Sectoral impact and propagation of weather shocks

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Abstract

Despite the intensification of international trade and the fragmentation of production processes, local weather shocks have only been shown to damage local economic activity. This paper introduces the role of input-output sectoral interlinkages as a transmission mechanism of weather shocks in a production network model and tests the empirical implications using a six-sector global dataset from 1975 to 2020. First, I document that agriculture is the most harmed sector by a range of weather shocks, including hot and cold days, droughts, and cyclones. Second, I find that sectors at later stages of the supply chain, though non-responsive to local weather, suffer from substantial and persistent losses over time due to domestic and foreign heat shocks in agriculture that propagate downstream. Using counterfactual scenarios, I show a substantial underestimation of the economic cost of temperature increases accounting for shocks across trade partners since 2000 and I characterize global losses depending on the sectoral centrality in the production network.

Keywords: Climate change, sectoral shocks, spillovers, weather shocks

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1 Introduction

There is a large and urgent demand for data-driven estimates of climate damages to properly account for the benefits of additional climate change mitigation efforts (Newell et al., 2021). Despite recent methodological advancements to estimate the relationship between climatic conditions and economic outcomes (Auffhammer, 2018; Hsiang, 2016), previous empirical studies investigate the responses of local aggregate measures of economic activity to isolated local weather shocks (see Kolstad and Moore (2020) for a review). In an increasingly interconnected world with international trade and supply-chain relations in production networks, the potential transmission of non-local weather shocks is a crucial mechanism for accurate quantification of climate damages. On the one hand, the openness to international trade and the fragmentation of production processes can help increase diversification in the supply chain and lower volatility (Caselli et al., 2020; Nath, 2020), on the other hand, however, it can increase exposure to shocks with effects rippling through the supply chain.

This paper examines how weather shocks heterogeneously affect annual sectoral production and traces their propagation in international production networks over time by using cross-country global sector-level data combined with high-resolution weather data and input-output sectoral interlinkages. To show the importance of weather shocks hitting other sectors and affecting sectoral production through sectoral interlinkages, I formalize a model of production networks (Acemoglu, Akcigit, et al., 2016; Carvalho & Tahbaz-Salehi, 2019), which provides intuition behind the potential bias of estimates based on local response function estimations to local weather shocks. Neglecting the interconnections among sectors while weather shocks are spatially correlated leads to contraventions of common identifying assumptions, by violating the stable unit treatment value assumption. Consequently, partial equilibrium estimates of the relationship between weather and economic outcomes become biased. This approach highlights a new mechanism in the climate impact literature adding real-world features omitted in previous reduced-form attempts to quantify the economic cost of climate change.

The empirical analysis is conducted in two steps. First, I estimate the sector-specific response in per capita gross value added growth rate to weather shocks in a pooled multi-country sample of sectoral production across 183 countries between 1975 and 2020 for six sectors.[1] The effect of weather shocks on production is identified using plausibly exogenous year-to-year variation in the distribution of daily temperature and precipitation (Carleton et al., 2022; Deschênes & Greenstone, 2011), or in monthly dryness and wind speed to measure respectively droughts and cyclones. Second, I analyze how weather shocks hitting customer/supplier sectors domestically and abroad propagate through input-output interlinkages and affect sectoral economic production. I construct downstream and upstream, domestic and foreign network shocks using the global input-output tables from EORA26 (Kanemoto et al., 2011) combined with a vector of weather shocks.

In line with previous findings (Acevedo et al., 2020; Dell et al., 2012), I document that agriculture is the most harmed sector. In particular, using daily average temperature, I find that heat shocks, defined as an additional day above the 95^{th} percentile of the country-specific daily temperature distribution, reduce the agricultural growth rate by 16% of its sample mean. Using a measure of dryness from the Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010), I document a negative and substantial effect of droughts and dryness conditions on agricultural production. Conversely, drier weather, measured as the number of days below the 5^{th} percentile of the country-specific daily precipitation distribution or dryness conditions, exhibits a positive influence on productivity within the construction domain as well as the transport, storage, and communication sectors. These sectors encompass operational tasks conducted in exposed "interface" areas (Cachon et al., 2012), which exhibit heightened responsiveness to variations in precipitation abundance.

In the second part of the paper, I investigate whether sectors are affected by shocks on trade partners due to their propagation via supply chain interlinkages. I document that domestic and foreign heat shocks, respectively measured as weather shocks weighted by the relative importance of sectoral interlinkages within the same country and abroad, have a strong negative effect on several sectors' output, notably construction; other activities; transport, storage, and communication; wholesale, retail trade, restaurants and hotels.

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

The magnitude of the indirect effect is substantial and comparable to the direct effect of weather shocks on agricultural production. I further examine the mechanisms of the propagation effect and detect heat shocks in the agricultural sector as the main channel of downstream propagation to customer sectors. Results are stronger when accounting for the full propagation using the Leontief inverse matrix. Using local projections (Jordà, 2005), I find that the effect of network shocks is persistent over time, dampening sectoral growth up to five years after the shock.

Finally, I use the estimated parameters from the reduced-form specification as the basis of two counterfactual analyses. First, I quantify the contribution of input-output interlinkages between sectors to the average annual output loss due to recent warming from 2000 onwards. I consider a counterfactual world with no input-output linkages and with linearly trended daily temperatures from their baseline climate in 1970-2000. Accounting for network shocks, recent warming is responsible for an average annual output loss of 0.33%, compared to a 0.1% average loss omitting spillovers. In a second exercise, I obtain the average annual cost conditional on an additional hot day in a specific sub-region or a country. Average annual global costs are at their highest when heat shocks occur in countries with high centrality in the production networks, such as China, Brazil, France, India, and the United States.

Altogether, these findings provide evidence of the role of input-output sectoral interlinkages as an important mechanism for the propagation and amplification of weather shocks. They also highlight a substantial underestimation when omitting sectoral linkages and underline the importance of this channel as a component of the total economic impact of climate change.[2]

The contributions of this article relate to two main strands of literature. First, this paper contributes to the climate economics literature by providing disaggregated 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 (Akyapi et al., 2022; Burke et al., 2015; Burke & Tanutama, 2019; Kahn et al.,

[2]For example, Kahn et al. (2021) show that an average increase by 0.01ºC is associated with 0.02% decrease in the annual growth rate of global economic output (see Tol (2022) for a complete meta-analysis of the economic impact of climate change).

2021; Kalkuhl & Wenz, 2020; Kotz et al., 2021) to measure the impact of temperature fluctuations. Previous articles often use a coarse sectoral tripartition of the economy into agriculture, manufacturing, and services 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 similar sector-disaggregated global analysis of the effect of tropical cyclones, however, estimating each sector's equation separately, whereas Hsiang (2010) focuses only on the Caribbean and Central America area. This paper contributes to this strand of the literature by providing jointly estimated sector-specific response functions to a wide range of weather shocks, covering the whole world with six-sector economic production from 1975 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 (Wenz & Willner, 2022). The existing literature has 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). 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. This paper contributes to the macroeconomic literature on the propagation of shocks by studying weather shocks in the supply chain through sectoral interlinkages. 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 to quantify the economic damages of climate and compute the social cost of carbon, exploring a new channel of transmission of weather shocks that can amplify their effects on the economy.

The remainder of the paper is structured as follows. Section 2 lays out a conceptual framework of the importance of input-output sectoral interlinkages for the empirical estimation of weather shocks. Section 3 describes the data used in the empirical analysis. Section 4 introduces the empirical approach adopted. Section 5 shows and summarizes the sectoral impact of weather shocks. Section 6 contains the main empirical results of the propagation of weather shocks through the economy, which I then use as the basis of counterfactual analyses in Section 7. Section 8 concludes.

2 Conceptual framework

2.1 Local economic response to local weather shocks

This section briefly discusses the conceptual framework underlying the estimates based on local economic response functions to local weather shocks. The majority of the reduced-form climate impact literature motivates productivity specifications with a partial equilibrium model of production (Burke et al., 2015; Dell et al., 2012; Kahn et al., 2021; Kalkuhl & Wenz, 2020). Regardless of the level of spatial disaggregation of the analysis - firm, grid cell, region, or country - production possibilities for each unit $i = 1, .., n$ are usually described by the following neoclassical homogeneous of degree one production function:

$$Y_{it} = \mathcal{F}\left(\mathcal{Z}_{it}, L_{it}, K_i\right) \tag{1}$$

I consider each unit i to be a sector-country and define it as a market. Each market has aggregate total factor productivity $\mathcal{Z}_{it} = \overline{z_i} \cdot \exp(f(T_{it}, \beta_i))$ that comprises unit-specific exogenous non-weather base productivity determinants and a vector of market-specific temperature effects[3], L_{it} is labor (inelastically supplied by workers so that total population can be used as synonym), and K_i is capital.[4] At each time t, in a simple constant returns-to-scale Cobb-Douglas version of the model with $\lambda \in [0, 1]$ the output elasticity of capital, the production function is written as

$$Y_{it} = \overline{z}_i \exp(f(T_{it}, \beta_i)) K_i^{\lambda} L_{it}^{1-\lambda} \tag{2}$$

Taking the log of both sides and rearranging in terms of output per worker, one obtains:

$$\log \frac{Y_{it}}{L_{it}} = \log \overline{z}_i + f(T_{it}, \beta_i) + \frac{\lambda}{1-\lambda} \log \left(\frac{K_i}{Y_{it}} \right) \tag{3}$$

In a reduced-form fixed effects econometric specification, regressing output per capita on a function of temperature and the unit- and period-specific fixed effects that absorb $\overline{z}_i$ would identify the effect of temperature under the assumption that the residual variation in temperature is not correlated with the error term and unit-specific capital-to-output ratio is constant. In a setting without spatially correlated patterns in temperature shocks and where production linkages between sectors and countries are negligible, $\hat{\beta}$ would identify the effect of temperature on production.

2.2 Weather shocks in a production network model

Idiosyncratic micro shocks can propagate through input-output production networks and impose substantial fluctuations at the aggregate level (Acemoglu et al., 2012; Carvalho et al., 2021). In this section, I present a simple model of production networks based on Acemoglu, Akcigit, et al. (2016) and Carvalho and Tahbaz-Salehi (2019) and originally introduced by Leontief (1941) to theoretically found the empirical analysis of heat shocks propagating through the economy by altering input prices/quantities or demand for inter-

[3]For illustrative simplicity, here I consider a simplified example with univariate climate, where productivity only depends on temperature without loss of generality, but one can include a matrix of weather variables and study Jacobian matrices instead of first-order derivatives.

[4]In this framework, I consider Hicks-neutral productivity shocks and abstract from other potential channels of the impact of temperature on production, which could affect effective units of labor input (Nath, 2020) and capital equipment and its effective utilization (Zhang et al., 2018). In this case, estimates of Equation 1 would compound these three channels which cannot be further disentangled.

mediate inputs. This approach captures additional real-world features missing in previous reduced-form attempts to quantify the economic costs of climate change.

Sectors intensively use intermediate inputs produced by other domestic and foreign sectors. I consider a two-tier Cobb-Douglas model of production networks with each sector's production function with constant returns to scale ($\omega_i + \sum_j^n \omega_{ij} = 1$), such that:

$$Y_{it} = \mathcal{Z}_{it}[K_i^{\lambda}, L_{it}^{1-\lambda}]^{\omega_i} \prod_j^n x_{ijt}^{\omega_{ij}} \tag{4}$$

where x_{ijt} is the quantity of intermediate inputs produced by market j used by market i. As before, I assume that, for each i, $\omega_i \in (0, 1]$, and $\omega_{ij} \in [0, 1]$ for all j, where ω_{ij} can be equal to zero if the output of market j is not used as an input by market i. The larger ω_{ij}, the more important sector j is as a supplier of intermediate inputs to sector i. Equation (1) is a simplified case in which input-output loops are removed and the shares of intermediate inputs in production are set equal to zero across all markets, such that $\omega_{ij} = 0$, for each i,j. Equation (4) allows for a rich input-output structure, since the intensity with which each sector's output is used as an intermediate input by other sectors varies across all sector pairs. In particular, input-output linkages between various markets can be summarized by the matrix $\boldsymbol{\Omega} = [\omega_{ij}]$, the direct requirements matrix defined as the first-degree input-output matrix, with some abuse of terminology (Carvalho & Tahbaz-Salehi, 2019). From the sectoral input-output interlinkages, one can also compute the Leontief inverse matrix as $\boldsymbol{L} = (\ \boldsymbol{I} - \boldsymbol{\Omega})^{-1}$, whose (i, j) elements are the importance of sector j as a direct and indirect input supplier to sector i.

Accounting for intermediate inputs sourced from multiple sectors introduces the concept of market access. This is a multilateral term, in which production in market i is a function of all market j's productivities, and therefore markets' temperature distributions (Rudik et al., 2022). Since inputs are sourced from various markets, temperature shocks to other markets can propagate across sectors and national borders and affect production in market i. From the Cobb-Douglas production technology assumed, it follows that a sector's expenditure on various inputs as a fraction of its output is invariant to the shocks and is thus exogenous in the model (Carvalho & Tahbaz-Salehi, 2019).[5]

[5]Carvalho et al. (2021) study a more complex case with the production functions with a nested

3 Data

This section provides a summary of the main data sources used to empirically test the hypothesis that weather shocks affect sectoral production and propagate through input-output interlinkages. To do so, the three major data sets are sector-level economic production (Section 3.1), weather data (Section 3.2), and sectoral interlinkages (Section 3.3).

3.1 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 type of economic activity following the International Standard Industrial Classification (ISIC rev. 3.1). It contains information from 1970 through 2020 for 205 countries.[6] GVA is measured in constant 2015 USD. The data set categorizes sectors into six broad groups (with the respective ISIC code in parentheses), which provides the most comprehensive data set of global economic production disaggregated by sector with the longest time horizon: 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).[7] The latter encompasses, among others, the financial sector, real estate, public administration, education and health. Table A1 presents summary statistics for sectoral production. Although unbalanced, the sector-country panel

constant elasticity of substitution (CES) structure and show the propagation of shocks through two distinct channels using a first-order approximation in the elasticities of substitution between various intermediate inputs or between the intermediates and primary factors of production different from one.

[6]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 A2.

[7]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.

dataset covers all countries in the world for most of the 46 years in the analysis.[8]

3.2 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. Section 3.2.1 describes temperature and precipitation data. Appendix C describes additional weather data used to construct measures of dryness, wetness and cyclones.

3.2.1 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.

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 days in coarser time intervals. This procedure guarantees to maintain weather variability that would be otherwise lost when averaging 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, I aggregate grid-cell level information using time-invariant population weights from the 2000 Landscan dataset (Bright & Coleman, 2001). When constructing measures for the

[8] On average, information for each sector-country tuple is available for 44 years. Most of the sectors are covered for the whole time period except for recent geopolitical changes.

agricultural sector, I weigh grid-cell data by the proportion of each grid cell under cropland in 2000, using the Global Agricultural Lands dataset (Ramankutty et al., 2010). To construct sector-specific weather shocks for certain countries, I rely on Eurostat data on GVA production by industry (NACE Rev. 2) at the sub-national level for 34 European countries[9] and take a weighted average of grid cell-level weather shocks by the average sectoral economic production in the first available five years (no earlier than 1995) for each sub-national administrative unit.

3.3 Sectoral interlinkages

Crucial to the analysis is the identification of domestic and foreign sectoral interlinkages. 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 1970 to 2021 and has the widest geographic coverage in terms of intersectoral linkages.[10] I retain information on the first available five years of the IO matrix (1970-1974) and examine the propagation of weather shocks through a pre-determined constant input-output network that does not endogenously respond to the shock itself.[11] I aggregate the 26 sectors to match the six sectors described in Section 3.1 as reported in Table A3.

[9] I use NUTS-3 level information of 31 countries (Albania, Austria, Belgium, Bulgaria, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Malta, Netherland, Norway, Poland, Portugal, Republic of North Macedonia, Romania, Serbia, Slovakia, Slovenia, Sweden, Türkiye, Serbia, Spain) and NUTS-2 level for three other countries (Cyprus, Luxembourg, Montenegro).

[10] 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.

[11] Kunze (2021) shows a small and negligible shift of sectoral interlinkages after tropical cyclones. I also test for this assumption in Appendix Section D and find little and no statistically significant effect of heat shocks on sectoral interlinkages.

3.3.1 Construction of network shocks

To account for propagation, I construct a measure of *network* shocks that hit other sectors and propagate through input-output interlinkages. I use sector-country level information in the first available five years of the IO matrix (1970-1974) to smooth annual variation and construct a weighting scheme that accounts for the importance of a sector depending on its geographic location and position in the supply chain. In robustness checks, I consider the propagation of weather shocks in a time-varying production network constructed using the first five-year average input-output interlinkages for each decade (see Appendix Section E for details).

First, I distinguish between shocks originating in the same country, domestic, and those originating in others, foreign. 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. 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. A prediction of the conceptual framework in Section 2 is that the supply-side shocks propagate downstream, whereas demand-side shocks propagate upstream (Acemoglu, Akcigit, et al., 2016; Carvalho & Tahbaz-Salehi, 2019). 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.

In addition to the local own shock hitting sector i 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:

$$\text{Shock}_{i,c,t}^{DnD} = \sum_{j\neq i} \omega_{i,c,j,c} \text{Shock}_{j,c,t}^{Own} \tag{5}$$

$$\text{Shock}_{i,c,t}^{UpD} = \sum_{j\neq i} \widehat{\omega}_{i,c,j,c} \text{Shock}_{j,c,t}^{Own} \tag{6}$$

$$\text{Shock}_{i,c,t}^{DnF} = \sum_{j} \sum_{k\neq c} \omega_{i,c,j,k} \text{Shock}_{j,k,t}^{Own} \tag{7}$$

$$\text{Shock}_{i,c,t}^{UpF} = \sum_{j} \sum_{k \neq c} \widehat{\omega}_{i,c,j,k} \text{Shock}_{j,k,t}^{Own} \tag{8}$$

where $\text{Shock}_{j,k,t}^{Own}$ is a weather shock hitting sector j in country k in year t.[12] I take a weighted average of the shocks hitting all sectors that sector i has a linkage with by constructing the weights from the inter-country IO tables described in Section 3.3. Based on previous approaches to model network shocks (Acemoglu, Akcigit, et al., 2016; Acemoglu, Autor, et al., 2016; Das et al., 2022), I construct weights differently for upstream and downstream shocks. From the perspective of sector i in country c, for downstream shocks, I construct weights as

$$\omega_{i,c,j,k} = \frac{\overline{input}_{jk \to ic}}{\sum\limits_{lf \in \Theta_{ic}} \overline{input}_{ic \to lf}} \tag{9}$$

i.e., the ratio of the inputs that sector i (in country c) uses that are produced by sector j (in country k) over the total inputs supplied to its set of customer sector-countries Θ_{ic}. These weights represent downstream propagation since they reflect how much input from sector-country jk is needed to produce one unit of output of sector-country ic (Acemoglu, Akcigit, et al., 2016). Conversely, the weights associated with measures of upstream shocks are constructed as

$$\widehat{\omega}_{i,c,j,k} = \frac{\overline{input}_{ic \to jk}}{\sum\limits_{lf \in \Theta_{ic}} \overline{input}_{ic \to lf}} \tag{10}$$

i.e., the ratio of the inputs of sector i (in country c) to each sector j (in country k) over the total inputs supplied to its set of customers Θ_{ic}. These represent upstream weights since they reflect the importance of each customer for the sector-country of interest ic.

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 ($\overline{\omega}_{icjk}$).

[12]Except for the agricultural sector all over the world and for all sectors in 33 European countries, weather shocks are not sector-specific, as detailed in Section 3.2.

4 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.

4.1 Local economic sector-specific response to local weather shocks

I estimate the sector-specific output-weather relationship using a pooled sample of sectoral GVA per capita growth rates across 183 countries over 45 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

$$\Delta \log(GVA)_{ict} = f_i(\mathbf{W}_{(i)ct}) + \alpha_{ic} + \mu_{it} + \varepsilon_{ict} \tag{11}$$

where I regress the growth rate of GVA per capita in sector i in country c in year t (approximated by the first difference in logarithms) on a sector-specific function of weather variables $\mathbf{W}$ in country c in year t. I include country-sector fixed effects to account for unobserved heterogeneity that influences countries' average sectoral growth rates, such as history, culture, or topography and time-invariant sectoral compositions of national output (Burke et al., 2015), and sector-year fixed effect to capture 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 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 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 in the same country over time.

Equation (11) relies on usual identifying assumptions in the climate impact literature (Hsiang, 2016), by exploiting plausibly exogenous within-country variation in changes in weather fluctuations, orthogonal to changes in sectoral economic production and to weather in spatial units different than i. 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.

From the beginning of the reduced-form approaches to the output-weather relation (Dell et al., 2012), temperature has been used in levels to estimate its impact on economic growth (Acevedo et al., 2020; Burke et al., 2015; Henseler & Schumacher, 2019). Since the GVA growth rate is stationary and temperature fluctuations in levels are non-stationary, studying the relationship between these two variables would reintroduce trends in the specification (for a deeper discussion, see Tol (2022) and Appendix Section F). For this reason, when I use temperature in levels, I consider it in first-differenced changes (see Appendix Section G) (Akyapi et al., 2022; Letta & Tol, 2019; Newell et al., 2021).[13] Although the use of changes in weather variables 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 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.

Using first-differenced weather changes, however, does not inform how atypical the weather realization was with respect to individual expectations since it neglects any information provided by the levels and assumes that individuals rationally update their beliefs annually, implicitly assuming an instantaneous model of adaptation. On the one hand, introducing both temperature levels and changes simultaneously would not resolve the trend problem surrounding the output growth specifications adopted in the literature (Kalkuhl & Wenz, 2020). On the other hand, weather realizations above or below certain absolute thresholds (e.g., 30°C) and binned response functions may not be globally informative since only a subset of countries experiences such levels, driving the variation and

[13] 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.

raising concerns on potential endogeneity (Osberghaus & Schenker, 2022).

For this reason, I rely on the fact that people's climate beliefs reflect long-run climatic conditions (Zappalà, 2023), and adaptive responses could reduce the impact of weather fluctuations on production if societies can anticipate them based on their expectations (Shrader, 2021). I consider country-specific temperature and precipitation distributions and compute the annual number of days that belongs to the p^{th}-percentile of the country-specific temperature and precipitation daily distribution over the fifty-year period (where $p \in \{1; 5; 10; 90; 95; 99\}$). These events should 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. Using this methodology, the measure is evenly distributed across countries, and any abnormal realization is compared to the country-specific climatic norm. Country-specific time-invariant thresholds account for the influence of long-run adaptation to climatic conditions on the effects of certain weather realizations. 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 (Carleton et al., 2022; Rode et al., 2021).

4.2 Propagation of weather shocks

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 this section, I design an econometric specification that examines a new impact channel of weather shocks rippling through the supply chain via sectoral interlinkages. To examine the importance of *network shocks* relative to own shocks on sectoral activity, I estimate the following econometric specification

$$\Delta \log(GVA)_{ict} = \gamma_i Shock_{ct}^{Own} + \sum_J \gamma_i^J Shock_{ct}^J + \alpha_{ic} + \mu_{it} + \eta_{ict} \tag{12}$$

where I expand Equation (11) 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 i with other sectors in the same country c and other countries (i.e., $J \in \{\text{D; F}\}$). Then, I also disentangle upstream and downstream weather shocks (i.e., $J \in \{\text{DnD; UpD; DnF; UpF}\}$).

