Estimating sectoral climate impacts in a global production network

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Abstract

Despite intensified international trade and production fragmentation, weather shocks have only been shown to affect local economic activity. This paper introduces input-output sectoral interlinkages as a transmission mechanism of weather shocks in a production network model. Using global sectoral production data from 1975 to 2020, I document that local daily temperature shocks negatively affect the agricultural sector. Accounting for network propagation, downstream sectors, which are non-responsive to local weather, incur substantial and persistent losses from temperature shocks in the upstream agricultural sector. Counterfactual scenarios reveal a threefold underestimation of aggregate costs induced by temperature increases accounting for shocks across trade partners. The analysis also highlights sectoral centrality in the production network as a determinant of global losses.

Keywords: Climate impacts, input-output supply chain interlinkages, production network, spillovers, weather shocks

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1 Introduction

There is a large and urgent demand for data-driven estimates of climate impacts to properly account for the benefits of additional climate mitigation efforts (Newell et al., 2021). Despite recent methodological advancements to estimate the relationship between climatic conditions and economic outcomes (Hsiang, 2016; Auffhammer, 2018), previous empirical studies investigate the response 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, intermediate inputs are a growing force of production networks. Non-local weather shocks can affect output production through intermediate input availability, as a crucial mechanism for an accurate quantification of climate damages. On the one hand, openness to international trade and production fragmentation can help increase diversification in the supply chain and lower volatility (Caselli et al., 2020; Nath, 2020), on the other hand, however, they can increase exposure to shocks with effects rippling through the supply chain (di Giovanni and Levchenko, 2009).

This paper examines how weather shocks heterogeneously affect sectoral economic activity 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 non-local weather shocks hitting other sectors and affecting sectoral production through sectoral interlinkages, I formalize a model of production networks (Carvalho and Tahbaz-Salehi, 2019; Acemoglu et al., 2016), 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. In this paper, I introduce sectoral interlinkages as a new mechanism in the climate impact literature 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 the growth rate of per capita gross value added 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 (Deschênes and Greenstone, 2011; Carleton et al., 2022). In line with previous findings (Dell et al., 2012; Acevedo et al., 2020), I document that agriculture is the most vulnerable sector. An additional day above the 95th percentile of the grid-specific daily temperature distribution reduces agricultural growth rate by 16% of its sample mean.

Second, I analyze how agricultural heat shocks propagate through input-output interlinkages domestically and abroad and affect other sectors' economic production. I construct downstream and upstream, domestic and foreign agricultural network shocks using the global input-output tables from EORA26 combined with a vector of weather shocks. I document that domestic and foreign heat shocks, respectively measured as days above the 95th percentile of the temperature distribution weighted by the relative importance of each sector's interlinkage with the agricultural sector within the same country and abroad, have a strong negative effect on downstream sectors' value added. The magnitude of the indirect effect is substantial and comparable to the local effect of heat shocks on agricultural production. 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

[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).

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 when omitting spillovers. Second, I obtain the average annual global cost for an additional hot day in a specific country. Average annual global costs are larger when heat shocks occur in countries with many supply chain interlinkages 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]

This paper contributes to the literature that measures economic damages from climate change. A rapidly growing number of studies analyze the impact of temperature fluctuations on national or regional GDP per capita around the world exploiting variation in weather within a given spatial area to estimate its effects on economic outcomes in a panel structure (Akyapi et al., 2022; Burke et al., 2015; Burke and Tanutama, 2019; Dell et al., 2012; Kahn et al., 2021; Kalkuhl and Wenz, 2020; Kotz et al., 2021, 2024; Nath et al., 2023; Newell et al., 2021). The identification of the effect of local temperatures rely, among others, on the stable unit treatment value assumption (SUTVA). Economic activity is a function of local weather shocks and production only depends on local weather, holding conditions in other locations fixed. Therefore, the temperature variation used as identifying variation should not have any effect on the potential outcome for other units in the panel. Trade interlinkages between spatial units might undermine the validity of this assumption. Another recent approach exploits time-series variation in global temperature (Berg et al., 2023; Bilal and Känzig, 2024). This method identifies the temperature effect inclusive of local variation, spatially correlated shocks and supply-chain interlinkages, without

[2]For example, Kahn et al. (2021) show that an average increase in temperature by 0.01ºC is associated with a 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).

unpacking the relative importance of each of these components.

This paper introduces a new mechanism in the climate impact literature. Besides spatial correlation as a channel for the global nature of climate change (Dingel et al., 2021), shocks can also propagate through production networks across geographically distant countries (Wenz and Willner, 2022). Recent empirical studies examine the propagation of natural disasters in the US (Barrot and Sauvagnat, 2016), floods in Pakistan (Balboni et al., 2023) and across the world (Pankratz and Schiller, 2023), or after a localized single natural disaster such as the 2011 Japan earthquake (Carvalho et al., 2021; Boehm et al., 2019) or Hurricane Sandy in the US (Kashiwagi et al., 2021). Input-output linkages have been shown to matter for the economic cost of climate change in the US (Rudik et al., 2022). This paper contributes to the macroeconomic literature on the propagation of shocks by providing the first global estimate of the total economic cost of temperature increases accounting for sectoral interlinkages.

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. Section 5 shows and summarizes the sectoral impact of weather shocks. Section 6 describes 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 Theoretical framework

This section discusses the traditional conceptual framework adopted to derive empirical estimates of the effect of local weather shocks of local economic response functions and then introduces a production network model to capture the role of sectoral interlinkages as a propagation mechanism.

2.1 Local economic response to local weather shocks

The majority of the reduced-form climate impact studies motivates productivity econometric specifications with a partial equilibrium model of production where the economy consists of N regions (Burke et al., 2015; Dell et al., 2012). To match the theoretical framework with the empirical approach, I describe here an economy consisting of N regions, each populated with J sectors. Production possibilities for sector i in region n are described by a constant returns-to-scale Cobb-Douglas technology whose inputs are capital and labor:

$$Y_{nt}^i = \mathcal{Z}_{nt}^i (K_n^i)^\lambda (L_{nt}^i)^{1-\lambda} \tag{1}$$

where total factor productivity $\mathcal{Z}_{nt}^i$ is a product of three components: (i) a region-sector specific component $\overline{z}_n^i$, (ii) a sector-year specific component $\tilde{z}_t^i$ (capturing for instance sector-specific global technological innovations), (iii) an exponential vector of temperature effects T_{nt}^i with sector-specific elasticities β_i. Taking the log and rearranging in terms of output per worker, one obtains:

$$\log \frac{Y_{nt}^i}{L_{nt}^i} = \frac{1}{1-\lambda}[\log \overline{z}_n^i + \log \overline{z}_t^i + f(T_{nt}^i, \beta_i)] + \frac{\lambda}{1-\lambda} \log \left(\frac{K_n^i}{Y_{nt}^i} \right) \tag{2}$$

Traditionally, one would estimate the reduced-form effect of temperature $\hat{\beta}$ on output per capita under the assumption that the residual variation in temperature once absorbed unit- and time-specific unobserved heterogeneity is not correlated with the error term and that unit-specific capital-to-output ratio is constant.[3] The following section outlines a production network model where weather shocks propagate through the economy by altering input prices/quantities or demand for intermediate inputs. This approach introduces additional real-world features to previous reduced-form at-

[3]For illustrative simplicity, 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. I consider Hicks-neutral productivity shocks and abstract from other potential channels of the impact of temperature, which could affect effective units of labor input (Nath, 2020) and capital equipment (Zhang et al., 2018). In this case, estimates of Equation 2 would compound these three channels which cannot be further disentangled.

tempts to quantify the economic cost of climate change.

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 (Carvalho et al., 2021; Acemoglu et al., 2012). I present a simple model that is able to capture how weather shocks can propagate through the production network, affecting sectors not directly hit by the shock (Carvalho and Tahbaz-Salehi, 2019; Acemoglu et al., 2016; Carvalho, 2014). As before, consider an economy that consists of N regions, each with J sectors specialized in different goods. The production process at each of these sectors i is approximated by a Cobb–Douglas technology, similar to the one presented in Section 2.1, with the major exception that intermediate inputs from other sectors and regions enter the production function with constant returns to scale ($\omega_n^i + \sum_{j,m}^{J,N} \omega_{nm}^{ij} = 1$), such that

$$Y_{nt}^i = \mathcal{Z}_{nt}^i [(K_n^i)^\lambda (L_{nt}^i)^{1-\lambda}]^{\omega_n^i} \prod_{j,m}^{J,N} \left(x_{nmt}^{ij}\right)^{\omega_{nm}^{ij}} \tag{3}$$

where x_{nm}^{ij} is the input from sector j in region m used in the production of good i in region n. The exponent $\omega_{nm}^{ij} \in [0, 1]$ represents the share of good j from region m in the total intermediate input use by sector i in region n, which can be equal to zero if it is not used. The larger ω_{nm}^{ij}, the more important the good from the sector-region tuple (j, m) is. To keep the model simple, all production technologies have the same capital intensity λ and the only difference arises from the the intensity with which each sector's good is used as an intermediate input by other sector-regions.

