultural, manufacturing and service sectors to study the channels of the impact, finding that agricultural production is the most damaged and industrial and service output are sheltered (Acevedo et al., 2020; Dell et al., 2012). Kunze (2021) conducts a sector-disaggregated global analysis of the effect of tropical cyclones, however, estimating each sector's equation separately. Regional studies examine the effect of temperature and cyclones on sectoral production in the Caribbean and Central America area (Hsiang, 2010) and of temperature variability in Europe (Linsenmeier, 2021). This paper contributes to this strand of the literature by providing jointly estimated sector-specific response functions to temperature and precipitation anomalies, dryness conditions, and cyclone intensity with global coverage of a six-sector economic production from 1970 through 2020.

Second, this paper introduces a new important element in the climate impact literature. Previous studies examine economic losses as a function of local weather shocks, assuming that production depends only on local weather and holding conditions in other locations fixed (Miller et al., 2021). Besides spatial correlation considerations to account for the global nature of climate change (Dingel et al., 2021), shocks can also propagate through production networks across countries geographically distant. Previous studies have investigated how input-output interlinkages amplify and propagate economic shocks across US firms (Cravino & Levchenko, 2017; Giroud & Mueller, 2019) or sectors (Acemoglu, Akcigit, et al., 2016; Acemoglu, Autor, et al., 2016), and across countries (Das et al., 2022). Theoretical studies and simulations show how natural disasters can spread depending on the network structure (Henriet et al., 2012; Shughrue et al., 2020). Recent empirical studies examine the propagation of natural disasters within the US (Barrot & Sauvagnat, 2016) or after a localized single natural disaster such as the 2011 Japan earthquake or Hurricane Sandy in the US (Boehm et al., 2019; Carvalho et al., 2021; Kashiwagi et al., 2021). Pankratz and Schiller (2021) show that temperature shocks and flood events in supplier locations reduce customer firms' performance. Studies at the firm level do not justify whether idiosyncratic weather shocks have an important role in explaining macroeconomic fluctuations, which should wash out once aggregated across units (Lucas, 1977). This paper contributes to the macroeconomic literature on the propagation of shocks by studying weather shocks in the supply chain through sectoral interlinkages. Feng and Li (2021) study international spillovers of climate damage and risks on stock market valuation but use natural disaster data based on reported damages. The closest article is Kunze (2021), which considers endogenous network sectoral interlinkages and finds limited indirect effects of tropical cyclones due to stickiness in the production processes. The findings can have substantial implications in terms of correct quantification of economic damages of climate impact and the computation of the social cost of carbon, exploring a new channel of spatial transmission of weather shocks that can amplify their effects on the economy.

The remainder of the paper is structured as follows. Section 2 describes the data used in the empirical analysis. Section 3 introduces the empirical approach adopted. Section 4 shows and summarizes the sectoral impact of weather shocks and Section 5 describes the propagation of weather shocks through the economy. Section 6 concludes.

2 Data

This section provides a summary of the main data sources used for the empirical analysis.

2.1 Sectoral production data

The sectoral economic production data come from the Economic Statistics Branch of the United Nations Statistical Division (UNSD, 2022). The National Accounts Main Aggregates database provides the Gross Value Added (GVA) by kind of economic activity following the International Standard Industrial Classification (ISIC) revision number 3.1. It contains information from 1970 through 2020 and for 205 countries.[2] GVA is measured in constant 2015 USD. The data set groups sectors in six broad groups (with the respective ISIC code in parentheses): agriculture, hunting, forestry, and fishing (A&B); mining, manufacturing and utilities (C-E); construction (F); wholesale, retail trade, restaurants, and hotels (G–H); transport, storage, and communication (I); other activities (J–P).[3] The latter encompasses, among others, the financial sector, real estate, public administration, education and health. This is, to the best of my knowledge, the most comprehensive data set of economic production disaggregated by sector with global coverage and with the longest time horizon.

2.2 Weather data

I combine three main sources of weather data that use geophysical climatic information to construct measures of weather fluctuations and extreme weather events. The use of these data, exogenous to the political and economic situations of the countries, overcomes the endogeneity concerns in damage data sets based on reports and insurance data, such

[2]The sample of countries is larger than the number of recognized sovereign states since it also includes quasi-autonomous countries such as Curaçao or Puerto Rico. Since the input-output data used as part of the analysis do not contain information on these countries, the final sample does not consider these countries. The final sample of countries and their frequency is reported in Table A1.

[3]The original data are available for seven sectors, since GVA in manufacturing (ISIC D) is also provided standalone. I depart from previous articles using these data (Hsiang, 2010; Kunze, 2021) and consider mining, manufacturing and utilities (ISIC C-E) as one single sector, since it is not possible to obtain a separate measure of GVA sectoral production in mining and utilities (ISIC C & E) from manufacturing (ISIC D) because value added across sectors is not additive.

as the Emergency Events Database (EM-DAT), which is positively correlated with GDP (Felbermayr & Gröschl, 2014) and prone to measurement error (Kousky, 2014).

2.2.1 Temperature and precipitation

I use temperature and precipitation data from the global reanalysis ERA-5 dataset compiled by the European Centre for Medium-Range Weather Forecasts (ECMWF) (Muñoz Sabater, 2019). Reanalysis data combine model data with observations from across the world into a globally complete and consistent dataset using the laws of physics and rely on information from weather stations, satellites and sondes, removing biases in measurement and creating a coherent, long-term record of past weather (see Auffhammer et al. (2013) for a discussion of reanalysis weather data). ERA-5 is available on a $0.25° \times 0.25°$ resolution grid ($\approx$ 28km at the Equator) from 1950 to the present. The original temporal frequency is hourly, but I aggregate it into daily data for the empirical analysis.[4]

Following the standard methodology in the climate impact literature (Hsiang, 2016), I compute any nonlinear transformation of temperature and precipitation at the grid cell level before averaging values across space using grid-level weights and accounting for fractional grid cells that partially fall within a country, and lastly summing or averaging over days within coarser time intervals. This procedure guarantees to maintain weather variability that would be otherwise lost when averaging weather variables over an entire country. To have a measure of weather exposure for the average individual in a country and to avoid giving excessive importance to weather in areas with little economic contribution to sectoral production, when I aggregate grid-cell level information, I use time-invariant population weights from the 2000 Landscan dataset (Bright & Coleman, 2001). When constructing measures for the agricultural sector, I weigh grid-cell data by the proportion of each grid cell that is under cropland in 2000, using the Global Agricultural Lands dataset (Ramankutty et al., 2010).

[4] In particular, I use "2m Temperature", i.e. the temperature of the air at 2 meters above the surface of land, sea or inland waters, originally expressed in Kelvin (K) and converted to degree Celsius (°C) and "Total precipitation", which accounts for the accumulated liquid and frozen water, comprising rain and snow, fallen to the Earth's surface measured in meters.

2.2.2 Dryness and wetness

To introduce a measure of dryness and wetness, I use the Standardized Precipitation Evapotranspiration Index (SPEI), a climatological index used to measure dry and wet periods that combines temperature variability, precipitation and potential evapotranspiration to estimate cumulative deviations in soil moisture from normal conditions. This index compares the amount of precipitation in a given area with its evapotranspiration needs. This measure is considered superior to indices that only use information on rainfall to predict droughts caused by climate change.

Vicente-Serrano et al. (2010) show that the effects of warming temperatures on droughts predicted by global climate models can be clearly seen in the SPEI, whereas indices based only on precipitation data such as the Standardized Precipitation Index (SPI) do not reflect expected changes in drought conditions. The SPEI also outperforms another drought index, the Palmer Drought Severity Index (PDSI) (Palmer, 1965), which lacks of the multiscalar character essential for assessing drought in relation to different hydrological systems. By combining the sensitivity of PDSI to changes in evaporation demand, caused by temperature fluctuations and trends, with the multitemporal nature of the SPI, the SPEI is the most accurate climatological measure of dryness and wetness (Vicente-Serrano et al., 2012). To allow for water deficit accumulation over the entire year, I use the SPEI-12, the version of SPEI computed at a 12-month time scale.

The SPEI is constructed using monthly precipitation and potential evapotranspiration from the Climatic Research Unit of the University of East Anglia and it is normally distributed within each grid cell with $0.5° \times 0.5°$ resolution (around 56 km at the Equator). Negative values represent conditions drier than the historical average, whereas positive values represent conditions wetter than the historical average for a given grid cell.

I construct two types of measures of dryness and wetness. First, I take a weighted average of the negative monthly values and obtain the average annual dryness with respect to historical conditions. Second, to capture extreme conditions during a year I build two variables measuring the share of total grid-months subject to extreme droughts (SPEI $\leq$ -2), and to periods with extreme wetness (SPEI $\geq$ 2) (McKee et al., 1993; Paulo et al., 2012). For each category, I consider the share of affected grid-cells in the month where the share is at its maximum for each year (Akyapi et al., 2022).

2.2.3 Tropical cyclones

The last type of extreme weather event I consider is tropical cyclones. The measure of tropical cyclones is taken from Kunze (2021), which uses meteorological data on wind speed as previously introduced in the literature (Bakkensen & Barrage, 2018; Hsiang, 2010; Hsiang & Jina, 2014). The annual measure of tropical cyclones is a non-linear function of wind speed which includes the cube of wind speed when wind speed is above a 92 km/h threshold, where wind speed is computed accounting for the maximum sustained wind speed, the forward speed, the distance from the storm center and the radius of the maximum wind (see Kunze (2021) for additional methodological details).

2.3 Sectoral interlinkages

Crucial to my analysis is the identification of sectoral interlinkages both domestic and abroad. I use Input-Output (IO) data from EORA26 (Kanemoto et al., 2011; Lenzen et al., 2012) to analyze how idiosyncratic weather shocks propagate through the economy. This data set contains information on 26 sectors for 189 countries from 1990 to 2021 and has the widest geographic coverage in terms of intersectoral linkages.[5] I only retain information on the first available year of the IO matrix (1990) and consider propagation of weather shocks through a pre-determined constant input-output network that does not endogenously respond to the shock itself (Kunze (2021) shows a small and negligible shift of sectoral interlinkages after tropical cyclones). I aggregate the 26 sectors to the six sectors described in Section 2.1 to match the production network with sectoral output as reported in Table A2.

[5] This data set contains, to the best of my knowledge, the richest information in terms of geographic, temporal and sectoral information on input-output interlinkages. However, the data set presents few limitations since some data are estimated and not measured and it is slightly less accurate than the full EORA MRIO due to the aggregation of sectors from the higher sectoral detail of Eora to the lower detail of EORA26, and to the conversion of Supply/Use tables to IO tables, which involves both a net information loss and the introduction of some new assumptions.

2.3.1 Construction of network shocks

To account for and quantify the propagation of weather shocks through the economy, I construct a measure of *network* shocks that hit other sectors and that propagate through trade interlinkages. I use sector-country level information in the IO matrix to construct a weighting scheme that accounts for the importance of a sector depending on its geographic location and position in the supply chain.

I distinguish network shocks along two dimensions that relate to geographic location and supply chain stage. First, I distinguish between shocks originating in the same country as the sector of interest, domestic, and those originating in other countries, foreign (Das et al., 2022). Second, I classify network shocks into downstream and upstream depending on whether they hit sectors that are respectively suppliers or customers of the sector of interest (Acemoglu, Akcigit, et al., 2016; Acemoglu, Autor, et al., 2016). From the perspective of the sector of interest, downstream shocks originate in supplier sectors and propagate downstream. Conversely, upstream shocks hit customer sectors and travel upstream to the sector of interest.

In addition to the local own shock hitting sector s in country c, there are four different types of network shocks depending on the supply chain position and geographic location: upstream domestic (UpD), upstream foreign (UpF), downstream domestic (DnD), and downstream foreign (DnF), constructed as follows:

$$\text{Shock}_{s,c,t}^{DnD} = \sum_{j \neq s} \omega_{s,c,j,c} \text{Shock}_{j,c,t}^{Own} \tag{1}$$

$$\text{Shock}_{s,c,t}^{UpD} = \sum_{j \neq s} \widehat{\omega}_{s,c,j,c} \text{Shock}_{j,c,t}^{Own} \tag{2}$$

$$\text{Shock}_{s,c,t}^{DnF} = \sum_{j} \sum_{k \neq c} \omega_{s,c,j,k} \text{Shock}_{j,k,t}^{Own} \tag{3}$$

$$\text{Shock}_{s,c,t}^{UpF} = \sum_{j} \sum_{k \neq c} \widehat{\omega}_{s,c,j,k} \text{Shock}_{j,k,t}^{Own} \tag{4}$$

where $\text{Shock}_{j,k,t}^{Own}$ is a weather shock hitting sector j in country k in year t.[6] I take

[6]Except for weather shocks in the agricultural sector which are obtained weighting weather variables

a weighted average of the shocks hitting all sectors that sector s has a linkage with by constructing the weights from the inter-country IO tables described in Section 2.3. Weights are differently built for upstream and downstream shocks. From the perspective of sector s in country c, for downstream shocks, I construct weights as

$$\omega_{s,c,j,k} = \frac{\text{input}_{jk \to sc}}{\sum\limits_{lf \in \Theta_{sc}} \text{input}_{lf \to sc}} \tag{5}$$

i.e., the ratio of the inputs supplied by sector j (in country k) to sector s (in country c) over the total inputs that sector s sources from its set of supplier sector-countries Θ_{sc}. These weights represent downstream propagation since they reflect the relative importance of each supplier for the sector-country of interest sc.

The weights associated with measures of upstream shocks are constructed as

$$\widehat{\omega}_{s,c,j,k} = \frac{\text{input}_{sc \to jk}}{\sum\limits_{lf \in \widehat{\Theta}_{sc}} \text{input}_{sc \to lf}} \tag{6}$$

i.e., the ratio of the inputs of sector s to each sector j over the total inputs supplied by sector s to all sector-countries lf in its set of customers $\widehat{\Theta}_{sc}$. These weights represent upstream weights since they reflect the importance of each customer for the sector-country of interest sc. Given the level of aggregation of sectors, all six sectors are included in both upstream and downstream weights. Figure A1 shows the average upstream and downstream weights of each sector across countries (both domestic and foreign).

As a first step in the analysis, I consider network shocks only based on the geographic location (domestic or foreign) of partners. In this case, I take an unweighted average of upstream and downstream weights to obtain a measure of the average relative importance of each sector-country.

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by agricultural land coverage as detailed in Section 2.2, all other sectors in the same country as the sector of interest s have the same weather shock.

2.4 Summary Statistics

Table 1 presents summary statistics for sectoral production and bilateral IO interlinkages. Although unbalanced, the sector-country panel dataset covers all countries in the world for most of the fifty available years. On average, information for each sector-country tuple is reported for 48 years.[7]

Table 1: Summary statistics on sectoral production and interlinkages

	N	mean	SD	min	max
Log GVA per capita	50,223	6.147	1.796	-2.880	11.534
GVA per capita growth rate	50,223	0.016	0.120	-3.299	2.572
io Downstream (ω)	1,284,822	0.00083	0.01429	2.68e-11	0.99976
io Upstream ($\widehat{\omega}$)	1,284,822	0.00084	0.01432	8.50e-11	0.9944
io Total ($\overline{\omega}$)	1,284,822	0.00083	0.01132	1.65e-10	0.73665
Sector					
Agriculture, hunting, forestry, fishing (ISIC A-B)	7,472	0.003	0.104	-1.691	0.745
Mining, Manufacturing, Utilities (ISIC C-E)	8,572	0.012	0.125	-3.169	2.430
Construction (ISIC F)	8,566	0.015	0.167	-3.299	2.572
Wholesale, retail trade, restaurants and hotels (ISIC G-H)	8,522	0.016	0.108	-1.639	1.502
Transport, storage and communication (ISIC I)	8,519	0.027	0.109	-2.514	2.030
Other Activities (ISIC J-P)	8,572	0.019	0.085	-1.513	1.261
Number of countries	184				
Number of sectors	6				
Number of years per country-sector		47.92	6.27	12	50

Table 2 shows summary statistics for the main measures of weather shocks on temperature and precipitation, dryness and wetness, and tropical cyclones. I first construct a measure of changes in temperature and precipitation distribution, considering a binary variable that takes value one if daily temperature and precipitation are larger than the previous year. Then, I consider how much daily temperatures and precipitation are larger/smaller than the previous year. To avoid relying on absolute thresholds, I also consider country-specific temperature and precipitation distributions and compute the annual number of days above/below a certain percentile. As detailed in Section 2.2.2, to measure dryness and wetness, I use the annual average of monthly conditions drier than historical averages (in absolute value, so positive changes mean drier conditions) and the maximum annual share of grid-months subject to extreme droughts or extreme wetness periods, where values can range from 1 to -1, where unity means that all grids in a coun-

[7] Most of the sectors are covered for the whole time period except for recent geopolitical changes.

try were affected by an extreme droughts/wetness month and none of them was in the previous year. Summary statistics on additional weather variables used in the analysis are reported in Appendix Table A4.

Table 2: Summary statistics on weather shocks

	N	mean	SD	min	max
Temperature and precipitation					
Positive difference in daily temperature sum {0;1}	8,572	0.524	0.499	0	1
Positive difference in daily precipitation sum {0;1}	8,572	0.497	0.500	0	1
Changes in daily temperature sum (Δ°C)	8,572	9.556	197.755	-1594.597	1704.612
Changes in daily precipitation sum (Δ m)	8,572	0.0008	0.010	-0.092	0.095
Temperature above 95$^{\text{th}}$ percentile (days/year)	8,572	18.986	16.5	0	152
Temperature below 5$^{\text{th}}$ percentile (days/year)	8,572	17.870	14.185	0	156
Precipitation above 95$^{\text{th}}$ percentile (days/year)	8,572	18.244	6.613	1	78
Precipitation below 5$^{\text{th}}$ percentile (days/year)	8,572	15.633	10.182	0	86
Dryness and wetness					
Average dryness ($\Delta\ \overline{SPEI} < 0$)	6,204	-0.009	0.496	-2.181	1.924
Extreme drought prevalence (Δ share grid-months$_{SPEI<-2}$)	8,448	0.002	0.252	-1	1
Extreme wetness prevalence (Δ share grid-months$_{SPEI>2}$)	8,448	-0.001	0.195	-1	1
Tropical cyclones					
Cubic wind speed (Δ km^3/h^3)	7,371	659.399	672,647.087	-17,838,080	17,856,152

Notes: Summary statistics are computed using country-year observations using only population-weighted weather shocks to avoid double counting. Where Δ is indicated in parentheses, variables are in first-difference, measuring changes in weather conditions from the previous year.

3 Empirical Approach

The empirical analysis is conducted in two steps. First, I estimate the sector-specific response in per capita GVA growth rate to weather shocks. Second, I analyze how weather shocks hitting customer/supplier sectors domestically and abroad affect sectoral economic production.

3.1 Sectoral impact of weather shocks

I estimate the sector-specific output-weather relationship using a pooled sample of sectoral GVA per capita growth rates across 184 countries over 50 years. The effect of temperature and precipitation on production is identified using year-to-year variation in the distribution of daily weather, following, *inter alia*, Carleton et al. (2022) and Deschênes and Greenstone (2011). Specifically, the baseline specification is written as

$$\Delta \log(GVA)_{sct} = f_s(\Delta \mathbf{W}_{ct}) + \alpha_{cs} + \lambda_{st} + \varepsilon_{sct} \tag{7}$$

where I regress the growth rate of GVA per capita in sector s in country c in year t (approximated by the first difference in logarithms) on a sector-specific function of first difference of weather variables $\mathbf{W}$ in country c in year t. I include country-sector, and sector-year fixed effects to account for unobserved heterogeneity, such as history, culture, geography and time-invariant sectoral compositions of national output, and year-specific worldwide shocks, such as El Niño events or global recessions, and to specific sectors (e.g. agricultural commodity price shocks). For instance, differences in country sizes and different reactions to the same weather shocks do not pose a problem in the identification strategy. I do not include any other traditional time-varying determinants of sectoral production - such as investments or capital stocks - since they are endogenous to weather variations themselves and may thus introduce bias in the estimates (Dell et al., 2014). Standard errors are clustered at the country level to account for spatial correlation of the error terms across sectors operating in the same country over time.

Equation (7) exploits plausibly exogenous within-country variation in changes in weather fluctuations. This approach uses random weather shocks as identifying variation, which differ from climate change (Mendelsohn & Massetti, 2017). Short-run and long-run elasticities to weather fluctuations are the same only under certain assumptions (Lemoine, 2021), therefore one should be cautious in extrapolating long-term impacts from the estimated short-term responses (Tol, 2022).

Since GVA growth rate is stationary and temperature fluctuations in levels are non-stationary, studying the relationship between GVA growth and weather variables would reintroduce trends in the specification (for a deeper discussion, see Newell et al. (2021) and Tol (2019)). For this reason, I consider first-differenced, stationary weather variables, whereby I first compute any non-linear function and then take the first difference, following a more recent approach (Akyapi et al., 2022; Kahn et al., 2021; Kotz et al., 2021; Letta & Tol, 2019; Newell et al., 2021) rather than using levels in weather variables (Acevedo et al., 2020; Burke et al., 2015; Dell et al., 2012; Henseler & Schumacher, 2019).[8]

Although the use of changes in weather realizations already de-trends the variables in the model, I test for the robustness of the model in alternative specifications including country-specific linear (and quadratic) time trends to allow for non-linear evolution of underlying country's characteristics, such as demographic transitions and institutional changes. In additional robustness checks, I also account for dynamics and serial correlation in the dependent variable by including the lagged dependent variable among the regressors.

3.2 Propagation of weather shocks

To quantify the importance of *network shocks* relative to own shocks on sectoral activity, I expand the specification accounting for weather shocks elsewhere, constructed as explained in Section 2.3.1. The econometric specification is written as

$$\Delta \log(GVA)_{sct} = \gamma_s Shock_{sct}^{Own} + \sum_J \gamma_s^J Shock_{sct}^J + \alpha_{cs} + \lambda_{st} + \eta_{sct} \tag{8}$$

where I expand Equation (7) with shocks in partner sectors J by geographic location and supply chain position. I begin by including domestic and foreign weather shocks weighted by the average interdependence of sector s with other sectors in the same country c and other countries (i.e., $J \in \{\text{domestic; foreign}\}$). Then, I also disentangle upstream and downstream weather shocks (i.e., $J \in \{\text{domestic downstream; domestic upstream; foreign downstream; foreign upstream}\}$). The remainder of the specification is similar to Equation (7), accounting for sector-country and sector-year unobserved heterogeneity.

This approach aims at quantifying the impact on sectoral production of trade-induced exposure to weather shocks in other sectors. A typical panel fixed effects model would study the effect of weather variations in a given location while weather elsewhere is fixed. Climate change, however, is expected to alter atmospheric conditions across the world. For this reason, the estimates obtained in Equation (7) would be biased by omitting spatial considerations that are of first-order relevance because production and climate are

[8]I reject the null hypothesis of non-stationary series for all first-differenced economic and weather variables performing the Im-Pesaran-Shin (2003) panel unit root test. Results are reported in Table A5.

spatially linked, leading to violations of common identifying assumptions with first-order effects. Weather shocks elsewhere affect sectoral market access which could improve or deteriorate depending on market forces and trade relationships with other sectors. Although I have no way to formally pin down the channel through which weather shocks affect supplier production functions and customer demand (e.g. infrastructure or facility damages, labor productivity losses), this approach uncovers the role of the propagation channel for quantifying sectoral weather shocks. Omitting trade linkages across sectors while weather shocks are positively spatially correlated would violate the stable unit treatment value assumption (SUTVA) and produce bias in the estimates. The direction of the bias is ex-ante ambiguous since it depends on market forces and on the network structure of the trade relationship. On the one hand, weather shocks on trade partners can have a positive effect on sectoral production through improvements in market access and lower productivity of its competitors. On the other hand, shocks on trade partners characterized by input specificity with low elasticity of substitution can impose declines in production.

4 Sectoral impact of weather shocks

The first part of the results explores the extent to which local weather shocks in the form of temperature and precipitation fluctuations (Sections 4.1 and 4.2) and extreme weather events such as droughts and cyclones (Section 4.3) affect sectoral economic production.