This approach aims at quantifying the impact on sectoral production of trade-induced exposure to weather shocks in other sectors. Weather shocks elsewhere affect sectoral market access which could improve or deteriorate depending on market forces and trade relationships with other sectors. Although this paper does not 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, capital equipment efficiency), this approach uncovers the role of the propagation channel for quantifying sectoral weather shocks. 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. A negligible or null direct effect of weather shocks on a given sector may be amplified by weather shocks hitting other sectors with strong commercial interlinkages.

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 (Dingel et al., 2021). For this reason, the estimates obtained in Equation (11) of the effect of local weather variations on local economic production may be biased when omitting trade linkages across observational units while weather shocks are spatially correlated by violating the stable unit treatment value assumption (SUTVA). Spatial considerations are of first-order relevance because the economy and climate are linked across space, which results in violations of common identifying assumptions with first-order effects. One approach to address this concern is to use economic primitives as the outcome of the regression, such as productivity or the share of expenditure on goods from other markets over own expenditures. This approach eliminates the multilateral trade effects and correlated spatial patterns in temperature shocks (Rudik et al., 2022). By comparison, the use of local economic production measures such as GDP, value added in productivity, or other proxies including nighttime lights suffers from bias induced by spatial considerations through the multilateral trade effects and correlated spatial patterns in temperature.

The direction of the bias is ex-ante ambiguous since it depends on market forces, the network structure of the trade relationship and on the supply chain position of the treated trade partners (Acemoglu, Akcigit, et al., 2016). Most importantly, differently from other sectoral shocks previously studied (Atalay, 2017), weather shocks can a priori be either demand- or supply-side shocks. On the one hand, they can induce changes in input demands by customer sectors. In this case, weather-induced demand shocks would propagate upstream and affect suppliers of the sectors hit. At the same time, network weather shocks can have a positive effect on sectoral production through improvements in market access, due to the lower productivity of its competitors. On the other hand, an adverse weather shock can reduce the production of a sector (Graff Zivin et al., 2018; Nath, 2020), and induce an increase in the price. This effect would ripple down to downstream customer sectors to use the input less intensively and thus reduce their own production. Through these two mechanisms, non-local weather shocks can impact sectoral production creating powerful propagation. Omitting market access from the estimating equation will bias the estimate of the effect of own temperature which will also capture the market access effect. The simplified conceptual framework with a Cobb-Douglas production function facilitates the study of the two mechanisms at play where downstream effects emerge only in the case of supply-side shocks and upstream effects from demand-side shocks.

5 Sectoral impact of weather shocks

I first explore the extent to which local abnormal temperature and precipitation realizations affect sectoral economic production. In Appendix Section G, I present the results using alternative measures of temperature and precipitation and in Appendix Section H, I discuss the sector-specific impact of droughts and cyclones.

5.1 Abnormal weather realizations

I exploit within-sector year-to-year fluctuations in changes in temperature and precipitation to identify their causal effect on economic sectoral 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 (11). This model allows me to jointly estimate responses of sectoral economic production to weather shocks and compare the different response functions. I estimate the effect of an increase in the number of days of abnormal weather realizations in a year both for temperature and precipitations. 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 1 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 1a confirms findings consistent with the prior literature that agriculture is the sector that is most harmed 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 (16% of its sample mean). Cold temperature shocks have a similar effects 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 8% of its sample mean. Most of the other sectors seem not to respond to temperature shocks, neither hot nor cold, and estimates 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 1b) except for a positive effect of an additional day of precipitations above the 95^{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. To partially address the first concern, in Section H, I further explore sector-specific responses to a 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 show for aggregate measures of economic activity in Europe (Holtermann, 2020) and across the world (Damania et al., 2020; Kotz et al., 2022) that precipitation anomalies reduce economic growth. Future data collection efforts should be steered towards globally comprehensive measures of disaggregated sectoral production at finer geographic levels.

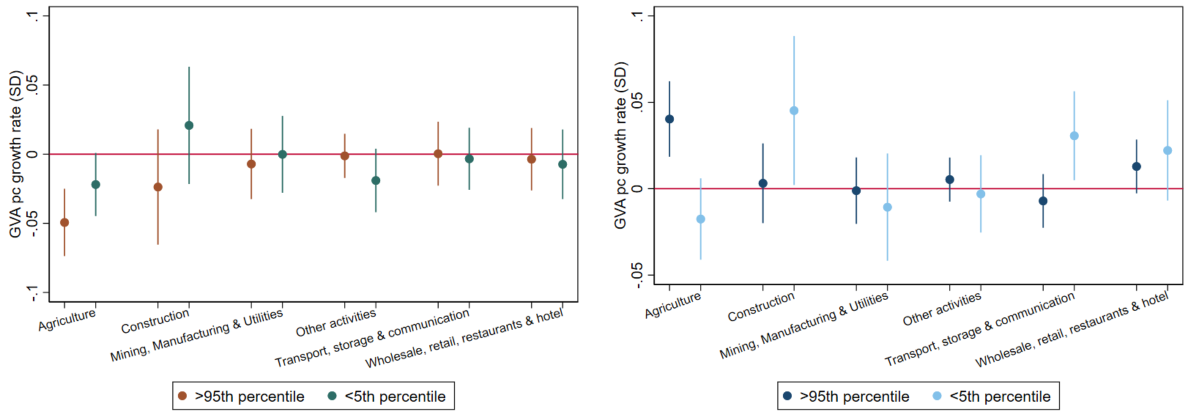
The baseline results are robust to how "abnormal" is defined, whether I use the top/bottom first or tenth percentile of the daily distribution (Figures A7 and A8 replicate the same exercise using the 1^{st} and 99^{th}, and 10^{th} and 90^{th} percentile). Results are also robust to estimating the baseline equation in a balanced panel (Figure A9a), excluding large countries (i.e., Brazil, China, India, Russia, US) that may suffer from aggregation bias in cross-country analysis (Figure A9b) and controlling for lagged growth rate and including linear and quadratic country-specific time trends or sub-region by year fixed effects (Figure A9c).

Time-varying climate norms. 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 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). In all three cases,

Figure 1: 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 95th and below the 5th 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.

I consider data starting from 1990 to compare estimates across time-varying historical norms with different time spans from the same sample.

Figure A10 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 evidence of adaptation to abnormally cold shocks with the point estimate that is not significant using a 40-year climate norm and increases in magnitude and becomes statistically significant as one increases the speed of adaption and belief formation up to 20 years. One cannot reject the hypothesis that adaptation has not taken place in other sectors (transport, storage and communication; other activities), where output losses are mitigated, and sometimes become gains, for faster time-varying climate norms. Results are similar and robust to the use of the 1st and 99th, and 10th and 90th percentile (Figures A11 and A12).

6 Propagation of weather shocks

In this section, I investigate the propagation of weather shocks across the economy through input-output networks. I focus on abnormal weather realizations as a shock. Appendix Section I discusses the propagation of extreme drought prevalence and tropical cyclones as two additional weather shocks.

6.1 Abnormal weather realizations

I consider the number of days above the 95^{th} percentile of the country-specific temperature daily distribution and estimate Equation (12) including an average of the heat shocks in domestic and foreign trade partners weighted by the input-output interlinkages at the baseline with each specific sector.

Domestic and foreign shocks. Figure 2 displays the standardized estimated coefficients associated with own and *network* heat shocks decomposed into domestic and foreign with the vertical error bars indicating 95% confidence intervals based on clustered standard errors at the level of the country. The coefficient on the direct heat shock is negative and significant only for agriculture, replicating the results in Section 5. Domestic shocks have a significant negative and sizable effect on economic production in the sectors of construction, transport, storage and communication, and wholesale, retail trade, restaurants, and hotels. The effect of domestic heat shocks on mining, manufacturing and utilities, and other activities is also negatively but imprecisely estimated. In particular, the magnitude of the effect of domestic network shocks is substantially large for the construction sector, which relies heavily on various inputs from agriculture (e.g., timber, bamboo, straw and hay, natural fibers, plant-based binders, soil and gravel, biofuels, geotextiles) and produces investment goods, more vulnerable to climate change than e.g. the retail sector, which primarily produces consumption services (Casey et al., 2021). Foreign shocks also have a negative significant effect on sectoral production of other activities and wholesale, retail, restaurants and hotels. These results indicate that heat shocks propagate to other sectors which are usually non-responsive to direct weather shocks.

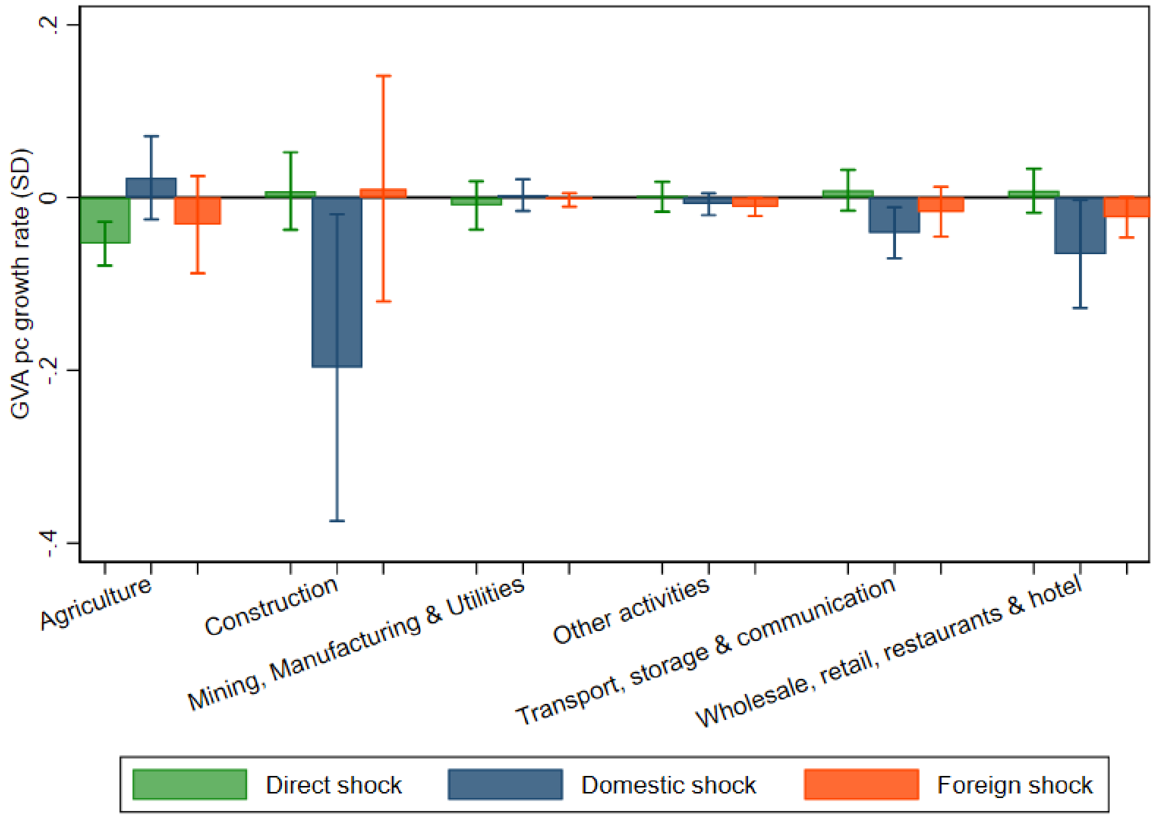
These findings have two consequences in the interpretation of previous results. First, sector-specific estimates that account only for the direct impact of weather shocks may be biased since shocks propagating from other sectors are omitted. This result underlines the importance of separately capturing direct and indirect effects and the statistical significance of coefficients on *foreign* network weather shocks suggests that also geographically distant weather realizations matter through trade interlinkages. Second, until now, the climate impact literature has focused on sector-specific impacts (Carleton & Hsiang, 2016) and identified agriculture as the most affected sector. Nevertheless, accounting for input-output interlinkages shows that weather shocks are amplified in the economy and *indirectly* affect 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.[14]

Dry network shocks. An additional result from the sectoral analysis in Section 5 shows that sectors mostly relying on "interface" areas benefit from extremely drier conditions. I further explore the robustness of these results when accounting for days below the 5^{th} percentile of the precipitation distribution for each country-sector in the trade network. Figure A14 shows the estimates associated with dry direct, domestic and foreign shocks. When accounting for drier conditions elsewhere in the production network, the sectors of construction and transport, storage and communication show a net overall negative effect, raising further concerns about the validity of naive local weather-local output regressions.

Agricultural channel. To explore the consequences of sector-specific heat shocks and test the hypothesis that shocks in agriculture ripple through the supply chain, I estimate Equation 12 accounting only for heat shocks in the agricultural sector. Figure A16 reports the estimated coefficients. The coefficients on domestic heat shocks in all sectors (except mining, manufacturing and utilities) are largely negative and significant suggesting that heat shocks affecting the agricultural sector lower economic output in other sectors within the same country. Estimates of foreign agricultural heat shocks are negative but often imprecisely estimated.

[14] 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 2: Domestic and foreign heat shocks on 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 95% 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 accounting for fixed effects at time-varying coarser spatial levels than the unit of observation (Deschênes & Meng, 2018). Figure A17 shows the estimated coefficients in a regression that additionally controls for subregion-by-year and continent-by-year fixed effects.[15] 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 and are due to trade interlinkages and not spatially correlated shocks. The strong negative effect of domestic shocks is robust to the inclusion of these additional fixed effects.

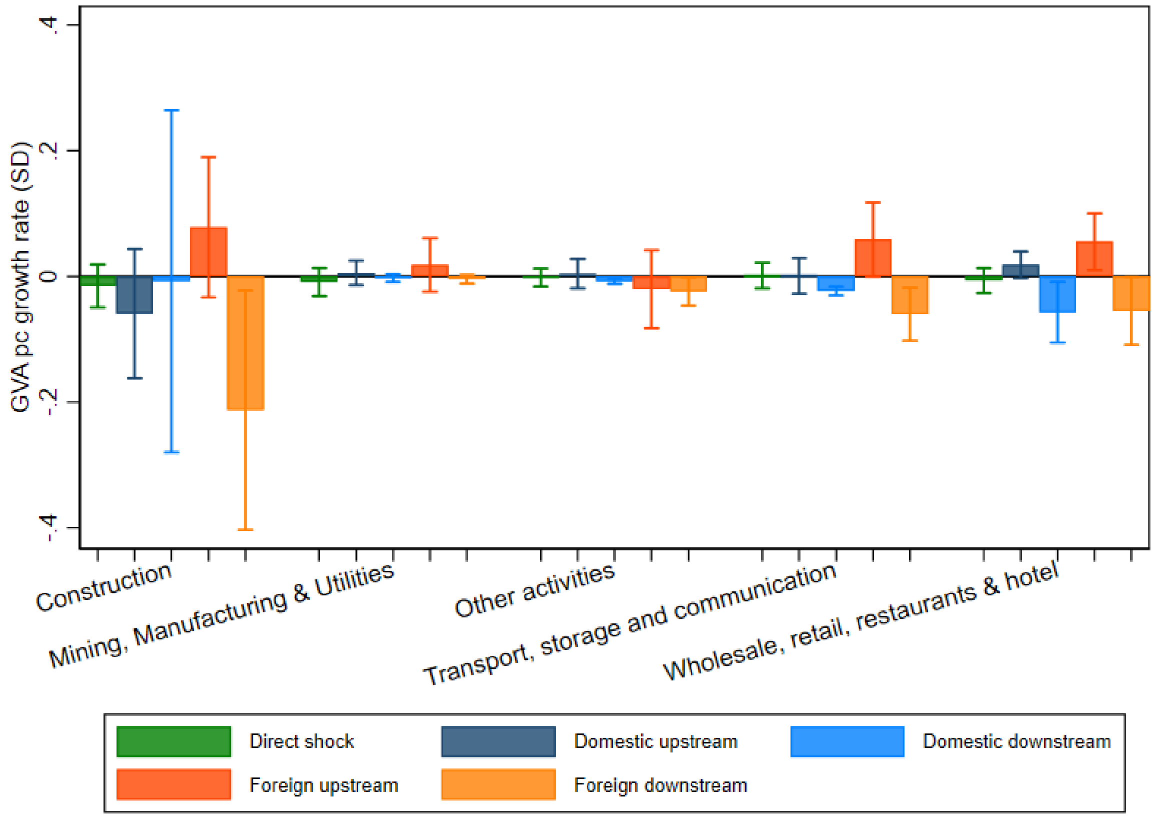
Exposure shares do not account for own trade, therefore the total sum of trade interlinkages varies across observations. To account for incomplete shares, I interact period fixed effects with the sum of exposure shares (Borusyak et al., 2022). The effects are robust to this specification (Figure A18a). Results are also robust to estimating the equation in a balanced panel (Figure A18b), excluding large countries (i.e., Brazil, China, India, Russia, US) (Figure A18c), using different cut-offs to compute percentiles of abnormal weather realizations (Figures A18d and A18e) and using a decadal time-varying production network (Figure A18f).

Upstream and downstream shocks. Shocks in trade partner locations can propagate differently from different stages of the supply chain (Acemoglu, Akcigit, et al., 2016; Das et al., 2022). I decompose domestic and foreign agricultural shocks into upstream and downstream as detailed in Section 3.3.1. Since temperature and precipitation are direct inputs to crop production and thus agricultural output, heat shocks can be interpreted as weather-induced supply shocks, and from the conceptual framework, it follows that such shocks should propagate downstream to customer sectors. Figure 3 displays the five coefficients on network shocks and local shocks for each sector. All five sectors have negative coefficients associated with both foreign and domestic downstream, indicating that heat shocks in the agricultural sector are amplified by market reactions that slow down downstream production (Wenz & Levermann, 2016).

Beyond first-degree sectoral interlinkages. The analysis so far has relied on the transmission of weather shocks from first-degree sectoral interlinkages in the production network. To account for the full transmission of shocks over the network, one can use the input-output analysis, initiated by Leontief (1941). From the input-output coefficients

[15] 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

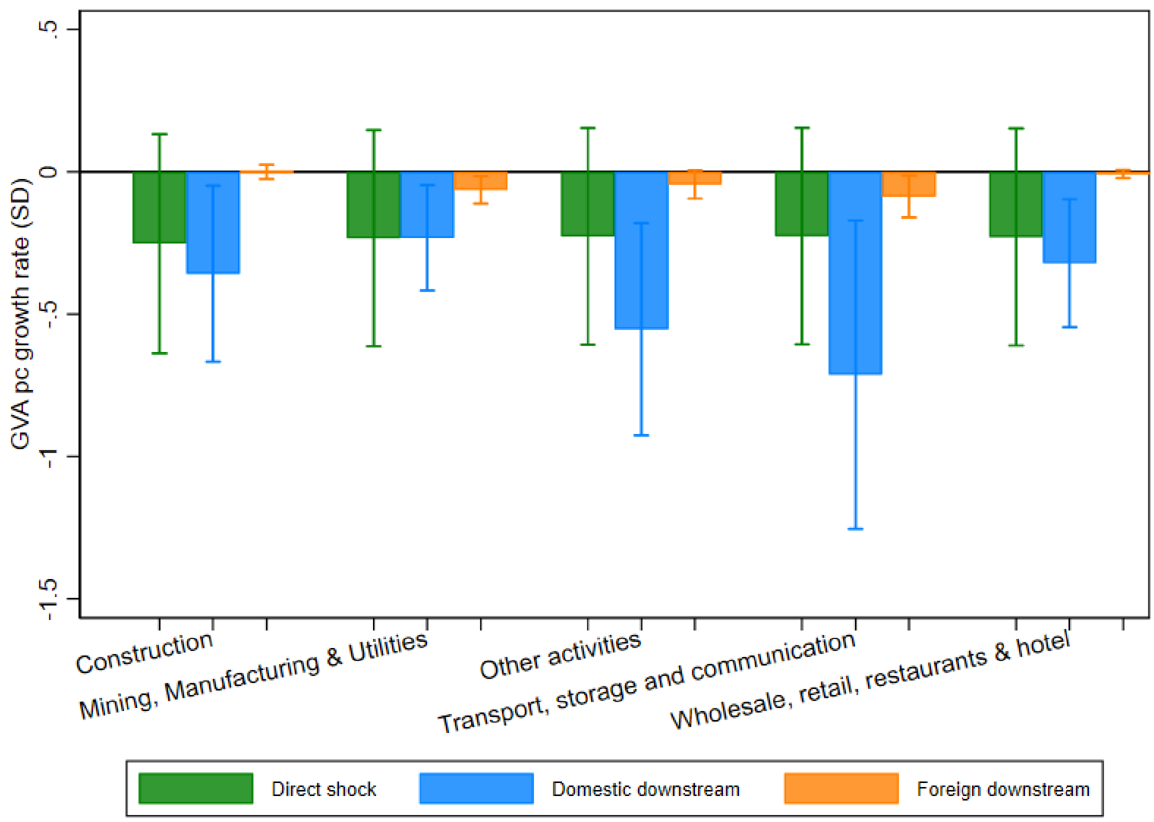
Figure 3: Network abnormally hot temperature shocks and sectoral production



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.

ω, I obtain the Leontief inverse matrix, which summarizes the sector-specific technical coefficients of the shock propagation through a power series representation of the Leontief inverse (Leontief, 1970). By taking the inner product of agricultural heat shocks and the Leontief inverse matrix, I obtain a sector-specific shock that takes full inter-sectoral relations into account. I estimate a specification including the agricultural heat shocks weighted by the Leontief-derived downstream coefficients and report the coefficients in Figure 4. Both domestic and foreign agricultural heat shocks are strongly negative and statistically significant, with domestic shocks larger in magnitude. The results suggest that downstream propagation of heat-induced productivity shocks in the agricultural sector has quantitatively sizable effects on the rest of the economy.

Figure 4: Sector-specific response to agriculture heat shock in a Leontief matrix



Notes: Bars represent the (standardized) sector-specific coefficients associated with direct shocks and domestic and foreign downstream shocks in the agricultural sector, using the average number of days above the 95th percentile of the daily temperature distribution weighted by the Leontief inverse matrix obtained from the downstream sectoral interlinkages obtained as in Section 3.3.1. The specification jointly estimates all sector-specific coefficients in a stacked regression model fully saturated with country-sector, country-year, sector-year and region-year fixed effects and accounting for sector-specific responses to temperature realizations below the 5th percentile and sector-specific responses to precipitation realizations below the 5th and above the 95th percentile. Bins represent the 90% confidence intervals with standard errors clustered at the country level.

Time persistence of network shocks. While the results show that domestic and foreign shocks, particularly those originating from agriculture, matter for sectoral economic output, the estimates focus only on short-run, contemporaneous impacts. It remains an open question whether the shocks have persistent effects on the level or on the growth rate 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 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 local and network agricultural heat 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

$$\Delta \log \left(\mathrm{GVA}\right)_{ict+h} = \gamma_{ih} Shock^{Own}_{ict} + \gamma^{D}_{i,h} Shock^{D} + \gamma^{F}_{i,h} Shock^{F} + \alpha_{ic} + \mu_{ct} + \varepsilon^{h}_{ict} \tag{13}$$

where I project the cumulative growth rate of sectoral per capita GVA between horizons $t-1$ and $t+h$ ($h \in \{0;5\}$ indexes the time horizon measured in intervals of up to five years) on direct and network shocks accounting for dynamics.