To understand the role of production network in propagating local sector-specific weather shocks, consider the example of two sectors i and j in two different regions n and m and assume for simplicity that the latter's output is the only intermediate input that i needs. Therefore, sector i's output (with lowercase letters indicating logs) is written as:

$$
\begin{aligned}
y_{nt}^{i} &= \underbrace{\log \overline{z}_{n}^{i} + \log \overline{z}_{t}^{i} + f(T_{nt}^{i}, \beta_i) + \omega_{n}^{i} \lambda k_{n}^{i} + \omega_{n}^{i}(1-\lambda) l_{nt}^{i}}_{\Xi_{nt}^{i}} + \omega_{nm}^{ij} \log\left(x_{nm}^{ij}\right) \\
&= \Xi_{nt}^{i} + \omega_{nm}^{ij}\left(\ldots + f(T_{mt}^{j}, \beta_j) + \ldots\right)
\end{aligned}
\tag{4}
$$

Using Equation 2 to move from the first to the second line, this example showcases that changes in temperature alter input production j in region m and affect sector i's output in region n through the production network with elasticity ω_{nm}^{ij}. The relative weight of shocks in the production network is given by the share of good j within the total intermediate inputs used by sector i, which corresponds to the entries of the $(J \cdot N \times J \cdot N)$ input-output matrix $\boldsymbol{\Omega} = [\omega_{nm}^{ij}]$.[4] The matrix (whose rows sum up to one because of constant return-to-scale technologies, and whose columns are the shares of sector j's output within the total inputs used by the other sectors) accounts for first-order effects of propagation through first-degree sectoral interlinkages. To account for higher-order interlinkages, one can compute the Leontief inverse matrix as $\boldsymbol{L} = (\boldsymbol{I} - \boldsymbol{\Omega})^{-1}$, whose (i, j) elements denote the importance of sector j as a direct and indirect supplier to sector i. The inner product of elements ω in the input-output matrix $\boldsymbol{\Omega}$ (or ℓ in the Leontief matrix) and the temperature vector gives the aggregate economic cost of warming. Hereinafter, I explain how I bring this model to the data and quantify the cost of local and indirect weather shocks on the economy.

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, I combine data on sector-level economic pro-

[4] The Cobb-Douglas production technology ensures 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 et al. (2021) study a more complex case with production functions with a nested constant elasticity of substitution 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.

duction (Section 3.1), weather (Section 3.2), and sectoral interlinkages (Section 3.3).

3.1 Sectoral production data

The Economic Statistics Branch of the United Nations Statistical Division (UNSD, 2022) provides Gross Value Added (GVA) in constant 2015 USD following the International Standard Industrial Classification (ISIC rev. 3.1) for all countries from 1970 through 2020.[5] The data set categorizes sectors into six broad groups (ISIC code in parentheses), which provides the most comprehensive source of global economic production disaggregated by sector: 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).[6] 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 dataset covers all countries in the world for most of the 46 years in the analysis.[7]

3.2 Weather data

I use daily 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).[8] ERA-5 is available on a $0.25° \times 0.25°$ resolution grid ($\approx$ 28km at the Equator) from 1950 to the present.

I compute any nonlinear transformation at the grid cell level before averaging

[5]The final sample of countries and their frequency is reported in Table A2.

[6]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 (Kunze, 2021; Hsiang, 2010) 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.

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

[8]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).

values across space using grid-level weights and accounting for fractional grid cells that partially fall within a country (Hsiang, 2016). To construct a measure of weather exposure for the average individual in a country, I aggregate grid-cell level information using time-invariant population weights from the 2000 Landscan dataset (Bright and Coleman, 2001). When constructing measures for the 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). Where available, I construct sector-specific weather shocks relying on the first available five years of the sub-national distribution of sectoral activities.[9]

Since the beginning of the reduced-form approaches to the output-temperature relationship, temperature has been used in levels (Burke et al., 2015; Dell et al., 2012). The non-stationarity of temperature levels, however, introduces concerns on the identification strategy (for a deeper discussion, see Appendix Section C and Tol (2022); Kahn et al. (2021)).[10] To construct an unexpected plausibly exogenous shock in temperature, I rely on people's climate beliefs being built upon long-run climatic conditions (Carleton et al., 2022), and adaptive responses based on their expectations (Shrader, 2021). I compute the annual number of days that belongs to the top/bottom p^{th}-percentile of each grid-specific distribution over the fifty-year period (where $p \in \{1; 5; 10\}$). 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

[9] I rely on Eurostat data on GVA by industry (NACE Rev. 2) at the sub-national level for 34 European countries. I use NUTS-3 level information from 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). For the United States, data at the sub-national level come from the Bureau of Economic Analysis. State-level sectoral data for Brazil are taken from the Brazilian Institute of Geography and Statistics. Sectoral value added data across provinces for Canada is obtained from the Statistics of Canada. Value added data across states for China are taken from the Macro Economy Statistics Yearbook.

[10] An alternative solution examined in Appendix Section F is to use changes in temperature levels (Akyapi et al., 2022; Newell et al., 2021; Letta and Tol, 2019). Nevertheless, this measure does not inform how atypical the weather realization is with respect to individual expectations since it neglects any information provided by the levels and assumes that individuals rationally update their beliefs annually, under an implicit instantaneous model of adaptation. Similarly, 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 (Osberghaus and Schenker, 2022).

and precipitation. Using this methodology, the measure is evenly distributed across countries, and any abnormal realization is compared to the country-specific climatic norm.[11] 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.

3.3 Production network

I use Input-Output (IO) data from EORA26 (Lenzen et al., 2012; Kanemoto et al., 2011) to define the production network and analyze how idiosyncratic weather shocks propagate. This data set contains information on 26 sectors for 189 countries from 1970 to 2021.[12] I examine the propagation of weather shocks through a pre-determined slowly evolving production network, where input-output interlinkages are averaged over previous five years for each decade to smooth annual variation and account for the intensification of inter-sectoral production linkages over time with more fragmented global supply chains and intensive use of intermediate inputs.

A potential concern is that the production network endogenously adjusts to weather shocks. I allay this concern in three ways. First, Kunze (2021) documents a small and negligible shift of sectoral interlinkages after tropical cyclones at the same level of sectoral disaggregation. Second, I also test for this assumption in Appendix Section D and find a small and no statistically significant effect of heat shocks on sectoral interlinkages. Third, as a robustness, I construct a time-invariant production network using the first five years of the IO matrix (see Appendix Section E for details).

3.3.1 Construction of network shocks

I construct *network* shocks that the agriculture sector and propagate through input-output interlinkages accounting for the geographic location and position in the supply

[11] I reject the null hypothesis of non-stationary series for all these variables performing the Im-Pesaran-Shin (Im et al., 2003) panel unit root test. Results are reported in Table A4.

[12] I map the 26 sectors to the six sectors described in Section 3.1 as reported in Table A3.

chain of trade partners. 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 the relative importance of agriculture respectively as a supplier or customer of the sector of interest. From the perspective of the sector of interest, downstream shocks originate in agriculture as a supplier sectors and travel in the same direction as intermediate inputs. In contrast, upstream shocks hit agriculture as a customer sector and travel upstream to the sector of interest.[13]

As theoretically described in Section 2.2, network shocks are constructed using entries from the inter-country IO tables described in Section 3.3 with different weights for upstream and downstream shocks. From the perspective of sector i in country n, agricultural downstream shocks are weighted by

$$\omega_{i,n,Ag,m,\tau} = \frac{\overline{input}_{Ag,m\tau \to in\tau}}{\sum\limits_{jf \in \Theta_{in}} \overline{input}_{in\tau \to jf\tau}} \tag{5}$$

i.e., the average ratio of the inputs of i in country n produced by the agriculture sector (Ag) in country m over total inputs supplied to its set of customer sector-countries Θ_{in} over the previous five years τ for each decade. These weights reflect the inputs sector-country in needs from the agriculture sector in country m to produce one output unit. Conversely, the weights associated with agricultural upstream shocks are constructed as

$$\widehat{\omega}_{i,n,Ag,m,\tau} = \frac{\overline{input}_{in\tau \to Ag,m\tau}}{\sum\limits_{lf \in \hat{\Theta}_{in}} \overline{input}_{in\tau \to lf\tau}} \tag{6}$$

i.e., the ratio of the inputs of sector-country in to the agriculture sector (Ag) in country m over the total inputs supplied to its set of customers Θ_{in}. These upstream weights reflect the importance of each the agriculture sector in country m for the sector-country of interest in.

[13] Appendix Figure A1 shows the average upstream and downstream weights of each sector across countries.

As a first step, I consider network shocks based on geographic location of the agricultural sector (domestic or foreign), taking an unweighted average of upstream and downstream weights. When distinguishing by supply chain position, there are four different network shocks: downstream domestic (DnD), upstream domestic (UpD), downstream foreign (DnF), and upstream foreign (UpF), constructed as follows:

$$\text{Shock}_{i,n,t}^{DnD} = \omega_{i,n,Ag,n,\tau}\text{Shock}_{Ag,n,t}^{Own} \tag{7}$$

$$\text{Shock}_{i,n,t}^{UpD} = \widehat{\omega}_{i,n,Ag,n,\tau}\text{Shock}_{Ag,n,t}^{Own} \tag{8}$$

$$\text{Shock}_{i,n,t}^{DnF} = \sum_{m \neq n} \omega_{i,n,Ag,m,\tau}\text{Shock}_{Ag,m,t}^{Own} \tag{9}$$

$$\text{Shock}_{i,n,t}^{UpF} = \sum_{m \neq n} \widehat{\omega}_{i,n,Ag,m,\tau}\text{Shock}_{Ag,m,t}^{Own} \tag{10}$$

where $\text{Shock}_{Ag,m,t}^{Own}$ is a weather shock hitting agriculture in country m in year t.