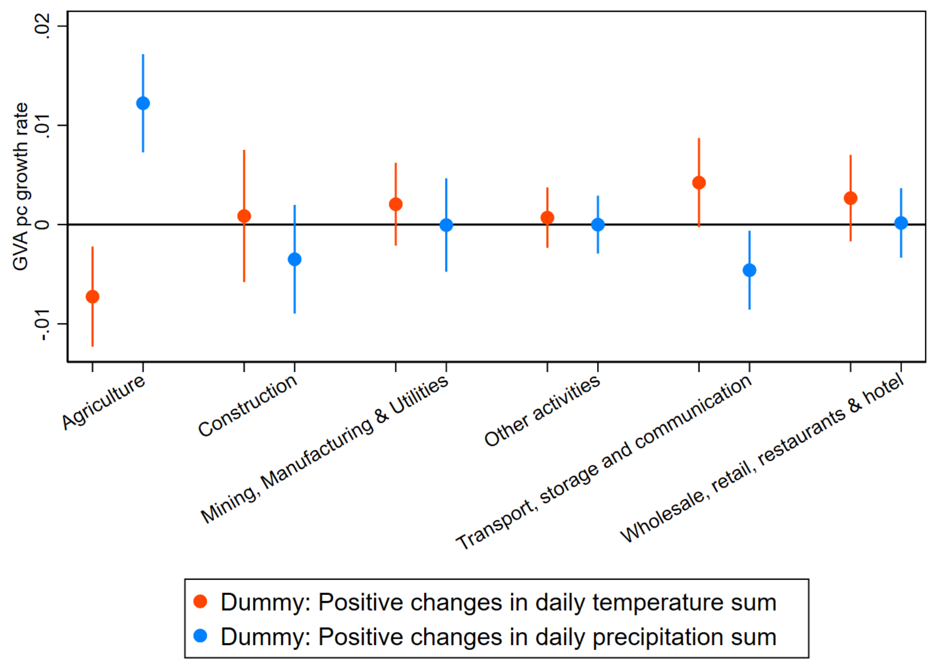
4.1 Changes in temperature and precipitation distribution

I exploit within-sector and across-countries year-to-year fluctuations in changes in temperature and precipitation to identify their causal effect on economic production. Differently than previous cross-country empirical evidence on the channels of the impact of weather shocks on sectoral outcomes (Acevedo et al., 2020; Dell et al., 2012; Kunze, 2021), I estimate a pooled, multi-country, sector-specific response function as detailed in Equation (7). This model allows me to jointly estimate responses of sectoral economic production to weather shocks and compare the different response functions.

To provide some initial suggestive evidence on the heterogeneous sectoral response to weather shocks, I begin the analysis by using as a measure of weather shock a binary variable indicating whether first-differenced annual changes in daily average temperature and total precipitation are positive or negative. Figure 1 displays the 12 estimated coefficients from the same pooled regression (6 sectors × 2 weather variables). Consistent with prior literature (e.g., Acevedo et al. (2020)), I uncover substantial heterogeneity across sectors in the multicountry sample. The agricultural sector responds the most to both temperature and precipitation fluctuations. In particular, if daily average temperature is larger than in the previous year, the agricultural GVA growth rate decreases by 0.7 percentage points (point estimates are reported in Table A6), which translates into a 284% decrease with respect to the sample average (0.002). The effect is large but comparable to previous estimates on the effect of heat waves and tropical cyclones on agricultural growth rate (Kunze, 2021; Miller et al., 2021). Conversely, agriculture seems to benefit from more precipitation, as documented in prior literature (Cunado & Ferreira, 2014; Deschênes & Greenstone, 2007; Schlenker & Roberts, 2009). The only other sector that responds elastically to variations in annual temperature and precipitation distribution is transport, storage and communication, which marginally benefits from hotter (15% increase of sample mean) and drier (17% increase of sample mean) conditions that, for instance, facilitate transportation and storage and service communication.

I further investigate the effect of changes in the average daily temperature and precipitation distribution with the variables standardized to facilitate comparison. Figure 2 shows the estimated coefficients (see Table A7 for tabular results). As previously documented, agriculture strongly negatively reacts to positive hot temperature shocks but benefits from more precipitation. In particular, a 0.01°C daily increase with respect to the previous year's temperature (around 30% of the sample mean) is associated with a decrease in agricultural per capita growth rate by 3% of the sample mean. Surprisingly, all the other sectors positively respond to increases in the average daily temperatures, although few sectors' responses are estimated with less precision (other activities; transport, storage and communication; wholesale, retail trade, restaurants and hotel). Conversely, production in other sectors does not respond to changes in precipitations, except for the transportation sector which benefits from drier conditions.

Figure 1: Sector-specific impact of positive annual temperature and precipitation changes

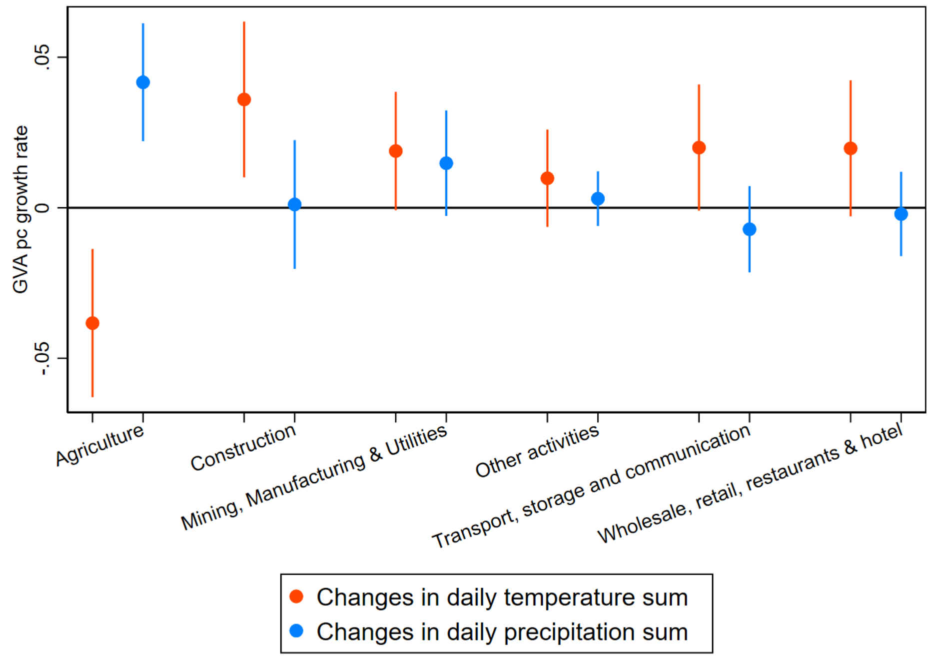


Notes: The figure shows the OLS coefficients associated with the response of sectoral GVA per capita growth rate to an indicator variable that takes value one if the sum of average daily temperature and precipitation is larger than the previous year's. The regression controls for lagged sectoral GVA growth rate, country-sector, sector-year fixed effects. Bins represent the 90% confidence intervals around point estimates. Standard errors are clustered at the country level.

Heterogeneity across adaptation potential. Until now, results referred to the average treatment effect for each sector across countries. One, however, may expect the marginal effect of changes in temperature distribution to differ as a result of factors that influence the adaptation potential of countries, namely climate and income. First, a hotter climate may differentially incentivize governments and individuals to invest in adaptive behavior as returns to adaptation would be relatively higher for more frequent temperature changes. Second, richer countries have less binding budget constraints and wider adaptation capacity to cope with weather fluctuations. Omitting income and climate differences while allowing for heterogeneous marginal effects of temperature can lead to biased estimates by attributing part of the response to income or climate effects.

To model heterogeneity on the temperature-production relationship accounting for adaptation, I consider income groups as defined by the World Economic Outlook (IMF, 2022) and average temperature over the fifty years (i.e., long-run climate). These two

Figure 2: Sector-specific impact of annual temperature and precipitation changes



Notes: The figure shows the OLS coefficients associated with the response of sectoral GVA per capita growth rate to changes in the annual sum of average daily temperature. The regression controls for lagged sectoral GVA growth rate, country-sector, sector-year fixed effects. Bins represent the 90% confidence intervals around point estimates. Standard errors are clustered at the country level.

factors account for differential adaptation potential (Acevedo et al., 2020; Carleton et al., 2022; Kahn et al., 2021). Firstly, I augment the baseline specification with an interaction term distinguishing between advanced economies, emerging market economies, and low-income developing countries. In a latter exercise, I include an interaction term that splits the sample of countries in terciles depending on the average long-run temperature in the fifty years for countries with cold, temperate and hot climate (Figure A2 shows the sample composition). I obtain sector-specific response functions that are also income group- and climate-specific allowing for these adaptation margins to influence the shape of the output-temperature relationship. Since neither climate terciles nor income groups have quasi-experimental variation as opposed to weather, the heterogeneous results shall be interpreted as associational (Carleton et al., 2022).

Figure A3 graphically presents the results for the coefficient associated with annual changes in the average daily temperature distribution interacted with income groups

(Panel a) and with climate terciles (Panel b). Tabular results are reported in Table A8 and A9. As conjectured, results are consistent with the hypothesis that income is protective (Figure A3a). Advanced economies are not harmed by increases in temperature distribution. Importantly, agriculture production is sheltered in advanced economies to the extent that the coefficient is positive and statistically significant. Some other sectors (construction; mining, manufacturing, utilities; transport, storage and communication; wholesale, retail trade, restaurants and hotels) also benefit from temperature increases among the richest countries. Nevertheless, the coefficient of temperature increases on agriculture remains strongly negative for emerging market economies and low-income developing countries. Moreover, these two income groups do not appear to benefit from increases in temperatures in other sectors, with low-income developing countries' estimates that are always smaller in magnitude than for emerging market economies.

Very similar estimates are obtained exploring the climate adaptive margin. Figure A3b shows a persistent and negative effect of increases in temperature on agricultural production across different climates (smaller in magnitude in absolute value in the cold climate countries and imprecisely estimated in the hot climate countries). Increases in temperature harm other sectors in hot climate countries (construction; other activities; wholesale, retail trade, restaurants and hotels), whereas they benefit production in both the industrial and services sectors (construction; mining, manufacturing, utilities; other activities; wholesale, retail trade, restaurants, hotel) in cold climate countries.

4.2 Abnormal weather realizations

Using first-differenced weather variables does not inform on how much atypical the weather realization was with respect to individual expectations since it implicitly assumes that individuals rationally update their beliefs annually and neglect baseline levels of the changes. However, people's climate beliefs are formed over long-run climatic conditions (Zappalà, 2022b) and adaptive responses could reduce the impact of weather fluctuations on production if societies can anticipate them based on their expectations (Shrader, 2021). Moreover, weather realizations above or below certain absolute thresholds may not be informative on global response functions since only a subset of countries could actually experience such levels (Osberghaus & Schenker, 2022).

For this reason, I investigate the effect of abnormal weather realizations defined as the number of days in a year that belongs to the p^{th}-percentile of the country-specific temperature and precipitation daily distribution over the fifty-year period (where $p \in \{1; 5; 10; 90; 95; 99\}$). Using this methodology, the measure is evenly distributed across countries in the world and any abnormal realization is compared to the country-specific *normal* distribution. Location-specific time-invariant thresholds account for the influence of long-run adaptation to climatic conditions on the effects of certain weather realizations. In particular, this approach considers an implicit model of adaptation assuming that societies adapt using as a baseline a fifty-year time-invariant climate norm. This methodology is consistent with previous results that condition the temperature-production response function on long-run average temperature. These events shall be interpreted as abnormally cold and hot, or dry and wet, respectively, for the bottom and top percentile of the distribution of temperature and precipitation.

I estimate the effect of an increase in the number of abnormal weather realizations in a year both for temperature and precipitations in a pooled multi-sector model so that estimates can be directly compared. The identification strategy relies on the estimation of the impact of increases in the number of abnormally cold and hot, dry and wet days using days in the rest of the distribution as the baseline category. Figure 3 shows the (standardized) coefficients associated with the number of days above the 95^{th} and below the 5^{th} percentile of the fifty-year daily temperature and precipitation distribution. Figure 3a confirms the previous findings consistent with prior literature that agriculture is the most harmed sector by heat shocks. An additional day above the 95^{th} percentile of the daily temperature distribution in the sample reduces the agricultural growth rate by 0.03 percentage points (11% of its sample mean). Cold temperature shocks have a similar sizeable effect on agriculture, harming crops that cannot grow below a certain temperature. An additional day below the 5^{th} percentile reduces the agricultural growth rate by 10% of its sample mean. Most of the other sectors seem not to respond to temperature shocks neither hot nor cold, except for the construction sector, which is marginally affected by increases in temperature realizations above the 95^{th} percentile (growth rate decreases by

1.2% of sample mean) and benefits from cold temperature shocks (growth rate increases by 1.8% of sample mean). The estimates of hot and cold shocks are very similar in magnitude, providing little evidence of asymmetry in the relationship between sectoral production and abnormal realizations of temperature from its historical norm.

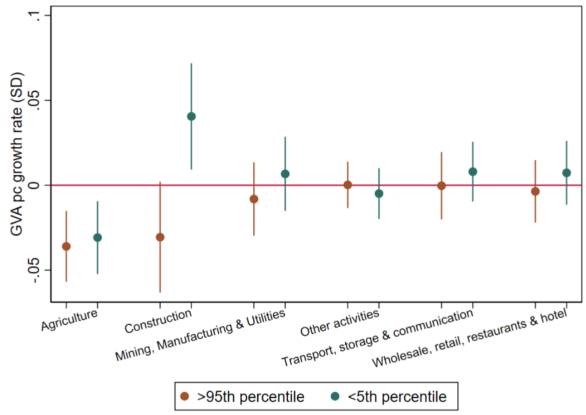
Conversely, wet precipitation shocks do not affect sectoral production (Figure 3b) except for a positive effect of an additional day of precipitations above the 95$^{\text{th}}$ percentile on agricultural production. There are two potential explanations behind these findings, coherent with prior literature. First, excessive and insufficient precipitation may not be adequate indicators of water availability (Proctor et al., 2022; Russ, 2020). Second, precipitation as a weather phenomenon exhibits considerable spatial variation and aggregation at the country level may mask too much meaningful variation that could explain the null and noisy estimates associated with precipitation variables. In order to partially address the first concern, in Section 4.3, I further explore sector-specific responses to a different measure of dryness that accounts for potential evapotranspiration and provides a more complete picture of the water availability cycle. The second concern cannot be overcome due to the lack of data availability of sectoral production at finer administrative levels across the whole world. Previous sub-national studies have shown for aggregate measures of economic activity in Europe (Holtermann, 2020) and across the world (Kotz et al., 2022) that precipitation anomalies reduce economic growth. Future data collection efforts should be steered towards obtaining globally comprehensive and comparable measures of disaggregated sectoral production at finer geographic levels.

The baseline results are robust to how "abnormal" is defined, whether I use the top/bottom first, fifth or tenth percentile of the daily distribution (Figures A4 and A5 replicate the same exercise using the 1$^{\text{st}}$ and 99$^{\text{th}}$, and 10$^{\text{th}}$ and 90$^{\text{th}}$ percentile). Results are also robust to estimating the baseline equation in a balanced panel (Figure A6a) and excluding large countries (i.e., Brazil, China, India, Russia, US) that may suffer from aggregation bias in cross-country analysis (Figure A6b).

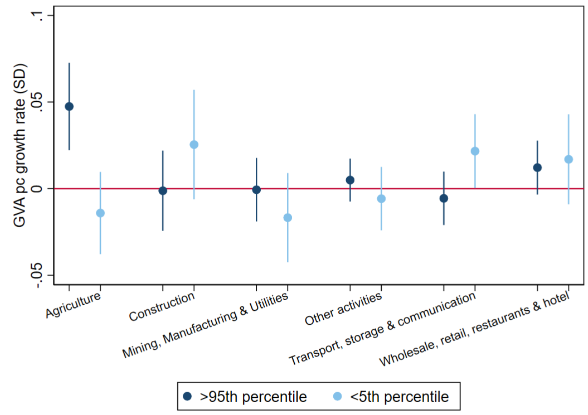
Time-varying climate norms. Lastly, instead of fixing the weather distribution to the fifty-year period, one can construct measures of temperature and precipitation relative to their time-varying historical norms. Following Kahn et al. (2021), I construct time-varying

Figure 3: Abnormal weather realizations

(a) Hot and cold temperature shocks



(b) Wet and dry precipitation shocks



Notes: The figure shows the (standardized) regression estimates for the country-average number of days above the 95$^{\text{th}}$ and below the 5$^{\text{th}}$ percentile of the daily distribution in temperature (Panel (a)) and in precipitation (Panel (b)). All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects. Bins represent the 90% confidence intervals around point estimates. Standard errors are clustered at the country level.

country-specific distributions over the preceding m years for each t, where $m \in \{20; 30; 40\}$. I exploit the temporal horizon of the weather data that start from 1950. The official World Meteorological Organization definition of climate (i.e., norm) corresponds to thirty years (Arguez et al., 2012), but I check for robustness considering other time spans. Different lengths of historical norms imply different belief formation and adaptation processes (the longer the time span of the historical norm, the slower individuals update their beliefs and treat the new distribution as the new norm). Smaller climate damage for shorter time spans over which the distribution is computed would provide suggestive evidence on the rate of speed of adaptation (Kahn et al., 2021). Although the sectoral production data begin in 1970, to compare estimates across time-varying historical norms with different time spans, I consider data starting from 1990.

Figure A7 shows the coefficients associated with abnormal temperature and precipitation realizations with respect to a time-varying country-specific daily distribution. Results are very similar to baseline estimates, showing that agriculture is negatively affected by hot temperature shocks. Assuming different speeds of change for the historical climate distribution (20-, 30- or 40-year) does not significantly alter the point estimates. The negative effect of heat shocks on agricultural production is persistent, suggesting that adaptation has not entirely offset climate damages. There is some suggestive, although small, degree of adaptation in other sectors (transport, storage and communication; mining, manufacturing and utilities; wholesale, retail trade, restaurants and hotel), where output losses are mitigated and converted into gains, for faster time-varying climate norms. Results are similar and robust to the use of the 1^{st} and 99^{th}, and 10^{th} and 90^{th} percentile (Figures A8 and A9).

4.3 Sectoral impact of extreme weather events

The first set of results has shown that, consistent with prior literature, agriculture is the most directly harmed sector by temperature and, to a lesser extent, precipitation fluctuations and anomalies. In this section, I turn on investigating whether similar results hold when using physical measures of intensity of extreme weather events for droughts and cyclones.

4.3.1 Dryness and wetness

First, I study the effect of changes in average dryness conditions as the first-differenced average of monthly negative values of the SPEI in a country in a year. Next, I focus on the changes in the prevalence of extreme dryness and wetness conditions, using the annual maximum share of grid-months with extreme drought (SPEI$<$-2) and extreme wetness (SPEI$>$2) conditions in a country. Figure A10 shows the (standardized) sector-specific coefficients obtained from a multi-country, sector-specific response function for the three different measures of dryness and wetness. Tabular results are reported in Table A10. As previously documented, I find a strong negative effect of dry conditions on agriculture. In particular, a 1 SD increase in changes in average dryness conditions is associated with a 75% decrease in agricultural growth rate with respect to its sample mean. All other sectors are not significantly affected.

Moving to measures of extreme drought and wetness prevalence, the results are consistent with previous findings. Agricultural growth rate is largely negatively affected by changes in extreme drought prevalence. In other sectors, where precipitation can negatively affect the productivity of workers and the operation of machinery and infrastructure, the effect varies. The construction growth rate benefits from positive changes in droughts, and so does the transport, storage and communication sector, although imprecisely estimated, whereas all the other sectors are not affected. These findings confirm that sectors that rely on roads, building construction and storage infrastructure may benefit from relatively drier conditions than historical averages with no excessive water surplus. The negative, although imprecisely estimated, coefficient associated with extreme wetness prevalence on production in the transport sector corroborates this hypothesis. These sectors have "interface" areas, such as loading and unloading areas (Cachon et al., 2012), which are more subject to weather variations and difficult to be protected with shelters (Colacito et al., 2019). In all the other sectors, extreme wetness conditions do not have any statistically significant effect, as previously documented using wet precipitation shocks.

4.3.2 Tropical cyclones

Tropical cyclones are the only extreme weather event on which there is previous evidence of their impact on sectoral growth worldwide (Kunze, 2021). I replicate and extend previous analysis estimating a pooled stacked multi-sector regression with jointly estimated sector-specific coefficients instead of separate regressions, which allows me to directly compare the coefficients to identify the effect of tropical cyclones.[9] As in previous estimations, I do not allow for a relationship between the GVA sector and the level of intensity in tropical cyclones as measured by wind speed, and instead, consider changes.

Figure A11 presents the sector-specific (standardized) coefficients associated with changes in tropical cyclone intensity. Tabular results are displayed in Table A11. Tropical cyclones have the largest negative effect on agriculture. A 1 SD increase in changes in tropical cyclone intensity is associated with a drop by 2.8 percentage points in the annual growth rate of agriculture (comparable to a 2.62 decrease documented in Kunze (2021)). Results differ, however, for the other sectors. Most importantly, I document that changes in wind

[9] My analysis also differs in the definition of the sectors since I do not account for the manufacturing sector separately as explained in Section 2.1.

speed have a strong negative effect on other activities, suggesting that this sector contracts production in response to positive changes in cyclone intensity. I also do not recover a significant negative effect on the wholesale, retail trade, restaurants and hotel sector but I find a small effect indistinguishable from zero. Although similar results are found in the analysis of the effect of tropical cyclones in the agriculture sector (Hsiang, 2010; Loayza et al., 2012), the contraction in economic production in other activities sector, which includes the financial and government sectors, is a new result, suggesting a negative effect on the economy overall in the short-run.

5 Propagation of weather shocks

The previous section has shown that even in a highly disaggregated sector analysis, agriculture is the most damaged sector by weather fluctuations and extreme weather events. In the second part of the empirical analysis, I investigate the propagation of weather shocks across the economy through input-output networks. I focus on three weather shocks: abnormal temperature shocks (Section 5.1), extreme drought prevalence and tropical cyclones (Section 5.2).

5.1 Abnormally hot temperature shocks

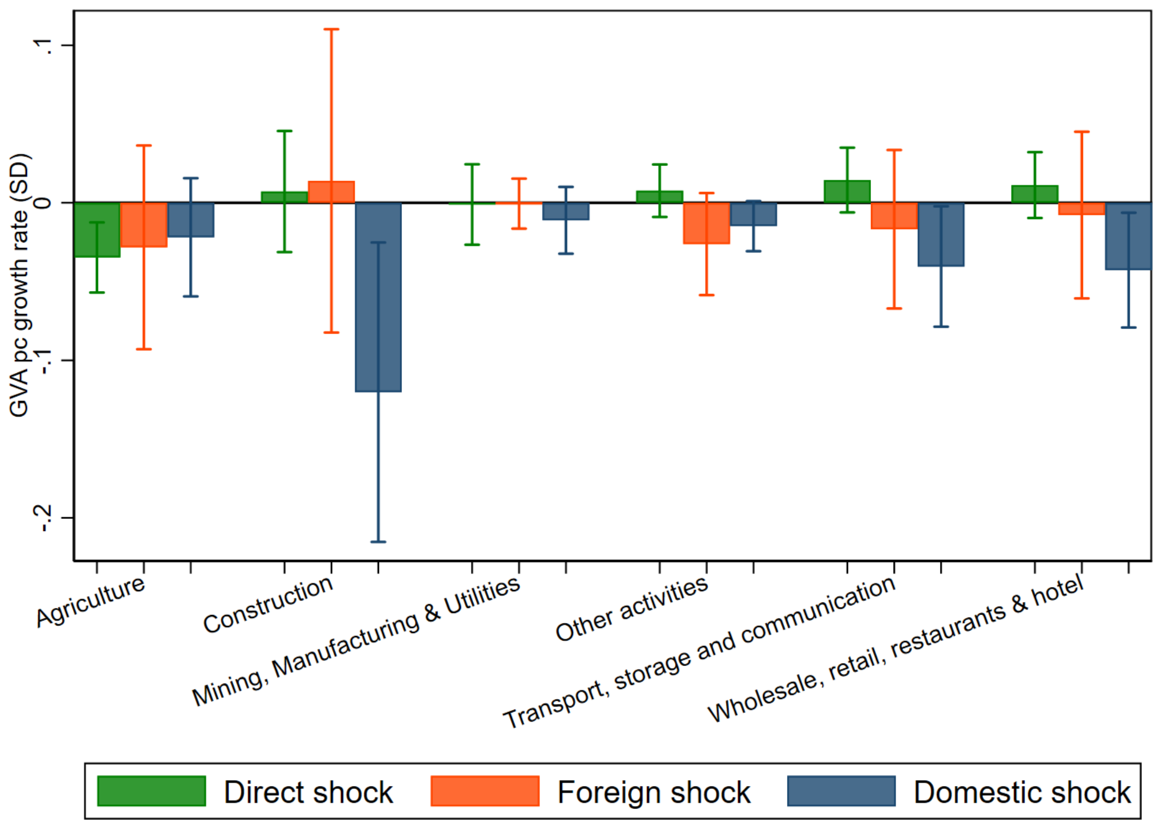
The first weather shock uses abnormally hot temperature realizations measured as the number of days above the 95$^{\text{th}}$ percentile of the country-specific temperature daily distribution. I begin the analysis by estimating Equation (8) including an average of the heat shocks in domestic trade partners weighted by the input-output interlinkages (as an unweighted average of upstream and downstream interlinkages) with each specific sector. The hypothesis behind this approach is that by only considering the *direct* impact of weather shocks on a given sector, one is omitting the amplification and transmission of such shocks due to the intersectoral reliance. In other words, a negligible or null direct effect of weather shocks on a given sector may be amplified by the same weather shock hitting other sectors in the same country that have a relatively strong commercial interlinkage with the sector of interest.