First, I estimate local projections on the total gross value added at the country level. Figure A19 shows the impulse response functions for a standardized domestic (Panel a) and foreign (Panel b) heat shock. Both domestic and foreign heat shocks have a small, noisy effect on total value-added levels that is statistically not distinguishable from zero. Using aggregate measures of country-level value added shows that the effect of network heat shock is not persistent.

Figure 5 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 direct and foreign shocks. Results show that aggregation masks substantially heterogeneous effects. Domestic agricultural heat shocks have negative persistent effects in the sectors of construction; other activities; transport, storage and communication; and wholesale, retail trade, restaurants and hotels.

Figures A20 and A21 display the impulse response functions using own direct and foreign shocks. First, direct shocks do not have a persistent effect on sectoral production.

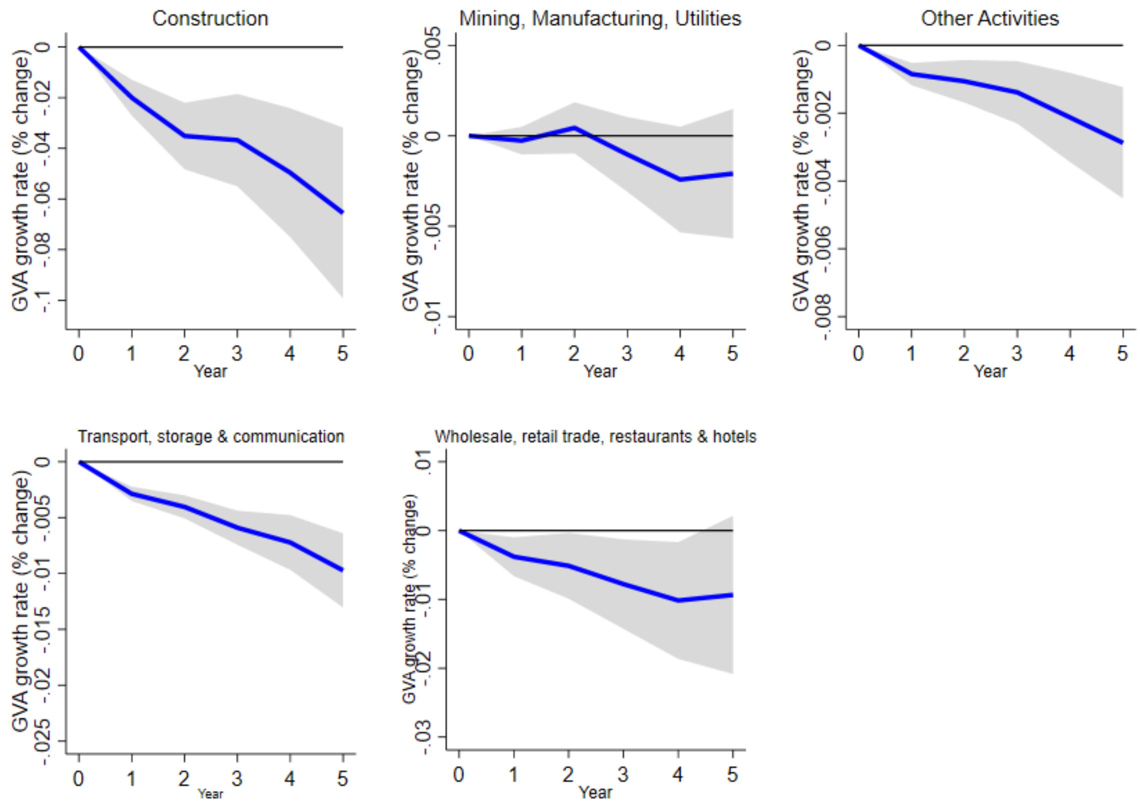
Agriculture is the only sector that is harmed, whereas the others appear relatively inelastic to abnormally hot temperature shocks (with the exception of transport, storage and communication, in which the negative effect of weather shocks manifests only after four years). The negative significant effect on agriculture lasts only one year and dissipates thereafter, confirming no visible long-run growth effects, but only a temporary effect on agricultural GVA levels. Second, the estimates on foreign shocks are small in magnitude and not distinguishable from zero, except in the case of other activities, which is strongly negatively affected by foreign agricultural heat shocks. The stickiness of the production processes at the sectoral and geographic level of aggregation of the analysis may explain the persistence of network heat shocks (Kunze (2021) and Appendix Section D). Allowing for a decadal time-varying production network shows robust persistent growth effect of domestic and foreign agricultural heat shocks (Figure A22). Agricultural heat shocks spill over other sectors also when accounting for continent-sector-year fixed effects (Figure A23) and for continent-sector linear trends (Figure A24), to control for spurious correlation between differential regional trends in warming and sectoral economic performance.

7 Counterfactual analysis: Cost of recent warming

To assess the economic importance of the propagation of weather shocks through production networks, I perform two counterfactual analyses. First, I compare the differential sectoral output losses/benefits as a result of recent historical warming. Prior research quantifies and projects 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, I simulate how much slower or faster each sector would have grown over the 2001-2020 period, compared to a counterfactual in which daily temperature linearly evolves from its 1970-2000 long-run average, omitting and accounting for temperature shocks in a slowly evolving production network (see Appendix Section J for additional details).

Omitting shocks in sector partners substantially underestimates the losses due to recent warming (Figure A27). The average annual GVA per capita loss across sectors considering only sector-specific local shocks is 0.02% (-0.08% median, IQR [-0.29, 0.09]),

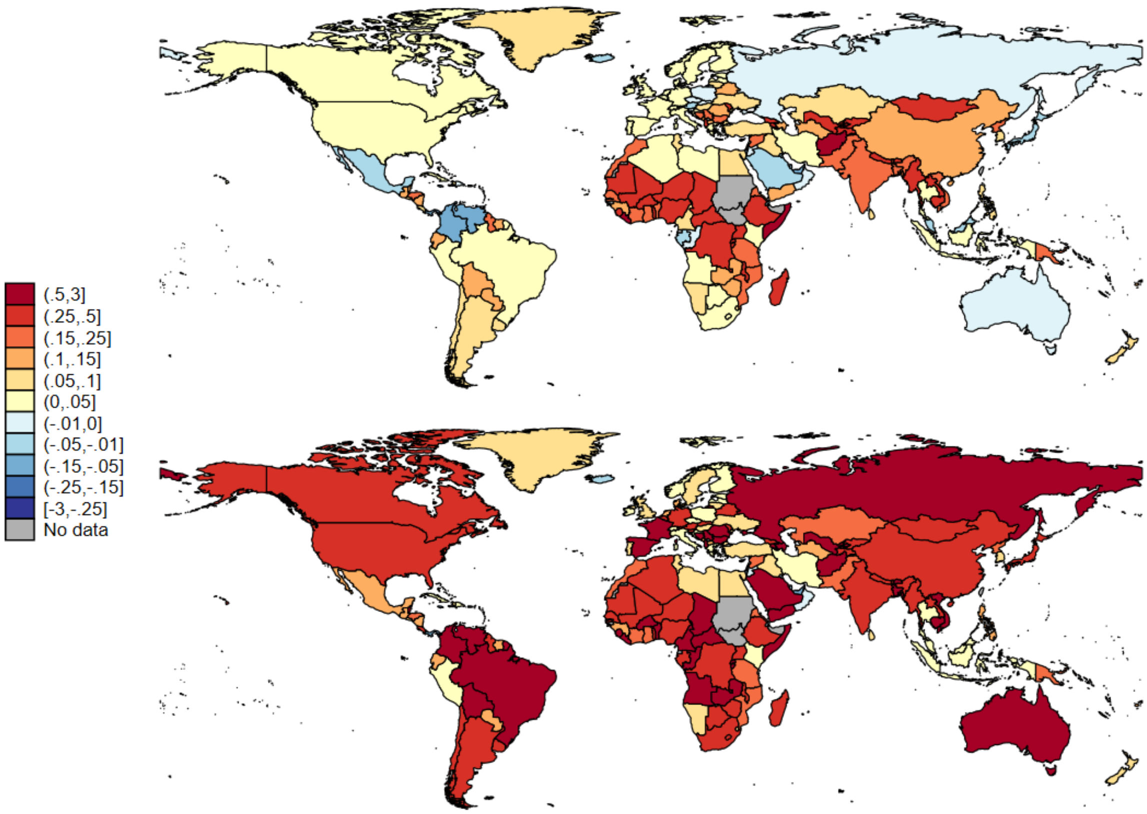
Figure 5: Local projections of domestic agricultural heat shocks on sectoral production



Notes: Panels show the sector-specific impulse response function of sectoral per capita GVA growth rate to a 1 SD increase in the domestic agricultural heat 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.

whereas accounting for network shocks is 0.32% (0.15% median, IQR [-0.13, 0.73]). Damages are particularly larger in those sectors that appear sheltered from local shocks (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, Latin America and South-East Asia are offset by modest benefits in Northern Europe and the Middle East. Using each country's baseline average sectoral breakdown of total GVA between 1996 and 2000, I aggregate sector-specific damages to obtain the total national average relative losses. Accounting for indirect heat shocks, country-level damages are substantial (0.33% mean, 0.26% median, IQR [0.06, 0.53]) and largely underestimated when omitting heat shock propagation (0.10% mean, 0.05% median, IQR [0.00, 0.17]) (Figure 6).

Figure 6: 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 (%) compared to a counterfactual daily temperature evolved linearly from the trend estimated in 1970-2000. Sector-specific damages are weighted by the average sectoral share of total GVA between 1996 and 2000. The world map above only accounts for sector-specific direct heat and cold shocks defined as the number of days above the 95$^{\text{th}}$ and below the 5$^{\text{th}}$ percentile of the temperature distribution. The world map below accounts for shocks in other partner sectors using sector-specific semi-elasticities from bootstrapping 1000 times the underlying panel estimates of Equation (12), where indirect shocks are constructed with a time-varying production network that uses the first five-year average input-output interlinkages for each decade. Sector-specific losses are reported in Figure A27, Table A13 reports the sector-specific losses significant at 95% level estimated with 1000 bootstrap replications with replacement.

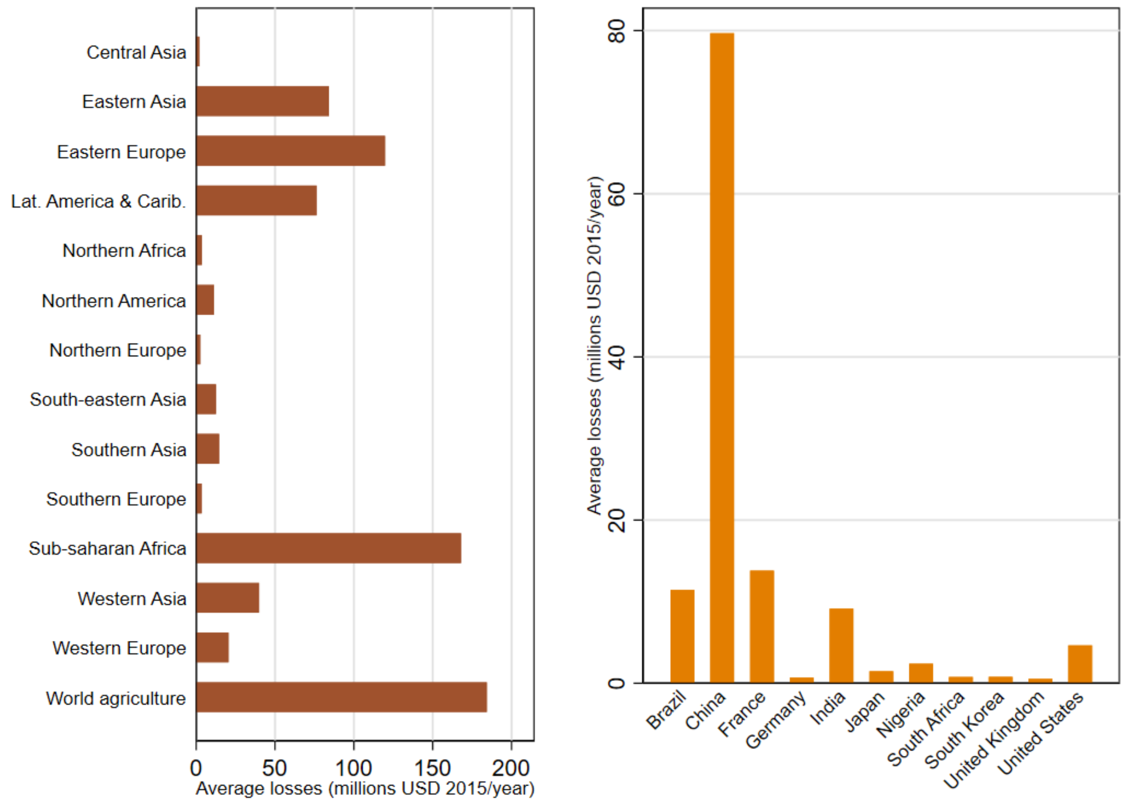
In a second exercise, I quantify the macroeconomic impact of an increase in one abnormally hot day in a specific sub-region or country from 2000 onwards. Figure 7 reports the average annual global losses. The highest average loss ($\approx$ 185 million 2015US\$) is recorded if each agricultural sector in the world experiences an additional hot day. Large losses are also recorded if Sub-Saharan Africa, Eastern Europe, Eastern Asia or Latin

America and the Caribbean suffer an additional hot day. These regions, if experiencing additional heat, induce larger losses on average due to larger relative damages on local economic production. An alternative mechanism could be explained by a scale effect since these regions have the largest number of countries contemporaneously shocked. For this reason, on the right-hand side of the Figure, I also report average annual global losses if one single country experiences an additional hot day. Results show that the centrality of the country in the production networks substantially matters for losses induced by heat shocks. On average, global losses are at the highest for an additional hot day in China ($\approx$ 80 million 2015US$) and in other countries such as Brazil ($\approx$ 12 million 2015US$), France ($\approx$ 14 million 2015US$), India ($\approx$ 10 million 2015US$), and the United States ($\approx$ 5 million 2015US$). These losses are sizable considering they only represent global averages for one abnormally hot day in each of these countries, where hot days have substantially increased over the sample period. For example, the decadal average number of hot days in China in the 1970s was 11.8 and it reached 29.5 in the 2010s. Similarly, the number of hot days in Brazil increased from 6.3 to 42.4 and from 7.9 to 30.3 in the US in the same time period.

8 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. 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.

Figure 7: Average annual global losses due to an additional abnormally hot day in a specific sub-region (left) or country(right)



Notes: The figure shows the average annual global losses in 2015$ million by perturbing the production network with an additional abnormally hot day in the sub-region (resp. country) reported in the x-axis (y-axis), using sector-specific semi-elasticities from Equation (12), where indirect shocks are constructed with a time-varying production network that uses the first five-year average input-output interlinkages for each decade. Global averages only consider country-specific losses significant at the 95% level using 1000 bootstrap replications with replacement.

Sectors unresponsive to local weather suffer economic losses due to the interdependence of their production process with other domestic or foreign sectors that are hit by weather shocks. 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 effect of domestic agricultural heat shocks in certain sectors' output (construction; other activities; transport, storage and communication; wholesale, retail trade, restaurants and hotels) up to five years after the shock. 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.

The findings point to the structure of sectoral production network linkages as a key driver of aggregate fluctuations induced by weather shocks. In particular, they indicate that even if most sectors with the exception of agriculture are sheltered from weather fluctuations, the potential propagation of shocks over the economy's production network can impact them, thus resulting in movements in macroeconomic aggregates. In particular, using counterfactual simulations based on my empirical estimates, I show that the omission of input-output linkages as a mechanism for the propagation and amplification of shocks may lead to substantial underestimation of the effect of recent warming around the world and global losses are sizable even for just a single country being shocked in isolation, suggesting that countries that are more central in production network can induce larger global losses if hit by heat shocks.

Several important issues remain open to future research. First, the analysis provides modest but suggestive evidence on the role of adaptation of countries to enhance their resilience to climate damages, in particular, that the effect of weather shocks depends on income. 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 lower climate damage. Accounting for other adaptive margins may also differentially drive the propagation of shocks in countries that are more sheltered from weather shocks.

Second, 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.

Third, 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 that differ by industry supplier competitiveness, input concentration, and supplier diversification (Pankratz & Schiller, 2021). These channels have only been documented at the firm level and such additional layers of heterogeneity could shed light on the exact channel of transmission of weather shocks through the economy.

Fourth, sectoral reallocation is increasingly acknowledged and studied as a potential adaptive margin to climate change (Desmet & Rossi-Hansberg, 2015; Nath, 2020). The analysis has focused on the propagation of weather shocks in a pre-determined or slowly evolving production network. Adjustments in trade patterns from the substitution of affected sectors with sectors in unaffected places as a response to idiosyncratic weather shocks seem a promising avenue for future research.

Last, the analysis is mostly silent about decision-makers' climate beliefs and expectation formation processes. Despite the use of implicit models of adaptation accounting for climate as the most important factor, 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, 2022). Similarly, expectations also matter in accounting for adaptation costs and benefits (Carleton et al., 2022; Shrader, 2021). Future research should focus on accounting for heterogeneous beliefs and expectations in production networks and supply-chain relationships.

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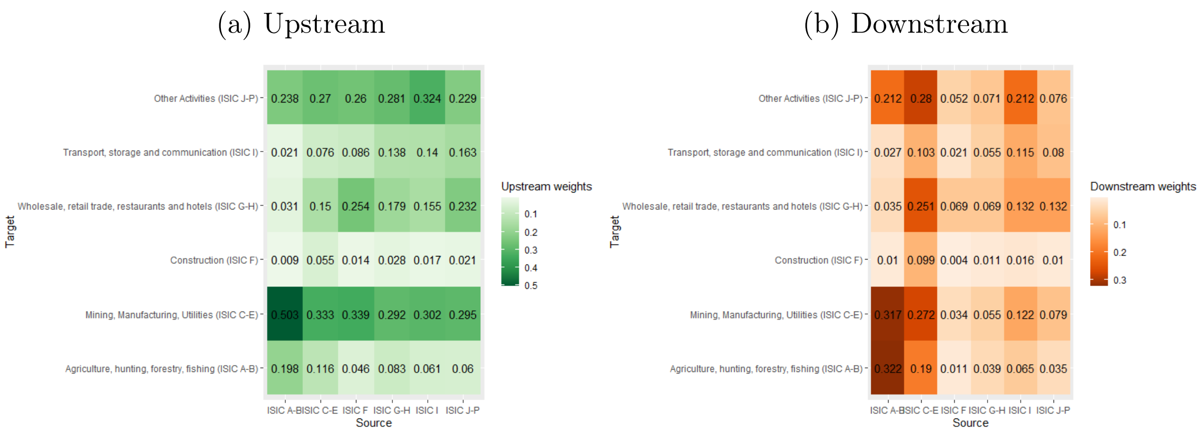
Appendix

Table of Contents

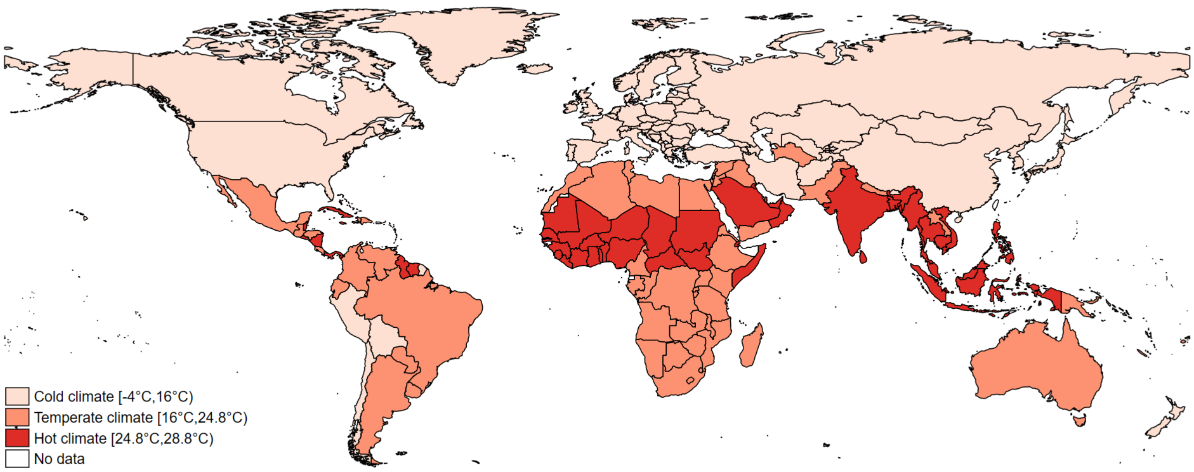
A Additional figures

Figure A1: Average upstream and downstream weights across countries



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

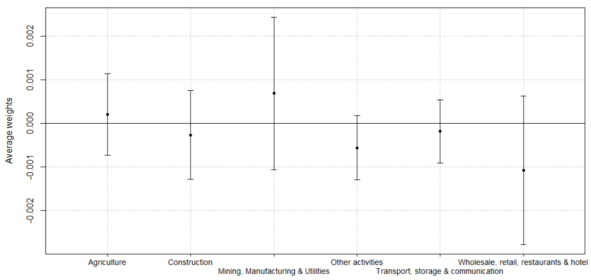
Figure A2: Countries in the sample by climatic zone



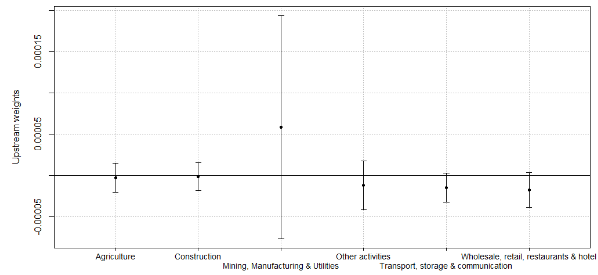
Notes: The map represents the countries in the sample divided by climatic zones, defined as terciles of the average annual temperature from 1970 through 2020. The classification is implemented in order to compute heterogeneous treatment effects as reported in Figure A6.