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 introduce a parametric measure of spillovers to analyze how weather shocks hitting agriculture domestically and abroad affect sectoral economic production.

4.1 Sector-specific response to local weather shocks

The baseline specification estimates the sector-specific output response to local weather shocks using a pooled sample of sectoral GVA per capita growth rates across 183 countries over 45 years:

$$\Delta \log(GVA)_{int} = f_i(\mathbf{W}_{n(i)t}) + \alpha_{in} + \mu_{it} + \varepsilon_{int} \tag{11}$$

where I regress the growth rate of GVA per capita in sector i in country n in year t (approximated by the first difference in logarithms) on a sector-specific func-

tion of weather variables $\mathbf{W}$ in country n 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).[14] 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.

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), I estimate a pooled, multi-country, sector-specific response function. This model allows me to jointly estimate responses of sectoral economic production to weather shocks and compare the different response functions.

Based on the construction of weather shocks explain in Section 3.2, I estimate the effect of an increase in the number of days of abnormal weather realizations in a year for temperature and precipitation using days in the rest of the distribution as the baseline category. Equation (11) relies on conventional identifying assumptions in climate impact studies, exploiting plausibly exogenous within-country variation in annual weather fluctuations, orthogonal to changes in sectoral economic production and to weather in other locations (Hsiang, 2016).[15]

In particular, the traditional fixed-effect models implicitly assume that the residual variation in weather is orthogonal to variations in weather elsewhere. Climate change, however, is expected to alter atmospheric conditions across the world inducing changes in productivity that are spatially correlated (Dingel et al., 2021). Estimates obtained from Equation (11) may thus be biased when omitting trade linkages across observational units while weather shocks are spatially correlated by

[14] 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).

[15] This approach uses random weather shocks as identifying variation, which differ from climate change (Mendelsohn and Massetti, 2017). Short-run and long-run elasticities to weather fluctuations are the same only under certain assumptions (Lemoine, 2023), therefore one should be cautious in extrapolating long-term impacts from the estimated short-term responses.

violating the stable unit treatment value assumption (SUTVA). Potential outcomes for a sector-country may vary with the treatment assigned to other sector-countries they use inputs from. 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 (Rudik et al., 2022). Conversely, equations using economic production measures such as GDP or GVA suffer from bias induced by spatial considerations through the multilateral trade effects and correlated spatial patterns in temperature. In the following section, I describe an econometric specification that introduces a parametric measure of spillovers induced by sectoral interlinkages.

4.2 Propagation of weather shocks

To introduce a new impact channel of weather shocks rippling through the supply chain via sectoral interlinkages, I design an econometric specification that accounts for *network* shocks:

$$\Delta \log(GVA)_{int} = \gamma_i Shock_{nt}^{Own} + \sum_{J \in \{D;F\}} \sum_{L \in \{Up;Dn\}} \gamma_i^{J,L} Shock_{nt}^{J,L} + \alpha_{in} + \mu_{it} + \eta_{int} \quad (12)$$

where I include weather shocks in agriculture by geographic location J and supply chain position L. I begin by distinguishing between domestic and foreign agricultural shocks, weighted by the average interdependence of sector i with agriculture in the same country n and other countries (i.e., $J \in \{\text{D; F}\}$), then, I also disentangle upstream and downstream shocks (i.e., $L \in \{\text{Dn;Up}\}$).

This approach aims at quantifying the impact on sectoral production of trade-induced exposure to weather shocks in agriculture. 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 agricultural sector's production function and demand, this approach uncovers the role of the propagation channel for quantifying sectoral weather shocks. By only considering the *direct* impact of local 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 effect of local weather shocks on a given sector may be amplified or mitigated by weather shocks hitting other sectors with strong commercial interlinkages.[16]

The direction of the potential bias induced by violating the SUTVA assumption 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 et al., 2016). Differently from other sectoral shocks previously studied (Atalay, 2017), weather shocks can a priori be either demand- or supply-side shocks and have ambiguous effects and directions of propagation. As formulated in the theoretical framework, adverse weather shock may reduce the productivity of a sector (Nath, 2020; Graff Zivin et al., 2018). In this case, the effect would ripple down to downstream customer sectors that use the input less intensively and thus reduce their own production. 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. The assumption on the 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. Through either of these mechanisms, non-local weather shocks can impact sectoral production creating powerful propagation.

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 F, I present

[16] A potential worry about 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.

the results using alternative measures of temperature and precipitation.

5.1 Abnormal weather realizations

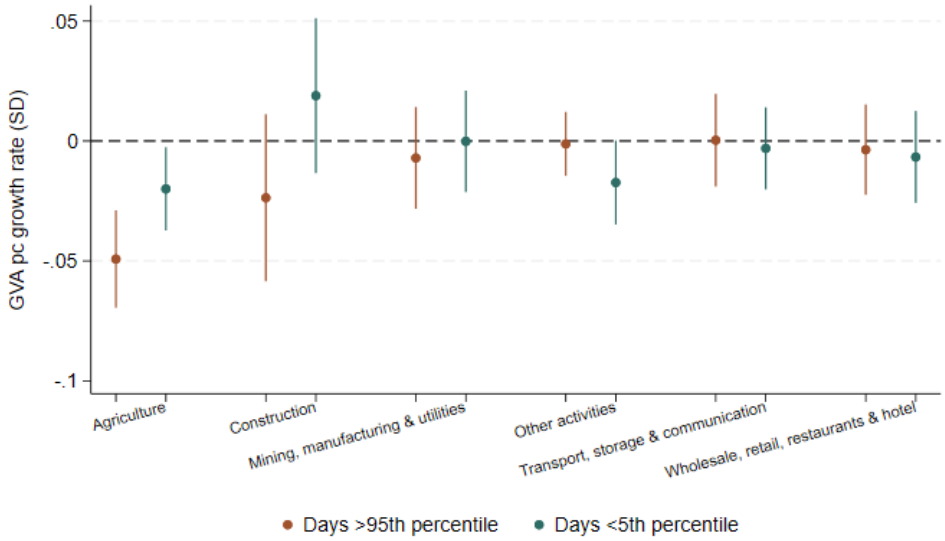
Figure 1 shows the (standardized) coefficients associated with the number of days above the 95th and below the 5th percentile of the temperature and precipitation distribution. Figure 1a confirms findings consistent with prior literature that agriculture is the sector that is most harmed by heat shocks. An additional day above the 95th 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 effect, by harming crops that cannot grow below a certain temperature. An additional day below the 5th 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, precipitation shocks do not substantially affect sectoral production, except for a positive effect of wet days on agricultural production and dry days on transport, storage, and communication (Figure 1b).[17]

Heterogeneity across adaptation potential. The impact of weather shocks may differ as a function of factors that influence the adaptation potential of countries, including income and climate. First, richer countries have less binding budget constraints and wider adaptation capacity to cope with weather fluctuations. Second, a

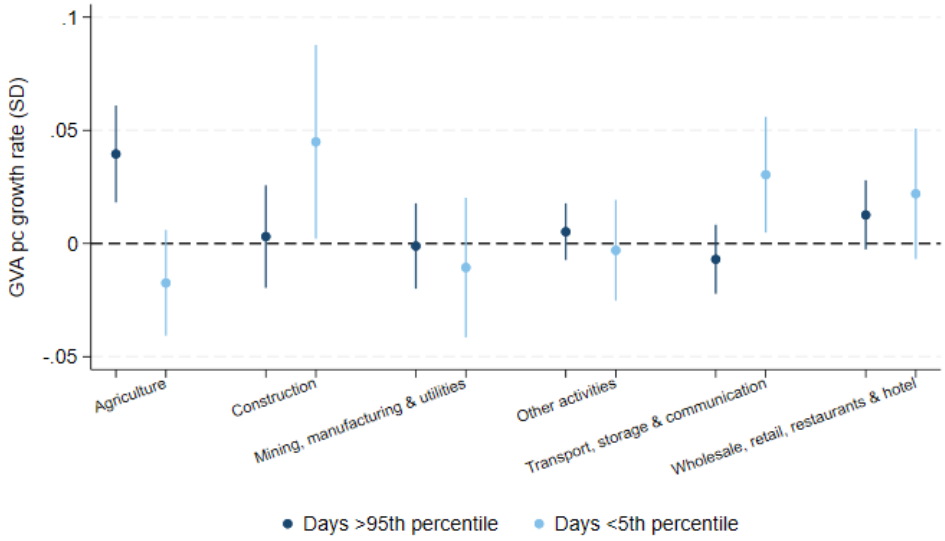
[17]There are two potential explanations. First, wet and dry shocks may not be adequate indicators of water availability (Russ, 2020; Proctor et al., 2022). In an earlier draft of this paper (Zappalà, 2023), I explore sector-specific responses to a measure of dryness that accounts for potential evapotranspiration (SPEI) using a more complete picture of the water availability cycle and document a strong negative effect of dryness on agriculture and a masked response in other sectors. Second, precipitation exhibits considerable spatial variation and aggregation at the country level may mask meaningful variation, as documented by studies showing that precipitation anomalies reduce sub-national economic growth (Holtermann, 2020; Damania et al., 2020; Kotz et al., 2022).