Domestic shocks. Figure A12 presents the estimates of own and network domestic shocks when weighing weather shocks in sector s's domestic trade partners by the input-output interlinkages. All coefficients are standardized and show distinctly that sectors are negatively harmed by abnormally hot temperatures through network shocks. The only sector that is directly harmed by weather shocks is agriculture. Comparing the point estimates of the direct shocks with the estimates obtained without accounting for network shocks (Figure 3a), the effect on agriculture is still negative but slightly smaller in magnitude in absolute value (-0.036 instead of -0.039), whereas the coefficients on the other sectors are now positive but not statistically different than zero.

These findings have two consequences in the interpretation of previous results. First, sector-specific estimates that account only for the direct impact of weather shock may be downward biased since shocks propagating from other sectors are omitted. This result underlines the importance of separately capturing direct and indirect effects, which are highly correlated due to the spatial clustering of weather shocks. Second, until now, the climate impact literature has focused on sector-specific impacts (Carleton & Hsiang, 2016) and identified agriculture as the main channel. Nevertheless, accounting for the input-output interlinkages of the sector shows that weather shocks are amplified in the economy and *indirectly* affect the other sectors, too. In terms of magnitude, the effect of domestic network shocks on the other sectors is comparable with the direct damage estimated on agriculture. This implies that recent estimates on the economy have been largely underestimated due to the propagation of shocks across sectors.

Foreign shocks. The analysis can be expanded by including *foreign* shocks, as the average of weather shocks in foreign sector-countries weighted by input-output interlinkages. Figure 4 displays the coefficients associated with own and *network* heat shocks decomposed into domestic and foreign. Domestic shocks have a negative and sizable effect on economic production across all sectors. Although imprecisely estimated for agriculture and mining, manufacturing and utilities, the coefficients on domestic shocks are larger in absolute value. This suggests that accounting for *foreign* weather shocks corrects for the upward bias in the previous estimation and contradicts the hypothesis that geographically distant weather shocks are idiosyncratic and orthogonal to local ones. Conversely, foreign shocks have a negative effect across all sectors - except for construction - although never statistically significant, mostly due to large imprecision in the estimates. A potential worry on firms within a sector endogenously selecting trade partners based on their location and their exposure to weather shocks would not be a threat to the identification of the transmission of shocks, since it would bias the results against finding any effect.

Figure 4: Domestic and foreign heat shocks and sectoral production



Notes: Bars represent the (standardized) sector-specific coefficients associated with direct shocks and domestic and foreign shocks, using the average number of days above the 95$^{\text{th}}$ percentile of the daily temperature distribution. Domestic shocks are constructed as the average weather shock in the other sectors in the same country as the sector of interest weighted by the average of upstream and downstream interdependence with each sector. Symmetrically, foreign shocks are constructed as the average weather shock in the other sectors in all the other countries weighted by the average of upstream and downstream interdependence with each sector. All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects and accounting for sector-specific responses to temperature realizations below the 5$^{\text{th}}$ percentile and sector-specific responses to precipitation realizations below the 5$^{\text{th}}$ and above the 95$^{\text{th}}$ percentile. Bins represent the 90% confidence intervals with standard errors clustered at the country-level.

Although the analysis underlines the importance of trade interlinkages as a transmission channel of weather shocks, identifying this mechanism is still subject to a fundamental challenge posed by spatial correlation due to the global nature of the phenomenon altering weather conditions everywhere (Dingel et al., 2021). To address this potential concern, I estimate a more conservative specification that exploits weather variation that is spatially uncorrelated. This is done by employing fixed effects at spatial levels broader than the unit of observation (Deschenes & Meng, 2018). Figure A13 shows the estimated coefficients in a regression that additionally controls for subregion-by-year and continent-by-year fixed effects.[10] This approach identifies weather variation that is local to the unit of observation and uncorrelated with weather elsewhere within the same subregion/continent, suggesting that network effects persist, these are due to trade interlinkages and not spatially correlated shocks. The strong negative effect of domestic shocks in the construction; other activities; transport, storage and communication; wholesale, retail trade, restaurants and hotel sectors is robust to the inclusion of these additional fixed effects.

Exposure shares do not account for own trade, therefore the total sum of trade interlinkages varies across observations. To account for incomplete shares, I interact period fixed effects with the sum of exposure shares (Borusyak et al., 2022). The effects are robust to this specification (Figure A14a). Results are also robust to estimating the equation in a balanced panel (Figure A14b), excluding large countries (i.e., Brazil, China, India, Russia, US) (Figure A14c) and starting the analysis from 1990, allowing for strongly exogenous pre-determined sectoral interlinkages (Figure A14d).

Upstream and downstream shocks. Besides geographic heterogeneity, shocks in trade partners in different stages of the supply chain can propagate differently. I decompose domestic and foreign shocks into upstream and downstream, weighing weather shocks by the relative inputs sourced from or supplied by a sector, as detailed in Section 2.3.1. Figure 5 zooms into the effect for three specific sectors at the extremes of the supply chain. Agriculture is an example of a sector in the early stages of the supply chain, while

[10]Subregions divide the world in 17 zones: Australia and New Zealand, Central Asia, Eastern Asia, Eastern Europe, Latin America and the Caribbean, Melanesia, Northern Africa, Northern America, Northern Europe, Polynesia, South-eastern Asia, Southern Asia, Southern Europe, Sub-Saharan Africa, Western Asia, Western Europe

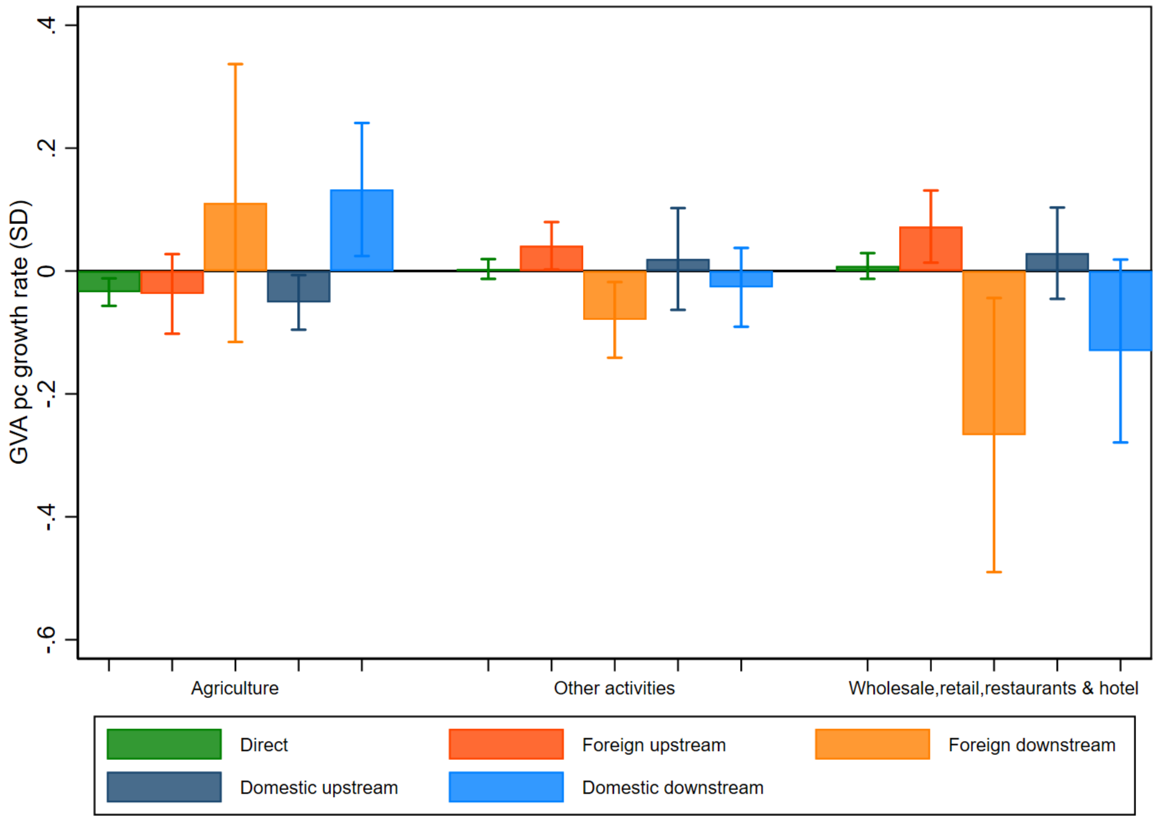
other activities, and wholesale, retail trade, restaurants and hotel are two examples of sectors in later stages (Figure A15 shows the complete results for the six sectors).

The agricultural sectoral growth rate mostly suffers from upstream weather shocks, which are negative both for domestic and foreign shocks, and benefits from downstream weather shocks, positive both for domestic and foreign, although foreign shocks are imprecisely estimated. This result supports the hypothesis that weather shocks affect sectors in early stages of the supply chain as a demand-side shock that propagates upstream. Weather damages to agriculture go beyond their impact on crop productivity and the sector is also harmed by changes in input demands from its downstream customers.

In contrast, sectors in the later stages of the supply chain present opposite results. On the one hand, their growth rate is harmed by abnormally hot temperature shocks in supplier sectors both domestically and abroad, which propagate downstream. Regardless of the channel through which supplier sectors are damaged (e.g. capital/infrastructure destruction, labor productivity losses), climate impact on customer sectors is amplified by market reactions that slow down downstream production (Wenz & Levermann, 2016). For example, a fall in agricultural productivity reduces the demand for local non-traded goods such as services. On the other hand, foreign and domestic upstream shocks have positive effects, with shocks happening in other countries larger in magnitude and statistically significant, indicating potential mitigation of climate damages arising from competition and effects on prices. The downstream propagation of shocks on suppliers to their customers confirms at the macro-level previous results documented at the firm-level (Barrot & Sauvagnat, 2016), whereas the upstream propagation of demand-side weather shocks from customer sectors in the early stages of the supply chain sheds light on a new transmission channel.

Persistence of network shocks over time. While the findings show clearly that domestic and foreign shocks matter for sectoral economic output, the estimates focus only on short-run, contemporaneous impacts. It remains an open question whether the shocks have permanent effects on the level of GVA per capita. There is a long-standing debate on the "growth-vs-level" effect of weather shocks and extreme weather events (see Tol (2022) for a review). With the exception of persistent growth effects on aggregate output in Kahn

Figure 5: Network abnormally hot temperature shocks and sectoral production



Notes: Bars represent the (standardized) sector-specific coefficients associated with direct shocks and domestic and foreign shocks distinguished between upstream and downstream, using the average number of days above the 95$^{\text{th}}$ percentile of the daily temperature distribution. Domestic upstream (resp. downstream) shocks are constructed as the average weather shock in the other sectors in the same country as the sector of interest weighted by the upstream (resp. downstream) interdependence with each sector. Symmetrically, foreign upstream (resp. downstream) shocks are constructed as the average weather shock in other sectors abroad weighted by the upstream (resp. downstream) interdependence with each sector. The figure reports only the coefficients associated with agriculture, other activities and wholesale, retail trade, restaurants and hotel, the specification jointly estimates all sector-specific coefficients in a stacked regression model fully saturated with country-sector and sector-year fixed effects and accounting for sector-specific responses to temperature realizations below the 5$^{\text{th}}$ percentile and sector-specific responses to precipitation realizations below the 5$^{\text{th}}$ and above the 95$^{\text{th}}$ percentile. Bins represent the 90% confidence intervals with standard errors clustered at the country-level.

et al. (2021), recent evidence has consistently documented level effects of temperature (Akyapi et al., 2022; Kalkuhl & Wenz, 2020; Newell et al., 2021). I examine longer-run effects of direct and network shocks estimating a set of local projections (Jordà, 2005) to obtain impulse response functions. Local projections are more robust to misspecification of the data-generating process and to lag length by not imposing dynamic restrictions as in autoregressive distributed lag models. The set of estimating equations is written as

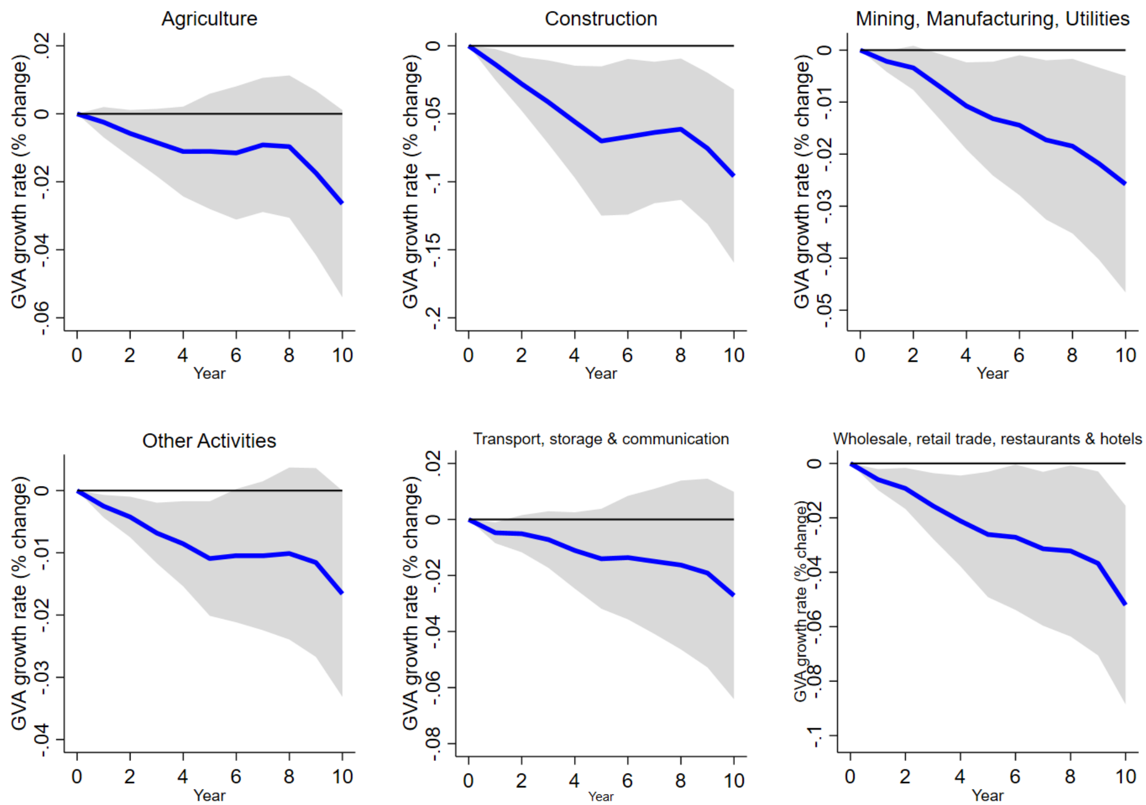
$$\Delta \log(GVA)_{sct+h} = \gamma_{sh} Shock^{Own}_{sct} + \sum_J \gamma^J_{s,h} Shock^J + \alpha_{sc} + \mu_{ct} + \varepsilon^h_{sct} \tag{9}$$

where $h \geq 0$ indexes the time horizon measured in years up to 10 and when $h = 0$, the equation reduces to Equation (8). The goal is to estimate, for each horizon h, the effect of network shock J (where J $\in$ {Domestic; Foreign}) accounting for dynamics up to 10 years after the shock. The dependent variable is then the cumulative growth rate of sectoral per capita production between horizons $t-1$ and $t+h$, proxied by the difference in the natural logarithms of per capita GVA.

Before examining the sector-specific results, I estimate local projections on total value added at the country level. Figure A16 shows the impulse response functions for a standardized domestic (Panel a) and foreign (Panel b) heat shock. Domestic shocks are the average number of days above the 95^{th} percentile of the country-specific daily temperature distribution weighted by the trade interlinkages across sectors within the country. Foreign shocks aggregate heat shocks in other countries across sectors. Domestic heat shocks have a persistent effect on total value-added levels, with the coefficient estimate that does not increase in absolute value over time. The estimates are however small in magnitude, noisy, and not distinguishable from zero. Foreign heat shocks have a positive significant effect starting from five years after the shock, suggesting competition and price effects are at play.

Figure 6 displays the sector-specific impulse response functions for a standardized domestic heat shock obtained from the estimation of a stacked, multi-country, sector-specific regression that also includes own and foreign shocks. Results show that aggregation was hiding substantially heterogeneous effects. Several sectors all along the value chain do not recover from abnormally hot weather shocks from domestic partners, with strong negative growth effects in construction; mining, manufacturing and utilities; and wholesale, retail trade, restaurants and hotels sectors. A domestic weather shock has a negative growth effect also on other activities, that however lasts only five years and estimates then become statistically indistinguishable from zero.

Figure 6: Local projections of domestic abnormally hot temperature shocks on sectoral production



Notes: Panels show the sector-specific impulse response function of sectoral per capita GVA growth rate to a 1 SD increase in the domestic abnormally hot temperature shocks estimated in a stacked regression model fully saturated with country-sector and sector-year fixed effects and accounting for sector-specific responses to direct and foreign abnormally hot temperature shocks, to abnormally cold temperature shocks (below the 5^{th} percentile) and to precipitation realizations below the 5^{th} and above the 95^{th} percentile. Horizon 0 is the year of the shock. Shaded areas represent the 90% confidence intervals with standard errors clustered at the country-level.

Figures A17 and A18 display the impulse response functions using own and foreign shocks. First, in line with prior country-level evidence using aggregate measures of economic production, I find that direct shocks do not have a persistent growth effect on sectoral production. Agriculture is the only sector that is harmed, whereas the others appear relatively inelastic to abnormally hot temperature shocks (with the exception of transport, storage and communication, in which the negative effect of weather shocks manifests only after five years). Nevertheless, in the case of agriculture, the negative effect lasts only one year and dissipates thereafter, confirming no visible long-run growth effects. Second, considering foreign shocks, estimates are very small in magnitude and positive but not distinguishable from zero at any lag, suggesting that sectoral economic production could benefit from abnormally hot foreign weather shocks, potentially due to competition and price effects. Focusing on a more spatially disaggregated definition of foreign shocks seems a promising avenue for future research. Overall, results demonstrate the importance of accounting for trade-induced propagation of weather shocks in affecting local economic outcomes and their persistence over time.

5.2 Other extreme weather events

Droughts. The next analysis considers changes in droughts hitting trade partners domestically and abroad. Dryness conditions have been shown to directly harm agriculture and marginally benefit sectors that would be less productive under wetter conditions than the historical average, such as transportation and construction. The structure of Figure A19 is identical to that examining heat shocks. The results are also similar. Even when accounting for network shocks, agriculture is the only sector that is directly harmed by drought shocks, with a sizeable negative effect of 0.09 p.p. (sample mean is 0.002) associated with a 1 SD increase in the dryness conditions in the country. Conversely, own drought shocks strongly benefit economic production in other sectors (construction; mining, manufacturing and utilities; and transport, storage and communication sectors) improving the precision of the positive estimates obtained when omitting network shocks. Industries in the tertiary sector at later stages of the value chain, such as wholesale, retail trade, restaurants and hotel, and other activities, are virtually not impacted at all by their own drought shocks, with a coefficient very close to zero.

Focusing on network shocks, domestic shocks have a strong negative effect only on economic production in mining, manufacturing and utilities, whereas their negative effect on construction; transport, storage and communication; and wholesale, retail trade, restaurants and hotel are imprecisely estimated. Conversely, foreign shocks have a sizable negative effect on other activities and wholesale, retail trade, restaurants and hotel suggesting strong propagation of droughts through the economy and across countries in later stages of the supply chain. Peculiar and outstanding is the case of mining, manufacturing and utilities sector which is strongly harmed by domestic droughts, with a magnitude comparable to the coefficient associated with own shocks, suggesting that the net effect of droughts in a country on this sector is not as positive as own shocks alone indicated. Accounting for both domestic and foreign network shocks sheds light on the true overall sectoral damage due to droughts accounting for shocks hitting other partner sectors.

Tropical cyclones. The last shock considers changes in tropical cyclone intensity as measured by wind speed. This shock has been shown in Section 4.3.2 to have the widest impact across sectors, damaging agriculture and other activities. Since cyclones are an extreme weather event that may also have direct impact on capital stock destruction, trade linkages may either amplify or mitigate the aggregate damage suffered by sectors.

Figure A20 decomposes the network shocks by geographic location into foreign and domestic, besides including the sector-specific local shock. Agriculture and other activities remain the only two sectors directly harmed by tropical cyclones. Domestic shocks do not appear to have strong effects, particularly so at earlier stages of the value chain, whereas they have a strong negative effect on transport, storage and communication growth rate with an effect of magnitude comparable and larger than the direct effect on other activities. Foreign network shocks have a null effect for most of the sectors, except for wholesale, retail trade, restaurants and hotel which is positive. In particular, this is a sector that one would expect to benefit the most from international competition. Damages in other countries due to cyclone shocks may improve sectoral economic production.

6 Discussion and conclusion

Recent studies in the climate impact literature have pushed forward the frontier for a timely, accurate and local measure of climate damages across sectors. The findings can have substantial implications for an adequate quantification of the total economic impact of climate change (Tol, 2022). This paper contributes to this effort by shedding light on a new potential component of climate damages, arising from the propagation of weather shocks through production networks across sectors and countries, and over time. Complementing firm-level evidence on the spillover effects of natural disaster shocks, I find that the amplification mechanism persists when aggregating units at the sector level and generates substantial fluctuations in sectoral production. Accounting for the local effect of weather shocks on sectoral economic output is not sufficient for an accurate measure of total economic damages.

I find that sectors not negatively affected by local weather shocks suffer economic losses due to the interdependence of their production process with other sectors that are hit by weather shocks domestically or abroad. In particular, sectors at later stages of the supply chain, such as transport, storage and communication; wholesale, retail trade, restaurants and hotels and other activities are negatively impacted by heat shocks in other sectors, with a loss comparable in magnitude to the direct impact on agriculture. I also find a strong negative persistent growth effect of domestic shocks in certain sectors' output (construction; mining, manufacturing and utilities; wholesale, retail trade, restaurants and hotels) up to ten years since the shock occurred. In light of the negative and persistent impact of network shocks, these findings suggest that climate damages may be larger than indicated by standard empirical approaches and integrated assessment models.