Figure A3: Sectoral interlinkages' response to heat shocks

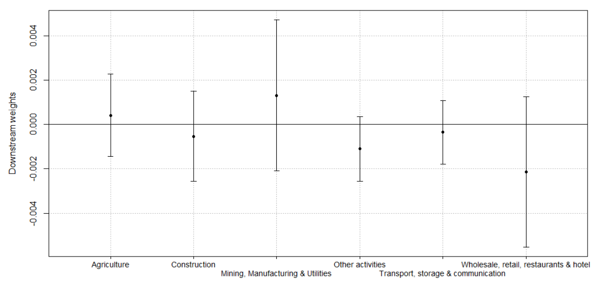
(a) Average weights



(b) Upstream weights

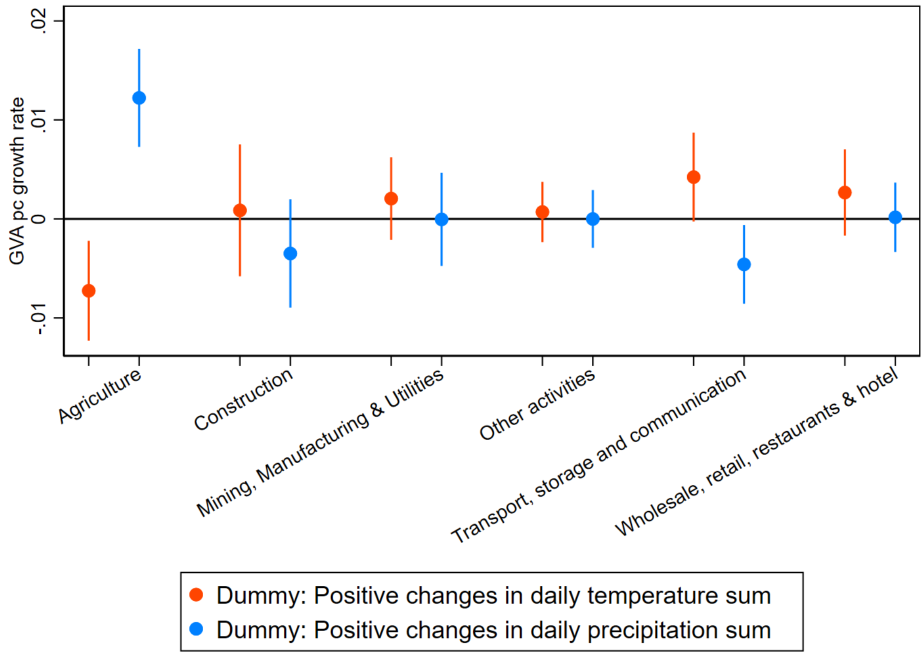


(c) Downstream weights



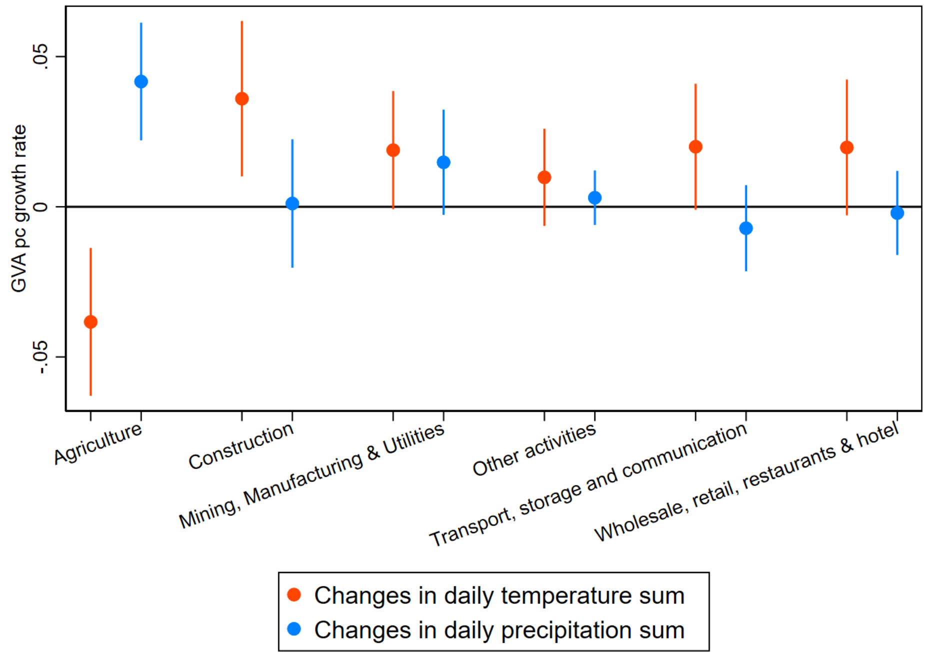
Notes: The figure shows the (standardized) coefficients associated with the response of bilateral sectoral interlinkages to heat shocks (measured as the number of days above the 95^{th} percentile of the temperature distribution) in the period between 1970 and 2019. All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and origin-destination bilateral sector, destination sector-country-year fixed effects. Bins represent the 90% confidence intervals with standard errors clustered at the country-level.

Figure A4: 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.

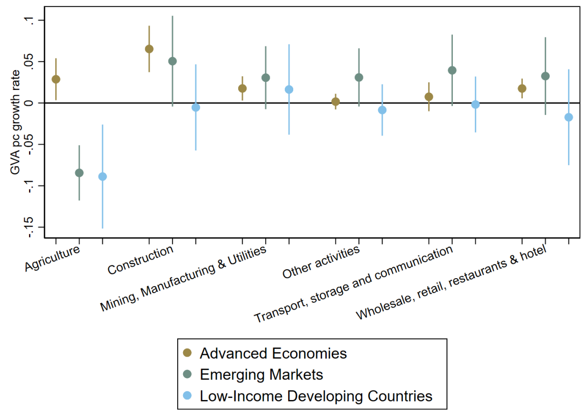
Figure A5: Sector-specific impact of annual temperature and precipitation changes



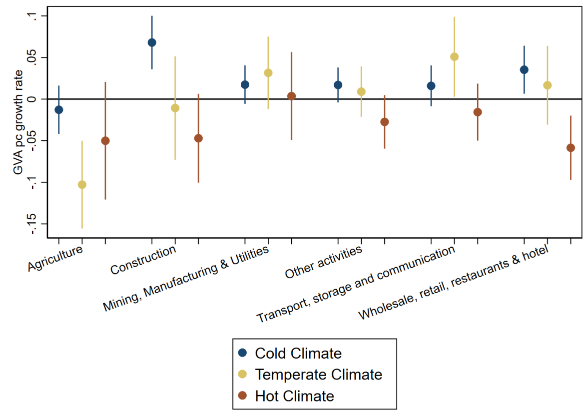
Notes: The figure shows the OLS coefficients associated with the response of sectoral GVA per capita growth rate to changes in the annual sum of average daily temperature. The regression controls for lagged sectoral GVA growth rate, country-sector, sector-year fixed effects. Bins represent the 90% confidence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

Figure A6: Heterogeneity in the GVA response to changes in temperature distribution

(a) Income groups



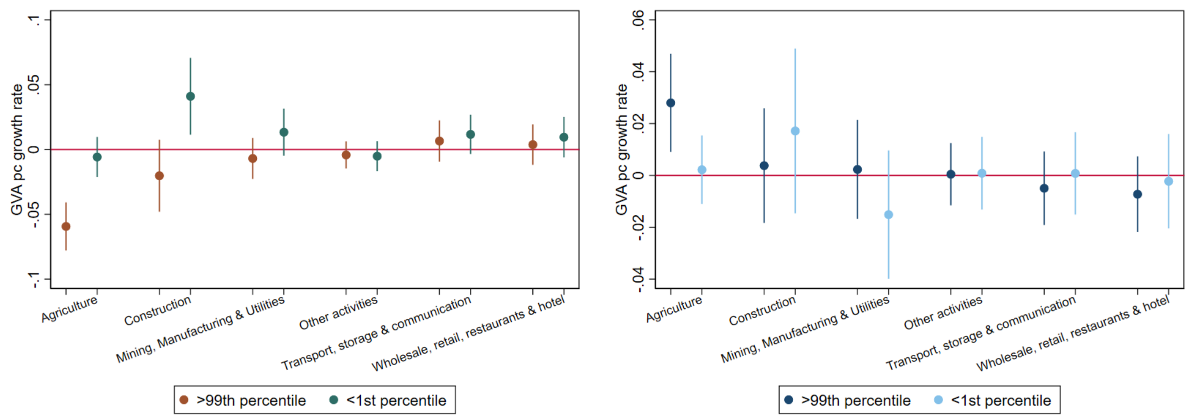
(b) Climate terciles



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 A7: Abnormal weather realizations using 1^{st} and 99^{th} percentiles

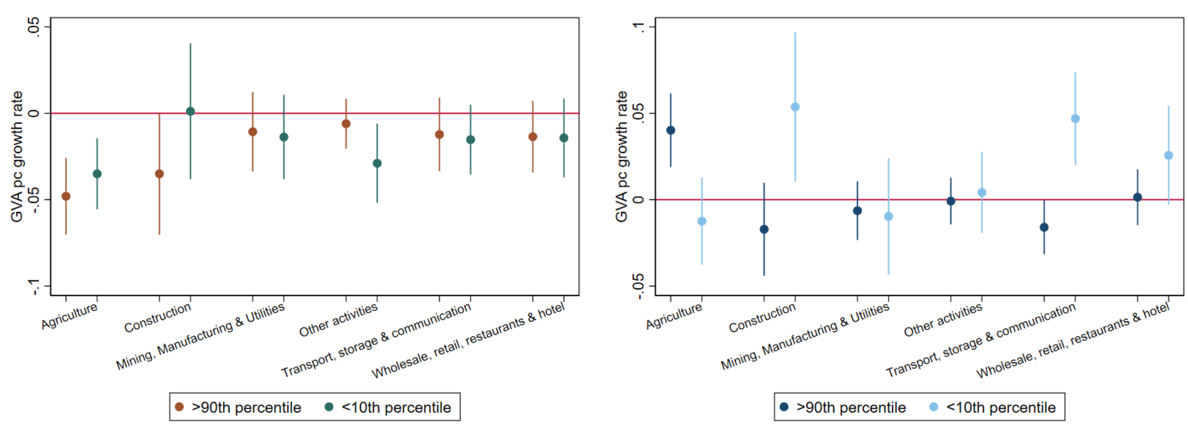
(a) Hot and cold temperature shocks (b) Wet and dry precipitation shocks



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 A8: Abnormal weather realizations using 10^{th} and 90^{th} percentiles

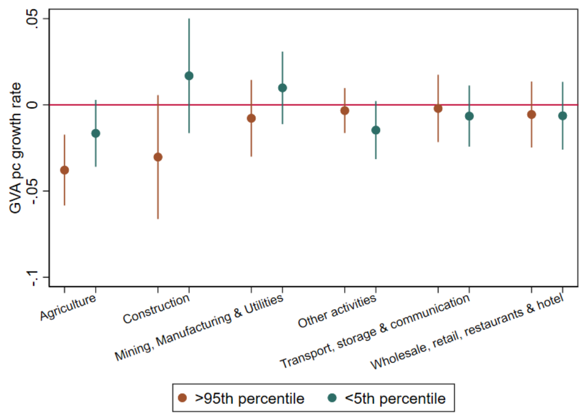
(a) Hot and cold temperature shocks (b) Wet and dry precipitation shocks



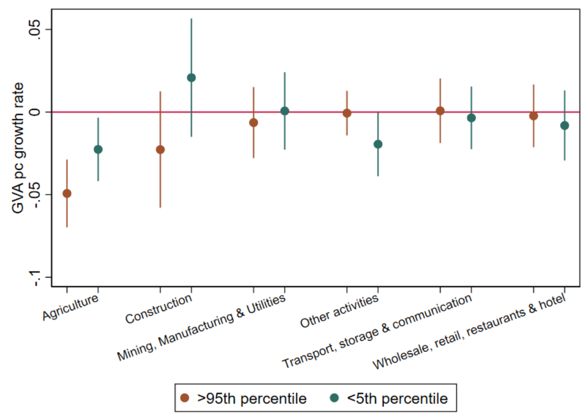
Notes: The figure shows the (standardized) regression estimates for the country-average number of days above the 90^{th} and below the 10^{th} percentile of the daily distribution in temperature (Panel (a)) and in precipitation (Panel (b)). All sector-specific coefficients are estimated jointly in a 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 A9: Robustness: Abnormal temperature realizations

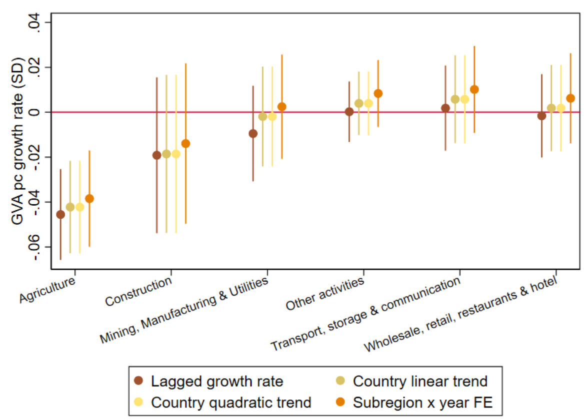
(a) Balanced panel



(b) Excluding "large" countries



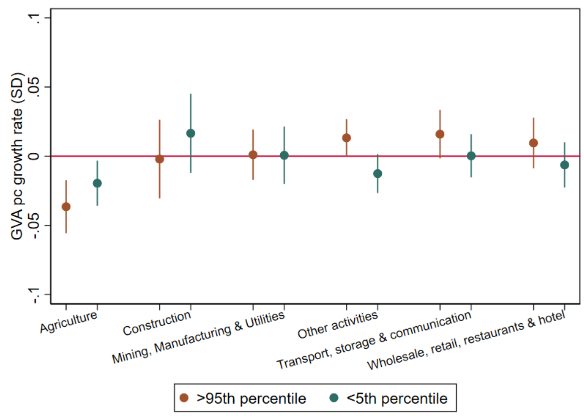
(c) Heat shocks - Additional controls and FE



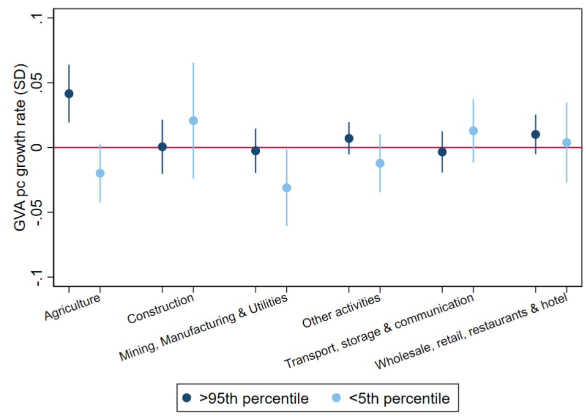
Notes: The figure shows the (standardized) regression estimates for the country-average number of days above the 95^{th} and below the 5^{th} percentile of the daily distribution in temperature using a sector-country balanced panel (Panel (a)), excluding large countries (Brazil, China, India, Russia, US) (Panel (b)), and for days above the 95^{th} percentile including lagged growth rate, country-specific linear and quadratic trends and subregion-by-year fixed effects (Panel (c)). 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 A10: Abnormal weather realizations from time-varying climate norms using 5^{th} and 95^{th} percentiles

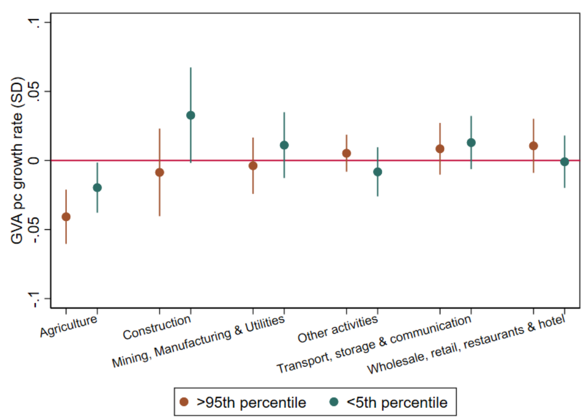
(a) Temperature - 20-year



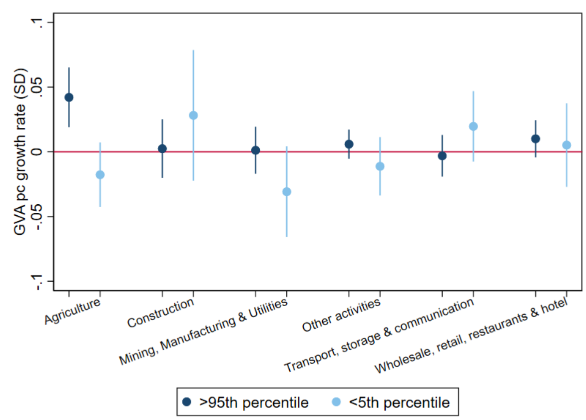
(b) Precipitation - 20-year



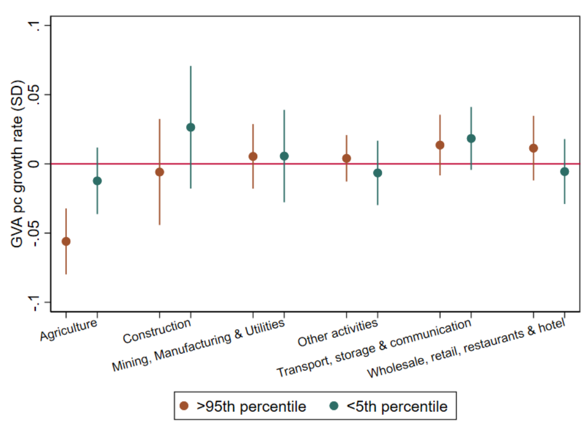
(c) Temperature - 30-year



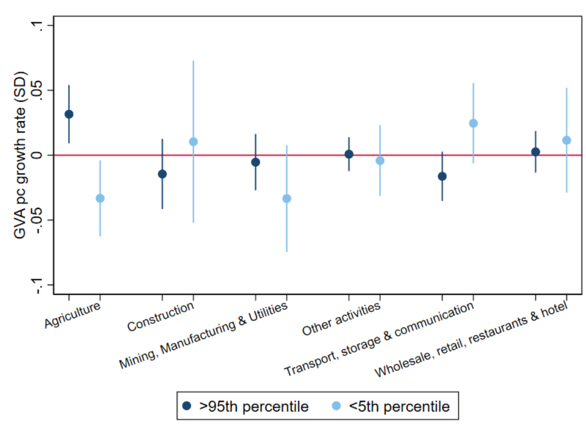
(d) Precipitation - 30-year



(e) Temperature - 40-year



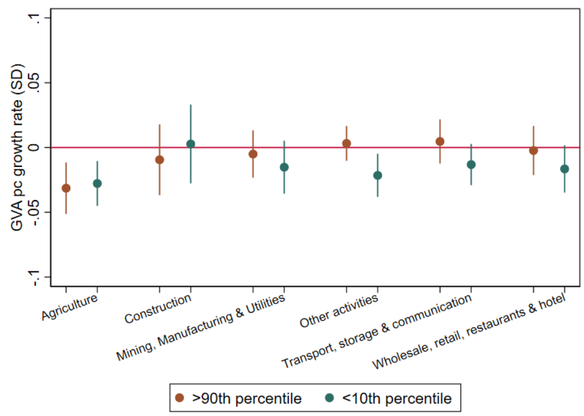
(f) Precipitation - 40-year



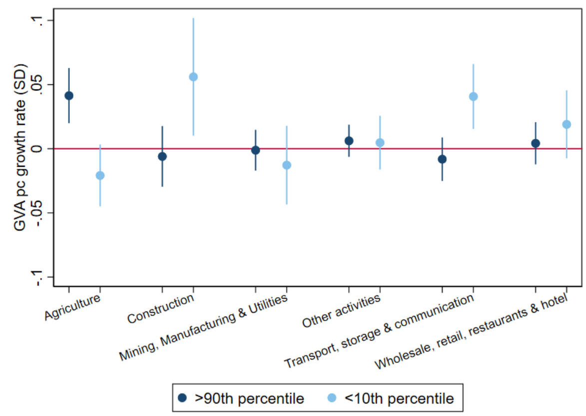
Notes: The figure shows the (standardized) regression coefficients on the number of days above the 90^{th} and below the 10^{th} percentile of the daily distribution in temperature (Panels (a-c-e)) and in precipitation (Panels (b-d-f)) using time-varying distributions (respectively, 20-year, 30-year 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 A11: Abnormal weather realizations from time-varying climate norms using 10th and 90th percentiles

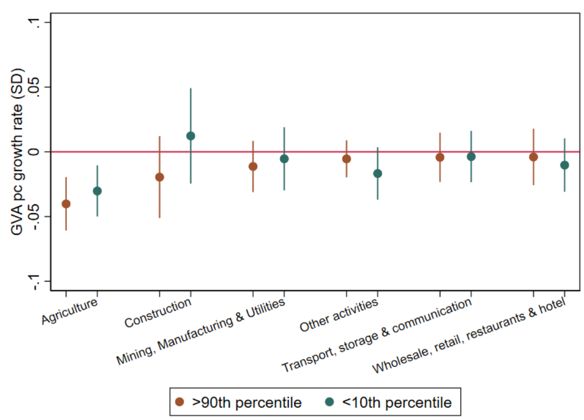
(a) Temperature - 20-year



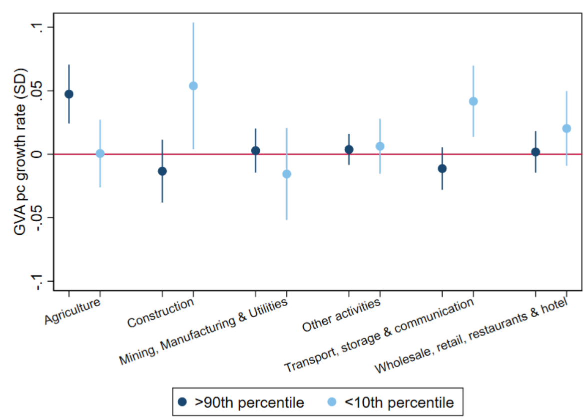
(b) Precipitation - 20-year



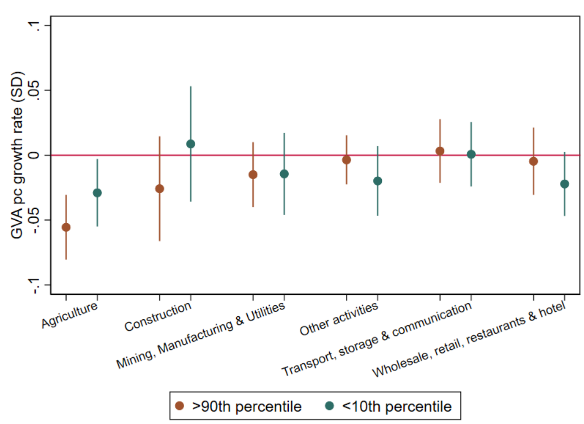
(c) Temperature - 30-year



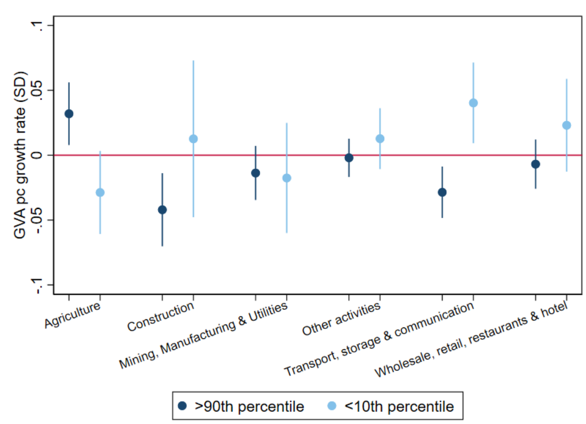
(d) Precipitation - 30-year



(e) Temperature - 40-year



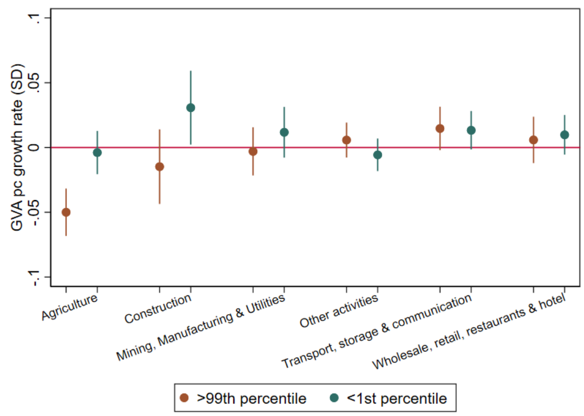
(f) Precipitation - 40-year



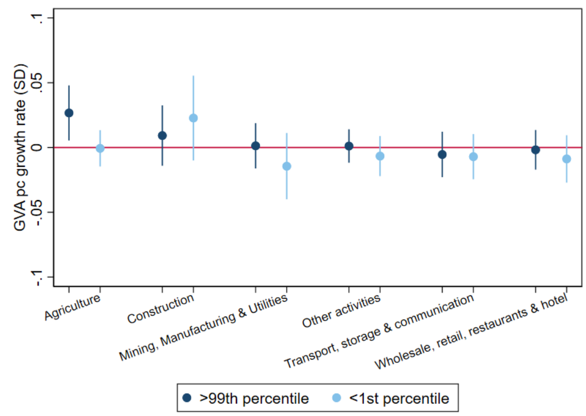
Notes: The figure shows the (standardized) regression coefficients on the number of days above the 90th and below the 10th percentile of the daily distribution in temperature (Panels (a-c-e)) and in precipitation (Panels (b-d-f)) using time-varying distributions (respectively, 20-year, 30-year and 40-year). 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 A12: Abnormal weather realizations from time-varying climate norms using 1^{st} and 99^{th} percentiles