Figure 1. Local abnormal weather realizations and sectoral value added

(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 95% confidence intervals around point estimates. Standard errors are clustered at the country level.

hotter climate may differentially incentivize adaptive investments as returns to adaptation would be relatively higher for more frequent temperature changes. I estimate heterogeneous temperature-output relationships by interacting the vector of temper-

ature and precipitation coefficients with income and climate terciles from long-run average value added per capita and temperature (Figure A2 shows the sample composition) (Nath, 2020; Carleton et al., 2022).

Figure A6 graphically presents the coefficient associated with heat shocks interacted with income and climate terciles. As conjectured, results are consistent with the hypothesis that income is protective (Panel a). Agriculture production is sheltered in high value-added economies and the negative effect of local heat shocks is significant across various sectors (construction; mining, manufacturing, utilities; transport, storage and communication; wholesale, retail trade, restaurants and hotels) in low value-added countries. Similarly, heat shocks are particularly harmful for agricultural production in cold countries (Panel b), where construction and transport sectors, however, benefit from hot days (since milder weather conditions can facilitate outdoor activities).

Robustness. The baseline results are robust to the definition of "abnormal" (using top/bottom 1st or 10st percentile of the daily distribution (Appendix Figures A7 and A8). Results are also robust to estimating the baseline equation in a balanced panel, excluding large countries (i.e., Brazil, China, India, Russia, US), controlling for lagged growth and to alternative specification and fixed effects (linear and quadratic country-specific trends, sub-region by year fixed effects) (Appendix Figure A9).

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, I construct time-varying grid-specific distributions over the previous m years for each t, where $m \in \{20; 30; 40\}$. 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, I consider data starting from 1990 to compare estimates across time-varying historical norms with different time spans from the same sample.

Results are very similar to baseline estimates (Appendix Figure A10). Assuming different speeds of change for the historical climate distribution (20-, 30- or 40-year) does not significantly alter the 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 cold shocks with the point estimate that is statistically significant and negative as one assumes the climate norm to last 20 years and is not significant using a 40-year climate norm. One cannot reject the hypothesis that adaptation has not taken place in other sectors (transport, storage and communication; other activities), where negative effects are more muted, and sometimes positive, for faster time-varying climate norms. Results are similar and robust alternative percentile cut-offs (Appendix Figures A11 and A12).

6 Heat shocks in a production network

In this section, I report the results from the estimation of Equation (12) that quantifies the propagation of heat shocks on agriculture across the economy through the production network.

Domestic and foreign shocks. Figure 2 displays the (standardized) coefficients associated with local and *network* heat shocks decomposed into domestic and foreign. Starting from the coefficients on local heat shocks, the estimated effect on all sectors is not distinguishable from zero.

Domestic shocks have a negative and sizable effect on economic production in all the sectors of the economy, although imprecisely estimated for mining, manufacturing, and utilities, and other activities. Similarly, although smaller in magnitude, foreign heat shocks also have a negative and significant effect on sectoral production in the economy, suggesting that heat shocks propagate to other sectors which are usually non-responsive to direct weather shocks. Aggregating domestic and foreign estimates, the magnitude of the effect of 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, geotex-

tiles) and produces investment goods, more vulnerable to climate change than e.g. the retail sector, which primarily produces consumption services (Casey et al., 2021).

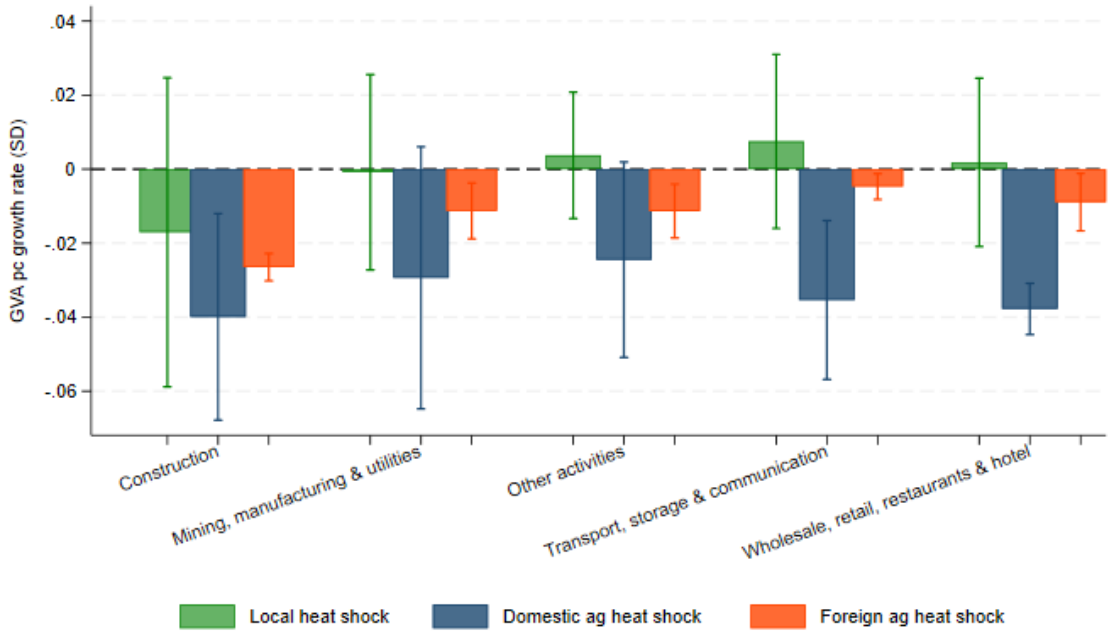
The findings have two consequences in the interpretation of previous temperature-output relationships. First, sector-specific estimates that only account for local weather shocks may be biased since the treatment status of other units in the sample alters the potential expected outcome through shocks propagating from other sectors. The statistical and economic significance of foreign network shocks suggests that also geographically distant weather fluctuations matter through trade interlinkages. Second, weather shocks are amplified in the economy through input-output interlinkages, affecting other sectors beyond agriculture and travelling beyond national borders. As a result, recent estimates on the economic damage of temperature increases may have been largely underestimated due to the omission of this propagation channel.

The global nature of climatic changes poses fundamental identification challenges on spillovers due to spatially correlated patterns in weather fluctuations everywhere (Dingel et al., 2021). To address this potential concern, in alternative specifications, I account for year-specific fixed effects at the continent and regional level (Deschênes and Meng, 2018).[18] This approach exploits local weather variation uncorrelated with contemporaneous weather elsewhere within the same continent/region. Domestic shocks have a strong negative effect, whereas foreign shocks are less precisely estimated, suggesting that most of the spillovers from foreign trade partners come from within the same continent (Appendix Figure A13). Results are also robust to estimating the equation in a balanced panel, excluding large countries, using different percentile cut-offs, and a time-invariant production network. Using a time-varying definition of climate norm over the previous 30 years, domestic heat shocks are not statistically significant, suggesting evidence of adaptation to local climate. Nevertheless, foreign heat shocks remain negative and significant, emphasizing the critical importance of accounting for the interconnected global supply-chain dynamics, as

[18]Regions divide the world into 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.

disruptions in other countries can reverberate domestically and impact sectoral production (Appendix Figure A14).

Figure 2. Domestic and foreign agricultural heat shocks on other sectors' production

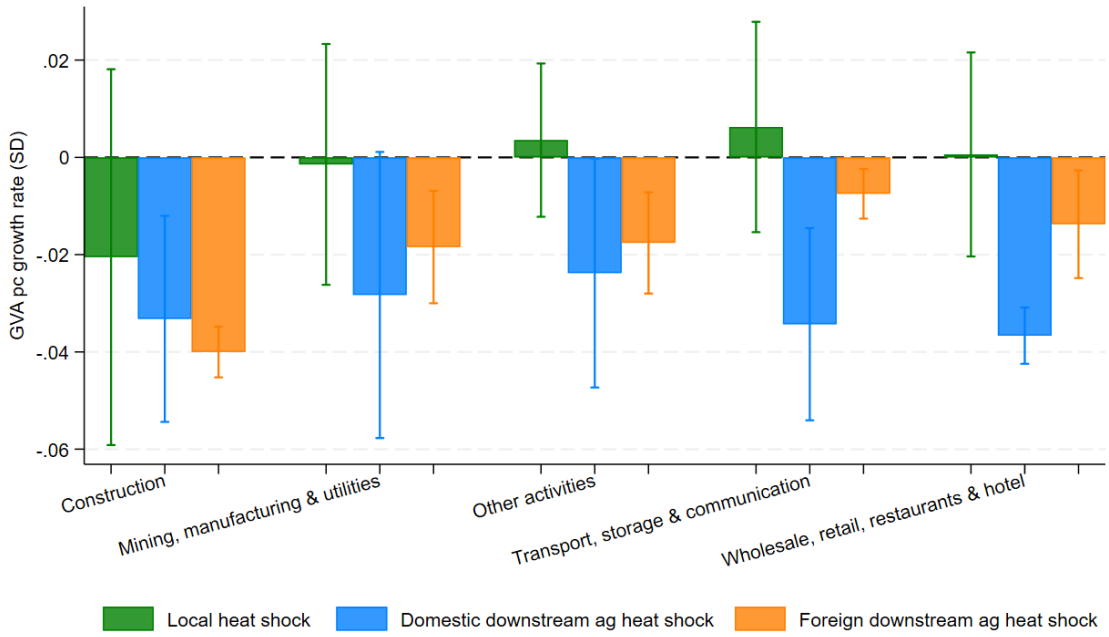


Notes: Bars represent the (standardized) sector-specific coefficients associated with direct shocks and domestic and foreign shocks, using the average number of days above the 95th percentile of the daily temperature distribution. Domestic shocks are constructed as the average heat shock in agriculture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