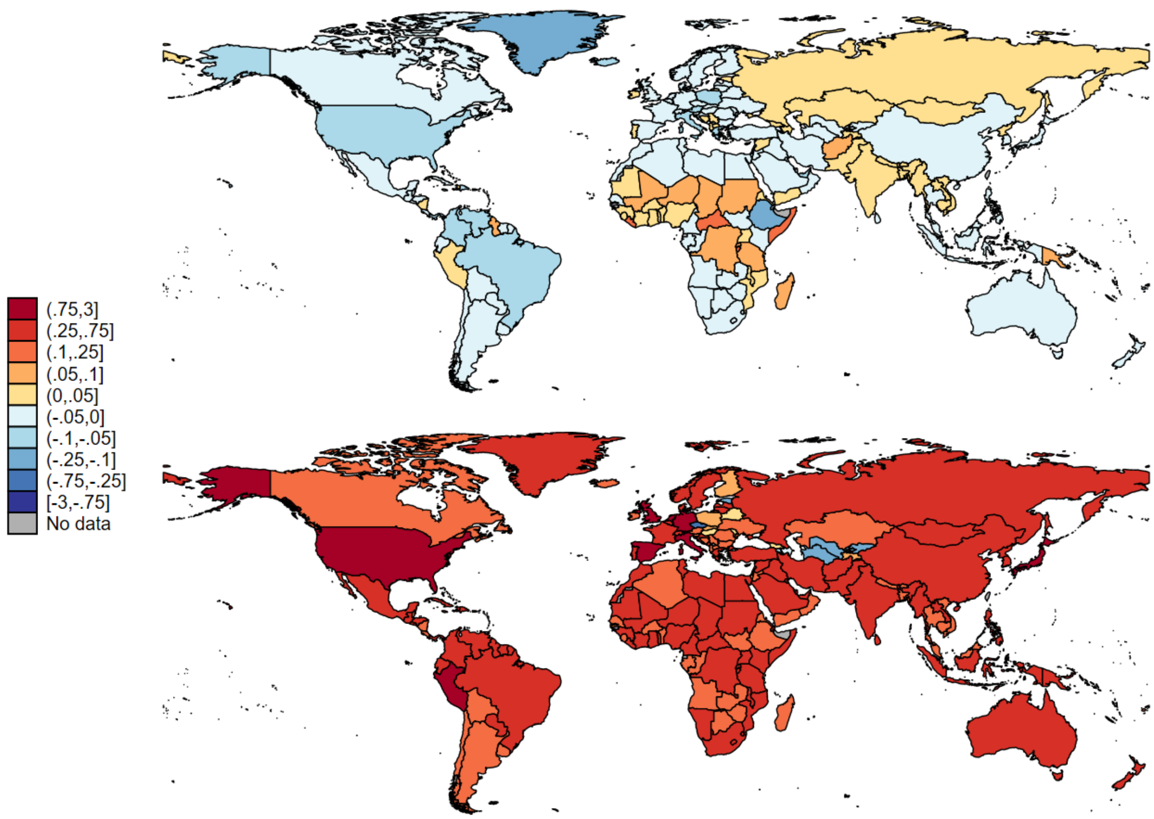
To assess the economic importance of the propagation of weather shocks through production networks, I compare the differential sectoral output losses/benefits as a result of recent historical warming. Prior research quantifies the impact of temperature increases assuming a counterfactual with no further warming (e.g., Burke et al., 2015; Burke & Tanutama, 2019; Kalkuhl & Wenz, 2020). To account for adaptive adjustments to changes in climate, using heat shocks, I simulate how much slower or faster each sector would have grown over the 2001-2020 period, compared to a counterfactual in which the number of abnormally hot days in each country evolves linearly from its 1970-2000 long-run average, omitting and accounting for the propagation of shocks (Figure A21, see Appendix Section A.3 for additional details).

Omitting heat shocks in sector partners substantially underestimates the losses due to recent warming. Even those countries at extreme latitudes, such as Canada, Greenland and Russia, previously deemed to be sheltered by climate damages and to benefit from gradual warming in agricultural production, experience sizable output reductions when accounting for shocks in the whole production network. The average annual relative GVA per capita loss across sectors due to recent warming considering only sector-specific local shocks is -0.02% (-0.04% median, IQR [-0.09,0.02]), whereas accounting for indirect heat shocks is 0.28% (0.24% median, IQR [0.04,0.44]). In particular, only agriculture and mining, manufacturing and utilities are damaged by local heat shocks compared to a counterfactual scenario where heat shocks increased linearly from the trend in 1970-2000. The other services sectors result sheltered.

Accounting for heat shocks in trade partners, damages are particularly larger in those sectors that appear sheltered from local shocks (mining, manufacturing, utilities; other activities; transport, storage and communications), while there is larger heterogeneity in relative losses in construction and wholesale, retail, hotel and restaurants: larger damages in Sub-Saharan Africa and South-East Asia are offset by modest benefits in Latin America and Europe. Using each country's average sectoral breakdown of total GVA between 2001 and 2020, I aggregate sector-specific damages to obtain the total average relative losses for each country. Accounting for indirect heat shocks, national damages are substantial (0.3% mean, 0.26% median, IQR [0.16,0.37]) and largely underestimated when omitting heat shocks propagation (-0.02% mean, -0.01% median, IQR [-0.04,0.05]) (Figure 7).

This article presents some limitations that open the avenue for further research. First, the analysis provides modest but suggestive evidence of the role of adaptation to enhance their resilience to climate damages. However, the analysis does not explicitly model adaptive investments, technological change, or other sector-specific adaptive responses (e.g. irrigation, sea walls...) that may heterogeneously affect the response functions and mitigate climate damage. Accounting for other adaptive margins may also differentially drive the propagation of shocks in countries that are more sheltered from weather shocks. Similarly, the analysis does not account for fiscal policy responses that can be implemented to address climate-induced economic losses (Nakatani, 2021; Noy & Nualsri, 2011). First, these policies play usually a role in the aftermath of natural disasters. Second, I study the transmission of weather shocks and not of shock-induced damages in other sectors and countries. Therefore, the estimates shall be interpreted as the net effect.

Figure 7: Average annual per capita GVA losses (%) due to recent warming



Notes: The figure shows the average annual losses (in red) and gains (in blue) in per capita GVA (%). Sector-specific damages are weighted by the average sectoral share of total GVA between 2001 and 2020. The world map at the top only accounts for sector-specific local heat shocks, the world map below accounts for shocks in other partner sectors using sector-specific semi-elasticities from Equation (8) estimated with 1000 bootstrap replications with replacement.

Second, the analysis is mostly silent about decision-makers climate beliefs and expectation formation processes. Despite the use of explicit and implicit models of adaptation accounting for the two most important factors that govern adaptation (climate and income), adaptive behavior reflects individual perceptions of climate change more than actual meteorological conditions, with inaccurate beliefs explaining substantial economic losses due to inadequate adaptation (Zappalà, 2022a). In a similar vein, expectations also matter in accounting for adaptation costs and benefits (Carleton et al., 2022; Shrader, 2021). Future research should focus on allowing for heterogeneous perceptions and expectations of climatic conditions in production networks and supply-chain relationships.

Third, the analysis is conducted at a spatial level that may yet mask substantial variation both in economic responses and local weather fluctuations. High spatial resolution particularly matters for estimating the effect of precipitation on economic output (Kotz et al., 2022). Replicating the analysis on disaggregated sector-level sub-national data could show new estimates on sector-specific elasticities to weather fluctuations and shed new light on within-country regional propagation of weather shocks across sectors.

Fourth, the transmission of weather shocks is studied through the relative importance of trade partners in input-output interlinkages. As previously shown (Barrot & Sauvagnat, 2016), the input specificity and elasticity of substitution are key drivers of the transmission of firm-level shocks. Weather shocks can differentially propagate in supply chains depending on search frictions and relation-specific investments that affect industry supplier competitiveness, input concentration, and supplier diversification (Eaton et al., 2022; Pankratz & Schiller, 2021). These channels have only been documented at the firm level and it would be interesting to examine these additional layers of heterogeneity in the exact channel of transmission of weather shocks through the economy.

Last, the analysis has focused on the propagation of weather shocks in an exogenous time-invariant trade network. Sectoral reallocation is increasingly acknowledged and studied as a potential adaptive margin to climate change (Desmet & Rossi-Hansberg, 2015; Nath, 2020), although only through calibrated simulations. Adjustments in trade patterns substituting affected sectors with sectors in unaffected places as a response to idiosyncratic weather shocks seem a promising avenue for future research.

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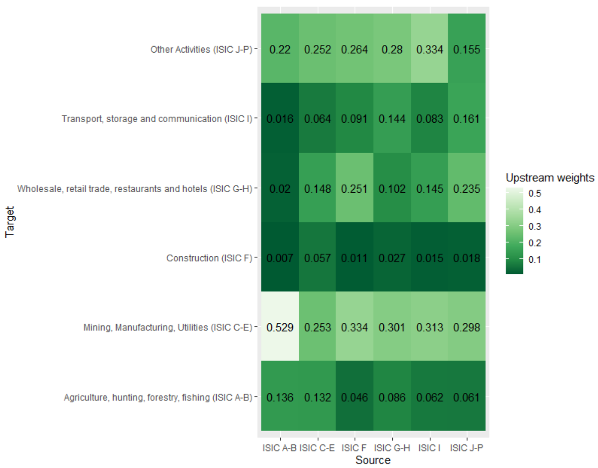
A Appendix

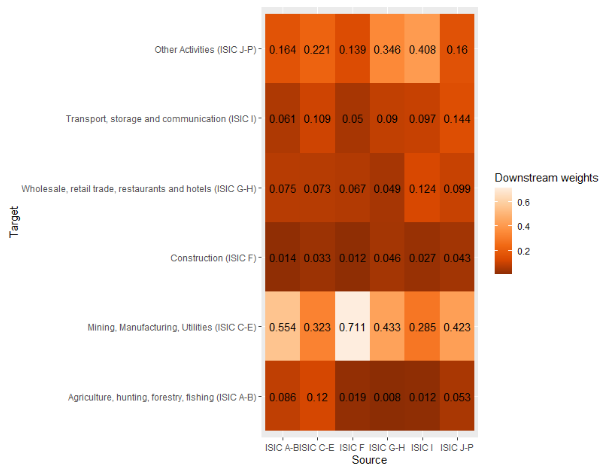
A.1 Figures

Figure A1: Average weights across countries

(a) Upstream

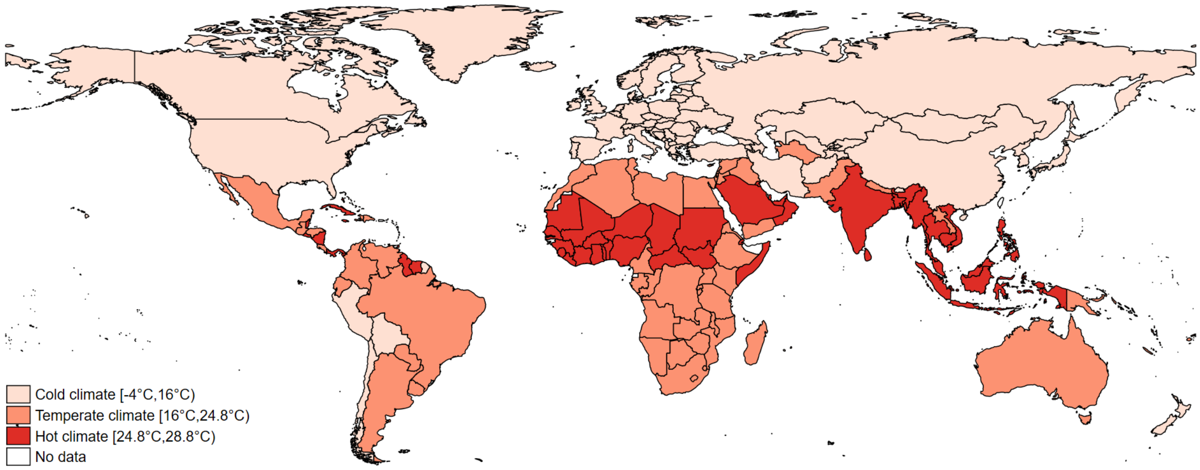


(b) Downstream



Notes: The figure shows the average weights across countries by sector for upstream and downstream weights. Both upstream and downstream weights are constructed from the perspective of Source sectors in the x-axis.

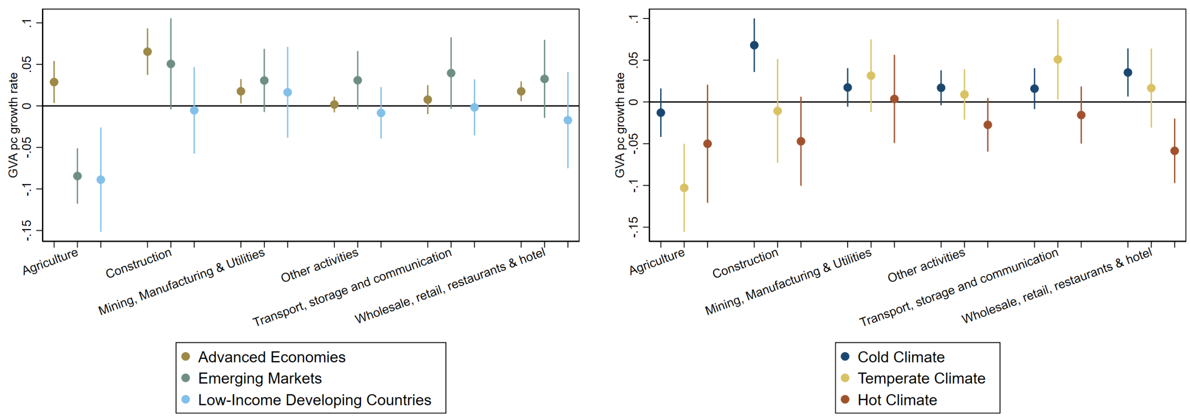
Figure A2: Countries in the sample by climatic zone



Notes: The map represents the countries in the sample divided by climatic zones, defined as terciles of the average annual temperature from 1970 through 2020. The classification is implemented in order to compute heterogeneous treatment effects as reported in Figure A3.

Figure A3: Heterogeneity in the GVA response to changes in temperature distribution

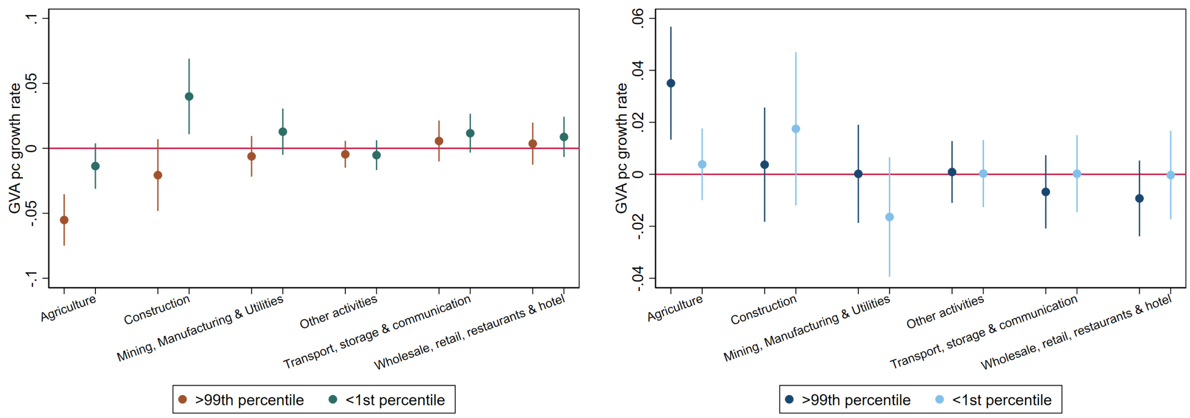
(a) Income groups (b) Climate terciles



Notes: The figure shows the (standardized) coefficients associated with the response of sectoral GVA per capita growth rate to an increase in the sum of average daily temperature in different sub-samples split by income groups according to the World Economic Outlook (IMF, 2022) and by climate split into terciles using the long-run average temperature. All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects. Bins represent the 90% confidence intervals with standard errors clustered at the country-level.

Figure A4: Abnormal weather realizations using 1^{st} and 99^{th} percentiles

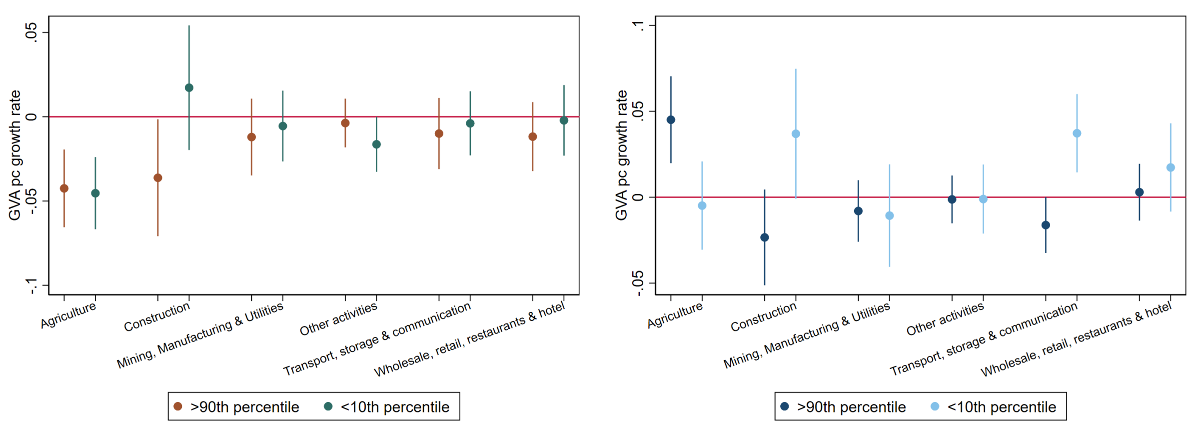
(a) Hot and cold temperature shocks (b) Wet and dry precipitation shocks



Notes: The figure shows the (standardized) regression estimates for the country-average number of days above the 99^{th} and below the 1^{st} percentile of the daily distribution in temperature (Panel (a)) and in precipitation (Panel (b)). All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects. Bins represent the 90% confidence intervals with standard errors clustered at the country-level.

Figure A5: Abnormal weather realizations using 10^{th} and 90^{th} percentiles

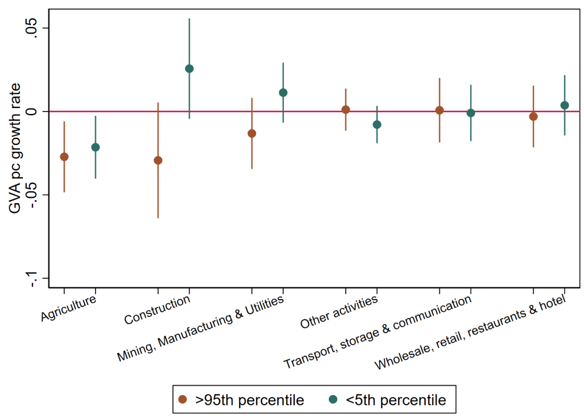
(a) Hot and cold temperature shocks (b) Wet and dry precipitation shocks



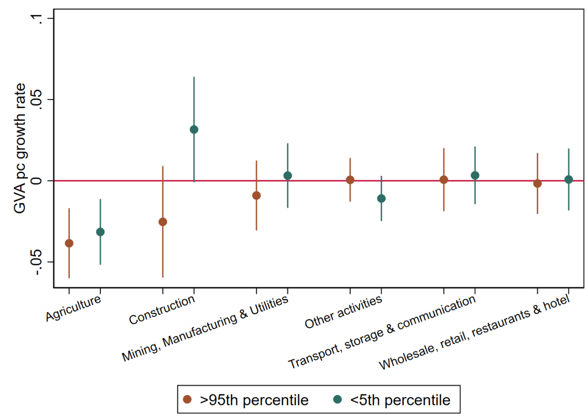
Notes: The figure shows the (standardized) regression estimates for the country-average number of days above the 90^{th} and below the 10^{th} percentile of the daily distribution in temperature (Panel (a)) and in precipitation (Panel (b)). All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects. Bins represent the 90% confidence intervals with standard errors clustered at the country-level.

Figure A6: Robustness: Abnormal temperature realizations

(a) Balanced panel



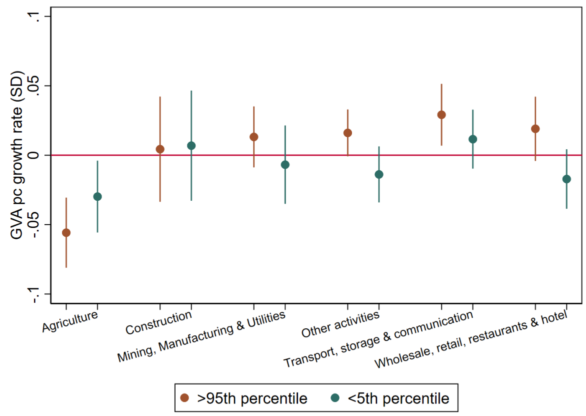
(b) Excluding "large" countries



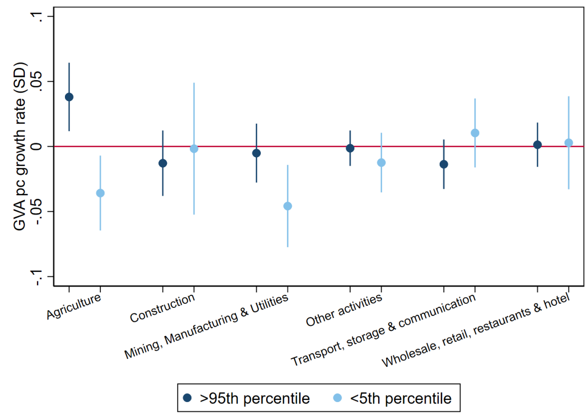
Notes: The figure shows the (standardized) regression estimates for the country-average number of days above the 95^{th} and below the 5^{th} percentile of the daily distribution in temperature using a sector-country balanced panel (Panel (a)) and excluding large countries (Brazil, China, India, Russia, US) (Panel (b)). All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects. Bins represent the 90% confidence intervals around point estimates.

Figure A7: Abnormal weather realizations from time-varying climate norms using 5^{th} and 95^{th} percentiles

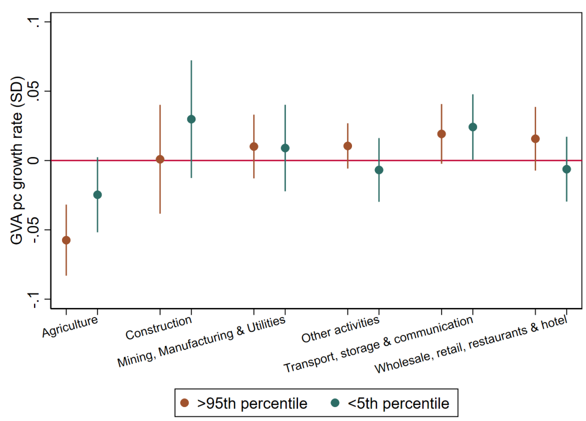
(a) Temperature - 20-year



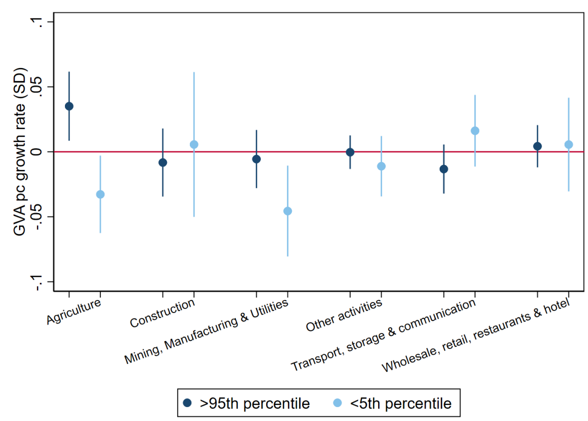
(b) Precipitation - 20-year



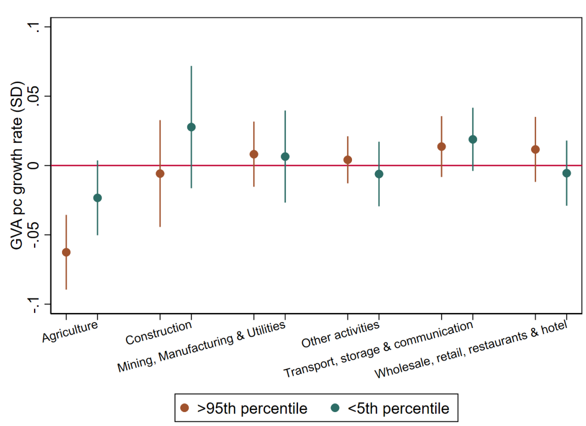
(c) Temperature - 30-year



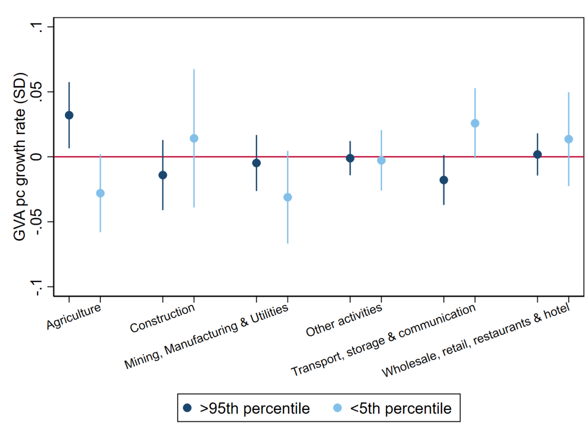
(d) Precipitation - 30-year



(e) Temperature - 40-year



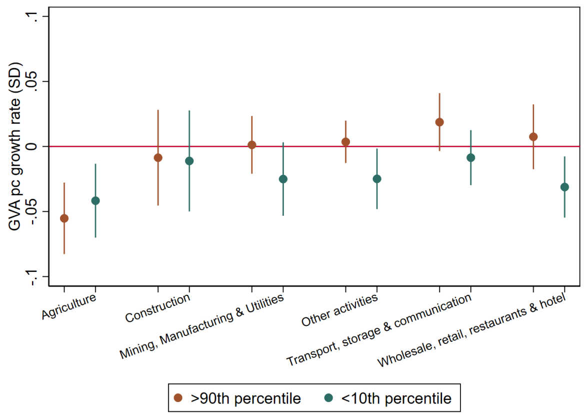
(f) Precipitation - 40-year



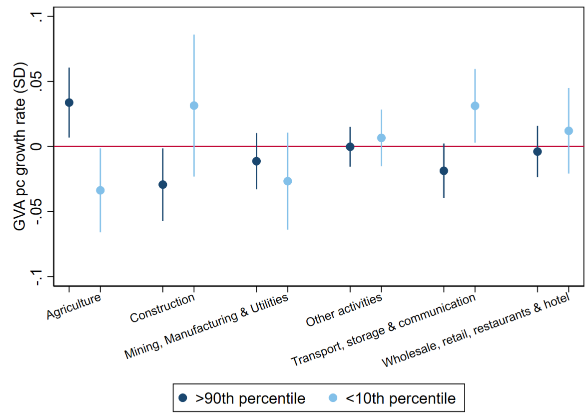
Notes: The figure shows the (standardized) regression coefficients on the number of days above the 90^{th} and below the 10^{th} percentile of the daily distribution in temperature (Panels (a-c-e)) and in precipitation (Panels (b-d-f)) using time-varying distributions (respectively, 20-year, 30-year and 40-year). The estimation sample starts from 1990. All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects. Bins represent the 90% confidence intervals with standard errors clustered at the country-level.