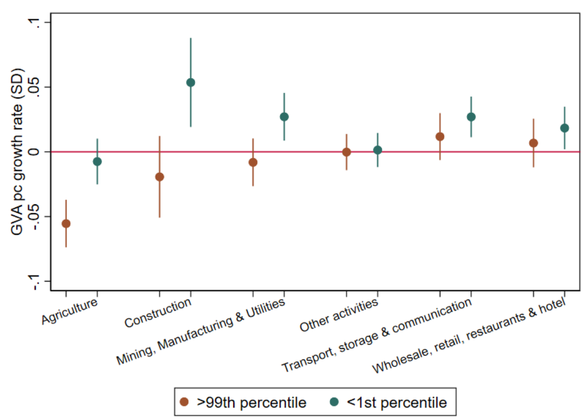
(a) Temperature - 20-year



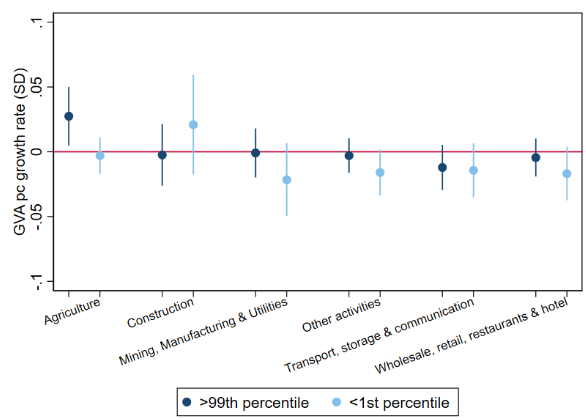
(b) Precipitation - 20-year



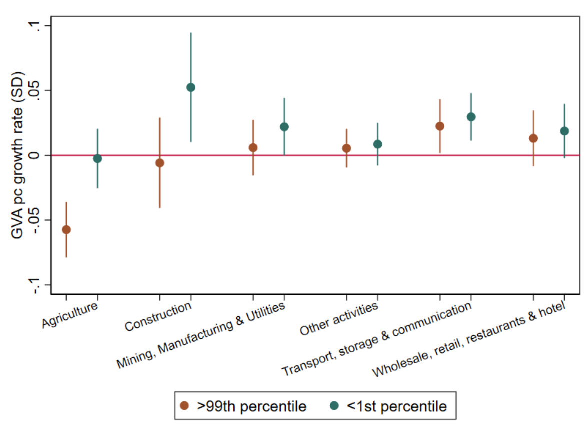
(c) Temperature - 30-year



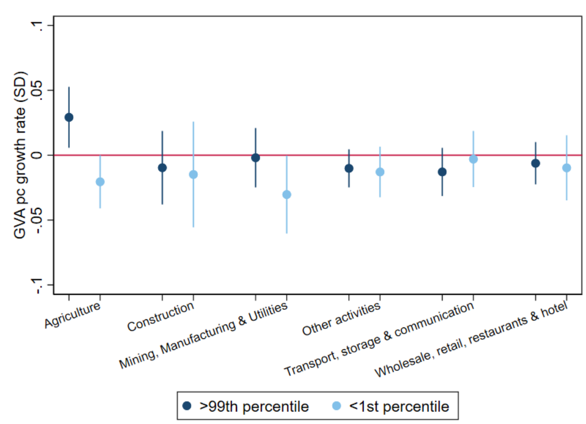
(d) Precipitation - 30-year



(e) Temperature - 40-year

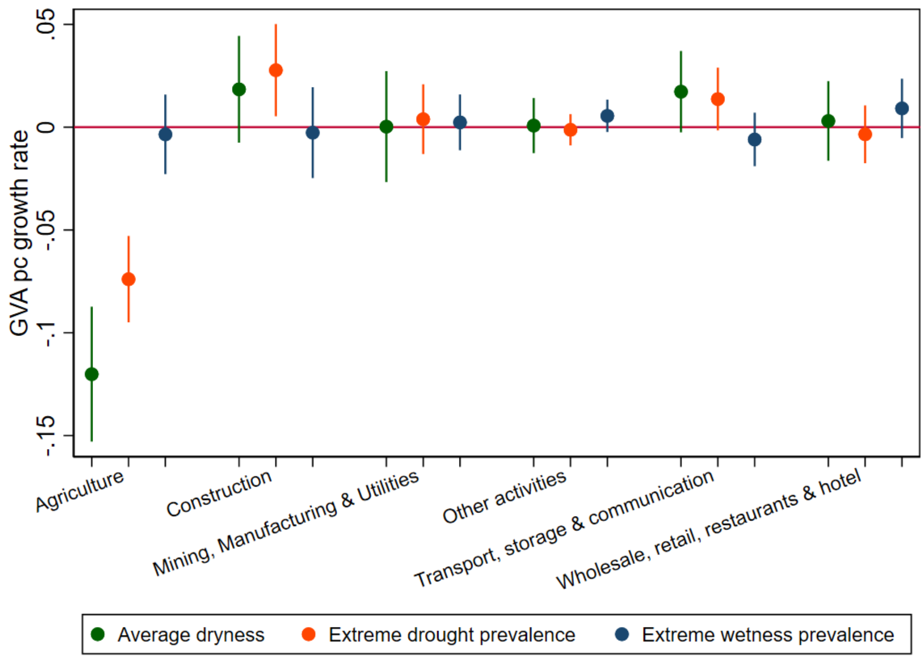


(f) Precipitation - 40-year



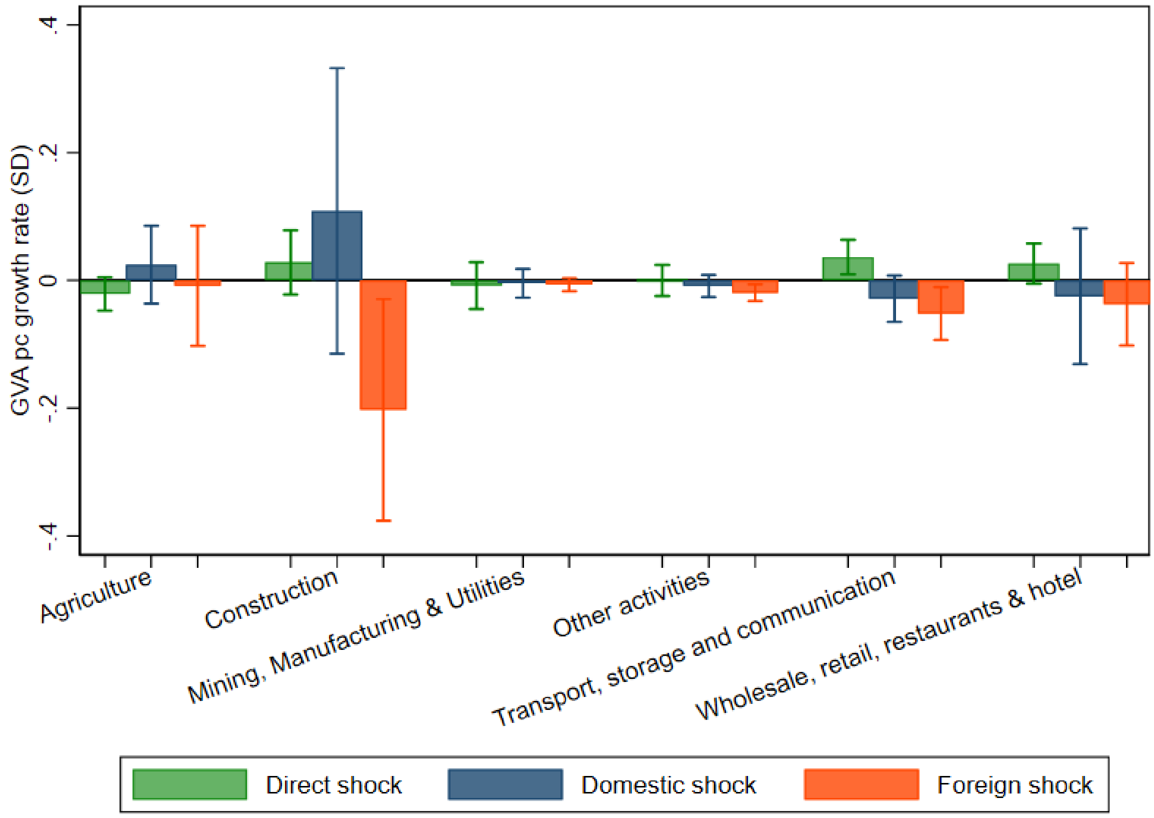
Notes: The figure shows the (standardized) regression coefficients on the number of days above the 99^{th} and below the 1^{st} percentile of the daily distribution in temperature (Panels (a-c-e)) and in precipitation (Panels (b-d-f)) using time-varying distributions (respectively, 20-year, 30-year and 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 A13: Extreme drought and wetness prevalence and sectoral production



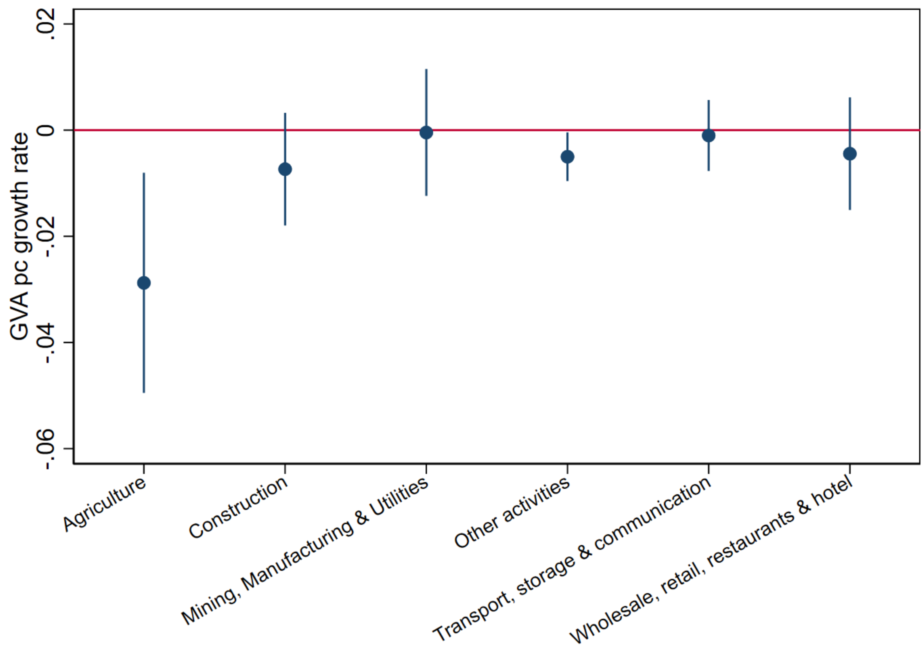
Notes: The figure shows the (standardized) coefficients from a stacked multi-sector regression model where changes in dryness and wetness variables are sector-specific. All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year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

Figure A14: Domestic and foreign dry shocks on sectoral production



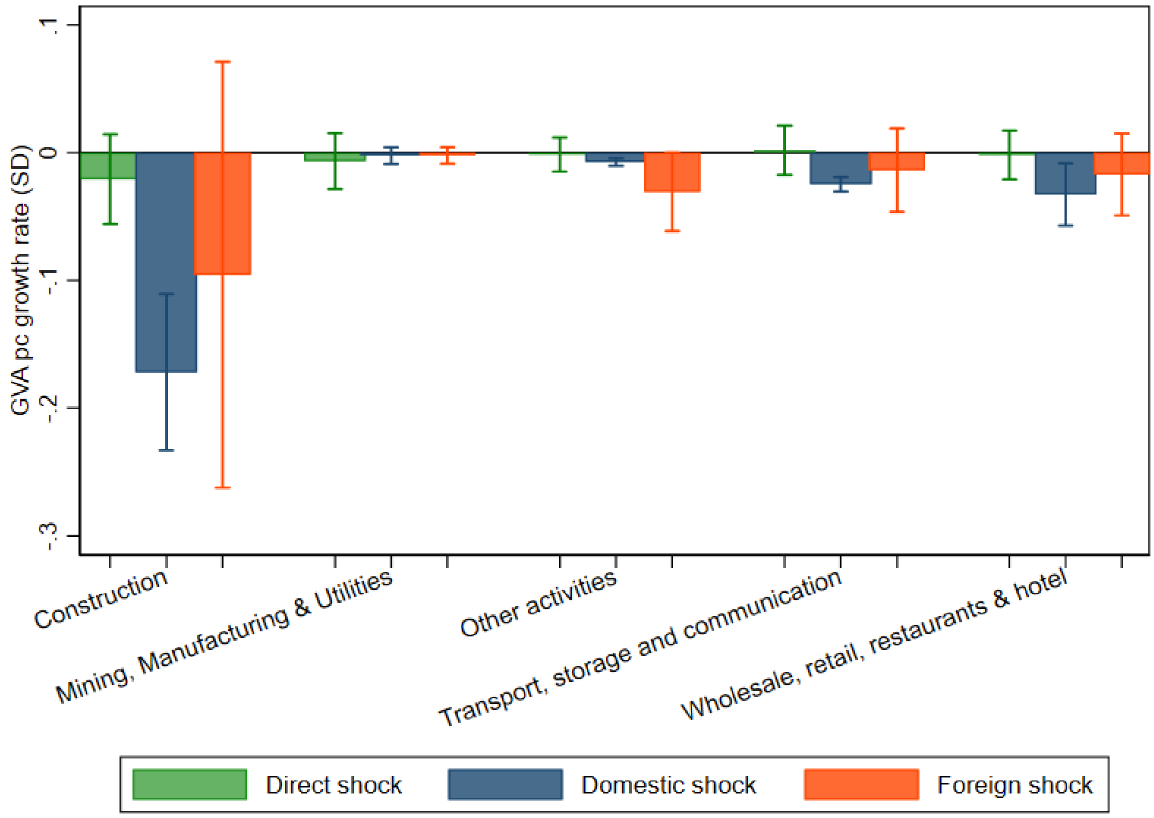
Notes: Bars represent the (standardized) sector-specific coefficients associated with direct shocks and domestic and foreign shocks, using the average number of days below the 5^{th} percentile of the daily precipitation distribution. Domestic shocks are constructed as the average weather shock in the 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^{th} and above the 95^{th} percentile and sector-specific responses to precipitation realizations above the 95^{th} percentile. Bins represent the 90% confidence intervals with standard errors clustered at the country-level.

Figure A15: 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 measured as first-differenced 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.

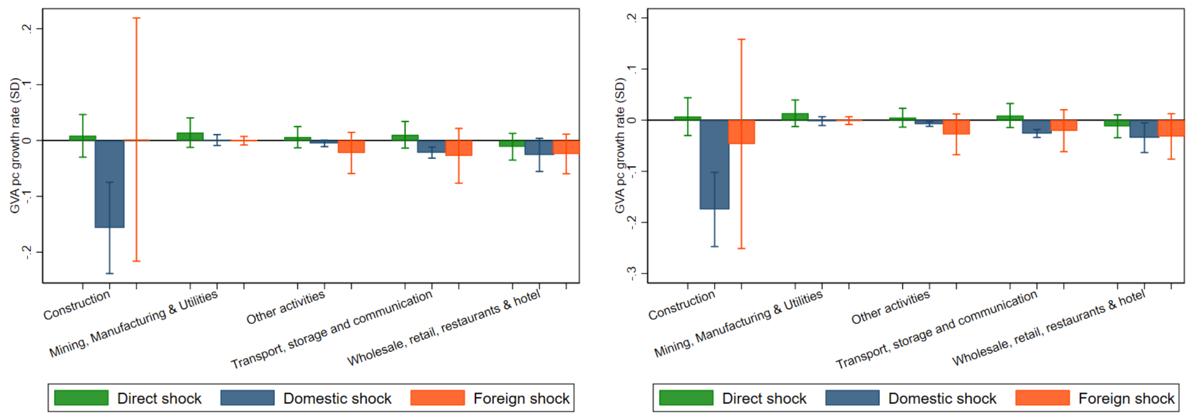
Figure A16: Domestic and foreign agricultural heat shocks on other sectors' production



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 heat shock in agriculture 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 agriculture 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 95% confidence intervals with standard errors clustered at the country-level.

Figure A17: Robustness: Spatial correlation

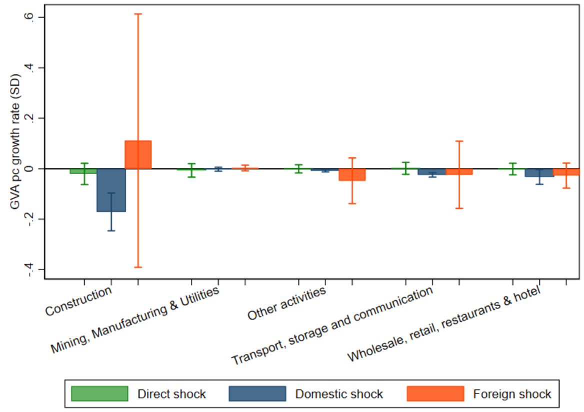
(a) Subregion-by-year FE (b) Continent-by-year FE



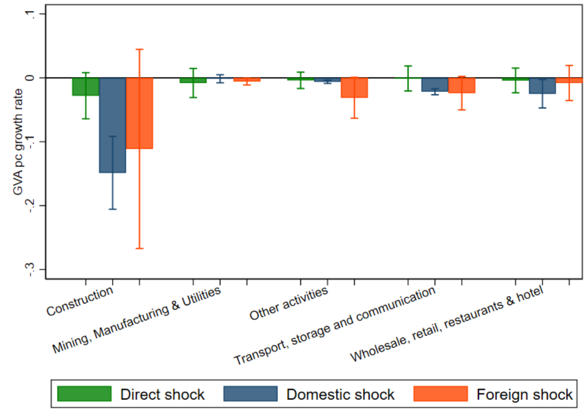
Notes: The figure shows the (standardized) sector-specific coefficients associated with direct shocks and domestic and foreign shocks, using the average number of days above the 95$^{\text{th}}$ percentile of the daily temperature distribution. Domestic shocks are constructed as the average weather shock in agriculture 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 agriculture 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 A18: Robustness: Domestic and foreign agricultural heat shocks

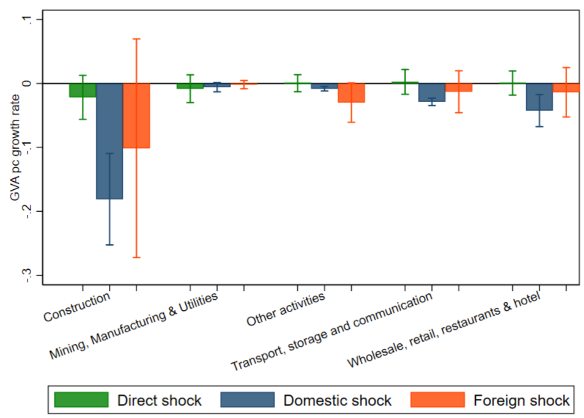
(a) Accounting for incomplete shares



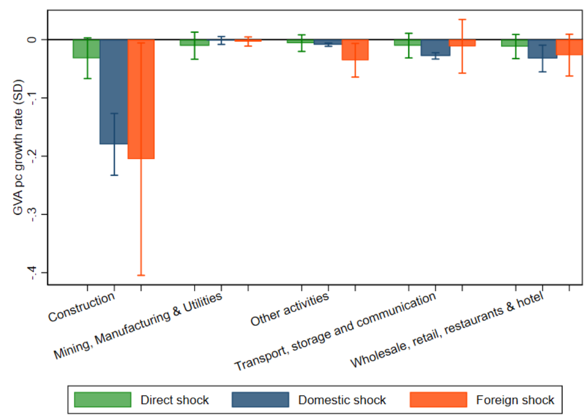
(b) Balanced panel



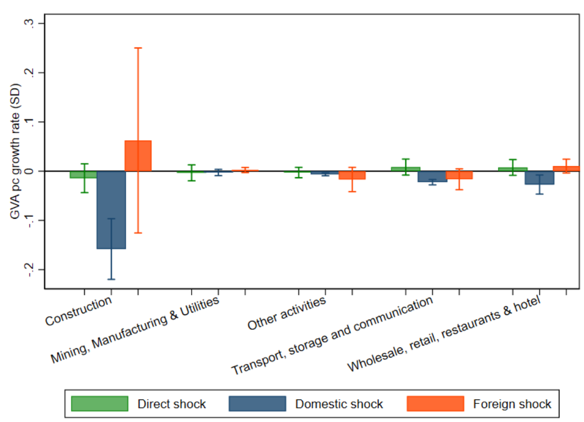
(c) Excluding "large" countries



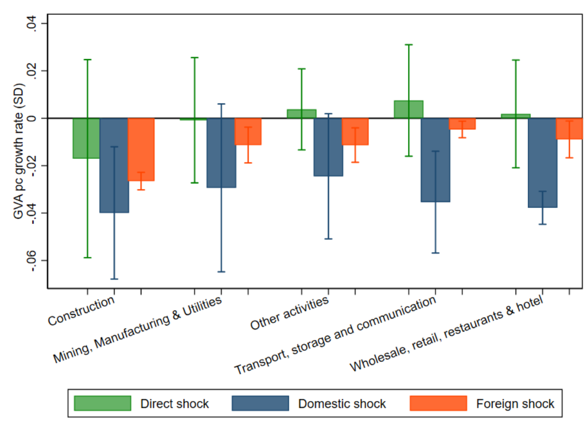
(d) Using 90^{th} percentile



(e) Using 99^{th} percentile



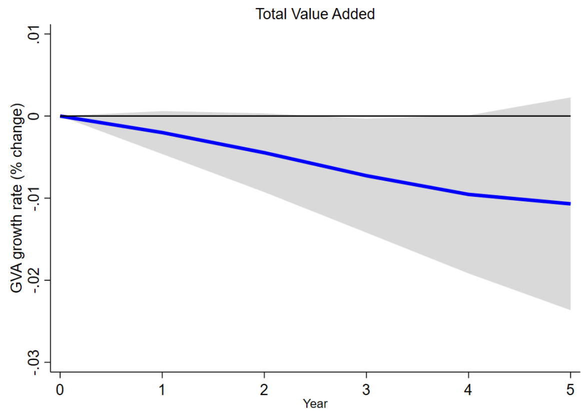
(f) Time-varying production network



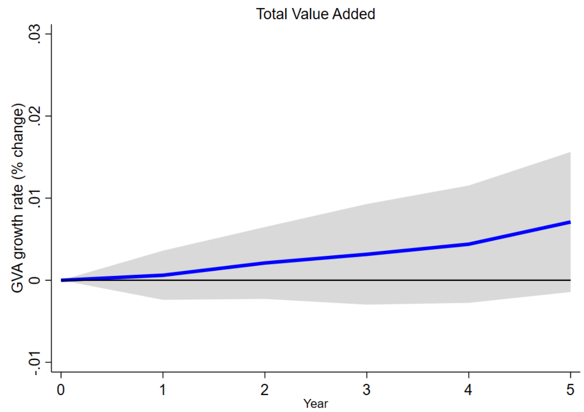
Notes: The figure shows the (standardized) sector-specific coefficients associated with direct shocks and domestic and foreign agricultural heat shocks, Panel (a) shows the estimates controlling for sector-year FE interacted with the sum of exposure shares. Panel (b) uses sector-country balanced panel, Panel (c) excludes large countries (Brazil, China, India, Russia, US), Panel (d) and panel (e) respectively used the 90^{th} and the 99^{th} percentile to construct heat shocks. Panel (f) uses a decadal time-varying production network constructed using the average of the first five-year input-output interlinkages for each decade. Bins represent the 90% confidence intervals around point estimates.