Upstream and downstream shocks. Since shocks can propagate differently from different stages of the supply chain (Acemoglu et al., 2016), I decompose domestic and foreign agricultural heat shocks into upstream and downstream. Temperature is a direct input to the agricultural production function, therefore heat shocks can be interpreted as shocks on the weather-related component of productivity. From the theoretical framework, it follows that supply shocks propagate downstream to

customer sectors. Figure 3 displays the five coefficients on network agricultural heat 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 and Levermann, 2016). As a test for the validity of the Cobb-Douglas production function assumed in Section 2, Appendix Figure A15 shows that heat shocks do not propagate upstream and thus should not be interpreted as demand-side shocks, but only as supply-side shocks that propagate downstream.

Figure 3. Local and downstream agricultural heat shocks on sectoral production



Notes: Bars represent the (standardized) sector-specific coefficients associated with direct shocks and domestic and foreign downstream shocks, using the average number of days above the 95th percentile of the daily temperature distribution. Domestic downstream shocks are constructed as the average weather shock in agriculture in the same country as the sector of interest weighted by the downstream interdependence with each sector. Symmetrically, foreign downstream shocks are constructed as the average weather shock in the agriculture sector abroad weighted by the downstream interdependence with each sector. 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 5th percentile and sector-specific responses to precipitation realizations below the 5th and above the 95th percentile. Bins represent the 95% confidence intervals with standard errors clustered at the country level.

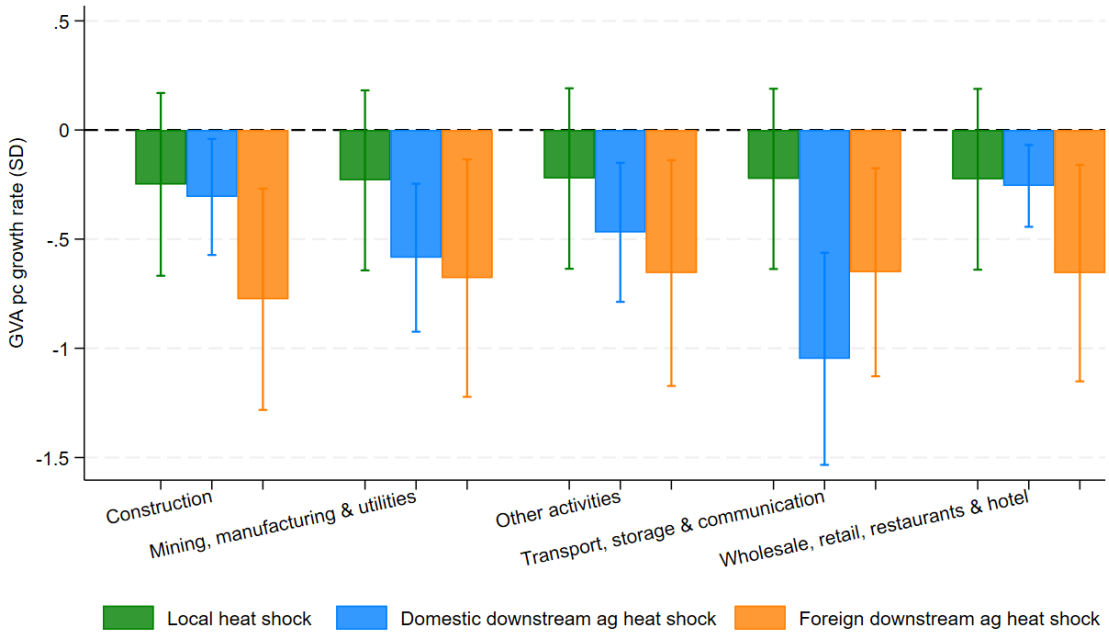
Beyond first-degree sectoral interlinkages. The analysis has so far relied on first-degree sectoral interlinkages in the production network. To account for the full transmission of shocks over the network, I construct the Leontief inverse matrix, which summarizes the sector-specific technical coefficients 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 with 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 both from direct and indirect suppliers.

Time persistence of network shocks. Results show the negative effect of short-run contemporaneous domestic and foreign agricultural shocks on sectoral value added. There is a long-standing debate on the "growth-vs-level" effect of temperature shocks (see Tol (2022) for a review), with evidence documenting both persistent (Nath et al., 2023; Kahn et al., 2021; Bastien-Olvera et al., 2022), and level effects (Akyapi et al., 2022; Newell et al., 2021; Kalkuhl and Wenz, 2020). I examine longer-run effects of local and network agricultural heat shocks estimating a set of local projections to obtain impulse response functions.[19] I begin by estimating local projections on the total gross value added at the country level and document an imprecise and quantitatively small effect of domestic and foreign heat shocks on total-value added, suggesting that country-level aggregate measures might mask the effect of network heat shock (Appendix Figure A16).

Figure 5 displays the sector-specific impulse response functions for a standardized heat shock obtained from the estimation of a stacked, multi-country, sector-specific regression. Local heat shocks do not have a persistent effect on sectoral production.

[19]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 (Jordà, 2005).

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

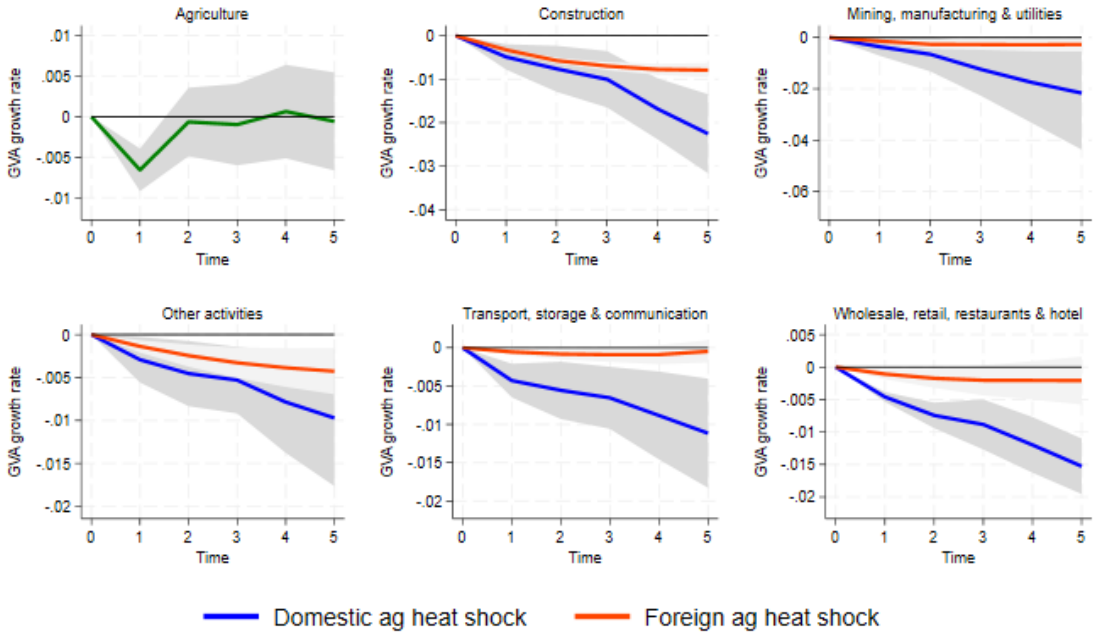


Notes: Bars represent the (standardized) sector-specific coefficients associated with direct shocks and domestic and foreign downstream shocks in the agricultural sector, using the average number of days above the 95th percentile of the daily temperature distribution weighted by the Leontief inverse 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 95% confidence intervals with standard errors clustered at the country level.

In particular, agriculture is the only sector that is harmed whereas the others appear relatively inelastic to heat shocks (Appendix Figure A17 displays the IRFs to local heat shocks for the other five sectors). The negative 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. Moving onto the persistence of agricultural heat shocks propagation in the other sectors, results show negative persistent effects throughout all the sectors. Losses are larger in magnitude for domestic heat shocks and for the construction, and the mining, manufacturing, and utilities sectors. The stickiness of the production processes at the sectoral and geographic level of the analysis may explain the persistence of network heat shocks (Kunze (2021) and

Appendix Section D).[20]

Figure 5. Local projections of agricultural heat shocks on sectoral value added



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 heat temperature shocks, to cold shocks (below the 5th percentile) and to precipitation realizations below the 5th and above the 95th percentile. Horizon 0 is the year of the shock. Shaded areas represent the 95% confidence intervals with standard errors clustered at the country level.