Figure A8: Abnormal weather realizations from time-varying climate norms using 10^{th} and 90^{th} percentiles

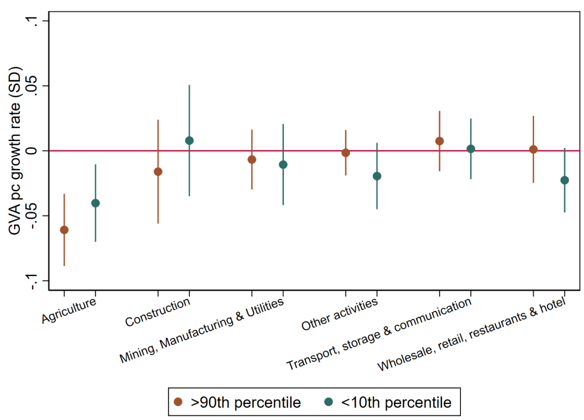
(a) Temperature - 20-year



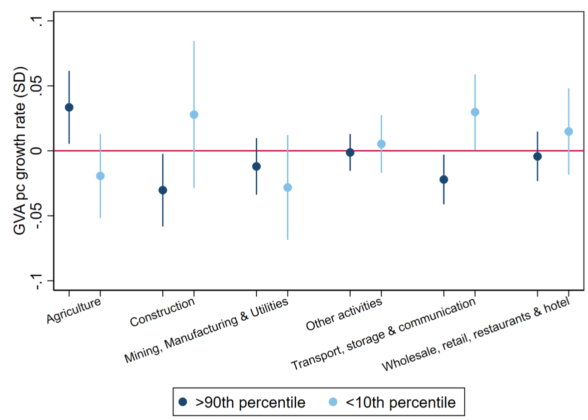
(b) Precipitation - 20-year



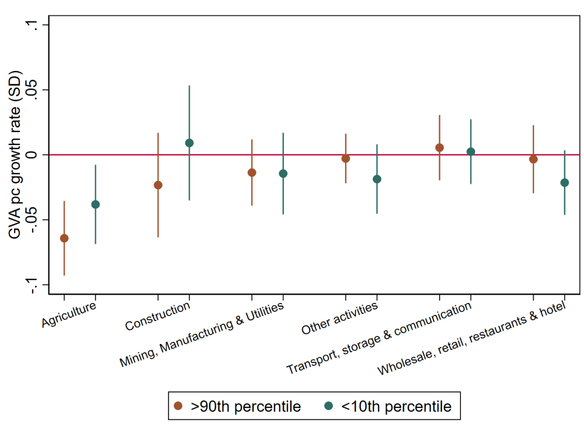
(c) Temperature - 30-year



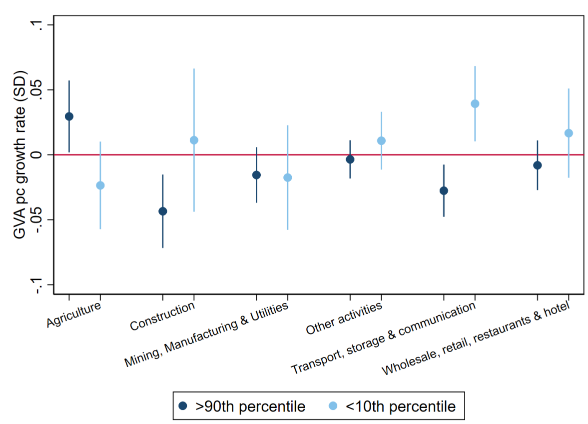
(d) Precipitation - 30-year



(e) Temperature - 40-year



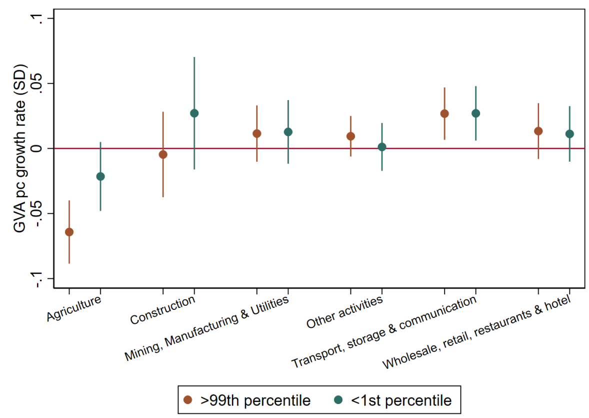
(f) Precipitation - 40-year



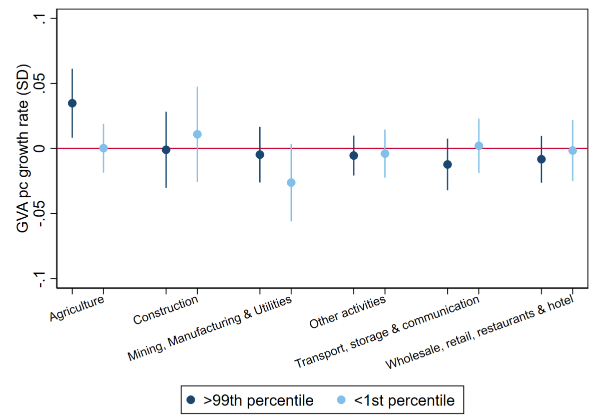
Notes: The figure shows the (standardized) regression coefficients on the number of days above the 90^{th} and below the 10^{th} percentile of the daily distribution in temperature (Panels (a-c-e)) and in precipitation (Panels (b-d-f)) using time-varying distributions (respectively, 20-year, 30-year and 40-year). The estimation sample starts from 1990. All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects. Bins represent the 90% confidence intervals with standard errors clustered at the country-level.

Figure A9: Abnormal weather realizations from time-varying climate norms using 1^{st} and 99^{th} percentiles

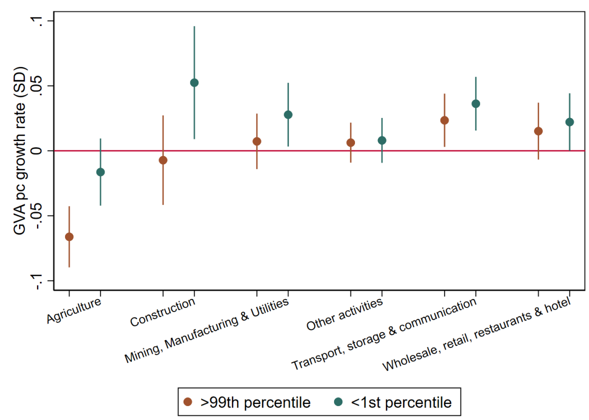
(a) Temperature - 20-year



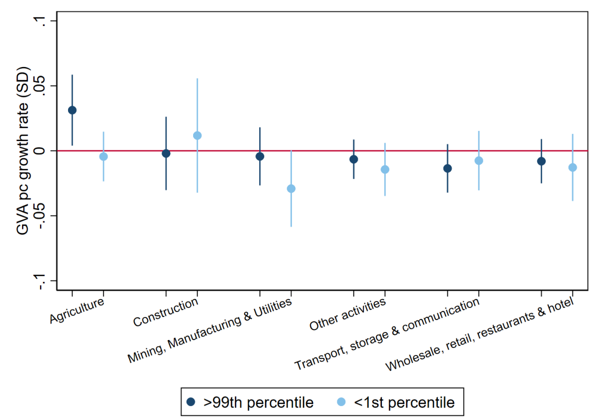
(b) Precipitation - 20-year



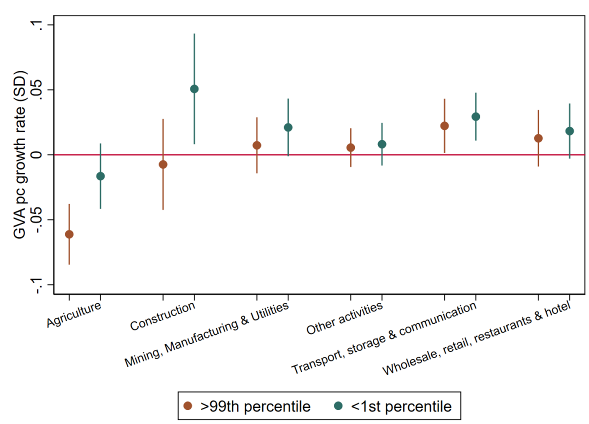
(c) Temperature - 30-year



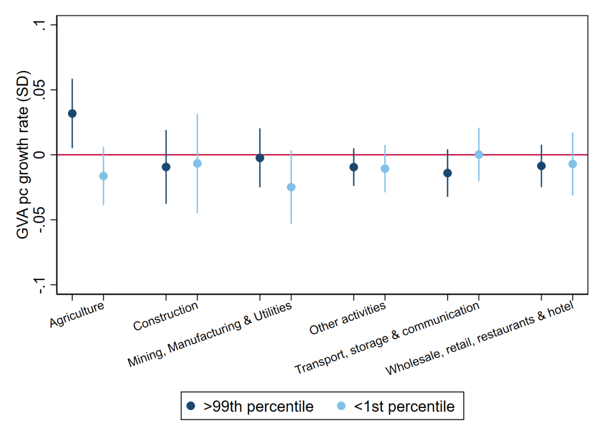
(d) Precipitation - 30-year



(e) Temperature - 40-year

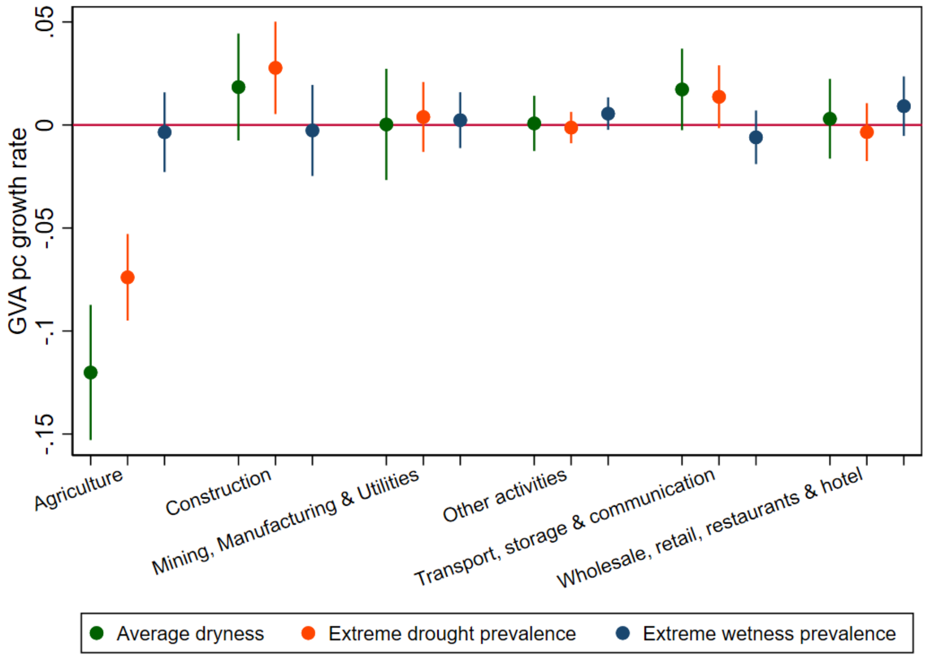


(f) Precipitation - 40-year



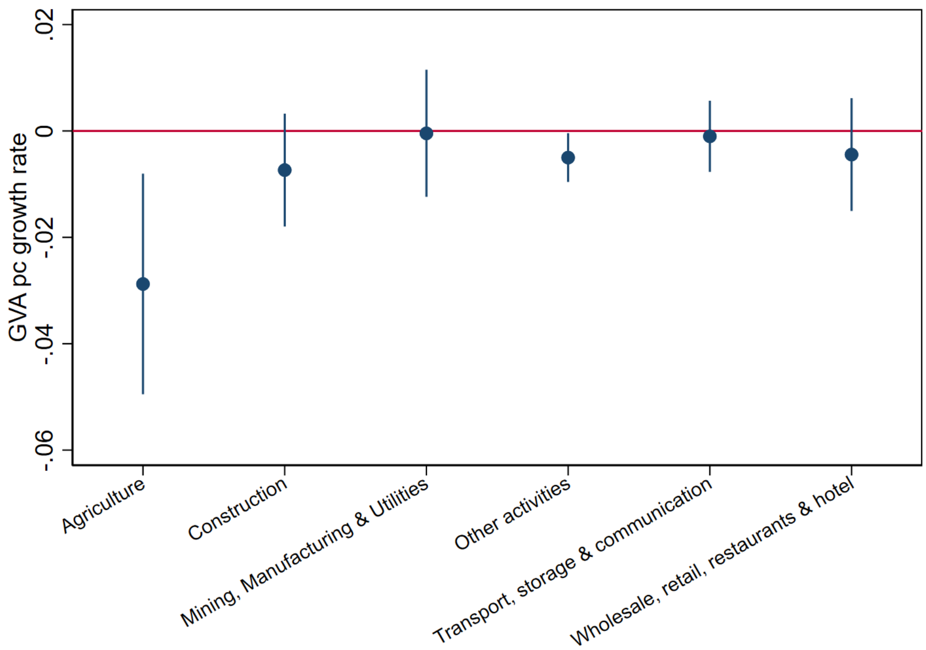
Notes: The figure shows the (standardized) regression coefficients on the number of days above the 99^{th} and below the 1^{st} percentile of the daily distribution in temperature (Panels (a-c-e)) and in precipitation (Panels (b-d-f)) using time-varying distributions (respectively, 20-year, 30-year and 40-year). The estimation sample starts from 1990. All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects. Bins represent the 90% confidence intervals with standard errors clustered at the country-level.

Figure A10: Extreme drought and wetness prevalence and sectoral production



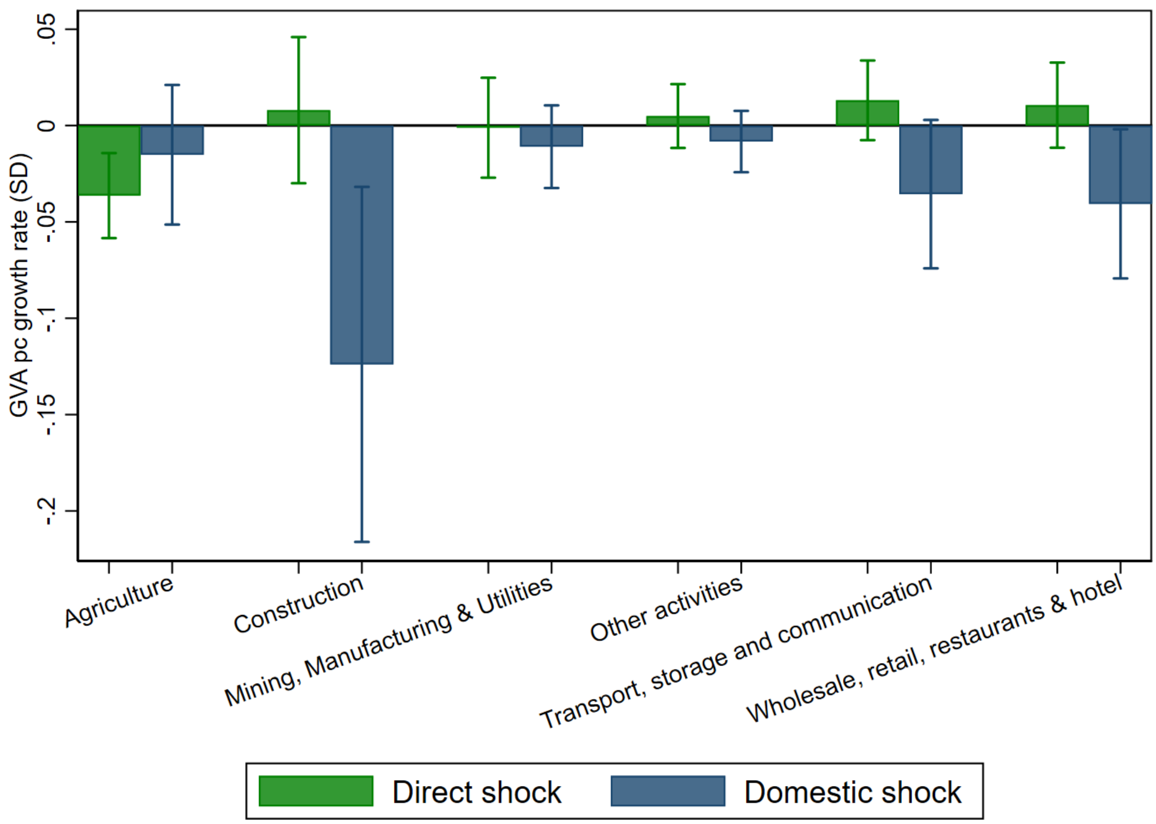
Notes: The figure shows the (standardized) coefficients from a stacked multi-sector regression model where changes in dryness and wetness variables are sector-specific. All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects. Bins represent the 90% confidence intervals with standard errors clustered at the country-level.

Figure A11: Tropical cyclone intensity and sectoral production



Notes: The figure shows the (standardized) sector-specific coefficients from a stacked multi-sector regression model where the main regressor is changes in damage intensity measure of tropical cyclones constructed from wind speed from Kunze (2021). All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects and controlling for country-specific linear time trends. Bins represent the 90% confidence intervals with standard errors clustered at the country-level.

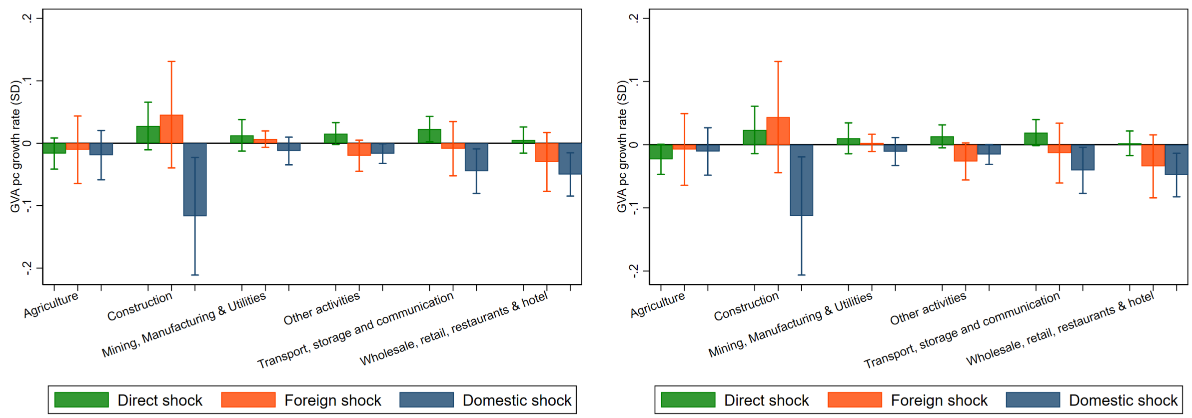
Figure A12: Domestic abnormally hot temperature shocks and sectoral production



Notes: Bars represent the (standardized) sector-specific coefficients associated with direct shocks and domestic shocks, using the average number of days above the 95$^{\text{th}}$ percentile of the daily temperature distribution. Domestic shocks are constructed as the average weather shock in the other sectors in the same country as the sector of interest weighted by the average of upstream and downstream interdependence with each sector. All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects and accounting for sector-specific responses to temperature realizations below the 5$^{\text{th}}$ percentile and sector-specific responses to precipitation realizations below the 5$^{\text{th}}$ and above the 95$^{\text{th}}$ percentile. Bins represent the 90% confidence intervals with standard errors clustered at the country-level.

Figure A13: Robustness: Spatial correlation

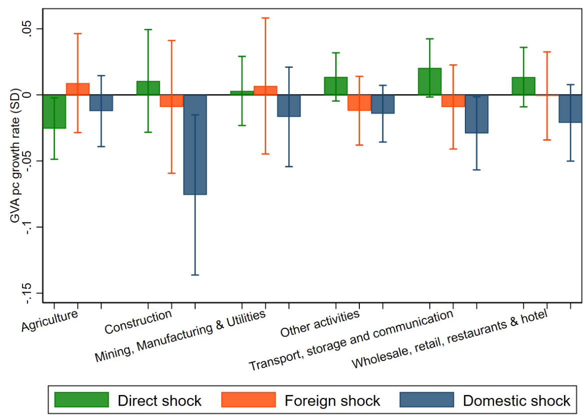
(a) Subregion-by-year FE (b) Continent-by-year FE



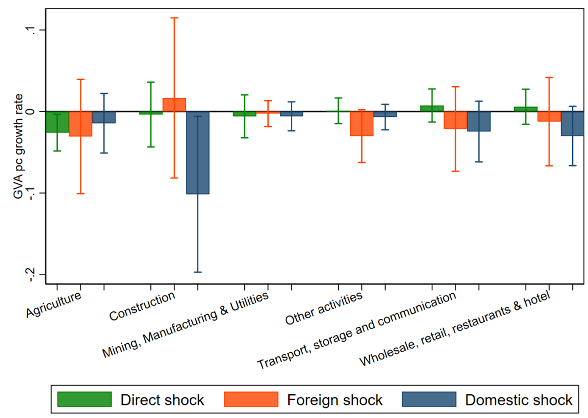
Notes: The figure shows the (standardized) sector-specific coefficients associated with direct shocks and domestic and foreign shocks, using the average number of days above the 95$^{\text{th}}$ percentile of the daily temperature distribution. Domestic shocks are constructed as the average weather shock in the other sectors in the same country as the sector of interest weighted by the average of upstream and downstream interdependence with each sector. Symmetrically, foreign shocks are constructed as the average weather shock in the other sectors in all the other countries weighted by the average of upstream and downstream interdependence with each sector. All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects and accounting for sector-specific responses to temperature realizations below the 5$^{\text{th}}$ percentile and sector-specific responses to precipitation realizations below the 5$^{\text{th}}$ and above the 95$^{\text{th}}$ percentile. Panel (a) shows the estimates in a regression that additionally accounts for subregion-by-year fixed effects, Panel (b) shows the estimates in a regression that additionally accounts for continent-by-year fixed effects. Bins represent the 90% confidence intervals around point estimates.