Figure A19: Local projections of domestic and foreign heat shocks on total value added

(a) Domestic heat shock

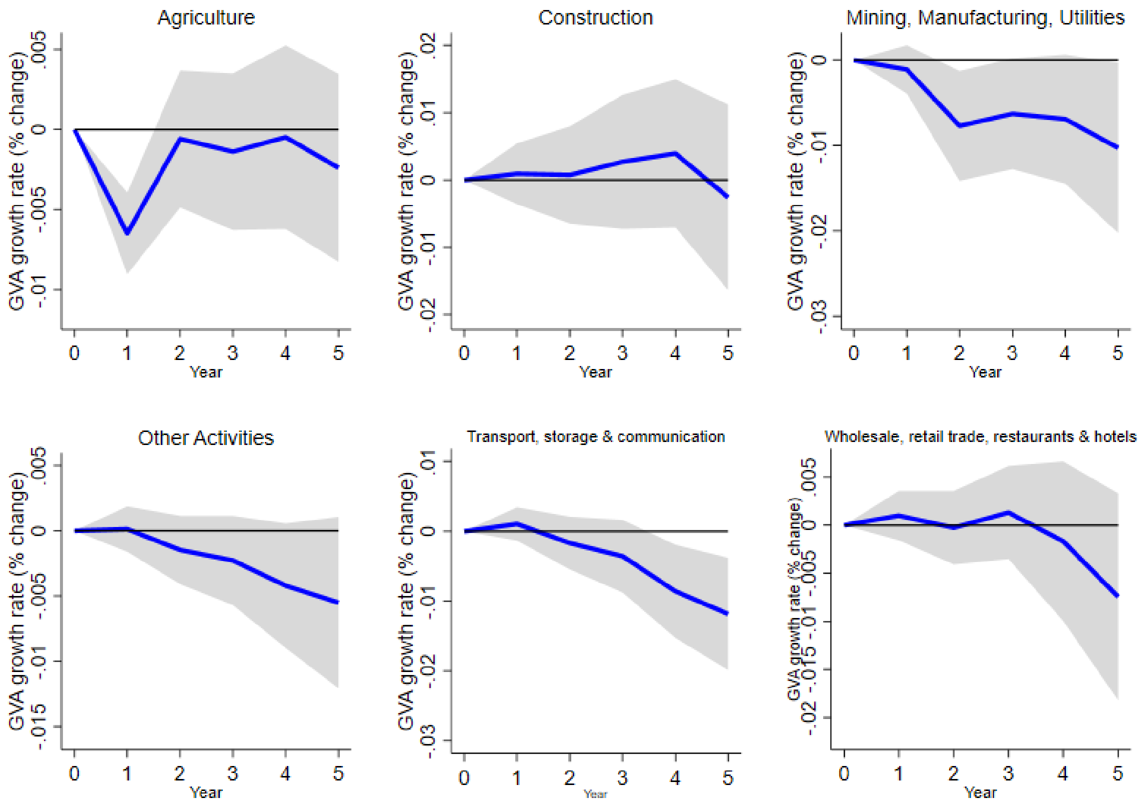


(b) Foreign heat shock



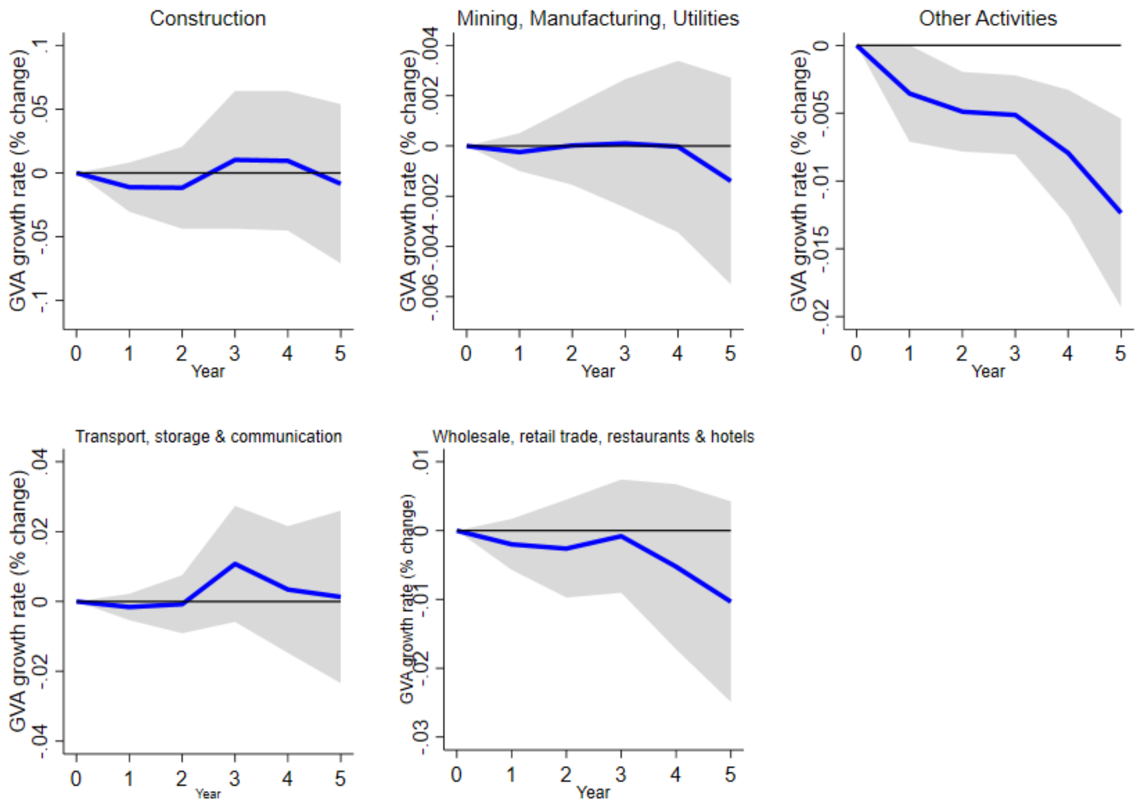
Notes: Panels show the impulse response function of per capita total value added growth rate to a 1 SD increase in heat shocks estimated in a stacked regression model with country and year fixed effects and accounting for abnormally cold temperature shocks (below the 5^{th} percentile) and precipitation 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 A20: Local projections of direct heat 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^{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.

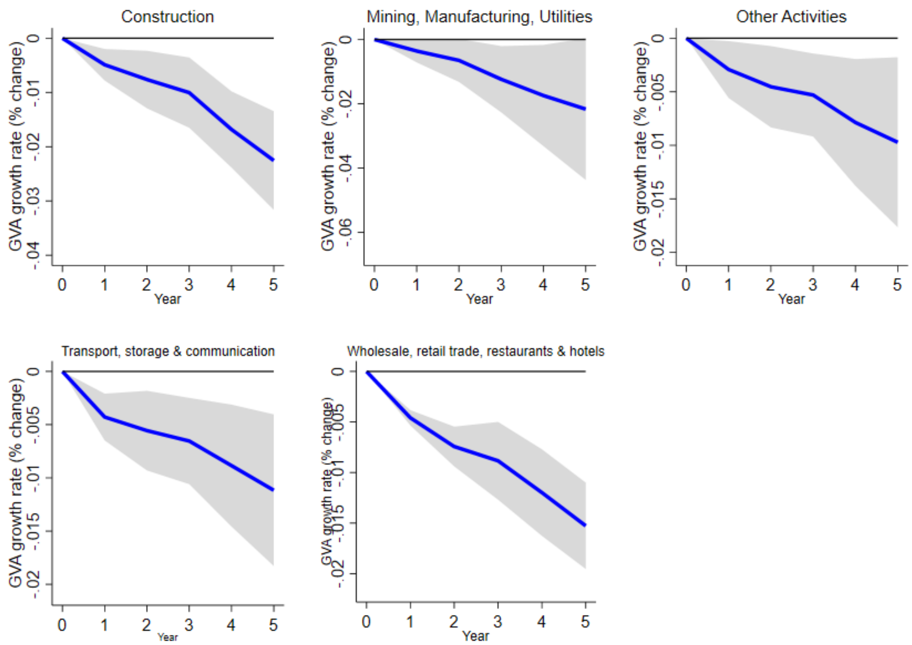
Figure A21: Local projections of foreign agricultural heat shocks on sectoral production



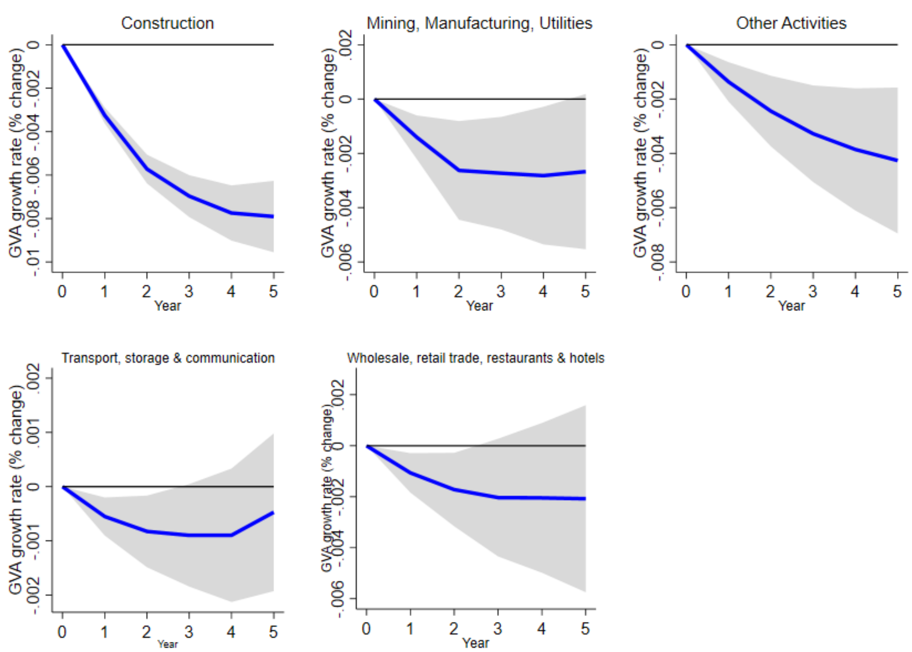
Notes: Panels show the sector-specific impulse response function of sectoral per capita GVA growth rate to a 1 SD increase in the foreign abnormally hot temperature shocks estimated in a stacked regression model fully saturated with country-sector and sector-year fixed effects and accounting for sector-specific responses to direct and domestic abnormally hot temperature shocks, to abnormally cold temperature shocks (below the 5^{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.

Figure A22: Local projections of domestic and foreign agricultural heat shocks on sectoral production. Time-varying production networks.

(a) Domestic



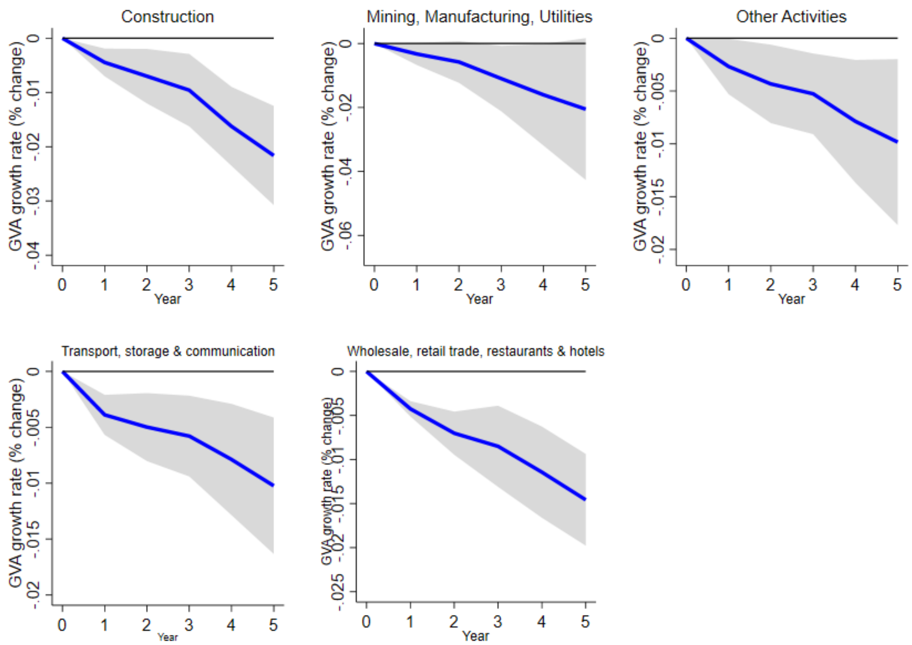
(b) Foreign



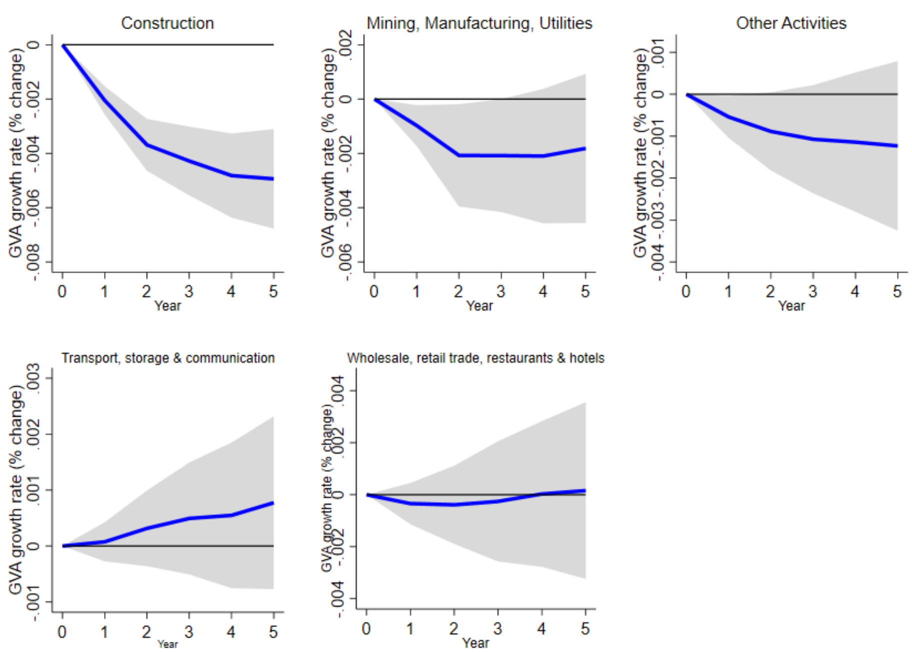
Notes: Panels show the sector-specific impulse response function of sectoral per capita GVA growth rate to a 1 SD increase in the foreign abnormally hot temperature shocks estimated in a stacked regression model fully saturated with country-sector and region-sector-year fixed effects and accounting for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

Figure A23: Local projections of domestic and foreign agricultural heat shocks on sectoral production. Continent-sector-year FE.

(a) Domestic



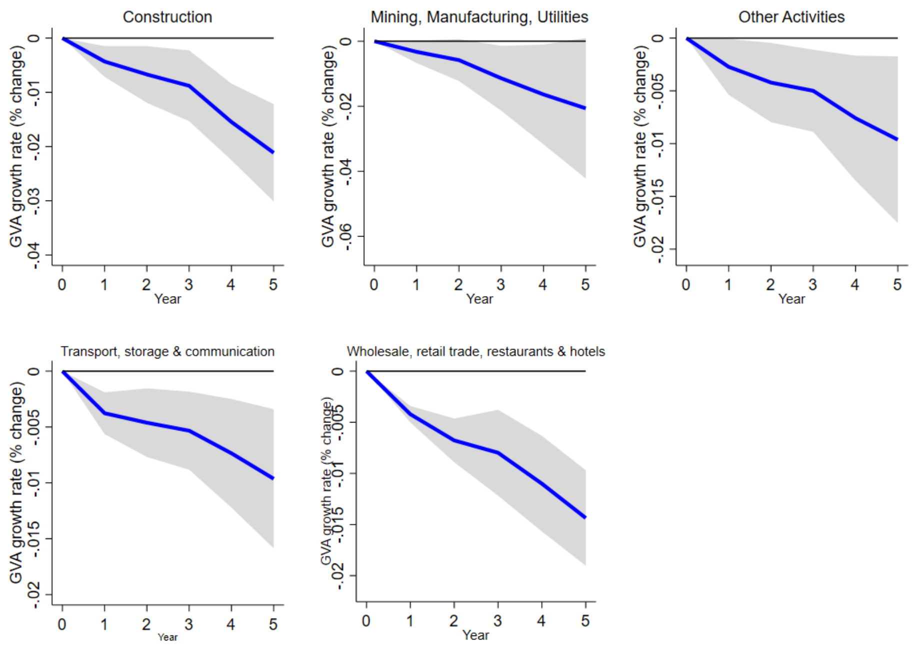
(b) Foreign



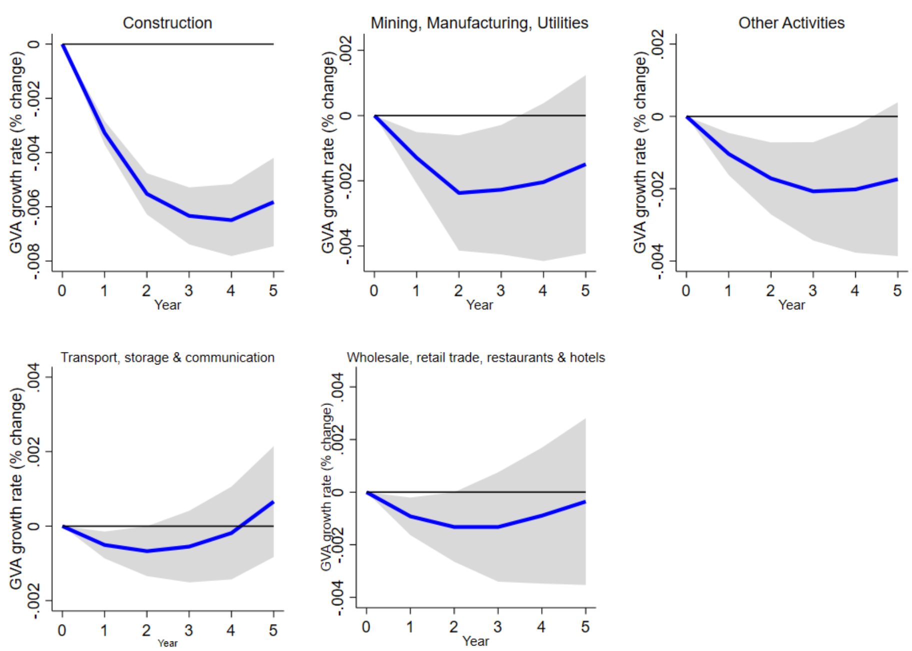
Notes: Panels show the sector-specific impulse response function of sectoral per capita GVA growth rate to a 1 SD increase in the foreign abnormally hot temperature shocks estimated in a stacked regression model fully saturated with country-sector and continent-sector-year fixed effects and accounting for sector-specific responses to direct and domestic abnormally hot temperature shocks, to abnormally cold temperature shocks (below the 5^{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.

Figure A24: Local projections of domestic and foreign agricultural heat shocks on sectoral production. Continent-sector linear trends.