7 Counterfactuals: Cost of recent warming in a production network

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

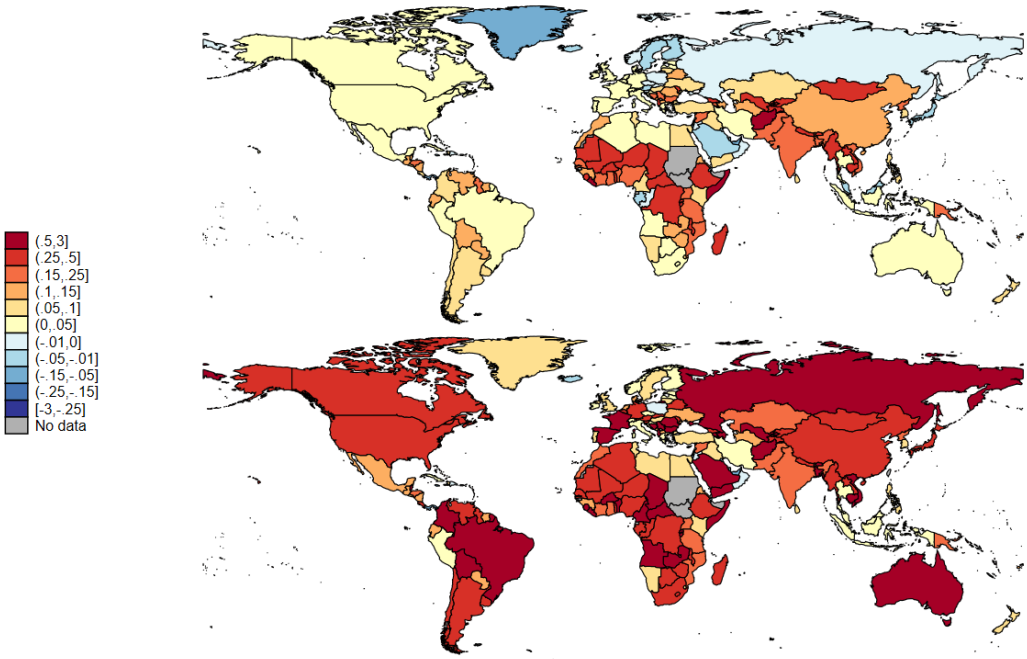
[20] Agricultural heat shocks spill over other sectors also when accounting for continent-sector-year fixed effects (Appendix Figure A18) and for continent-sector linear trends (Appendix Figure A19) to control for spurious correlation between differential regional trends in warming and sectoral economic performance.

a counterfactual with no further warming (Burke et al., 2015; Burke and Tanutama, 2019; Kalkuhl and 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 the production network (see Appendix Section G for additional details).

Omitting shocks in sector partners substantially underestimates the losses due to recent warming (Appendix Figure A20). The pooled average loss in annual GVA per capita across sectors using only local shocks is 0.02% (-0.08% median, IQR [-0.29, 0.09]), whereas it is 0.32% (0.15% median, IQR [-0.13, 0.73]), accounting for network shocks. 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 the country's baseline sectoral breakdown of total GVA between 1996 and 2000, I aggregate sector-specific damages to obtain the total national average relative losses. Accounting for network heat shocks, country-level damages are substantial (0.33% mean, 0.26% median, IQR [0.06, 0.53]) and around three times larger than when omitting agricultural heat shock propagation (0.10% mean, 0.05% median, IQR [0.00, 0.17]) (Figure 6).

In a second exercise, I quantify the macroeconomic impact of an increase in one abnormally hot day in a region or country from 2000 onwards. Figure 7 reports the average annual global losses. The highest average loss ($\approx$ 322 million 2015US$) is recorded if all agricultural sectors in the world experience 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 shocked, 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.

Figure 6. Average annual per capita GVA losses (%) due to recent warming

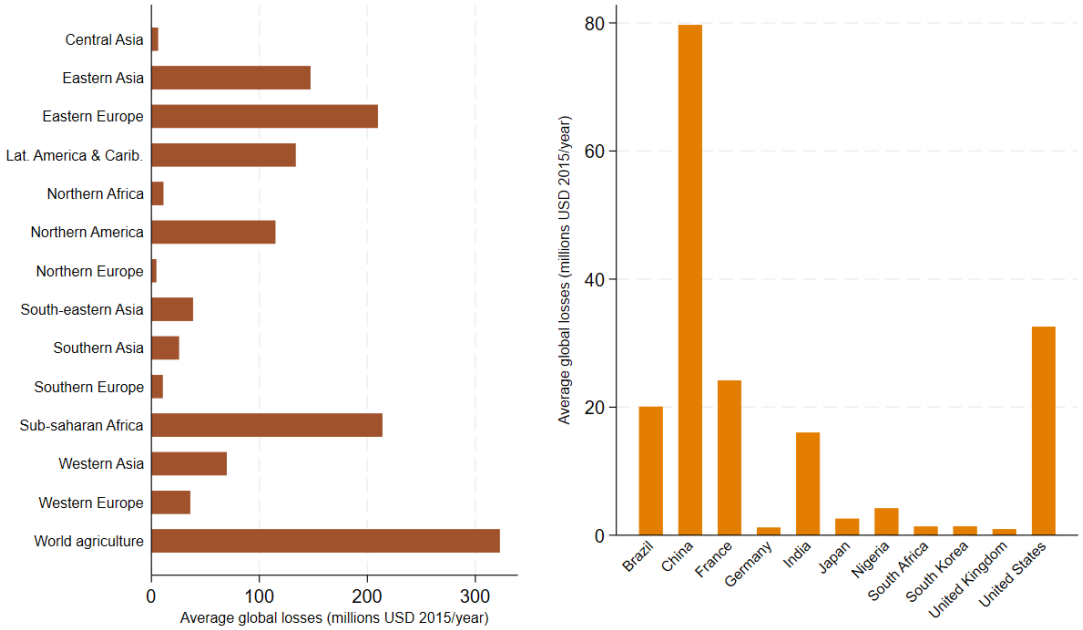


Notes: The figure shows the average annual losses (in red) and gains (in blue) in per capita GVA (%) compared to a counterfactual daily temperature evolved linearly from the trend estimated over the period 1970-2000. Sector-specific damages are weighted by the average sectoral share of total GVA between 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 95th and below the 5th percentile of the temperature distribution. The world map below accounts for shocks in agriculture 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 A20, Table A8 reports the sector-specific losses significant at 95% level estimated with 1000 bootstrap replications with replacement.

For this reason, I also compute average annual global losses if one single country experiences an additional hot day (right-hand side of Figure 7). The importance of the country in the production networks substantially matters for the magnitude of heat-induced losses. 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$ 20 million 2015US$), France ($\approx$ 24 million 2015US$), India ($\approx$ 16 million 2015US$), and the United States ($\approx$ 32 million 2015US$). These losses are sizable since they are obtained for one additional abnormally hot day. Hot days have substantially increased over the time period considered. For example, the decadal average number of hot days in China in the 1970s was 11.8 days/year and reached 29.5 days/year in

the 2010s. Similarly, the number of hot days in Brazil increased from 6.3 days/year to 42.4 days/year and from 7.9 days/year to 30.3 days/year in the US.

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 y-axis (x-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.

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 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 build on prior research on production

networks (Acemoglu et al., 2012) to quantify the economic cost of global warming. The methodology is applied to global production networks constructed from input-output sectoral interlinkages for the past 50 years and sectoral value added data combined with high-resolution daily temperature and precipitation data.

The analysis reveals that the amplification mechanism of weather shocks persists when aggregating units at the sector level and generates substantial fluctuations in sectoral production. Sectors unresponsive to local weather suffer economic losses due to the interdependence of their production process with the domestic and foreign agricultural sectors that are hit by weather shocks. In particular, sectors at later stages of the supply chain are negatively impacted by supply-side agricultural heat shocks that propagate downstream. I also document temporal persistence of network heat shocks. 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. Using the reduced-form estimates of my analysis to inform counterfactual simulations, 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 (0.1% vis-à-vis 0.33% GVApc accounting for sectoral interlinkages) and global losses are sizable even for just a single country being shocked in isolation, suggesting that countries that are more central in the 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, in particular, that the effect of weather shocks depends on climate and 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 transmission of weather shocks is studied through the relative importance of trade partners in input-output interlinkages. The input specificity and elasticity of substitution are key drivers of the transmission of firm-level shocks (Barrot and Sauvagnat, 2016). Weather shocks can differentially propagate in supply chains that differ by industry supplier competitiveness, input concentration, and supplier diversification (Pankratz and Schiller, 2023). 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.

Third, sectoral reallocation is increasingly studied as a potential adaptive margin to climate change (Nath, 2020; Desmet and Rossi-Hansberg, 2015). The analysis has focused on a 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 long-run climate, 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, 2024). Similarly, expectations also matter in accounting for adaptation costs and benefits (Shrader, 2021). Future research should focus on accounting for heterogeneous beliefs and expectations in production networks and supply-chain relationships.