Figure A14: Robustness: Domestic and foreign shocks

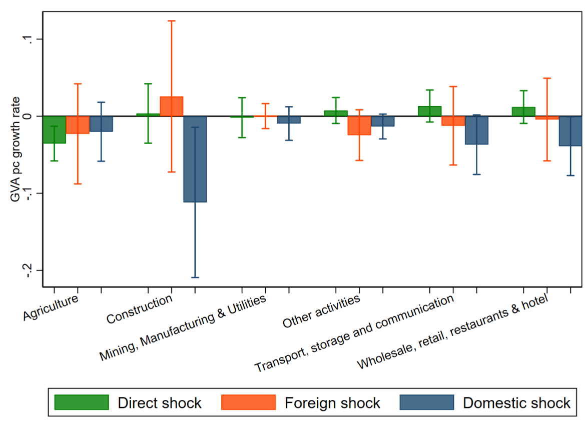
(a) Accounting for incomplete shares



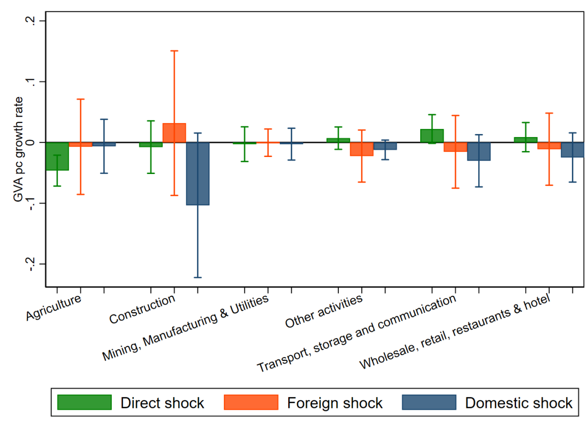
(b) Balanced panel



(c) Excluding "large" countries

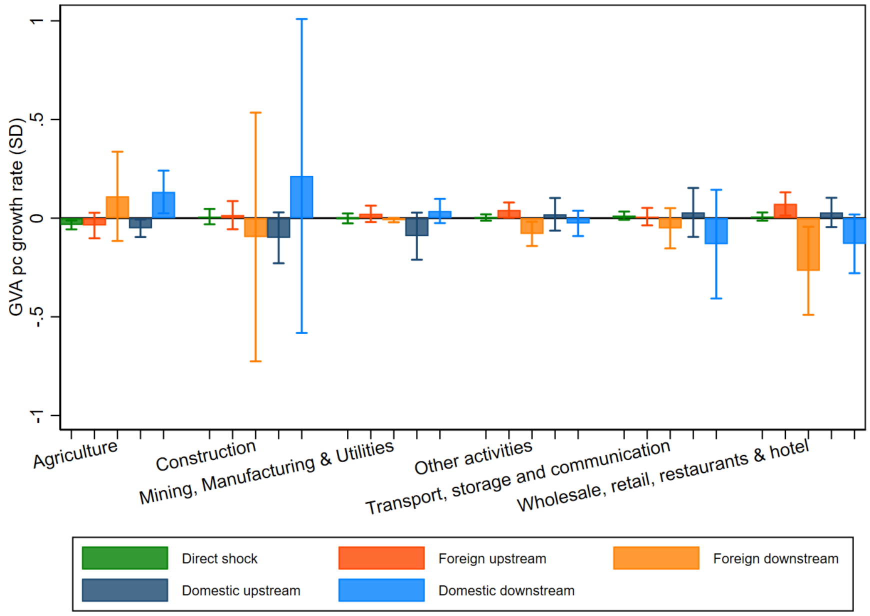


(d) After 1990 sample



Notes: The figure shows the (standardized) sector-specific coefficients associated with direct shocks and domestic and foreign shocks, using the average number of days above the 95$^{\text{th}}$ percentile of the daily temperature distribution. Domestic shocks are constructed as the average weather shock in the other sectors in the same country as the sector of interest weighted by the average of upstream and downstream interdependence with each sector. Symmetrically, foreign shocks are constructed as the average weather shock in the other sectors in all the other countries weighted by the average of upstream and downstream interdependence with each sector. All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects and accounting for sector-specific responses to temperature realizations below the 5$^{\text{th}}$ percentile and sector-specific responses to precipitation realizations below the 5$^{\text{th}}$ and above the 95$^{\text{th}}$ percentile. Panel (a) shows the estimates controlling for sector-year FE interacted with the sum of exposure shares. Panel (b) uses sector-country balanced panel, Panel (c) excludes large countries (Brazil, China, India, Russia, US), Panel (d) uses only the sample after 1990. Bins represent the 90% confidence intervals around point estimates.

Figure A15: Network abnormally hot temperature shocks and sectoral production

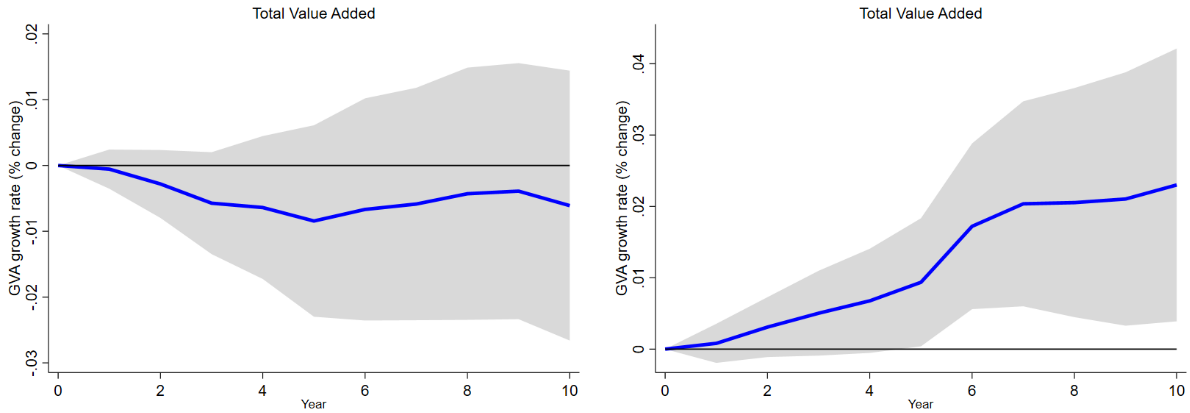


Notes: Bars represent the (standardized) sector-specific coefficients associated with direct shocks and domestic and foreign shocks distinguished between upstream and downstream, using the average number of days above the 95$^{\text{th}}$ percentile of the daily temperature distribution. Domestic upstream (resp. downstream) shocks are constructed as the average weather shock in the other sectors in the same country as the sector of interest weighted by the upstream (resp. downstream) interdependence with each sector. Symmetrically, foreign upstream (resp. downstream) shocks are constructed as the average weather shock in other sectors abroad weighted by the upstream (resp. downstream) interdependence with each sector. The coefficients are estimated in a specification that jointly estimates all sector-specific coefficients in a stacked regression model fully saturated with country-sector and sector-year fixed effects and accounting for sector-specific responses to temperature realizations below the 5$^{\text{th}}$ percentile and sector-specific responses to precipitation realizations below the 5$^{\text{th}}$ and above the 95$^{\text{th}}$ percentile. Bins represent the 90% confidence intervals with standard errors clustered at the country-level.

Figure A16: Local projections of domestic and foreign heat shocks on total value added

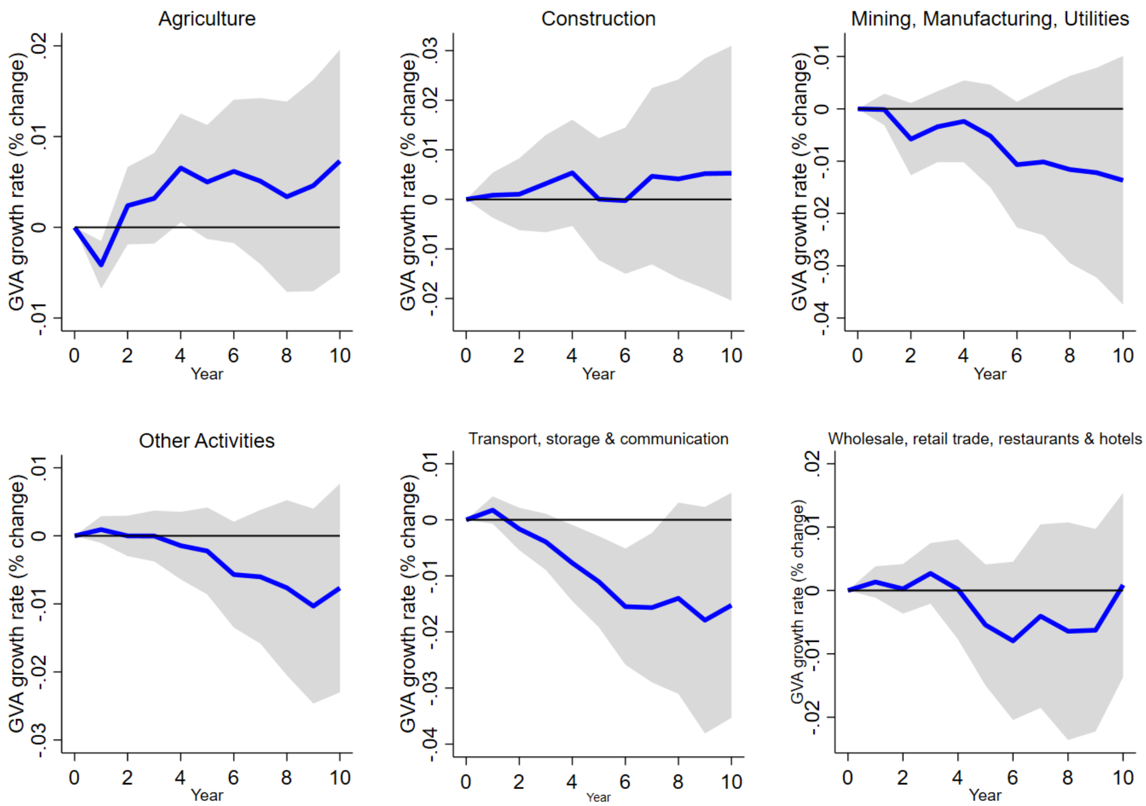
(a) Domestic heat shock

(b) Foreign heat shock



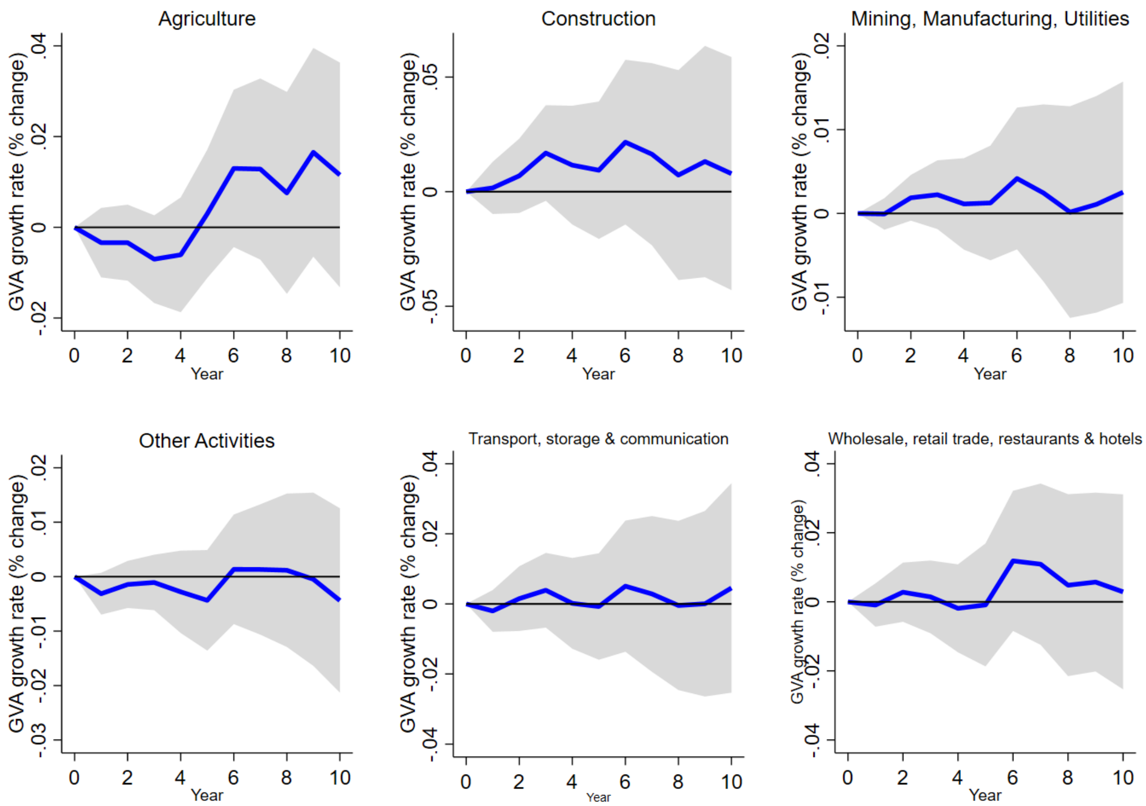
Notes: Panels impulse response function of per capita total value added growth rate to a 1 SD increase in heat shocks estimated in a stacked regression model with country and year fixed effects and accounting for abnormally cold temperature shocks (below the 5^{th} percentile) and precipitation realizations below the 5^{th} and above the 95^{th} percentile. Horizon 0 is the year of the shock. Shaded areas represent the 90% confidence intervals with standard errors clustered at the country level. Panel (a) shows the estimates for domestic shocks, and Panel (b) shows the estimates for foreign shocks.

Figure A17: Local projections of own abnormally hot temperature shocks on sectoral production



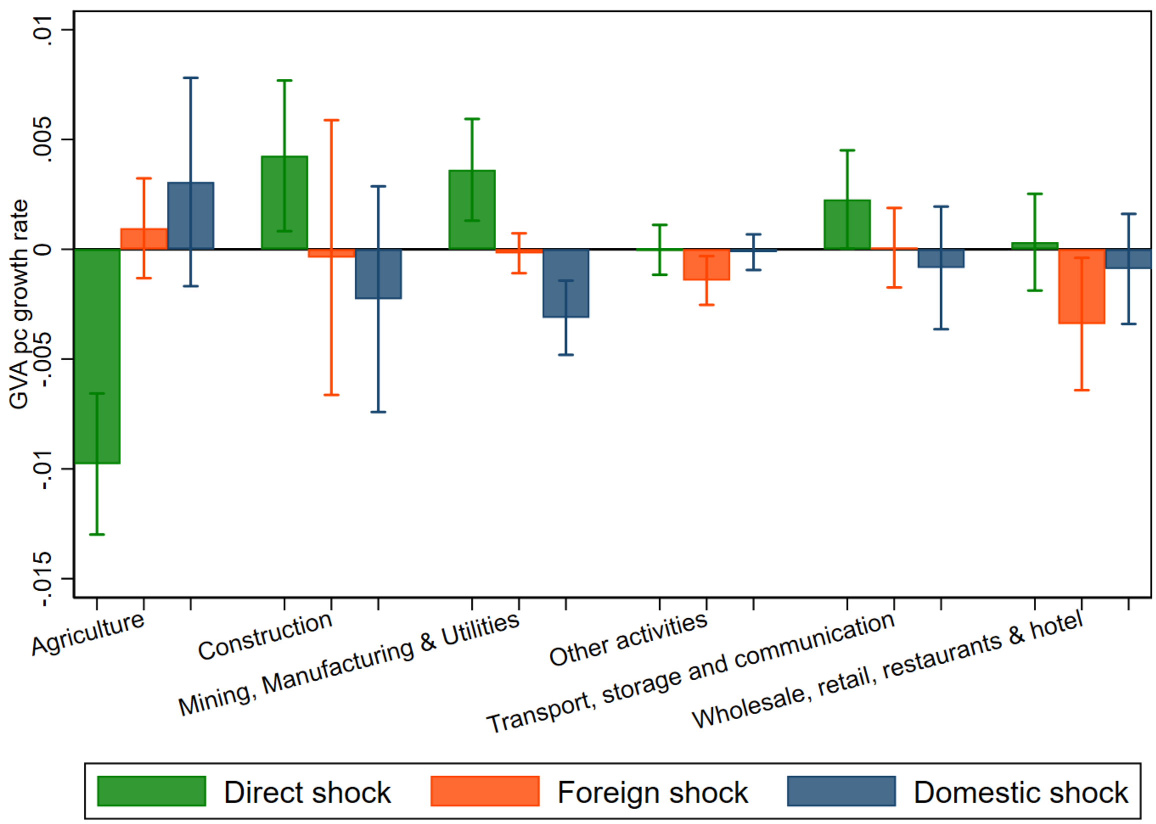
Notes: Panels show the sector-specific impulse response function of sectoral per capita GVA growth rate to a 1 SD increase in the abnormally hot temperature shocks estimated in a stacked regression model fully saturated with country-sector and sector-year fixed effects and accounting for sector-specific responses to domestic and foreign abnormally hot temperature shocks, to abnormally cold temperature shocks (below the 5$^{\text{th}}$ percentile) and to precipitation realizations below the 5$^{\text{th}}$ and above the 95$^{\text{th}}$ percentile. Horizon 0 is the year of the shock. Shaded areas represent the 90% confidence intervals with standard errors clustered at the country-level.

Figure A18: Local projections of foreign abnormally hot temperature shocks on sectoral production



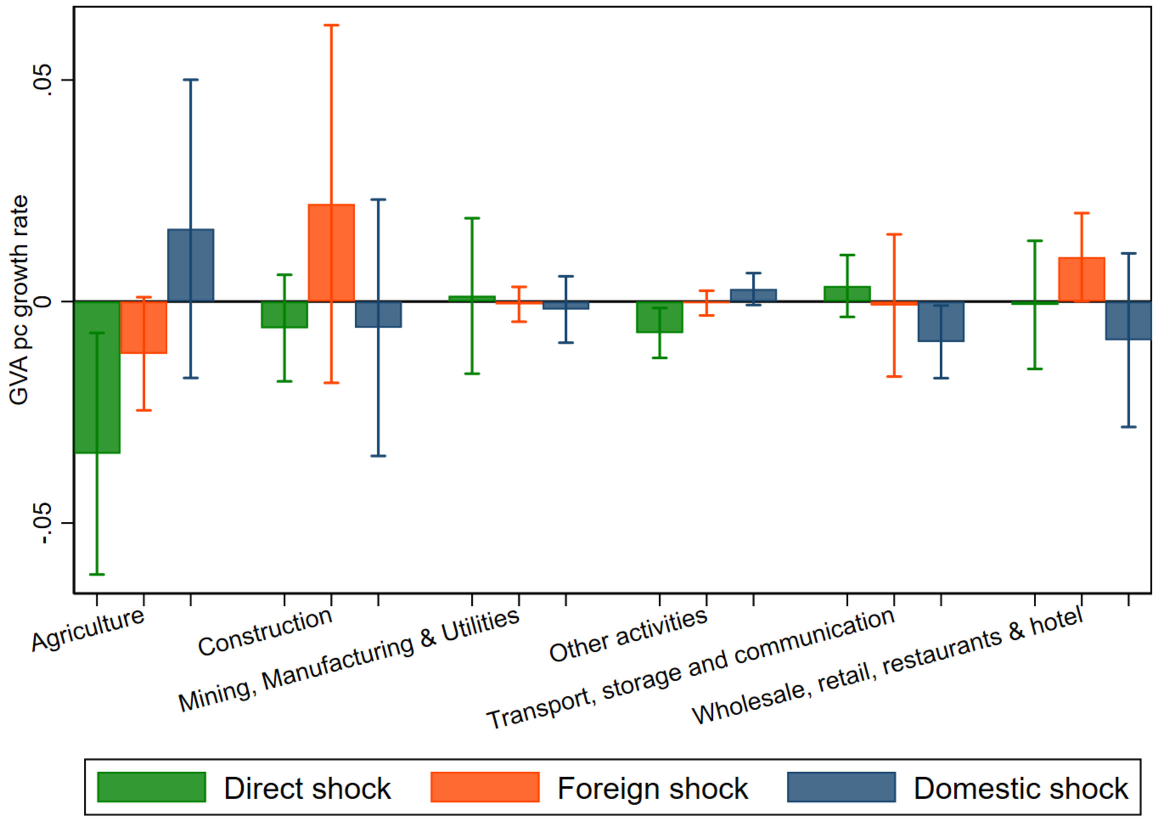
Notes: Panels show the sector-specific impulse response function of sectoral per capita GVA growth rate to a 1 SD increase in the foreign abnormally hot temperature shocks estimated in a stacked regression model fully saturated with country-sector and sector-year fixed effects and accounting for sector-specific responses to direct and domestic abnormally hot temperature shocks, to abnormally cold temperature shocks (below the 5$^{\text{th}}$ percentile) and to precipitation realizations below the 5$^{\text{th}}$ and above the 95$^{\text{th}}$ percentile. Horizon 0 is the year of the shock. Shaded areas represent the 90% confidence intervals with standard errors clustered at the country-level.

Figure A19: Direct and network drought shocks and sectoral production



Notes: Bars represent the (standardized) sector-specific coefficients associated with direct shocks and domestic and foreign shocks, using changes in extreme drought prevalence. Domestic shocks are constructed as the average shock in the other sectors in the same country as the sector of interest weighted by the average of upstream and downstream interdependence with each sector. Symmetrically, foreign shocks are constructed as the average shock in the other sectors in all the other countries weighted by the average of upstream and downstream interdependence with each sector. All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects. Bins represent the 90% confidence intervals with standard errors clustered at the country-level.

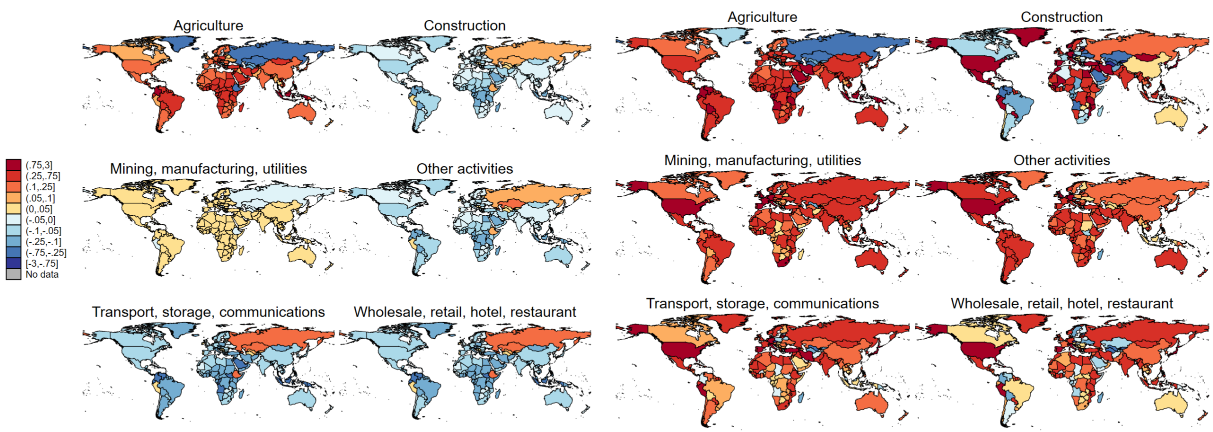
Figure A20: Direct and network cyclones shocks and sectoral production



Notes: Bars represent the (standardized) sector-specific coefficients associated with direct shocks and domestic and foreign shocks, using the changes in the wind speed measure by Kunze (2021). Domestic shocks are constructed as the average shock in the other sectors in the same country as the sector of interest weighted by the average of upstream and downstream interdependence with each sector. Symmetrically, foreign shocks are constructed as the average weather shock in the other sectors in all the other countries weighted by the average of upstream and downstream interdependence with each sector. All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects. Bins represent the 90% confidence intervals with standard errors clustered at the country-level.

Figure A21: Average annual relative sectoral GVA pc losses (%) due to recent warming

(a) Local sectoral heat shocks (b) Accounting for indirect heat shocks



Notes: The figure shows average annual losses (in red) and gains (in blue) in sectoral per capita GVA due to abnormally hot temperature shocks in the 2001-2020 period compared to a counterfactual in which heat shocks evolved linearly from their 1970-2000 averages. The two panels compare the average annual relative loss (% of per capita GVA) using sector-specific local heat shocks estimates (Panel a) and accounting for shocks in other partner sectors (Panel b) estimated from Equation (8). Averages are obtained from 1000 bootstrap estimations. In panel a), only estimates in Agriculture are statistically significant at 95% level. Table A12 reports the estimated average losses at the country-sector level significant at the 95% level.