(a) Domestic

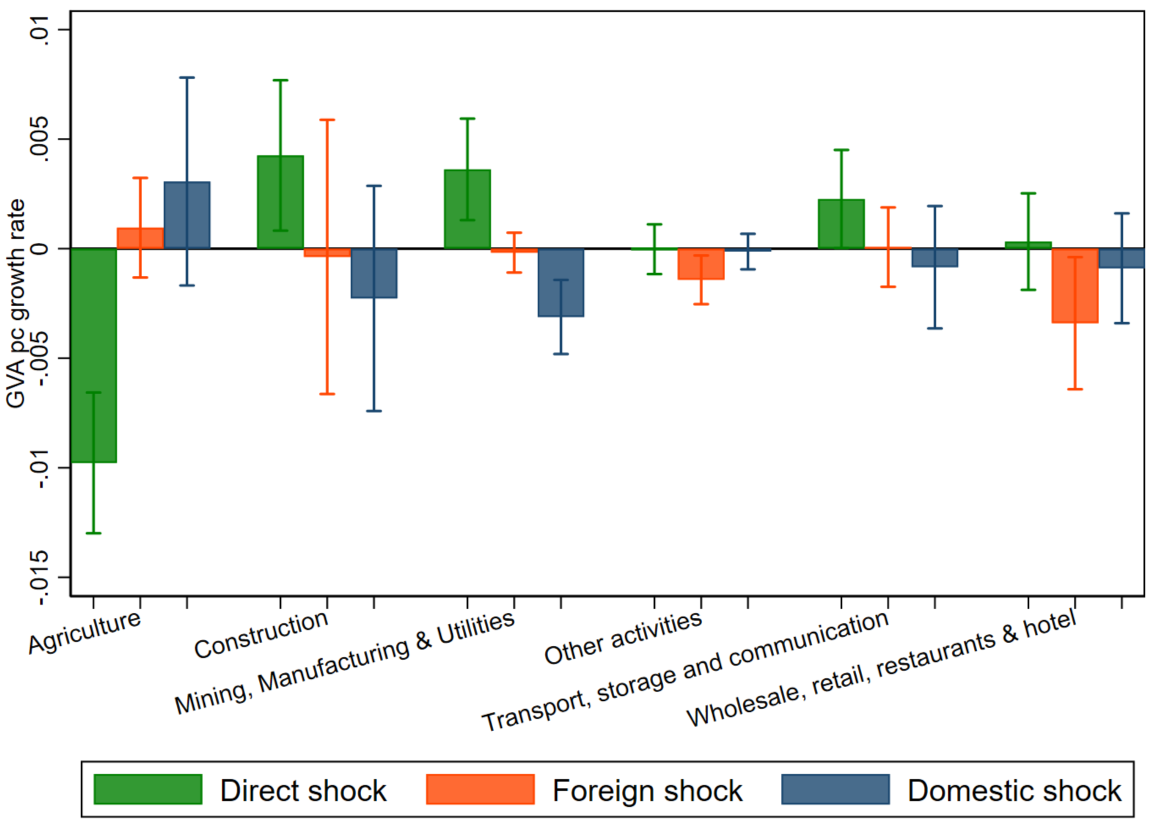


(b) Foreign



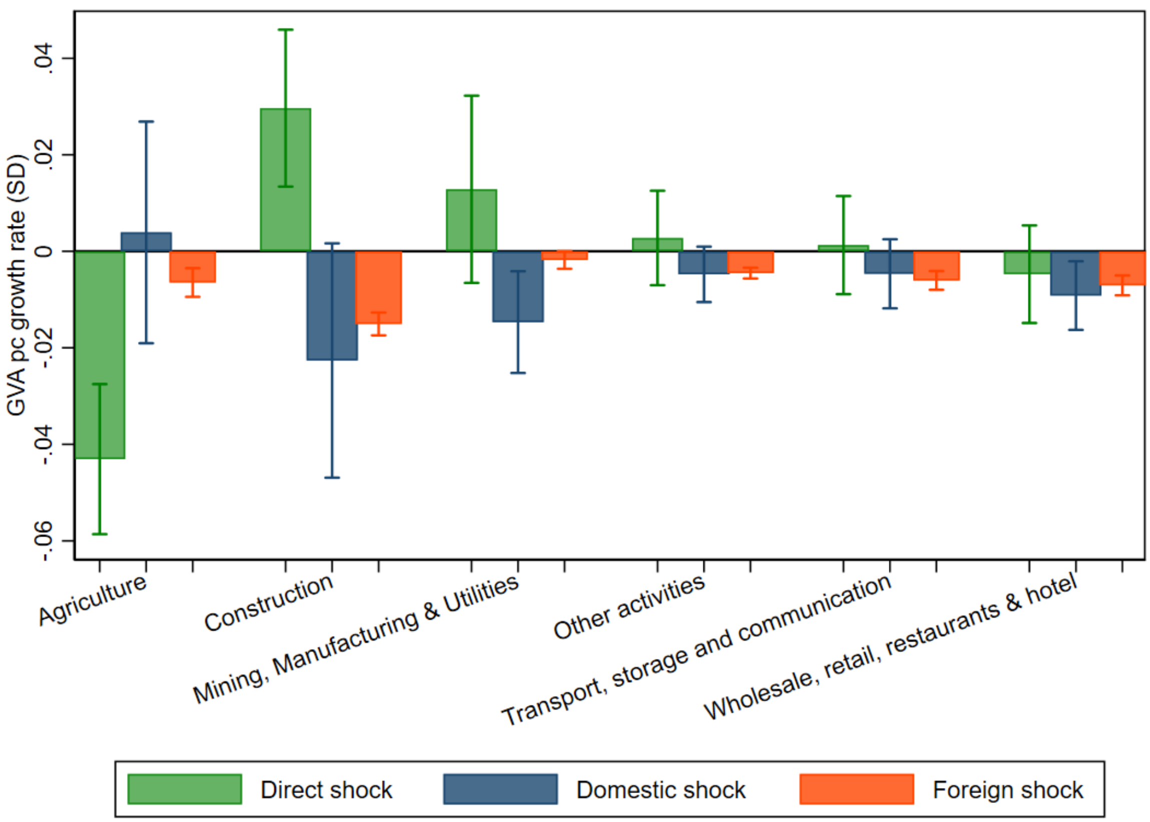
Notes: Panels show the sector-specific impulse response function of sectoral per capita GVA growth rate to a 1 SD increase in the foreign abnormally hot temperature shocks estimated in a stacked regression model fully saturated with country-sector and continent-sector linear annual trends and accounting 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 A25: Domestic and foreign 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.

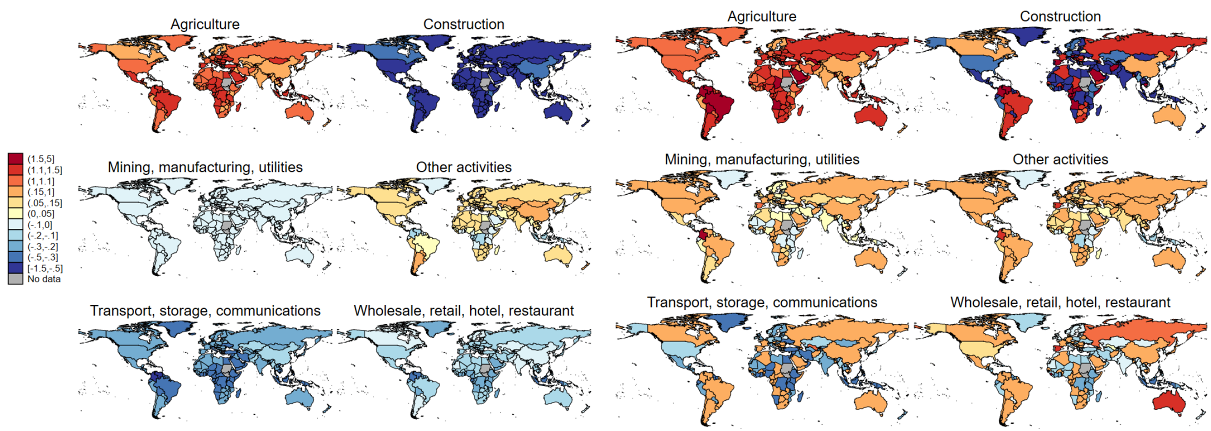
Figure A26: Domestic and foreign cyclones shocks and sectoral production



Notes: Bars represent the (standardized) sector-specific coefficients associated with direct shocks and domestic and foreign shocks, using the cubic 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 A27: Average annual relative sectoral GVA pc losses (%) due to recent warming

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



Notes: The figure shows average annual losses (in red) and gains (in blue) in sectoral per capita GVA due to abnormally hot and cold temperature shocks in the 2001-2020 period compared to a counterfactual in which 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 and cold shock estimates (Panel a) and accounting for semi-elasticities to shocks in other partner sectors (Panel b). Averages are obtained from 1000 bootstrap estimations of Equation (12), where indirect shocks are constructed with a time-varying production network that uses the first five-year average input-output interlinkages for each decade. In Panel a), only estimates for Agriculture are statistically significant at 95% level. Table A13 reports the estimated average losses significant at the 95% level for each country-sector when including indirect heat and cold shocks. Summary statistics on direct losses only considering 95% significant estimates: mean is 1.08%, median is 1.09%, IQR is [1.00%, 1.18%]. Summary statistics on losses accounting for indirect shocks only considering 95% significant estimates: mean is 1.29%, median is 1.21%, IQR is [1.04%, 1.44%].

B Additional tables

Table A1: Summary statistics on sectoral GVA growth rate

	N	mean	SD	min	max
Log GVA per capita	47,289	6.166	1.789	-2.880	11.534
GVA per capita growth rate	47,289	0.014	0.121	-3.299	2.572
Sector					
Agriculture, hunting, forestry, fishing (ISIC A-B)	7,860	0.002	0.104	-1.691	0.745
Mining, Manufacturing, Utilities (ISIC C-E)	7,900	0.013	0.170	-3.299	2.572
Construction (ISIC F)	7,906	0.010	0.128	-3.169	2.430
Wholesale, retail trade, restaurants and hotels (ISIC G-H)	7,906	0.018	0.087	-1.513	1.261
Transport, storage and communication (ISIC I)	7,857	0.026	0.112	-2.514	2.030
Other Activities (ISIC J-P)	7,860	0.015	0.110	-1.639	1.502
Number of countries	183				
Number of sectors	6				
Number of years per country-sector		44.220	5.235	12	46

Table A2: Countries and year-sectors in final sample

Country	Number of years-sectors	Country	Number of years-sectors	Country	Number of years-sectors
Afghanistan	276	French Polynesia	276	Nigeria	276
Albania	276	Gabon	276	North Korea	184
Algeria	276	Gambia	276	North Macedonia	180
Andorra	276	Georgia	180	Norway	276
Angola	276	Germany	276	Oman	276
Antigua and Barbuda	276	Ghana	276	Pakistan	276
Argentina	276	Greece	276	Palestine	180
Armenia	180	Greenland	276	Panama	276
Aruba	276	Grenada	276	Papua New Guinea	276
Australia	276	Guatemala	276	Paraguay	276
Austria	276	Guinea	276	Peru	276
Azerbaijan	180	Guyana	276	Philippines	276
Bahamas	296	Haiti	276	Poland	276
Bahrain	276	Honduras	276	Portugal	276
Bangladesh	276	Hungary	276	Qatar	276
Barbados	276	Iceland	276	Republic of the Congo	276
Belarus	180	India	276	Romania	276
Belgium	276	Indonesia	276	Russia	180
Belize	276	Iran	276	Rwanda	276
Benin	276	Iraq	276	Samoa	276
Bermuda	276	Ireland	276	San Marino	276
Bhutan	276	Israel	276	Saudi Arabia	276
Bolivia	276	Italy	276	Senegal	276
Bosnia and Herzegovina	180	Jamaica	276	Serbia	180
Botswana	276	Japan	276	Seychelles	276
Brazil	276	Jordan	276	Sierra Leone	276
British Virgin Islands	276	Kazakhstan	180	Singapore	276
Brunei	276	Kenya	276	Slovakia	180
Bulgaria	276	Kuwait	276	Slovenia	180
Burkina Faso	276	Kyrgyzstan	180	Somalia	276
Burundi	276	Laos	276	South Africa	276
Cabo Verde	276	Latvia	180	South Korea	276
Cambodia	276	Lebanon	276	South Sudan	72
Cameroon	276	Lesotho	276	Spain	276
Canada	276	Liberia	276	Sri Lanka	276
Cayman Islands	276	Libya	276	Sudan	72
Central African Republic	276	Liechtenstein	276	Suriname	276
Chad	276	Lithuania	180	Swaziland	276
Chile	276	Luxembourg	276	Sweden	276
China	276	Madagascar	276	Switzerland	276
Colombia	276	Malawi	276	Syria	276
Comoros	276	Malaysia	276	São Tomé and Príncipe	276
Costa Rica	276	Maldives	297	Tajikistan	178
Croatia	180	Mali	276	Tanzania	276
Cuba	276	Malta	276	Thailand	276
Cyprus	276	Mauritania	276	Togo	276
Czechia	180	Mauritius	276	Trinidad and Tobago	276
Côte d'Ivoire	276	Moldova	180	Tunisia	276
Democratic Republic of the Congo	276	Monaco	230	Turkey	276
Denmark	276	Mongolia	276	Turkmenistan	180
Djibouti	276	Montenegro	180	Uganda	276
Dominican Republic	276	Morocco	276	Ukraine	180
Ecuador	276	Mozambique	276	United Arab Emirates	276
Egypt	276	Myanmar	276	United Kingdom	276
El Salvador	276	México	276	United States	276
Equatorial Guinea	276	Namibia	276	Uruguay	276
Eritrea	126	Nepal	276	Uzbekistan	180
Estonia	180	Netherlands	276	Vanuatu	276
Ethiopia	180	New Caledonia	276	Venezuela	276
Fiji	276	New Zealand	276	Vietnam	276
Finland	276	Nicaragua	276	Yemen	186
France	276	Niger	276	Zambia	276
				Zimbabwe	276
Total	47,289				

Table A3: 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 A4: 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 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: Summary statistics on temperature and precipitation variables

	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 95th percentile (days/year)	8,572	18.986	16.5	0	152
Temperature below 5th percentile (days/year)	8,572	17.870	14.185	0	156
Precipitation above 95th percentile (days/year)	8,572	18.244	6.613	1	78
Precipitation below 5th percentile (days/year)	8,572	15.633	10.182	0	86
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

Notes: Summary statistics are computed using country-year observations. Where Δ is indicated in parentheses, variables are in first-difference, measuring changes in weather conditions from the previous year.

Table A7: Annual (binary) changes in temperature and precipitation on sectoral GVA.

	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 a binary variable equal to one if the annual temperature (resp. precipitation) is higher than the previous year. Standard errors are clustered at the country level. A graphical representation of the coefficients in column (2) is reported in Figure A4. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Annual changes in temperature and precipitation on sectoral GVA.

	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 changes in annual temperature and precipitation distributions from the previous year's. Standard errors are clustered at the country-level. A graphical representation of the coefficients in column (2) is reported in Figure A5. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: Heterogeneous effects 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 A6a. Standard errors are clustered at the country-level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: 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 A6a. Standard errors are clustered at the country-level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A11: 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 A13. 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 A12: 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 A15. 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 A13: Sector-country damages (% loss GVA per capita) significant at 95% level

Country	Sector	Average loss	95% CI
Afghanistan	Agriculture	1,25	[0,74 ; 1,78]
Albania	Agriculture	1,39	[0,81 ; 1,97]
Algeria	Agriculture	1,37	[0,81 ; 1,96]
Andorra	Agriculture	1,35	[0,80 ; 1,94]
Angola	Agriculture	1,74	[0,99 ; 2,50]
Antigua	Agriculture	1,62	[0,93 ; 2,32]
Argentina	Agriculture	1,30	[0,76 ; 1,88]
Armenia	Agriculture	1,19	[0,67 ; 1,72]
Aruba	Agriculture	1,31	[0,68 ; 1,95]
Australia	Agriculture	1,27	[0,75 ; 1,82]
Austria	Agriculture	1,33	[0,79 ; 1,92]
Azerbaijan	Agriculture	1,11	[0,61 ; 1,61]
Bahamas	Agriculture	1,70	[1,00 ; 2,45]
Bahrain	Agriculture	1,45	[0,85 ; 2,09]
Bangladesh	Agriculture	1,28	[0,74 ; 1,84]
Barbados	Agriculture	1,71	[0,96 ; 2,46]
Belarus	Agriculture	1,20	[0,64 ; 1,78]
Belgium	Agriculture	1,20	[0,71 ; 1,71]
Belize	Agriculture	1,69	[1,00 ; 2,41]
Benin	Agriculture	1,34	[0,78 ; 1,91]
Bermuda	Agriculture	1,58	[0,91 ; 2,28]
Bhutan	Agriculture	1,63	[0,94 ; 2,34]
Bolivia	Agriculture	1,78	[1,01 ; 2,56]
Bosnia and Herzegovina	Agriculture	1,43	[0,85 ; 2,05]
Botswana	Agriculture	1,30	[0,77 ; 1,87]
Brazil	Agriculture	1,66	[0,95 ; 2,39]
British Virgin Islands	Agriculture	1,62	[0,95 ; 2,31]
Brunei	Agriculture	1,57	[0,90 ; 2,26]
Bulgaria	Agriculture	1,27	[0,69 ; 1,88]
Burkina Faso	Agriculture	1,25	[0,70 ; 1,80]
Burundi	Agriculture	1,39	[0,80 ; 2,00]
Cambodia	Agriculture	1,21	[0,71 ; 1,72]
Cameroon	Agriculture	1,39	[0,79 ; 2,00]
Canada	Agriculture	1,00	[0,58 ; 1,45]
Cape Verde	Agriculture	1,65	[0,94 ; 2,37]
Cayman Islands	Agriculture	1,75	[1,01 ; 2,51]
Central African Republic	Agriculture	1,45	[0,86 ; 2,06]
Chad	Agriculture	1,52	[0,87 ; 2,20]
Chile	Agriculture	1,30	[0,76 ; 1,86]
China	Agriculture	0,84	[0,44 ; 1,26]
Colombia	Agriculture	1,60	[0,87 ; 2,34]
Congo	Agriculture	1,50	[0,85 ; 2,17]
Costa Rica	Agriculture	0,89	[0,45 ; 1,32]
Cote dIvoire	Agriculture	1,01	[0,43 ; 1,58]
Croatia	Agriculture	1,15	[0,55 ; 1,76]
Cuba	Agriculture	1,24	[0,60 ; 1,90]
Cyprus	Agriculture	1,09	[0,52 ; 1,68]
Czech Republic	Agriculture	1,09	[0,52 ; 1,67]
DR Congo	Agriculture	1,18	[0,50 ; 1,88]
Denmark	Agriculture	1,01	[0,48 ; 1,54]
Djibouti	Agriculture	1,14	[0,54 ; 1,74]
Dominican Republic	Agriculture	1,22	[0,54 ; 1,88]
Ecuador	Agriculture	1,29	[0,56 ; 2,01]
Egypt	Agriculture	1,21	[0,55 ; 1,86]
El Salvador	Agriculture	1,17	[0,56 ; 1,80]
Eritrea	Agriculture	1,15	[0,55 ; 1,76]
Estonia	Agriculture	0,99	[0,47 ; 1,52]
Ethiopia	Agriculture	1,09	[0,46 ; 1,72]
Fiji	Agriculture	1,16	[0,56 ; 1,78]
Finland	Agriculture	0,94	[0,44 ; 1,45]
France	Agriculture	1,31	[0,77 ; 1,87]
French Polynesia	Agriculture	1,38	[0,81 ; 1,97]
Gabon	Agriculture	1,28	[0,60 ; 1,95]
Gambia	Agriculture	1,41	[0,80 ; 2,04]
Gaza Strip	Agriculture	1,22	[0,56 ; 1,88]
Georgia	Agriculture	1,14	[0,56 ; 1,74]
Germany	Agriculture	1,05	[0,51 ; 1,61]
Ghana	Agriculture	1,05	[0,45 ; 1,65]
Greece	Agriculture	1,22	[0,59 ; 1,87]
Greenland	Agriculture	1,09	[0,47 ; 1,70]
Guatemala	Agriculture	1,19	[0,55 ; 1,83]
Guinea	Agriculture	0,92	[0,43 ; 1,42]
Guyana	Agriculture	1,10	[0,47 ; 1,75]
Haiti	Agriculture	1,13	[0,51 ; 1,74]
Honduras	Agriculture	1,09	[0,52 ; 1,66]
Hungary	Agriculture	1,08	[0,51 ; 1,66]
Iceland	Agriculture	1,08	[0,47 ; 1,69]
India	Agriculture	0,93	[0,45 ; 1,42]
Indonesia	Agriculture	1,22	[0,44 ; 2,00]
Iran	Agriculture	1,01	[0,46 ; 1,55]
Iraq	Agriculture	0,91	[0,44 ; 1,40]
Ireland	Agriculture	0,87	[0,40 ; 1,34]
Israel	Agriculture	1,22	[0,56 ; 1,88]
Italy	Agriculture	1,21	[0,58 ; 1,85]
Jamaica	Agriculture	1,23	[0,53 ; 1,94]
Japan	Agriculture	0,82	[0,40 ; 1,26]
Jordan	Agriculture	1,12	[0,53 ; 1,73]
Kenya	Agriculture	0,99	[0,41 ; 1,58]
Kuwait	Agriculture	1,11	[0,53 ; 1,71]
Kyrgyzstan	Agriculture	0,91	[0,43 ; 1,41]
Laos	Agriculture	1,12	[0,54 ; 1,72]
Latvia	Agriculture	1,03	[0,49 ; 1,59]
Lebanon	Agriculture	1,13	[0,54 ; 1,73]
Lesotho	Agriculture	1,09	[0,52 ; 1,68]
Liberia	Agriculture	1,03	[0,49 ; 1,59]
Libya	Agriculture	1,07	[0,51 ; 1,63]
Liechtenstein	Agriculture	1,08	[0,52 ; 1,66]
Lithuania	Agriculture	1,06	[0,50 ; 1,64]
Luxembourg	Agriculture	1,00	[0,47 ; 1,55]
Madagascar	Agriculture	1,26	[0,56 ; 1,94]
Malawi	Agriculture	1,06	[0,52 ; 1,62]
Malaysia	Agriculture	1,16	[0,47 ; 1,86]
Maldives	Agriculture	1,01	[0,43 ; 1,60]
Mali	Agriculture	1,09	[0,52 ; 1,68]
Malta	Agriculture	-0,11	[-0,18 ; -0,04]
Mauritania	Agriculture	1,03	[0,50 ; 1,58]
Mauritius	Agriculture	0,96	[0,36 ; 1,55]
Mexico	Agriculture	1,17	[0,56 ; 1,80]
Moldova	Agriculture	1,23	[0,59 ; 1,88]
Mongolia	Agriculture	1,21	[0,57 ; 1,86]
Montenegro	Agriculture	1,22	[0,58 ; 1,86]
Morocco	Agriculture	1,01	[0,48 ; 1,55]
Mozambique	Agriculture	1,04	[0,50 ; 1,61]
Myanmar	Agriculture	0,62	[0,29 ; 0,96]
Namibia	Agriculture	1,16	[0,55 ; 1,79]
Nepal	Agriculture	0,98	[0,46 ; 1,52]
Netherlands	Agriculture	1,00	[0,48 ; 1,53]
New Caledonia	Agriculture	1,03	[0,50 ; 1,58]
New Zealand	Agriculture	0,89	[0,41 ; 1,38]
Nicaragua	Agriculture	0,91	[0,40 ; 1,41]
Niger	Agriculture	1,12	[0,54 ; 1,72]
Nigeria	Agriculture	1,18	[0,56 ; 1,81]
North Korea	Agriculture	0,53	[0,19 ; 0,87]
Norway	Agriculture	0,91	[0,43 ; 1,39]
Oman	Agriculture	1,23	[0,56 ; 1,90]
Pakistan	Agriculture	0,86	[0,40 ; 1,32]
Panama	Agriculture	1,00	[0,43 ; 1,59]
Papua New Guinea	Agriculture	1,35	[0,57 ; 2,12]
Paraguay	Agriculture	1,07	[0,50 ; 1,64]
Peru	Agriculture	0,92	[0,39 ; 1,45]
Philippines	Agriculture	1,14	[0,48 ; 1,81]
Poland	Agriculture	1,13	[0,54 ; 1,73]
Portugal	Agriculture	1,00	[0,47 ; 1,55]
Qatar	Agriculture	1,19	[0,56 ; 1,84]
Romania	Agriculture	1,44	[0,86 ; 2,07]
Russia	Agriculture	1,38	[0,82 ; 1,99]
Rwanda	Agriculture	1,75	[0,95 ; 2,53]
San Marino	Agriculture	1,41	[0,83 ; 2,03]
Sao Tome and Principe	Agriculture	1,10	[0,66 ; 1,58]
Saudi Arabia	Agriculture	1,82	[1,04 ; 2,63]
Senegal	Agriculture	1,16	[0,69 ; 1,67]
Serbia	Agriculture	1,25	[0,71 ; 1,80]
Seychelles	Agriculture	1,43	[0,82 ; 2,06]
Sierra Leone	Agriculture	1,17	[0,69 ; 1,68]
Singapore	Agriculture	1,23	[0,55 ; 1,90]
Slovakia	Agriculture	1,33	[0,77 ; 1,89]
Slovenia	Agriculture	1,40	[0,83 ; 2,01]
Somalia	Agriculture	1,47	[0,82 ; 2,13]
South Africa	Agriculture	1,39	[0,83 ; 2,00]
South Korea	Agriculture	0,80	[0,37 ; 1,24]
Spain	Agriculture	1,21	[0,41 ; 1,94]
Sri Lanka	Agriculture	0,90	[0,43 ; 1,38]
Suriname	Agriculture	1,05	[0,44 ; 1,66]
Swaziland	Agriculture	0,91	[0,43 ; 1,40]
Sweden	Agriculture	0,96	[0,46 ; 1,47]
Switzerland	Agriculture	1,10	[0,52 ; 1,68]
Syria	Agriculture	1,16	[0,55 ; 1,79]
TFYR Macedonia	Agriculture	1,15	[0,55 ; 1,76]
Tajikistan	Agriculture	0,98	[0,47 ; 1,52]
Tanzania	Agriculture	1,29	[0,56 ; 2,01]
Thailand	Agriculture	0,90	[0,43 ; 1,38]
Togo	Agriculture	0,99	[0,43 ; 1,55]
Trinidad and Tobago	Agriculture	1,24	[0,50 ; 1,98]
Tunisia	Agriculture	1,12	[0,54 ; 1,72]
Turkey	Agriculture	1,19	[0,57 ; 1,83]
Turkmenistan	Agriculture	0,91	[0,43 ; 1,40]
UAE	Agriculture	1,24	[0,62 ; 1,88]
UK	Agriculture	1,01	[0,51 ; 1,52]
USA	Agriculture	1,04	[0,50 ; 1,58]
Uganda	Agriculture	1,04	[0,44 ; 1,64]
Ukraine	Agriculture	1,21	[0,58 ; 1,86]
Uruguay	Agriculture	1,39	[0,77 ; 2,02]
Uzbekistan	Agriculture	1,81	[0,71 ; 2,84]
Vanuatu	Agriculture	1,35	[0,81 ; 1,93]
Venezuela	Agriculture	1,85	[0,94 ; 2,75]
Viet Nam	Agriculture	2,03	[0,93 ; 3,12]
Yemen	Agriculture	1,53	[0,81 ; 2,24]
Zambia	Agriculture	1,34	[0,79 ; 1,91]
Zimbabwe	Agriculture	1,17	[0,68 ; 1,68]
Afghanistan	Construction	1,65	[0,26 ; 2,97]
Albania	Construction	1,59	[0,07 ; 3,04]
Angola	Construction	2,30	[0,61 ; 3,77]
Antigua	Construction	1,49	[0,13 ; 2,74]
Armenia	Construction	2,08	[0,53 ; 3,52]
Aruba	Construction	3,69	[1,44 ; 5,73]
Austria	Construction	1,70	[0,26 ; 3,07]
Azerbaijan	Construction	1,32	[0,08 ; 2,51]
Bahrain	Construction	1,98	[0,46 ; 3,39]
Bangladesh	Construction	1,49	[0,09 ; 2,83]
Barbados	Construction	1,92	[0,38 ; 3,25]
Belgium	Construction	1,25	[0,02 ; 2,41]
Benin	Construction	1,77	[0,43 ; 2,94]
Bhutan	Construction	2,67	[0,79 ; 4,41]
Bosnia and Herzegovina	Construction	1,38	[0,04 ; 2,67]
Brazil	Construction	1,39	[0,07 ; 2,63]
Brunei	Construction	2,16	[0,62 ; 3,50]
Bulgaria	Construction	1,43	[0,02 ; 2,77]
Burundi	Construction	1,47	[0,22 ; 2,58]
Cambodia	Construction	1,61	[0,33 ; 2,74]
Cameroon	Construction	2,02	[0,51 ; 3,32]
Cape Verde	Construction	1,44	[0,07 ; 2,73]
Cayman Islands	Construction	1,76	[0,19 ; 3,25]
Central African Republic	Construction	1,54	[0,24 ; 2,66]
Chad	Construction	1,45	[0,03 ; 2,81]
Colombia	Construction	1,60	[0,16 ; 2,88]
Congo	Construction	2,14	[0,56 ; 3,52]
Costa Rica	Construction	1,31	[0,17 ; 2,38]
France	Construction	1,28	[0,01 ; 2,50]
French Polynesia	Construction	1,61	[0,29 ; 2,81]
Gabon	Construction	2,17	[0,64 ; 3,55]
Gambia	Construction	1,37	[0,10 ; 2,60]
Russia	Construction	1,40	[0,07 ; 2,67]
Rwanda	Construction	2,20	[0,60 ; 3,58]
Saudi Arabia	Construction	2,15	[0,44 ; 3,65]
Senegal	Construction	1,17	[0,03 ; 2,27]
Serbia	Construction	1,42	[0,06 ; 2,72]
Slovakia	Construction	1,45	[0,07 ; 2,77]
Slovenia	Construction	2,01	[0,43 ; 3,48]
Somalia	Construction	1,57	[0,17 ; 2,92]
Spain	Construction	2,00	[0,14 ; 3,72]
Venezuela	Construction	2,02	[0,46 ; 3,37]
Aruba	Mining, manufacturing, utilities	1,62	[0,55 ; 3,38]
Colombia	Mining, manufacturing, utilities	2,30	[0,89 ; 4,62]
Spain	Mining, manufacturing, utilities	1,09	[0,09 ; 2,34]
Aruba	Other activities	1,32	[0,27 ; 2,48]
Australia	Other activities	0,57	[0,05 ; 1,09]
Bermuda	Other activities	0,72	[0,10 ; 1,37]
Cayman Islands	Other activities	0,73	[0,07 ; 1,42]
Colombia	Other activities	1,36	[0,22 ; 2,60]
France	Other activities	0,56	[0,04 ; 1,06]
Germany	Other activities	0,57	[0,08 ; 1,14]
Spain	Other activities	1,48	[0,77 ; 2,65]
Aruba	Transport, storage, communications	2,02	[0,58 ; 3,42]
Australia	Transport, storage, communications	0,69	[0,00 ; 1,35]
Bolivia	Transport, storage, communications	0,96	[0,03 ; 1,86]
Russia	Transport, storage, communications	0,77	[0,01 ; 1,49]
Singapore	Transport, storage, communications	1,71	[0,48 ; 2,94]
Uzbekistan	Transport, storage, communications	1,06	[0,22 ; 1,86]
Viet Nam	Transport, storage, communications	0,91	[0,07 ; 1,73]
Yemen	Transport, storage, communications	0,98	[0,03 ; 1,90]
Aruba	Wholesale, retail, hotel, restaurant	4,51	[2,23 ; 6,90]
Australia	Wholesale, retail, hotel, restaurant	1,37	[0,57 ; 2,17]
Bahamas	Wholesale, retail, hotel, restaurant	1,19	[0,30 ; 2,07]
Bahrain	Wholesale, retail, hotel, restaurant	0,79	[0,09 ; 1,47]
Belgium	Wholesale, retail, hotel, restaurant	0,83	[0,16 ; 1,49]
Bermuda	Wholesale, retail, hotel, restaurant	0,85	[0,10 ; 1,58]
Brazil	Wholesale, retail, hotel, restaurant	0,81	[0,09 ; 1,51]
Burkina Faso	Wholesale, retail, hotel, restaurant	0,76	[0,07 ; 1,42]
Russia	Wholesale, retail, hotel, restaurant	1,08	[0,33 ; 1,84]
Saudi Arabia	Wholesale, retail, hotel, restaurant	0,84	[0,01 ; 1,61]
Sierra Leone	Wholesale, retail, hotel, restaurant	1,92	[0,93 ; 2,92]
Singapore	Wholesale, retail, hotel, restaurant	1,33	[0,51 ; 2,14]
Spain	Wholesale, retail, hotel, restaurant	1,21	[0,29 ; 2,80]
Viet Nam	Wholesale, retail, hotel, restaurant	0,93	[0,17 ; 1,66]