References

Acemoglu, D., U. Akcigit, and W. Kerr (2016). Networks and the macroeconomy: An empirical exploration. *NBER macroeconomics annual 30*(1), 273–335.

Acemoglu, D., V. M. Carvalho, A. Ozdaglar, and A. Tahbaz-Salehi (2012). The network origins of aggregate fluctuations. *Econometrica 80*(5), 1977–2016.

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

Akyapi, B., M. Bellon, and E. Massetti (2022). Estimating macro-fiscal effects of climate shocks from billions of geospatial weather observations. *IMF Working Papers 2022*(156).

Atalay, E. (2017). How important are sectoral shocks? *American Economic Journal: Macroeconomics 9*(4), 254–280.

Auffhammer, M. (2018). Quantifying economic damages from climate change. *Journal of Economic Perspectives 32*(4), 33–52.

Auffhammer, M., S. Hsiang, W. Schlenker, and A. Sobel (2013). Using weather data and climate model output in economic analyses of climate change. *Review of Environmental Economics and Policy 7*(2), 181–198.

Balboni, C., J. Boehm, and M. Waseem (2023). Firm adaptation and production networks: Structural evidence from extreme weather events in Pakistan. Working Paper, Structural Transformation and Economic Growth (STEG). Forthcoming.

Barrot, J.-N. and J. Sauvagnat (2016). Input specificity and the propagation of idiosyncratic shocks in production networks. *The Quarterly Journal of Economics 131*(3), 1543–1592.

Bastien-Olvera, B. A., F. Granella, and F. C. Moore (2022). Persistent effect of temperature on gdp identified from lower frequency temperature variability. *Environmental Research Letters 17*(8), 084038.

Berg, K. A., C. C. Curtis, and N. Mark (2023). Gdp and temperature: Evidence on cross-country response heterogeneity. NBER Working Papers 31327, National Bureau of Economic Research.

Bilal, A. and D. R. Känzig (2024). The macroeconomic impact of climate change: Global vs. local temperature. Technical report, Working paper.

Boehm, C. E., A. Flaaen, and N. Pandalai-Nayar (2019). Input linkages and the transmission of shocks: Firm-level evidence from the 2011 Tōhoku earthquake. *Review of Economics and Statistics 101*(1), 60–75.

Bright, E. and P. Coleman (2001). Landscan global 2000 [data set]. *Oak Ridge National Laboratory. https://doi.org/10.48690/1524196*.

Burke, M., S. Hsiang, and E. Miguel (2015). Global non-linear effect of temperature on economic production. *Nature 527*(7577), 235–239.

Burke, M. and V. Tanutama (2019). Climatic constraints on aggregate economic output. NBER Working Papers 25779, National Bureau of Economic Research.

Carleton, T., A. Jina, M. Delgado, M. Greenstone, T. Houser, S. Hsiang, A. Hultgren, R. E. Kopp, K. E. McCusker, I. Nath, et al. (2022). Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits. *The Quarterly Journal of Economics 137*(4), 2037–2105.

Carvalho, V. M. (2014). From micro to macro via production networks. *Journal of Economic Perspectives 28*(4), 23–48.

Carvalho, V. M., M. Nirei, Y. U. Saito, and A. Tahbaz-Salehi (2021). Supply chain disruptions: Evidence from the Great East Japan earthquake. *The Quarterly Journal of Economics 136*(2), 1255–1321.

Carvalho, V. M. and A. Tahbaz-Salehi (2019). Production networks: A primer. *Annual Review of Economics 11*, 635–663.

Caselli, F., M. Koren, M. Lisicky, and S. Tenreyro (2020). Diversification through trade. *The Quarterly Journal of Economics 135*(1), 449–502.

Casey, G., S. Fried, and M. Gibson (2021). Understanding climate damages: Consumption versus investment. CESifo Working Paper 9499, CESifo.

Damania, R., S. Desbureaux, and E. Zaveri (2020). Does rainfall matter for economic growth? Evidence from global sub-national data (1990–2014). *Journal of Environmental Economics and Management 102*, 102335.

Dell, M., B. F. Jones, and B. A. Olken (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics 4*(3), 66–95.

Dell, M., B. F. Jones, and B. A. Olken (2014). What do we learn from the weather? the new climate-economy literature. *Journal of Economic Literature 52*(3), 740–98.

Deschênes, O. and M. Greenstone (2007). The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. *American Economic Review 97*(1), 354–385.

Deschênes, O. and M. Greenstone (2011). Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US. *American Economic Journal: Applied Economics 3*(4), 152–85.

Deschênes, O. and K. Meng (2018). Quasi-experimental methods in environmental economics: Opportunities and challenges. In P. Dasgupta, S. K. Pattanayak, and K. Smith (Eds.), *Handbook of Environmental Economics*, Volume 4, pp. 285–332. Elsevier.

Desmet, K. and E. Rossi-Hansberg (2015). On the spatial economic impact of global warming. *Journal of Urban Economics 88*, 16–37.

di Giovanni, J. and A. A. Levchenko (2009). Trade openness and volatility. *The Review of Economics and Statistics 91*(3), 558–585.

Dingel, J., K. Meng, and S. Hsiang (2021). Spatial correlation, trade, and inequality: Evidence from the global climate. NBER Working Papers 25447, National Bureau of Economic Research.

Graff Zivin, J., S. Hsiang, and M. Neidell (2018). Temperature and human capital in the short and long run. *Journal of the Association of Environmental and Resource Economists 5*(1), 77–105.

Holtermann, L. (2020). Precipitation anomalies, economic production, and the role of "first-nature" and "second-nature" geographies: a disaggregated analysis in high-income countries. *Global Environmental Change 65*, 102167.

Hsiang, S. (2010). Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America. *Proceedings of the National Academy of Sciences 107*(35), 15367–15372.

Hsiang, S. (2016). Climate econometrics. *Annual Review of Resource Economics 8*, 43–75.

Im, K. S., M. H. Pesaran, and Y. Shin (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics 115*(1), 53–74.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review 95*(1), 161–182.

Kahn, M. E., K. Mohaddes, R. N. Ng, M. H. Pesaran, M. Raissi, and J.-C. Yang (2021). Long-term macroeconomic effects of climate change: A cross-country analysis. *Energy Economics 104*, 105624.

Kalkuhl, M. and L. Wenz (2020). The impact of climate conditions on economic production. evidence from a global panel of regions. *Journal of Environmental Economics and Management 103*, 102360.

Kanemoto, K., M. Lenzen, A. Geschke, and D. Moran (2011). Building Eora: a global multi-region input output model at high country and sector. In *19th International Input-Output Conference*.

Kashiwagi, Y., Y. Todo, and P. Matous (2021). Propagation of economic shocks through global supply chains -— Evidence from Hurricane Sandy. *Review of International Economics 29*(5), 1186–1220.

Kolstad, C. D. and F. C. Moore (2020). Estimating the economic impacts of climate change using weather observations. *Review of Environmental Economics and Policy*.

Kotz, M., A. Levermann, and L. Wenz (2022). The effect of rainfall changes on economic production. *Nature 601*(7892), 223–227.

Kotz, M., A. Levermann, and L. Wenz (2024). The economic commitment of climate change. *Nature 628*(8008), 551–557.

Kotz, M., L. Wenz, A. Stechemesser, M. Kalkuhl, and A. Levermann (2021). Day-to-day temperature variability reduces economic growth. *Nature Climate Change 11*(4), 319–325.

Kunze, S. (2021). Unraveling the effects of tropical cyclones on economic sectors worldwide: direct and indirect impacts. *Environmental and Resource Economics 78*(4), 545–569.

Lemoine, D. (2023). Estimating the consequences of climate change from variation in weather. NBER Working Paper 25008, National Bureau of Economic Research.

Lenzen, M., K. Kanemoto, D. Moran, and A. Geschke (2012). Mapping the structure of the world economy. *Environmental Science & Technology 46*(15), 8374–8381.

Leontief, W. (1970). Environmental repercussions and the economic structure: an input-output approach. *The Review of Economics and Statistics*, 262–271.

Letta, M. and R. S. Tol (2019). Weather, climate and total factor productivity. *Environmental and Resource Economics 73*(1), 283–305.

Mendelsohn, R. O. and E. Massetti (2017). The use of cross-sectional analysis to measure climate impacts on agriculture: theory and evidence. *Review of Environmental Economics and Policy 11*(2), 1–20.

Miller, S., K. Chua, J. Coggins, and H. Mohtadi (2021). Heat waves, climate change, and economic output. *Journal of the European Economic Association 19*(5), 2658–2694.

Muñoz Sabater, J. (2019). ERA5 hourly data on single levels from 1950 to present. Accessed: 08-11-2022.

Nath, I. (2020). Climate change, the food problem, and the challenge of adaptation through sectoral reallocation. NBER Working Papers 27297, National Bureau of Economic Research.

Nath, I., V. A. Ramey, and P. J. Klenow (2023). How much will global warming cool global growth? *Working paper*.

Newell, R. G., B. C. Prest, and S. E. Sexton (2021). The GDP-temperature relationship: implications for climate change damages. *Journal of Environmental Economics and Management 108*, 102445.

Ortiz-Bobea, A., T. R. Ault, C. M. Carrillo, R. G. Chambers, and D. B. Lobell (2021). Anthropogenic climate change has slowed global agricultural productivity growth. *Nature Climate Change 11*(4), 306–312.