A.2 Tables

Table A1: Countries and year-sectors in final sample

Country	Number of years-sectors	Country	Number of years-sectors	Country	Number of years-sectors
Afghanistan	300	French Polynesia	300	Nigeria	300
Albania	300	Gabon	300	North Korea	200
Algeria	300	Gambia	300	North Macedonia	180
Andorra	300	Georgia	180	Norway	300
Angola	300	Germany	300	Oman	300
Antigua and Barbuda	300	Ghana	300	Pakistan	300
Argentina	300	Greece	300	Palestine	180
Armenia	180	Greenland	300	Panama	300
Aruba	300	Grenada	300	Papua New Guinea	300
Australia	300	Guatemala	300	Paraguay	300
Austria	300	Guinea	300	Peru	300
Azerbaijan	180	Guyana	300	Philippines	300
Bahamas	296	Haiti	300	Poland	300
Bahrain	300	Honduras	300	Portugal	300
Bangladesh	300	Hungary	300	Qatar	300
Barbados	300	Iceland	300	Republic of the Congo	300
Belarus	180	India	300	Romania	300
Belgium	300	Indonesia	300	Russia	180
Belize	300	Iran	300	Rwanda	300
Benin	300	Iraq	300	Samoa	300
Bermuda	300	Ireland	300	San Marino	300
Bhutan	300	Israel	300	Saudi Arabia	300
Bolivia	300	Italy	300	Senegal	300
Bosnia and Herzegovina	180	Jamaica	300	Serbia	180
Botswana	300	Japan	300	Seychelles	300
Brazil	300	Jordan	300	Sierra Leone	300
British Virgin Islands	300	Kazakhstan	180	Singapore	300
Brunei	300	Kenya	300	Slovakia	180
Bulgaria	300	Kuwait	276	Slovenia	180
Burkina Faso	300	Kyrgyzstan	180	Somalia	300
Burundi	300	Laos	300	South Africa	300
Cabo Verde	300	Latvia	180	South Korea	300
Cambodia	300	Lebanon	300	South Sudan	72
Cameroon	300	Lesotho	300	Spain	300
Canada	300	Liberia	300	Sri Lanka	300
Cayman Islands	300	Libya	300	Sudan	72
Central African Republic	300	Liechtenstein	300	Suriname	300
Chad	300	Lithuania	180	Swaziland	300
Chile	300	Luxembourg	300	Sweden	300
China	300	Madagascar	300	Switzerland	300
Colombia	300	Malawi	300	Syria	300
Comoros	300	Malaysia	300	São Tomé and Príncipe	300
Costa Rica	300	Maldives	297	Tajikistan	178
Croatia	180	Mali	300	Tanzania	300
Cuba	300	Malta	300	Thailand	300
Cyprus	300	Mauritania	300	Togo	300
Czechia	180	Mauritius	300	Trinidad and Tobago	300
Côte d'Ivoire	300	Moldova	180	Tunisia	300
Democratic Republic of the Congo	300	Monaco	250	Turkey	300
Denmark	300	Mongolia	300	Turkmenistan	180
Djibouti	300	Montenegro	180	Uganda	300
Dominican Republic	300	Morocco	300	Ukraine	180
Ecuador	300	Mozambique	300	United Arab Emirates	300
Egypt	300	Myanmar	300	United Kingdom	300
El Salvador	300	México	300	United States	300
Equatorial Guinea	300	Namibia	300	Uruguay	300
Eritrea	126	Nepal	300	Uzbekistan	180
Estonia	180	Netherlands	300	Vanuatu	300
Ethiopia	180	New Caledonia	300	Venezuela	300
Fiji	300	New Zealand	300	Vietnam	300
Finland	300	Nicaragua	300	Yemen	186
France	300	Niger	300	Zambia	300
				Zimbabwe	300
Total	51,129				

Table A2: Mapping between EORA26 sectors and UNSD industries

EORA26 Sector	UNSD industry
Agriculture	Agriculture, hunting, forestry, fishing (ISIC A-B)
Fishing	Agriculture, hunting, forestry, fishing (ISIC A-B)
Mining and Quarrying	Mining, Manufacturing, Utilities (ISIC C-E)
Electricity, Gas and Water	Mining, Manufacturing, Utilities (ISIC C-E)
Food & Beverages	Mining, Manufacturing, Utilities (ISIC C-E)
Textiles and Wearing Apparel	Mining, Manufacturing, Utilities (ISIC C-E)
Wood and Paper	Mining, Manufacturing, Utilities (ISIC C-E)
Petroleum, Chemical and Non-Metallic Mineral Products	Mining, Manufacturing, Utilities (ISIC C-E)
Metal Products	Mining, Manufacturing, Utilities (ISIC C-E)
Electrical and Machinery	Mining, Manufacturing, Utilities (ISIC C-E)
Transport Equipment	Mining, Manufacturing, Utilities (ISIC C-E)
Other Manufacturing	Mining, Manufacturing, Utilities (ISIC C-E)
Recycling	Mining, Manufacturing, Utilities (ISIC C-E)
Construction	Construction (ISIC F)
Maintenance and Repair	Construction (ISIC F)
Wholesale Trade	Wholesale, retail trade, restaurants and hotels (ISIC G-H)
Retail Trade	Wholesale, retail trade, restaurants and hotels (ISIC G-H)
Hotels and Restaurants	Wholesale, retail trade, restaurants and hotels (ISIC G-H)
Transport	Transport, storage and communication (ISIC I)
Post and Telecommunications	Transport, storage and communication (ISIC I)
Financial Intermediation and Business Activities	Other Activities (ISIC J-P)
Public Administration	Other Activities (ISIC J-P)
Education, Health and Other Services	Other Activities (ISIC J-P)
Private Households	Other Activities (ISIC J-P)
Others	Other Activities (ISIC J-P)
Re-export & Re-import	Other Activities (ISIC J-P)

Notes: Author's classification based on Kunze (2021) and adapted to six UNSD sectors.

Table A3: Classification of countries by income group

Group	Countries
Advanced Economies	Australia, Austria, Belgium, Canada, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Malta, Netherlands, New Zealand, Norway, Portugal, Puerto Rico, San Marino, Singapore, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Kingdom, United States
Emerging Market Economies	Albania, Algeria, Angola, Antigua and Barbuda, Argentina, Armenia, Azerbaijan, The Bahamas, Bahrain, Barbados, Belarus, Belize, Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, Cabo Verde, Chile, China, Colombia, Costa Rica, Croatia, Dominica, Dominican Republic, Ecuador, Egypt, El Salvador, Equatorial Guinea, Fiji, Gabon, Georgia, Grenada, Guatemala, Guyana, Hungary, India, Indonesia, Iran, Iraq, Jamaica, Jordan, Kazakhstan, Kuwait, Lebanon, Libya, Malaysia, Maldives, Marshall Islands, Mauritius, Mexico, Montenegro, Morocco, Namibia, Nauru, North Macedonia, Oman, Pakistan, Palau, Panama, Paraguay, Peru, Philippines, Poland, Qatar, Romania, Russia, Samoa, Saudi Arabia, Serbia, Seychelles, South Africa, Sri Lanka, St. Kitts and Nevis, St. Lucia, St. Vincent and the Grenadines, Suriname, Swaziland, Syria, Thailand, Timor-Leste, Tonga, Trinidad and Tobago, Tunisia, Turkey, Turkmenistan, Tuvalu, Ukraine, United Arab Emirates, Uruguay, Vanuatu, Venezuela
Low-Income Developing Countries	Afghanistan, Bangladesh, Benin, Bhutan, Bolivia, Burkina Faso, Burundi, Cambodia, Cameroon, Central African Republic, Chad, Comoros, Democratic Republic of the Congo, Republic of Congo,Côte d'Ivoire, Djibouti, Eritrea, Ethiopia, The Gambia, Guinea, Guinea-Bissau, Haiti,Honduras, Kenya, Kiribati, Kyrgyz Republic, Lao P.D.R., Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Moldova, Mongolia, Mozambique, Myanmar, Nepal, Nicaragua, Niger, Nigeria, Papua New Guinea, Rwanda, Senegal, Sierra Leone, Solomon Islands, Somalia, South Sudan, Sudan, São Tomé and Príncipe, Tajikistan, Tanzania, Togo, Uganda, Uzbekistan, Vietnam, Yemen, Zambia, Zimbabwe

Notes: Author's classification based on IMF World Economic Outlook (IMF, 2022) An anomaly is defined as the sum of the monthly deviations from the monthly 25-year moving average, distinguishing between positive and negative.

Table A4: Summary statistics on weather shocks

	N	mean	sd	min	max
Temperature and precipitation					
Temperature above 90th percentile (days/year)	8,548	37.487	23.610	0	222
Temperature below 10th percentile (days/year)	8,548	35.907	21.023	0	210
Precipitation above 90th percentile (days/year)	8,548	36.458	9.907	7	111
Precipitation below 10th percentile (days/year)	8,548	32.390	16.367	0	114
Temperature above 99th percentile (days/year)	8,548	3.851	6.145	0	94
Temperature below 1th percentile (days/year)	8,548	3.563	4.892	0	54
Precipitation above 99th percentile (days/year)	8,548	3.659	2.539	0	29
Precipitation below 1th percentile (days/year)	8,548	2.474	3.187	0	32
Negative temperature anomaly (°C)	7,817	3.274	3.353	0.00005	31.413
Positive temperature anomaly (°C)	7,817	6.33	4.728	0.0007	32.898
Negative precipitation anomaly (mm)	7,817	6.980	5.308	0.009	48.944
Positive precipitation anomaly (mm)	7,817	6.836	6.322	0.00008	89.33

Notes: Abnormal weather realizations and anomalies are measured in levels.

Table A5: Im-Pesaran-Shin unit-root test for main variables

	Statistic	p-value
GVA growth rate	-6.072	0.000
Abnormally dry precipitation shock (p^1)	-6.782	0.000
Abnormally dry precipitation shock (p^5)	-6.464	0.000
Abnormally dry precipitation shock (p^{10})	-6.456	0.000
Abnormally wet precipitation shock (p^{90})	-6.571	0.000
Abnormally wet precipitation shock (p^{95})	-6.600	0.000
Abnormally wet precipitation shock (p^{99})	-6.832	0.000
Abnormally cold temperature shock (p^1)	-6.541	0.000
Abnormally cold temperature shock (p^5)	-6.134	0.000
Abnormally cold temperature shock (p^{10})	-6.128	0.000
Abnormally hot temperature shock (p^{90})	-6.156	0.000
Abnormally hot temperature shock (p^{95})	-6.258	0.000
Abnormally hot temperature shock (p^{99})	-6.575	0.000

Notes: Null hypothesis of the unit-root test by Im et al. (2003) is that all panels contain unit roots against the alternative hypothesis that some panels are stationary. In performing the test, I do not include lags and remove cross-sectional means and include a time trend in the estimated equation. The test on the growth rate is performed on a balanced sector-country-year panel, whereas test on weather variables is performed on a balanced country-year panel using population-weighted weather variables.

Table A6: Sector-specific impact of positive annual temperature and precipitation changest

	GVA per capita growth rate		
	(1)	(2)	(3)
Temperature			
Agriculture, hunting, forestry, fishing	-0.00676**	-0.00726**	-0.00773**
	(0.00297)	(0.00305)	(0.00300)
Construction	0.000787	0.000861	0.000352
	(0.00401)	(0.00403)	(0.00403)
Mining, Manufacturing, Utilities	0.00229	0.00205	0.00162
	(0.00251)	(0.00253)	(0.00256)
Other Activities	0.000665	0.000697	0.000157
	(0.00183)	(0.00184)	(0.00183)
Transport, storage and communication	0.00410	0.00423	0.00370
	(0.00266)	(0.00271)	(0.00272)
Wholesale, retail trade, restaurants and hotels	0.00284	0.00266	0.00220
	(0.00260)	(0.00264)	(0.00266)
Precipitation			
Agriculture, hunting, forestry, fishing	0.0117***	0.0122***	0.0117***
	(0.00291)	(0.00299)	(0.00293)
Construction	-0.00378	-0.00349	-0.00380
	(0.00337)	(0.00331)	(0.00332)
Mining, Manufacturing, Utilities	-0.000347	0.000191	-0.000257
	(0.00278)	(0.00285)	(0.00285)
Other Activities	-0.000128	-0.00000690	-0.000466
	(0.00171)	(0.00177)	(0.00175)
Transport, storage and communication	-0.00514**	-0.00460*	-0.00505**
	(0.00233)	(0.00240)	(0.00238)
Wholesale, retail trade, restaurants and hotels	-0.000100	0.000159	-0.000298
	(0.00209)	(0.00212)	(0.00213)
GVA growth rate$_{t-1}$		0.0618**	0.0399
		(0.0264)	(0.0257)
Country-Sector FE	✓	✓	✓
Sector-Year FE	✓	✓	✓
Country linear time trends			✓
Country quadratic time trends			✓
N	51273	50162	50162
adj. R^2	0.043	0.046	0.060

Notes: The table reports the sector-specific coefficients associated with changes in annual temperature and precipitation distributions. Standard errors are clustered at the country-level. A graphical representation of the coefficients in column (2) is reported in Figure 1. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Sector-specific impact of annual temperature and precipitation changes

	GVA per capita growth rate		
	(1)	(2)	(3)
Temperature Changes			
Agriculture, hunting, forestry, fishing	-0.0351**	-0.0383**	-0.0379**
	(0.0144)	(0.0149)	(0.0149)
Construction	0.0402***	0.0360**	0.0362**
	(0.0153)	(0.0157)	(0.0155)
Mining, Manufacturing, Utilities	0.0220*	0.0189	0.0193
	(0.0112)	(0.0119)	(0.0118)
Other Activities	0.00974	0.00980	0.0101
	(0.00950)	(0.00978)	(0.00973)
Transport, storage and communication	0.0230*	0.0200	0.0205
	(0.0124)	(0.0127)	(0.0126)
Wholesale, retail trade, restaurants and hotels	0.0217	0.0197	0.0201
	(0.0135)	(0.0137)	(0.0137)
Precipitation Changes			
Agriculture, hunting, forestry, fishing	0.0405***	0.0417***	0.0409***
	(0.0114)	(0.0119)	(0.0117)
Construction	-0.00187	0.00110	0.000722
	(0.0129)	(0.0129)	(0.0129)
Mining, Manufacturing, Utilities	0.0130	0.0148	0.0147
	(0.0103)	(0.0106)	(0.0106)
Other Activities	0.00275	0.00302	0.00277
	(0.00532)	(0.00549)	(0.00545)
Transport, storage and communication	-0.00857	-0.00713	-0.00744
	(0.00821)	(0.00867)	(0.00851)
Wholesale, retail trade, restaurants and hotels	-0.00305	-0.00207	-0.00255
	(0.00839)	(0.00846)	(0.00836)
GVA growth rate$_{t-1}$		0.0616**	0.0400
		(0.0264)	(0.0257)
Country-Sector FE	✓	✓	✓
Sector-Year FE	✓	✓	✓
Country linear time trends			✓
Country quadratic time trends			✓
N	50223	49133	49133
adj. R^2	0.044	0.047	0.060

Notes: The table reports the (standardized) sector-specific coefficients associated with positive and negative changes in annual temperature and precipitation distributions. Standard errors are clustered at the country-level. A graphical representation of the coefficients in column (2) is reported in Figure 2. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Heterogeneous effect of annual changes in temperature and precipitation by income groups.

	GVA per capita growth rate		
	(1)	(2)	(3)
Temperature			
Advanced Economies			
Agriculture	0.0272	0.0287*	0.0284*
	(0.0176)	(0.0153)	(0.0151)
Construction	0.0668***	0.0653***	0.0651***
	(0.0198)	(0.0170)	(0.0167)
Mining, Manufacturing, Utilities	0.0153**	0.0176**	0.0180**
	(0.00689)	(0.00886)	(0.00856)
Other Activities	0.00399	0.00168	0.00196
	(0.00624)	(0.00571)	(0.00588)
Transport, storage and communication	0.00634	0.00756	0.00818
	(0.0104)	(0.0106)	(0.0108)
Wholesale, retail trade, restaurants and hotels	0.0223***	0.0176**	0.0177**
	(0.00844)	(0.00720)	(0.00716)
Emerging Economies			
Agriculture	-0.0804***	-0.0844***	-0.0845***
	(0.0191)	(0.0202)	(0.0202)
Construction	0.0482	0.0506	0.0501
	(0.0317)	(0.0331)	(0.0328)
Mining, Manufacturing, Utilities	0.0339	0.0306	0.0298
	(0.0220)	(0.0230)	(0.0228)
Other Activities	0.0295	0.0309	0.0301
	(0.0206)	(0.0213)	(0.0212)
Transport, storage and communication	0.0440*	0.0395	0.0389
	(0.0254)	(0.0261)	(0.0260)
Wholesale, retail trade, restaurants and hotels	0.0325	0.0325	0.0319
	(0.0284)	(0.0284)	(0.0285)
Low-Income Developing Countries			
Agriculture	-0.0762**	-0.0888**	-0.0852**
	(0.0354)	(0.0380)	(0.0384)
Construction	0.0240	-0.00530	-0.00178
	(0.0338)	(0.0314)	(0.0315)
Mining, Manufacturing, Utilities	0.0305	0.0164	0.0203
	(0.0288)	(0.0330)	(0.0331)
Other Activities	-0.00853	-0.00845	-0.00471
	(0.0199)	(0.0188)	(0.0189)
Transport, storage and communication	0.00991	-0.00175	0.00231
	(0.0206)	(0.0204)	(0.0200)
Wholesale, retail trade, restaurants and hotels	-0.0119	-0.0172	-0.0128
	(0.0331)	(0.0350)	(0.0347)
Precipitation			
Advanced Economies			
Agriculture	0.0650	0.0608	0.0605
	(0.0446)	(0.0450)	(0.0442)
Construction	0.0139	0.00437	0.00500
	(0.0212)	(0.0203)	(0.0200)
Mining, Manufacturing, Utilities	0.0107	0.0179	0.0173
	(0.0158)	(0.0166)	(0.0163)
Other Activities	-0.00760	-0.0148*	-0.0143*
	(0.00644)	(0.00756)	(0.00739)
Transport, storage and communication	-0.0101	-0.0133	-0.0130
	(0.0134)	(0.0143)	(0.0137)
Wholesale, retail trade, restaurants and hotels	-0.00675	-0.0141	-0.0138
	(0.0133)	(0.0126)	(0.0123)
Emerging Economies			
Agriculture	0.0225*	0.0222*	0.0217
	(0.0132)	(0.0133)	(0.0132)
Construction	-0.0121	-0.00820	-0.00856
	(0.0196)	(0.0190)	(0.0188)
Mining, Manufacturing, Utilities	0.00487	0.00631	0.00593
	(0.00768)	(0.00791)	(0.00788)
Other Activities	0.0120	0.0126*	0.0124
	(0.00758)	(0.00762)	(0.00751)
Transport, storage and communication	-0.00251	-0.00151	-0.00166
	(0.00680)	(0.00675)	(0.00664)
Wholesale, retail trade, restaurants and hotels	0.00435	0.00520	0.00505
	(0.00955)	(0.00969)	(0.00945)
Low-Income Developing Countries			
Agriculture	0.0466**	0.0488**	0.0477**
	(0.0195)	(0.0204)	(0.0203)
Construction	0.0233	0.0234	0.0236
	(0.0293)	(0.0301)	(0.0301)
Mining, Manufacturing, Utilities	-0.0111	-0.00924	-0.00957
	(0.0144)	(0.0151)	(0.0149)
Other Activities	-0.0177	-0.0153	-0.0222
	(0.0272)	(0.0273)	(0.0276)
Transport, storage and communication	-0.00977	-0.00897	-0.00955
	(0.0241)	(0.0255)	(0.0251)
Wholesale, retail trade, restaurants and hotels	-0.0260	-0.0237	-0.0247
	(0.0216)	(0.0216)	(0.0215)
GVA growth rate$_{t-1}$		0.0566**	0.0344
		(0.0280)	(0.0272)
Country-Sector FE	✓	✓	✓
Sector-Year FE	✓	✓	✓
Country linear time trends			✓
Country quadratic time trends			✓
N	46243	45235	45235
adj. R^2	0.047	0.050	0.064

Notes: The table reports the (standardized) income group-sector-specific coefficients associated with changes in annual sum of daily temperature and precipitation. A graphical representation of the coefficients associated with temperature is reported in Figure A3a. Standard errors are clustered at the country-level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: Heterogeneous effect of annual changes in temperature and precipitation by climate terciles.

	GVA per capita growth rate		
	(1)	(2)	(3)
Temperature			
Cold Climate			
Agriculture	-0.0105	-0.0128	-0.0138
	(0.0173)	(0.0176)	(0.0176)
Construction	0.0769***	0.0680***	0.0675***
	(0.0196)	(0.0194)	(0.0193)
Mining, Manufacturing, Utilities	0.0193	0.0174	0.0169
	(0.0128)	(0.0140)	(0.0138)
Other Activities	0.0167	0.0170	0.0166
	(0.0126)	(0.0127)	(0.0126)
Transport, storage and communication	0.0210	0.0160	0.0157
	(0.0147)	(0.0148)	(0.0147)
Wholesale, retail trade, restaurants and hotels	0.0392**	0.0353**	0.0351**
	(0.0172)	(0.0174)	(0.0174)
Temperate Climate			
Agriculture	-0.101***	-0.103***	-0.0998***
	(0.0312)	(0.0319)	(0.0321)
Construction	-0.0162	-0.0108	-0.00972
	(0.0364)	(0.0376)	(0.0371)
Mining, Manufacturing, Utilities	0.0357	0.0315	0.0330
	(0.0259)	(0.0263)	(0.0263)
Other Activities	0.00961	0.00898	0.00997
	(0.0179)	(0.0183)	(0.0186)
Transport, storage and communication	0.0488*	0.0509*	0.0520*
	(0.0283)	(0.0291)	(0.0291)
Wholesale, retail trade, restaurants and hotels	0.0135	0.0166	0.0173
	(0.0295)	(0.0287)	(0.0290)
Hot Climate			
Agriculture	-0.0413	-0.0501	-0.0470
	(0.0396)	(0.0428)	(0.0425)
Construction	-0.0491	-0.0471	-0.0438
	(0.0321)	(0.0323)	(0.0321)
Mining, Manufacturing, Utilities	0.0112	0.00361	0.00781
	(0.0308)	(0.0320)	(0.0319)
Other Activities	-0.0260	-0.0274	-0.0242
	(0.0184)	(0.0195)	(0.0194)
Transport, storage and communication	-0.0125	-0.0157	-0.0118
	(0.0203)	(0.0207)	(0.0203)
Wholesale, retail trade, restaurants and hotels	-0.0555**	-0.0585**	-0.0552**
	(0.0235)	(0.0234)	(0.0234)
Precipitation			
Cold Climate			
Agriculture	0.0389*	0.0395*	0.0405**
	(0.0205)	(0.0207)	(0.0205)
Construction	-0.00982	-0.00897	-0.00710
	(0.0179)	(0.0177)	(0.0176)
Mining, Manufacturing, Utilities	0.0179	0.0213	0.0234*
	(0.0137)	(0.0131)	(0.0131)
Other Activities	0.00360	-0.000150	0.00119
	(0.00786)	(0.00783)	(0.00775)
Transport, storage and communication	-0.00287	0.000371	0.00132
	(0.0151)	(0.0157)	(0.0151)
Wholesale, retail trade, restaurants and hotels	-0.0134	-0.0154	-0.0146
	(0.0139)	(0.0136)	(0.0134)
Temperate Climate			
Agriculture	0.0417*	0.0428*	0.0411*
	(0.0216)	(0.0224)	(0.0222)
Construction	0.00512	0.00888	0.00813
	(0.0180)	(0.0173)	(0.0174)
Mining, Manufacturing, Utilities	0.0151	0.0170	0.0163
	(0.0156)	(0.0158)	(0.0159)
Other Activities	0.0114	0.0127	0.0118
	(0.00801)	(0.00808)	(0.00808)
Transport, storage and communication	0.0113	0.0131	0.0122
	(0.0104)	(0.0108)	(0.0108)
Wholesale, retail trade, restaurants and hotels	0.0208*	0.0218*	0.0211*
	(0.0122)	(0.0127)	(0.0125)
Hot Climate			
Agriculture	0.0271*	0.0279*	0.0277*
	(0.0156)	(0.0164)	(0.0162)
Construction	-0.0193	-0.0146	-0.0154
	(0.0248)	(0.0251)	(0.0249)
Mining, Manufacturing, Utilities	0.00861	0.00897	0.00857
	(0.0209)	(0.0218)	(0.0218)
Other Activities	-0.00974	-0.00862	-0.00881
	(0.0101)	(0.0106)	(0.0105)
Transport, storage and communication	-0.0319**	-0.0314*	-0.0313*
	(0.0153)	(0.0163)	(0.0159)
Wholesale, retail trade, restaurants and hotels	-0.0296*	-0.0268*	-0.0274*
	(0.0154)	(0.0155)	(0.0154)
GVA growth rate$_{t-1}$		0.0620**	0.0404
		(0.0264)	(0.0258)
Sector FE	✓	✓	✓
Country FE	✓	✓	✓
Year FE	✓	✓	✓
Country linear time trends			✓
Country quadratic time trends			✓
N	50223	49133	49133
adj. R^2	0.044	0.047	0.060

Notes: The table reports the (standardized) climate tercile-sector-specific coefficients associated with binary variables indicating positive changes in annual sum of daily temperature and precipitation. A graphical representation of the coefficients associated with temperature is reported in Figure A3a. Standard errors are clustered at the country-level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: Dryness and wetness shocks and sectoral GVA.