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 and cold shocks. 95% confidence intervals are obtained from 1000 estimates from bootstrapping Equation 12, where indirect shocks are constructed with a time-varying production network that uses the first five-year average input-output interlinkages for each decade.

C Additional weather data

C.1 Dryness and wetness

To introduce a measure of dryness and wetness, I use the Standardized Precipitation Evapotranspiration Index (SPEI), a climatological index used by climate scientists 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, which are a function of temperature. 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 increasing 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 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 months 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 example, a value of SPEI equal to -1 can be interpreted as the difference between rain and potential evapotranspiration needs being one standard deviation lower 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 in each country 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 (with SPEI below -2) (McKee et al., 1993; Paulo et al., 2012), and to periods with extreme wetness (with SPEI above 2). For each year, I consider the share of affected grid-cells in the month where the share is at its maximum (Akyapi et al., 2022).

C.2 Tropical cyclones

The last type of extreme weather event I consider is tropical cyclones. The measure of tropical cyclones is taken from Kunze (2021), who uses meteorological data on wind speeds to obtain a measure of damage of tropical cyclones as previously introduced in the literature (Bakkensen & Barrage, 2018; Hsiang, 2010; Hsiang & Jina, 2014). The annual measure of tropical cyclones at the country level 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).

D Sectoral interlinkages' response to heat shocks

One of the main assumptions in the theoretical framework in Section 2 and the derived empirical approach in Section 3.3 is that weather shocks affect economic production via spillovers in a pre-determined exogenous production network that does not adjust in response to weather shocks. This assumption has been shown to hold empirically, reflecting the non-responsiveness of sectoral interlinkages to tropical cyclones exposure mostly due to the stickiness of production processes (Kunze, 2021). I empirically test this assumption by exploiting the time-varying nature of the sectoral interlinkages between 1970 and 2019. I estimate the following specification

$$\text{weight}_{icjkt} = f_i(\mathbf{W}_{ct}) + \alpha_{ic} + \mu_{ij} + \lambda_{jkt} + \varepsilon_{icjkt} \tag{D.1}$$

where the dependent variable $\text{weight}_{icjkt} \in \{\omega; \widehat{\omega}; \overline{\omega}\}$, respectively the downstream, upstream and average interlinkage between sector i in country c and sector j in country k in year t. The objective is to exploit inter-annual variation in weather conditions in the origin sector-country ic to test for within bilateral sector ij changes in interlinkages across countries. Given the level of aggregation of the sectors, the major concern on the endogenous adjustment of the production network regards the potential substitution of inputs across trade partners for a given sector. For this reason, the specification accounts for sector-country ic, origin-destination sector ij, and destination sector-country-year jkt fixed effects, where the latter accounts for changes in weather conditions in the destination country. Figure A3 reports the sector-specific coefficients associated with heat shocks on the three measures of sectoral interlinkages, displaying a small and not statistically significant effect across sectors and suggesting that the production network does not endogenously adapt to heat shocks.

E Time-varying production network

Production linkages have intensified over time with more fragmented global supply chains and intensive use of intermediate inputs produced in other domestic and foreign industries. In subsequent robustness checks, I relax the assumption that weather shocks affect economic production via spillovers in a pre-determined exogenous production network. To allow for slow-moving adjustments, I construct decade-specific time-varying production network. I retain the average of the first five-year input-output sectoral interlinkages for each decade τ (e.g., 1970-1974 average for shocks between 1975 and 1984; 1980-1984 average for shocks between 1985 and 1994), such that the downstream weights are constructed as

$$\omega_{i,c,j,k,\tau} = \frac{\overline{input}_{jk\tau \to ic\tau}}{\sum\limits_{lf \in \Theta_{ic}} \overline{input}_{ic\tau \to lf\tau}} \tag{E.1}$$

and upstream weights are constructed as

$$\widehat{\omega}_{i,c,j,k,\tau} = \frac{\overline{input}_{ic\tau \to jk\tau}}{\sum\limits_{lf \in \hat{\Theta}_{ic}} \overline{input}_{ic\tau \to lf\tau}} \tag{E.2}$$

From this, the construction of network shocks follows as detailed in Section 3.3.1.

F Reduced-form approach to the climate-economy relationship

Kahn et al. (2021) review the three main approaches that study the climate-economy relationship in reduced form in the literature (Burke et al., 2015; Dell et al., 2012; Kalkuhl & Wenz, 2020), highlighting the restrictive assumptions that each of these models requires to study the effect of temperature on output growth. In this Appendix section, I report an extension of these approaches discussed in Newell et al. (2021) and discuss the assumptions that it relies on. In an attempt to deal with the non-stationarity issue of trended temperatures and allow for the non-linear effect of temperature changes, one could include higher-order polynomials of first-differenced temperature as main regressors. Without loss of generality, the estimating equation considering only a second-order polynomial of differenced temperature is written as

$$\Delta y_{it} = \alpha_i + \delta_t + \lambda \Delta T_{it} + \psi \Delta [T_{it}^2] + \varepsilon_{it} \tag{F.1}$$

which uses the growth rate of log-differences of real GDP per capita of country i in year t as the dependent variable, the main regressors are the linear and quadratic differenced temperature, where the latter term is the change in temperature-squared (different from the squared change in temperature), a_i is the country-specific fixed effect and δ_t is the time-specific fixed effect. As in Kahn et al. (2021) and motivated by historical evidence, I assume that

$$T_{it} = a_{T_i} + b_{T_i} t + \nu_{T_i;t} \tag{F.2}$$

where, in line with historical evidence, $b_{T_i} > 0$, and $\mathbb{E}(\nu_{T_i;t}) = 0$ and $\mathbb{E}(\nu_{T_i;t}^2) = \sigma_{T_i}^2$. Substituting Equation (F.2) in Equation (F.1) and taking expectations yields

$$\mathbb{E}(\Delta y_{it}) = \mathbb{E}(\delta_t) + \alpha_i + b_{T_i}[\lambda + 2\psi a_{T_i}] + 2\psi b_{T_i}^2 t \tag{F.3}$$

To ensure that $\mathbb{E}(\Delta y_{it})$ is not trended, there are some restrictions to impose. First, since δ_t is unobserved, one can set $\mathbb{E}(\delta_t) = 0$ (Kahn et al., 2021), and then require that

$2\psi b_{T_i}^2 t = 0$ for all i. Therefore, this approach does not resolve the trend problem around the output growth-climate specifications, introducing a trend in the mean output growth, which is not supported empirically. An alternative approach would be to include region-year rt fixed effects in Equation (F.1), such that it becomes

$$\Delta y_{irt} = \alpha_{ir} + \delta_{rt} + \lambda \Delta T_{irt} + \psi \Delta [T_{irt}^2] + \varepsilon_{irt} \tag{F.4}$$

with $T_{irt} = a_{T_{i,r}} + b_{T_{i,r}} t + \nu_{T_{i;rt}}$, where the shock $\nu_{T_{i;rt}}$ for country i in region r in year t has zero mean and finite variance. Taking expectations as above, to have that $\mathbb{E}(\Delta y_{irt})$ is stationary, one would require no trend in temperature $b_{Ti;r} = 0$, or exact cancellation of quadratic trends in temperature at the regional level with the region-year fixed effects, i.e. $\delta_{rt} + \psi \overline{b}_{Tr}^2 t = 0$, for all r, where $\overline{b}_{Tr}^2 = \frac{1}{n} \sum_{i=1}^{n_r} b_{T_{i,r}}^2$.

G Changes in temperature and precipitation distribution

To provide additional evidence on the heterogeneous sectoral response to weather shocks, I consider first-differenced weather changes. First, I construct a binary measure of annual changes in temperature and precipitation distribution either larger or smaller than the previous year. Then, I consider how much daily temperatures and precipitation are larger/smaller than the previous year. Table A6 shows summary statistics for the measures of temperature and precipitation.

Figure A4 displays the 12 estimated coefficients from the same pooled regression using a binary measure of weather shock indicating whether first-differenced annual changes in daily average temperature and total precipitation are positive or negative. 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 the 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 A7), 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 benefits 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 A5 shows the estimated coefficients (see Table A8 for tabular results). As previously documented, agriculture reacts negatively to 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 respond positively to increases in the average daily temperatures, although a few sectors' responses are estimated with less precision (other activities; transport, storage and communication; wholesale, retail trade, restaurants and hotels). Conversely, production in other sectors does not respond to changes in precipitation, except for the transportation sector which benefits from drier conditions.

Heterogeneity across adaptation potential. Until now, results referred to the average treatment effect for each sector across countries. One may however expect the marginal effect of changes in the 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 fifty years (i.e., long-run climate). These two factors account for differential adaptation potential (Acevedo et al., 2020; Carleton et al., 2022; Kahn et al., 2021). First, I augment the baseline specification with an interaction term distinguishing between advanced economies, emerging market economies, and low-income developing countries. Second, 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 are interpreted as associational (Carleton et al., 2022).

Figure A6 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 A9 and A10. As conjectured, results are consistent with the hypothesis that income is protective (Figure A6a). Advanced economies are not harmed by increases in the 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 effect 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 A6b 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 and hotels) in cold climate countries.

H Sectoral impact of extreme weather events

The set of results in Section 5 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 investigate whether similar results hold when using measures of extreme weather events for droughts and cyclones.

H.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 A13 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 A11. 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 the 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. Agriculture's 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 sector's 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 are characterized by "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.

H.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 Kunze (2021)'s 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 estimated in the same model and identify the effect of tropical cyclones.[16] 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 A15 presents the sector-specific (standardized) coefficients associated with changes in tropical cyclone intensity. Tabular results are displayed in Table A12. 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 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 agricultural sector (Hsiang, 2010; Loayza et al., 2012), the contraction in economic production in the 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.

[16] My analysis also differs in the definition of the sectors since I do not account for the manufacturing sector separately as explained in Section 3.1.

I Propagation of extreme weather events

I.1 Droughts

I consider changes in drought shocks 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 A25 is identical to that of examining abnormal temperature shocks. The results are also similar. For example, 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 hotels are imprecisely estimated. Conversely, foreign shocks have a sizable negative effect on other activities and wholesale, retail trade, restaurants and hotels suggesting strong propagation of drought shocks through the economy and across countries in later stages of the supply chain. Peculiar and outstanding is the case of the mining, manufacturing and utilities sector which is strongly harmed by domestic drought shocks, with a magnitude comparable to the coefficient associated with direct shocks, suggesting that the net effect of drought shocks 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 drought shocks accounting for shocks hitting other partner sectors.

I.2 Tropical cyclones

I consider the propagation of tropical cyclones' intensity as measured by wind speed. This shock has been shown in Section H.2 to have the widest impact across sectors, damaging agriculture and other activities. Since cyclones are extreme weather events that may also have a direct impact on capital stock destruction, trade linkages may either amplify or mitigate the aggregate damage suffered by sectors.

Figure A26 decomposes the network shocks by geographic location into foreign and domestic, besides including the sector-specific direct shock. Agriculture remains the only sector directly harmed by tropical cyclones. Both domestic and foreign shocks have strong negative effects on construction; mining, manufacturing and utilities; transport, storage and communication; other activities; wholesale, retail trade, restaurants and hotels sectors.

J 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 the effect of own, domestic, and foreign heat and cold 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 daily temperature evolves linearly based on its historical trend of 1970-2000. To do so, I estimate country-specific regressions of the type $T_{dmct} = \alpha_c + \lambda_{dm} + \beta_c t + \varepsilon_{dmct}$ on the 1970-2000 sample, where T_{dmct} is the average temperature in day d in month m in year t in country c. I obtain country-specific historical trends in daily temperature exploiting within day-month variation between 1970 and 2000 and use $\hat{\beta}_c$ to construct a counterfactual daily temperature $\tilde{T}_{dmct}$ between 2001 and 2020 that is then used to compute the counterfactual number of *cold* and *hot* days. I assume that the trend is linear and that such a trend does not affect the volatility of temperature shocks, which most likely results in an underestimation of the adverse effects of abnormal temperatures.

I then average these effects over the 2001-2020 period to obtain a sector-specific relative measure of estimated losses in value added. I finally compare the estimated losses in value added omitting and accounting for the transmission of shocks across countries through trade interlinkages. 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 (Burke & Tanutama, 2019).

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

$$g_{ict}^{direct} = \widehat{\gamma_i^{95}}(T_{ict}^{95} - \tilde{T}_{ict}^{95}) + \widehat{\gamma_i^{5}}(T_{ict}^{5} - \tilde{T}_{ict}^{5}) \tag{J.1}$$

$$\begin{aligned} g_{ict}^{spillover} &= (\widehat{\gamma_i^{95}}T_{ict}^{95} + \widehat{\gamma_i^{D,95}}T_{ict}^{95,D} + \widehat{\gamma_i^{F,95}}T_{ict}^{95,F} + \widehat{\gamma_i^{5}}T_{ict}^{5} + \widehat{\gamma_i^{D,5}}T_{ict}^{5,D} + \widehat{\gamma_i^{F,5}}T_{ict}^{5,F}) \\ &- (\widehat{\gamma_i^{95}}\tilde{T}_{ict}^{95} + \widehat{\gamma_i^{D,95}}\tilde{T}_{ict}^{95,D} + \widehat{\gamma_i^{F,95}}\tilde{T}_{ict}^{95,F} + \widehat{\gamma_i^{5}}\tilde{T}_{ict}^{5} + \widehat{\gamma_i^{D,5}}\tilde{T}_{ict}^{5,D} + \widehat{\gamma_i^{F,5}}\tilde{T}_{ict}^{5,F}) \end{aligned} \tag{J.2}$$

where T_{ict}^{95} is the observed number of days above 95^{th} percentile in sector i in country c in year t, $\tilde{T}_{ict}^{95}$ is the counterfactual predicted number had the 1970-2000 average evolved linearly, $T_{ict}^{95,J}$ 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 i in country c in year t. $\widehat{\gamma_i^{95}}$'s are the sector-specific estimates for the effect of own, domestic and foreign heat shocks on the sectoral growth rate (symmetrically for $\widehat{\gamma_i^5}$) obtained from bootstrapping 1000 times the underlying panel estimates from Equation (12) where indirect shocks are constructed with a time-varying production network that uses the first five-year average input-output interlinkages for each decade. I compute sector i's counterfactual value added levels in year t omitting and accounting for indirect shocks

$$\hat{Y}_{ict}^{p} = Y_{ict-1} + y_{ict} + g_{ict}^{p} \tag{J.3}$$

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 i in country c over the 2001-2020 period as

$$\%\overline{\text{LOSS}}_{ic}^{p} = \frac{1}{T} \sum_{t=2001}^{2020} \frac{e^{\hat{Y}_{ict}^{p}} - e^{Y_{ict}}}{e^{Y_{ict}}} \tag{J.4}$$

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 A27).

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

$$\%\overline{\text{LOSS}}_{c}^{p} = \sum_{s} \%\lambda_{ic} \overline{\text{LOSS}}_{ic}^{p} \tag{J.5}$$

where λ_{ic} is the baseline five-year average share of total GVA of sector i in country c between 1996 and 2000. The country-level losses omitting and accounting for indirect heat shocks are reported in Figure 6.