	Average dryness (1)	Extreme drought prevalence (2)	Extreme wetness prevalence (3)
Agriculture, hunting, forestry, fishing	-0.119***	-0.0733***	-0.00346
	(0.0197)	(0.0126)	(0.0116)
Construction	0.0184	0.0281**	-0.00293
	(0.0156)	(0.0135)	(0.0133)
Mining, Manufacturing, Utilities	0.000256	0.00354	0.00218
	(0.0162)	(0.0102)	(0.00818)
Other Activities	0.00204	-0.000846	0.00545
	(0.00813)	(0.00459)	(0.00474)
Transport, storage and communication	0.0184	0.0143	-0.00588
	(0.0119)	(0.00916)	(0.00785)
Wholesale, retail trade, restaurants and hotels	0.00414	-0.00304	0.00900
	(0.0117)	(0.00846)	(0.00869)
GVA growth rate$_{t-1}$	0.0687**	0.0605**	0.0605**
	(0.0282)	(0.0263)	(0.0263)
Country-Sector FE	✓	✓	✓
Sector-Year FE	✓	✓	✓
N	35911	49578	49578
adj. R^2	0.049	0.047	0.046

Notes: The table reports the (standardized) sector-specific coefficients associated with the three measures in first difference constructed from the SPEI database. A graphical representation of the coefficients is reported in Figure A10. Column (1) uses a measure of average dryness (as the average of monthly negative realizations of SPEI in each country), column (2) uses extreme drought prevalence as the maximum share of grid-months with extreme drought conditions (SPEI<-2); column (3) uses extreme wetness as the maximum share of grid-months with extreme wetness conditions (SPEI>2) in a country in a year. Standard errors are clustered at the country-level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A11: Tropical cyclones and sectoral GVA.

	GVA per capita growth rate		
	(1)	(2)	(3)
Agriculture, hunting, forestry, fishing	-0.0288**	-0.0297**	-0.0315***
	(0.0125)	(0.0126)	(0.0119)
Construction	-0.00735	-0.00749	-0.00717
	(0.00642)	(0.00648)	(0.00651)
Mining, Manufacturing, Utilities	-0.000445	-0.000488	0.000405
	(0.00723)	(0.00737)	(0.00767)
Other Activities	-0.00500*	-0.00504*	-0.00603**
	(0.00278)	(0.00282)	(0.00289)
Transport, storage and communication	-0.00101	-0.00107	-0.000670
	(0.00404)	(0.00410)	(0.00376)
Wholesale, retail trade, restaurants and hotels	-0.00444	-0.00463	-0.00412
	(0.00641)	(0.00637)	(0.00657)
GVA growth rate$_{t-1}$		0.0262	0.0417
		(0.0259)	(0.0264)
Country-Sector FE	✓	✓	✓
Sector-Year FE	✓	✓	✓
Country linear time trends		✓	✓
Country quadratic time trends			✓
N	44167	44167	44167
adj. R^2	0.053	0.053	0.053

Notes: The table reports the sector-specific (standardized) coefficients associated with the changes in wind speed as constructed in Kunze (2021). A graphical representation of the coefficients estimated in column (1) is reported in Figure A11. Standard errors are clustered at the country-level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Tropical cyclones data are available until 2015.

Table A12: Sector-country damages (% loss GVA per capita) significant at 95% level

Country	Sector	Average loss	95% CI
Afghanistan	Agriculture	0.48	[0.14 0.81]
Albania	Agriculture	0.42	[0.06 0.79]
Algeria	Agriculture	0.22	[0.01 0.43]
Andorra	Agriculture	0.17	[0.08 0.28]
Angola	Agriculture	0.91	[0.18 1.66]
Argentina	Agriculture	0.44	[0.04 0.86]
Australia	Agriculture	0.41	[0.06 0.77]
Austria	Agriculture	0.37	[0.15 0.59]
Azerbaijan	Agriculture	-0.70	[-1.35 -0.07]
Bahrain	Agriculture	0.17	[0.07 0.28]
Bangladesh	Agriculture	0.45	[0.11 0.79]
Belize	Agriculture	0.86	[0.07 1.65]
Benin	Agriculture	0.43	[0.15 0.71]
Bosnia and Herzegovina	Agriculture	-0.11	[-0.18 -0.03]
Botswana	Agriculture	0.15	[0.06 0.25]
Brazil	Agriculture	0.63	[0.10 1.18]
Brunei	Agriculture	0.55	[0.15 0.95]
Bulgaria	Agriculture	0.30	[0.12 0.48]
Burkina Faso	Agriculture	0.42	[0.12 0.72]
Burundi	Agriculture	0.57	[0.02 1.13]
Cambodia	Agriculture	0.29	[0.05 0.53]
Cameroon	Agriculture	0.66	[0.27 1.07]
Central African Republic	Agriculture	0.50	[0.09 0.92]
Chad	Agriculture	0.69	[0.22 1.17]
Chile	Agriculture	0.20	[0.02 0.37]
Colombia	Agriculture	1.26	[0.15 2.37]
Congo	Agriculture	0.97	[0.23 1.73]
Cote dIvoire	Agriculture	0.50	[0.13 0.87]
Croatia	Agriculture	0.30	[0.09 0.49]
Cyprus	Agriculture	0.32	[0.10 0.53]
DR Congo	Agriculture	0.71	[0.29 1.14]
Denmark	Agriculture	0.38	[0.05 0.72]
Djibouti	Agriculture	0.56	[0.15 0.94]
Dominican Republic	Agriculture	0.80	[0.21 1.36]
Ecuador	Agriculture	1.13	[0.37 1.85]
Egypt	Agriculture	0.74	[0.24 1.21]
El Salvador	Agriculture	0.61	[0.20 1.01]
Eritrea	Agriculture	0.24	[0.08 0.40]
Ethiopia	Agriculture	-0.35	[-0.71 0.00]
Finland	Agriculture	0.15	[0.06 0.25]
France	Agriculture	0.31	[0.08 0.53]
Gabon	Agriculture	0.83	[0.36 1.32]
Georgia	Agriculture	-0.44	[-0.70 -0.19]
Germany	Agriculture	0.40	[0.04 0.76]
Ghana	Agriculture	0.43	[0.20 0.68]
Greece	Agriculture	0.62	[0.18 1.03]
Guatemala	Agriculture	0.61	[0.27 0.96]
Guyana	Agriculture	0.51	[0.22 0.81]
Haiti	Agriculture	0.56	[0.16 0.95]
Honduras	Agriculture	0.47	[0.09 0.83]
Hungary	Agriculture	0.23	[0.10 0.37]
India	Agriculture	0.37	[0.04 0.70]
Indonesia	Agriculture	0.97	[0.45 1.52]
Israel	Agriculture	0.48	[0.15 0.82]
Italy	Agriculture	0.59	[0.13 1.04]
Jamaica	Agriculture	0.77	[0.34 1.23]
Jordan	Agriculture	0.40	[0.17 0.63]
Kenya	Agriculture	0.54	[0.23 0.87]
Kuwait	Agriculture	0.31	[0.09 0.53]
Kyrgyzstan	Agriculture	-0.23	[-0.40 -0.07]
Laos	Agriculture	0.40	[0.17 0.63]
Lebanon	Agriculture	0.41	[0.16 0.67]
Lesotho	Agriculture	0.42	[0.12 0.71]
Liberia	Agriculture	0.37	[0.14 0.60]
Libya	Agriculture	0.31	[0.11 0.51]
Liechtenstein	Agriculture	0.34	[0.14 0.55]
Lithuania	Agriculture	0.32	[0.04 0.60]
Luxembourg	Agriculture	0.23	[0.01 0.45]
Madagascar	Agriculture	0.75	[0.31 1.19]
Malaysia	Agriculture	0.69	[0.28 1.11]
Mali	Agriculture	0.39	[0.10 0.66]
Mauritania	Agriculture	0.32	[0.05 0.58]
Mexico	Agriculture	0.43	[0.08 0.78]
Mongolia	Agriculture	0.74	[0.06 1.42]
Morocco	Agriculture	0.44	[0.03 0.85]
Mozambique	Agriculture	0.45	[0.05 0.84]
Namibia	Agriculture	0.56	[0.24 0.90]
New Caledonia	Agriculture	-0.51	[-0.96 -0.09]
Niger	Agriculture	0.49	[0.16 0.80]
Nigeria	Agriculture	0.63	[0.15 1.09]
Norway	Agriculture	0.24	[0.02 0.47]
Oman	Agriculture	0.54	[0.25 0.85]
Pakistan	Agriculture	0.15	[0.02 0.27]
Panama	Agriculture	0.56	[0.24 0.89]
Papua New Guinea	Agriculture	0.83	[0.38 1.31]
Philippines	Agriculture	0.73	[0.31 1.18]
Poland	Agriculture	0.29	[0.04 0.57]
Romania	Agriculture	0.39	[0.00 0.79]
Rwanda	Agriculture	0.94	[0.06 1.82]
San Marino	Agriculture	0.35	[0.09 0.60]
Saudi Arabia	Agriculture	0.84	[0.16 1.54]
Senegal	Agriculture	0.14	[0.01 0.27]
Serbia	Agriculture	-0.09	[-0.17 -0.01]
Singapore	Agriculture	0.58	[0.17 1.00]
Slovakia	Agriculture	0.41	[0.18 0.65]
Slovenia	Agriculture	0.31	[0.13 0.49]
Somalia	Agriculture	0.52	[0.01 1.04]
South Africa	Agriculture	0.43	[0.10 0.76]
South Korea	Agriculture	0.15	[0.07 0.24]
South Sudan	Agriculture	0.85	[0.37 1.33]
Sudan	Agriculture	0.54	[0.23 0.86]
Suriname	Agriculture	0.55	[0.21 0.89]
Sweden	Agriculture	0.21	[0.09 0.33]
Switzerland	Agriculture	0.29	[0.12 0.46]
Syria	Agriculture	0.41	[0.18 0.65]
Tanzania	Agriculture	0.77	[0.34 1.22]
Thailand	Agriculture	0.06	[0.01 0.11]
Togo	Agriculture	0.56	[0.03 1.08]
Trinidad and Tobago	Agriculture	0.63	[0.18 1.11]
Tunisia	Agriculture	0.30	[0.07 0.51]
Turkey	Agriculture	0.72	[0.13 1.29]
UAE	Agriculture	0.46	[0.17 0.76]
UK	Agriculture	0.20	[0.02 0.38]
Uganda	Agriculture	0.57	[0.25 0.90]
Uruguay	Agriculture	0.28	[0.08 0.49]
Venezuela	Agriculture	1.11	[0.26 2.01]
Viet Nam	Agriculture	0.65	[0.03 1.31]
Zambia	Agriculture	0.22	[0.05 0.39]
Belarus	Construction	-0.36	[-0.66 -0.05]
Cote dIvoire	Construction	0.75	[0.15 1.37]
Croatia	Construction	0.27	[0.02 0.53]
Cuba	Construction	0.84	[0.19 1.51]
Cyprus	Construction	0.39	[0.07 0.73]
Czech Republic	Construction	-2.02	[-3.87 -0.17]
Denmark	Construction	0.89	[0.21 1.60]
Djibouti	Construction	1.04	[0.26 1.85]
Dominican Republic	Construction	1.64	[0.43 2.88]
Ecuador	Construction	1.04	[0.09 2.03]
Egypt	Construction	0.91	[0.16 1.66]
El Salvador	Construction	0.63	[0.08 1.21]
Eritrea	Construction	0.15	[0.03 0.26]
Estonia	Construction	-1.05	[-1.95 -0.16]
Georgia	Construction	-0.87	[-1.61 -0.17]
Germany	Construction	1.00	[0.23 1.80]
Greece	Construction	1.11	[0.27 1.98]
Greenland	Construction	1.05	[0.26 1.88]
Guatemala	Construction	0.77	[0.09 1.50]
Guinea	Construction	1.25	[0.25 2.26]
Haiti	Construction	1.17	[0.30 2.08]
Honduras	Construction	0.90	[0.23 1.59]
Iceland	Construction	0.56	[0.08 1.04]
India	Construction	0.72	[0.17 1.28]
Iran	Construction	1.39	[0.34 2.47]
Iraq	Construction	0.81	[0.16 1.47]
Ireland	Construction	0.28	[0.02 0.53]
Italy	Construction	1.30	[0.33 2.32]
Jamaica	Construction	0.75	[0.03 1.51]
Japan	Construction	1.40	[0.29 2.51]
Jordan	Construction	0.44	[0.05 0.85]
Kazakhstan	Construction	-0.64	[-1.28 -0.05]
Kuwait	Construction	1.00	[0.23 1.79]
Kyrgyzstan	Construction	-1.09	[-1.97 -0.25]
Laos	Construction	0.47	[0.06 0.90]
Latvia	Construction	1.54	[0.24 2.82]
Lebanon	Construction	0.56	[0.08 1.04]
Lesotho	Construction	0.99	[0.25 1.76]
Liberia	Construction	0.70	[0.18 1.25]
Libya	Construction	0.58	[0.14 1.03]
Liechtenstein	Construction	0.50	[0.09 0.92]
Lithuania	Construction	0.72	[0.17 1.29]
Luxembourg	Construction	0.77	[0.16 1.38]
Malawi	Construction	1.36	[0.26 2.45]
Maldives	Construction	1.35	[0.34 2.39]
Mali	Construction	0.88	[0.22 1.57]
Malta	Construction	0.55	[0.11 1.01]
Mauritania	Construction	0.59	[0.14 1.05]
Mexico	Construction	1.18	[0.26 2.12]
Moldova	Construction	-0.18	[-0.34 -0.03]
Monaco	Construction	0.43	[0.05 0.82]
Mongolia	Construction	0.90	[0.19 1.64]
Montenegro	Construction	0.94	[0.14 1.73]
Morocco	Construction	0.87	[0.21 1.56]
Mozambique	Construction	0.90	[0.22 1.61]
Myanmar	Construction	0.58	[0.13 1.04]
Namibia	Construction	0.50	[0.01 1.02]
Nepal	Construction	0.24	[0.04 0.44]
Netherlands	Construction	1.21	[0.23 2.17]
New Zealand	Construction	0.34	[0.09 0.61]
North Korea	Construction	1.60	[0.26 2.93]
Norway	Construction	0.92	[0.20 1.66]
Pakistan	Construction	0.36	[0.09 0.65]
Panama	Construction	0.72	[0.10 1.35]
Paraguay	Construction	1.02	[0.24 1.82]
Peru	Construction	1.58	[0.23 2.89]
Portugal	Construction	1.35	[0.20 2.46]
Qatar	Construction	0.77	[0.16 1.40]
Spain	Construction	1.73	[0.34 3.11]
Sri Lanka	Construction	0.48	[0.11 0.87]
Sudan	Construction	0.74	[0.13 1.37]
Suriname	Construction	0.66	[0.08 1.27]
Swaziland	Construction	0.96	[0.20 1.72]
Sweden	Construction	0.58	[0.15 1.03]
Switzerland	Construction	0.41	[0.07 0.76]
Syria	Construction	0.52	[0.06 1.01]
TFYR Macedonia	Construction	0.67	[0.08 1.23]
Tanzania	Construction	1.15	[0.19 2.13]
Thailand	Construction	0.20	[0.05 0.36]
Togo	Construction	1.45	[0.34 2.59]
Tunisia	Construction	0.66	[0.17 1.18]
Turkey	Construction	1.40	[0.36 2.49]
Turkmenistan	Construction	-1.21	[-2.22 -0.20]
UK	Construction	0.73	[0.14 1.31]
USA	Construction	1.15	[0.27 2.06]
Uganda	Construction	0.66	[0.03 1.31]
Ukraine	Construction	-0.69	[-1.30 -0.08]
Uzbekistan	Construction	-0.67	[-1.21 -0.16]
Viet Nam	Construction	0.55	[0.04 1.07]
Chile	Other activities	0.28	[0.01 0.62]
France	Other activities	0.67	[0.01 1.47]
Czech Republic	Transport. storage. communications	-0.80	[-1.66 0.00]
Ireland	Transport. storage. communications	0.16	[0.00 0.33]
Cuba	Wholesale, retail, hotel, restaurant	0.48	[0.01 0.94]
Czech Republic	Wholesale, retail, hotel, restaurant	-0.79	[-1.60 0.00]
Denmark	Wholesale, retail, hotel, restaurant	0.66	[0.02 1.29]
Eritrea	Wholesale, retail, hotel, restaurant	0.22	[0.00 0.42]
Estonia	Wholesale, retail, hotel, restaurant	-0.30	[-0.58 -0.01]
Germany	Wholesale, retail, hotel, restaurant	0.74	[0.02 1.43]
Guinea	Wholesale, retail, hotel, restaurant	0.68	[0.02 1.33]
India	Wholesale, retail, hotel, restaurant	0.39	[0.00 0.77]
Iraq	Wholesale, retail, hotel, restaurant	0.56	[0.02 1.10]
Ireland	Wholesale, retail, hotel, restaurant	0.17	[0.01 0.33]
Italy	Wholesale, retail, hotel, restaurant	0.78	[0.01 1.53]
Japan	Wholesale, retail, hotel, restaurant	0.96	[0.03 1.87]
Kyrgyzstan	Wholesale, retail, hotel, restaurant	-0.40	[-0.79 0.00]
Latvia	Wholesale, retail, hotel, restaurant	0.65	[0.03 1.26]
Lithuania	Wholesale, retail, hotel, restaurant	0.50	[0.01 0.98]
Luxembourg	Wholesale, retail, hotel, restaurant	0.31	[0.01 0.61]
Malawi	Wholesale, retail, hotel, restaurant	0.62	[0.02 1.20]
Maldives	Wholesale, retail, hotel, restaurant	1.05	[0.03 2.04]
Mauritania	Wholesale, retail, hotel, restaurant	0.22	[0.00 0.44]
Mexico	Wholesale, retail, hotel, restaurant	0.70	[0.01 1.37]
Montenegro	Wholesale, retail, hotel, restaurant	0.49	[0.02 0.96]
Morocco	Wholesale, retail, hotel, restaurant	0.43	[0.00 0.85]
Mozambique	Wholesale, retail, hotel, restaurant	0.51	[0.01 1.01]
Myanmar	Wholesale, retail, hotel, restaurant	0.56	[0.02 1.08]
Nepal	Wholesale, retail, hotel, restaurant	0.21	[0.01 0.40]
Netherlands	Wholesale, retail, hotel, restaurant	0.55	[0.01 1.06]
Norway	Wholesale, retail, hotel, restaurant	0.38	[0.01 0.74]
Pakistan	Wholesale, retail, hotel, restaurant	0.24	[0.01 0.46]
Peru	Wholesale, retail, hotel, restaurant	1.06	[0.05 2.06]
Portugal	Wholesale, retail, hotel, restaurant	0.61	[0.03 1.20]
Spain	Wholesale, retail, hotel, restaurant	0.77	[0.02 1.50]
Sri Lanka	Wholesale, retail, hotel, restaurant	0.39	[0.01 0.76]
Swaziland	Wholesale, retail, hotel, restaurant	0.38	[0.01 0.75]
TFYR Macedonia	Wholesale, retail, hotel, restaurant	0.20	[0.01 0.39]
Togo	Wholesale, retail, hotel, restaurant	0.59	[0.01 1.17]
Turkmenistan	Wholesale, retail, hotel, restaurant	-0.40	[-0.79 -0.01]
UK	Wholesale, retail, hotel, restaurant	0.51	[0.02 0.99]
USA	Wholesale, retail, hotel, restaurant	1.81	[0.07 3.51]
Ukraine	Wholesale, retail, hotel, restaurant	-0.21	[-0.42 -0.01]

Notes: The table reports the average loss for each sector as a % loss in GVA per capita relative to the observed production between 2001 and 2020, accounting for own, domestic and foreign heat shocks. 95% confidence intervals are obtained from 1000 estimates from bootstrapping Equation 8.

A.3 Computing the economic cost of the propagation of recent warming

To understand the differential cost of propagation of recent warming, I use the estimates of Equation (8) for the marginal effect of own, domestic and foreign heat shocks to simulate how much slower or faster each sector would have grown annually over the 2001-2020 period, compared to a scenario under which the number of *hot* days above the 95^{th} percentile increases according to its historical trend of 1970-2000. To do so, I estimate country-specific regressions of the type $T_{ct} = \alpha_c + \beta_c t + \varepsilon_{ct}$ in the 1970-2000 sample, where T_{ct} is the number of days above the 95^{th} percentile of the country-specific daily average temperature distribution, to obtain country-specific trends and use $\hat{\beta}_c$ to construct a counterfactual scenario $\tilde{T}^{95}_{sct}$ of the number of *hot* days. I assume that the trend is linear and such trend does not affect the volatility of temperature shocks, which most likely results in an under-estimation of the adverse effects.

I then average these effects over 2001-2020 period to obtain a sector-specific relative measure of estimated losses in value added. I finally compare the estimated losses in value omitting and accounting for the transmission of shocks across countries through trade interlinkages. As in Burke and Tanutama (2019), this computation does not necessarily represent the differential impact of recent anthropogenic warming accounting for network shocks and is instead agnostic to the cause of recent warming.

First, I compute the annual cost/benefit of annual warming in 2001-2020 compared to a counterfactual scenario in which the 1970-2000 average number of heat shocks evolves linearly and distinguish between omitting and accounting for weather shocks in trade partners:

$$g^{direct}_{sct} = \widehat{\gamma}_s (T^{95}_{sct} - \tilde{T}^{95}_{sct}) \tag{10}$$

$$g^{spillover}_{sct} = (\widehat{\gamma}_s T^{95}_{sct} + \widehat{\gamma^D}_s T^{95,D}_{sct} + \widehat{\gamma^F}_s T^{95,F}_{sct}) - (\widehat{\gamma}_s \tilde{T}^{95}_{sct} + \widehat{\gamma^D}_s \tilde{T}^{95,D}_{sct} + \widehat{\gamma^F}_s \tilde{T}^{95,F}_{sct}) \tag{11}$$

where T^{95}_{ct} is the observed number of days above 95^{th} percentile in sector s in country c in year t, $\tilde{T}^{95}_{sct}$ is the counterfactual predicted number had the 1970-2000 average evolved linearly, $T_{sct}^{95,J}$ is the weighted average number of days above 95$^{\text{th}}$ percentile in trade partners J (where J $\in$ {Foreign, Domestic}) from the perspective of sector s in country c in year t. γ_s's are the sector-specific coefficient estimates for the effect of own, domestic and foreign heat shocks on sectoral growth rate from Equation (8). I compute sector s's counterfactual value added level in year t omitting and accounting for indirect shocks

$$\hat{Y}_{sct}^{p} = Y_{sct-1} + y_{sct} + g_{sct}^{p} \tag{12}$$

where hatted term indicates a counterfactual, Y is the (log) GVA per capita, y is the observed growth rate and $p \in$ {direct, spillover}. I can then compute the average relative loss in GVA for sector s in country c over the 2001-2020 period as

$$\%\overline{\text{LOSS}}_{sc}^{p} = \frac{1}{T}\sum_{t=2001}^{2020} \frac{e^{\hat{Y}_{sct}^{p}} - e^{Y_{sct}}}{e^{Y_{sct}}} \tag{13}$$

to obtain a measure of the average cost of recent warming at the sector level omitting and accounting for the propagation of heat shocks (reported in Figure A21).

The aggregated average loss in GVA across sectors for country c is

$$\%\overline{\text{LOSS}}_{c}^{p} = \sum_{s} \%\lambda_{sc}\overline{\text{LOSS}}_{sc}^{p} \tag{14}$$

where λ_{sc} is the average share of total GVA of sector s in country c between 2001 and 2020. The country-level losses omitting and accounting for indirect heat shocks are reported in Figure 7.

PUBLICATIONS

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