Osberghaus, D. and O. Schenker (2022). International trade and the transmission of temperature shocks. *ZEW-Centre for European Economic Research Discussion Paper* (22-035).

Pankratz, N. M. and C. M. Schiller (2023). Climate change and adaptation in global supply-chain networks. Technical report.

Proctor, J., A. Rigden, D. Chan, and P. Huybers (2022). Accurate specification of water availability shows its importance for global crop production. *Nature Food* (3), 753–763.

Ramankutty, N., A. Evan, C. Monfreda, and J. A. Foley (2010). Global Agricultural Lands: Croplands, 2000.

Rudik, I., G. Lyn, W. Tan, and A. Ortiz-Bobea (2022). The economic effects of climate change in dynamic spatial equilibrium.

Russ, J. (2020). Water runoff and economic activity: The impact of water supply shocks on growth. *Journal of Environmental Economics and Management 101*, 102322.

Schlenker, W. and M. J. Roberts (2009). Nonlinear temperature effects indicate severe damages to us crop yields under climate change. *Proceedings of the National Academy of Sciences 106*(37), 15594–15598.

Shrader, J. (2021). Improving climate damage estimates by accounting for adaptation. *Mimeo*.

Tol, R. S. (2022). A meta-analysis of the total economic impact of climate change. *arXiv preprint arXiv:2207.12199*.

UNSD (2022). Gross Value Added by Kind of Economic Activity at constant (2015) prices - US dollars. ISIC Revision 3.1.

Wenz, L. and A. Levermann (2016). Enhanced economic connectivity to foster heat stress–related losses. *Science Advances 2*(6).

Wenz, L. and S. N. Willner (2022). Climate impacts and global supply chains: an overview. *Handbook on Trade Policy and Climate Change*, 290–316.

Zappalà, G. (2023). Sectoral impact and propagation of weather shocks. *IMF Working Papers 2023*(053).

Zappalà, G. (2024). Adapting to climate change accounting for individual beliefs. *Journal of Development Economics*, 103289.

Zhang, P., O. Deschênes, K. Meng, and J. Zhang (2018). Temperature effects on productivity and factor reallocation: Evidence from a half million Chinese manufacturing plants. *Journal of Environmental Economics and Management 88*, 1–17.

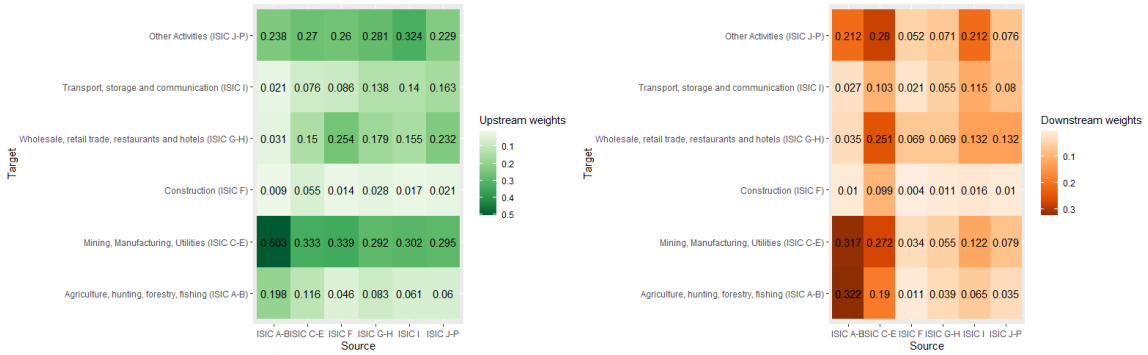
Appendix

Table of Contents

A Additional figures

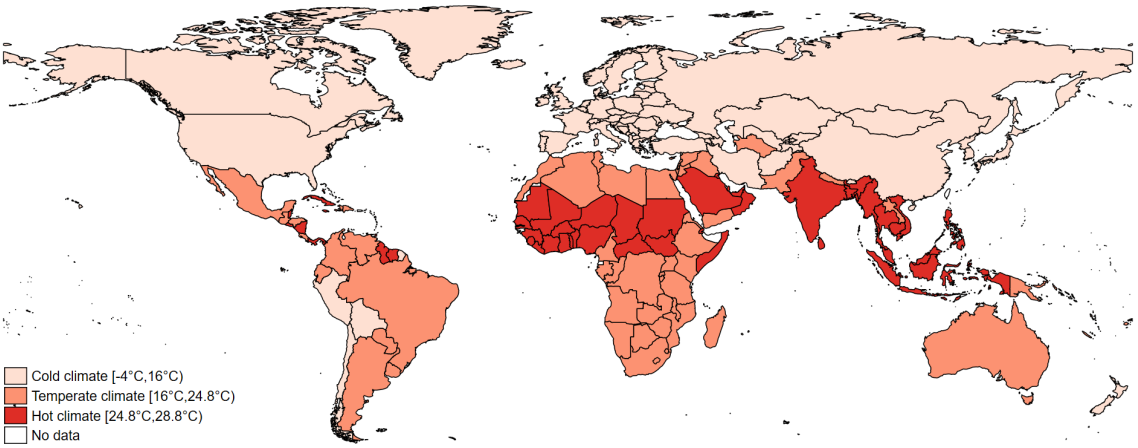
Figure A1. Average upstream and downstream weights across countries

(a) Upstream (b) Downstream



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 on the x-axis.

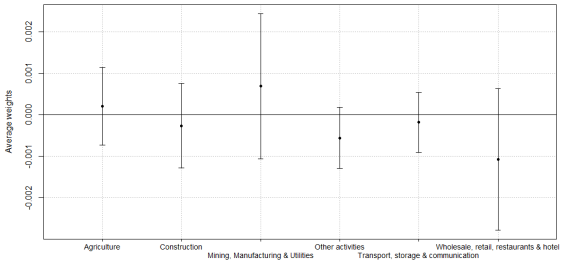
Figure A2. Countries in the sample by climatic zone



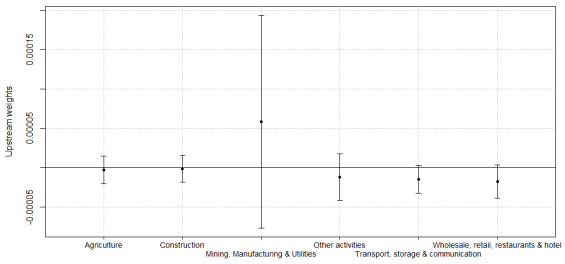
Notes: The map represents the countries in the sample divided by climatic zones, defined as terciles of the average annual temperature from 1970 through 2020. The classification is implemented in order to compute heterogeneous treatment effects as reported in Figure **??**.

Figure A3. Sectoral interlinkages' response to heat shocks

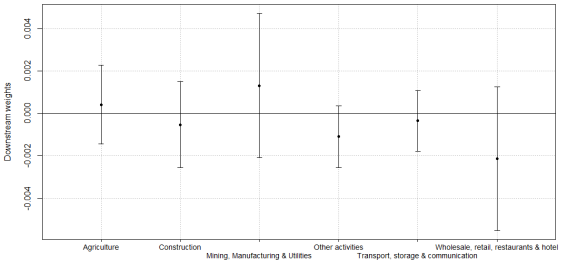
(a) Average weights



(b) Upstream weights

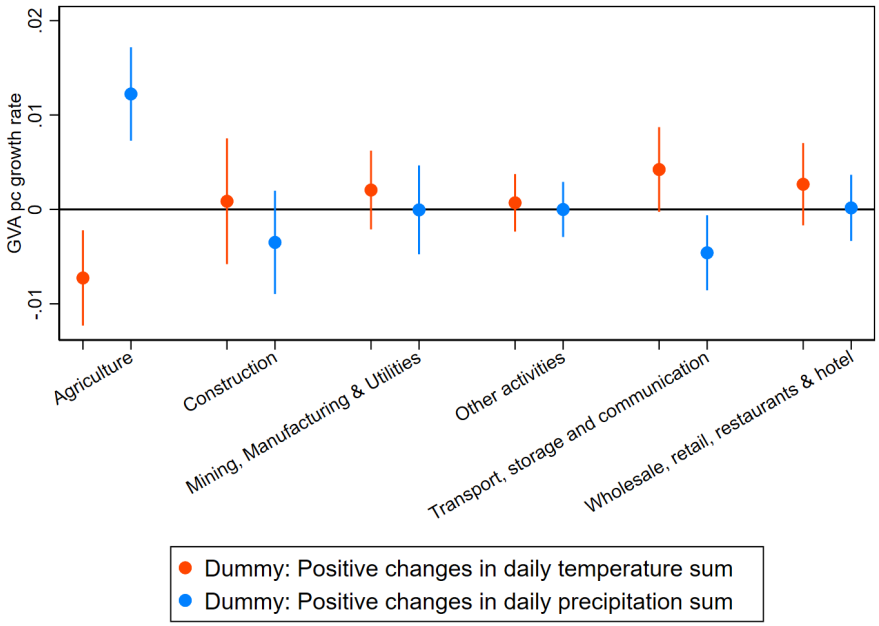


(c) Downstream weights



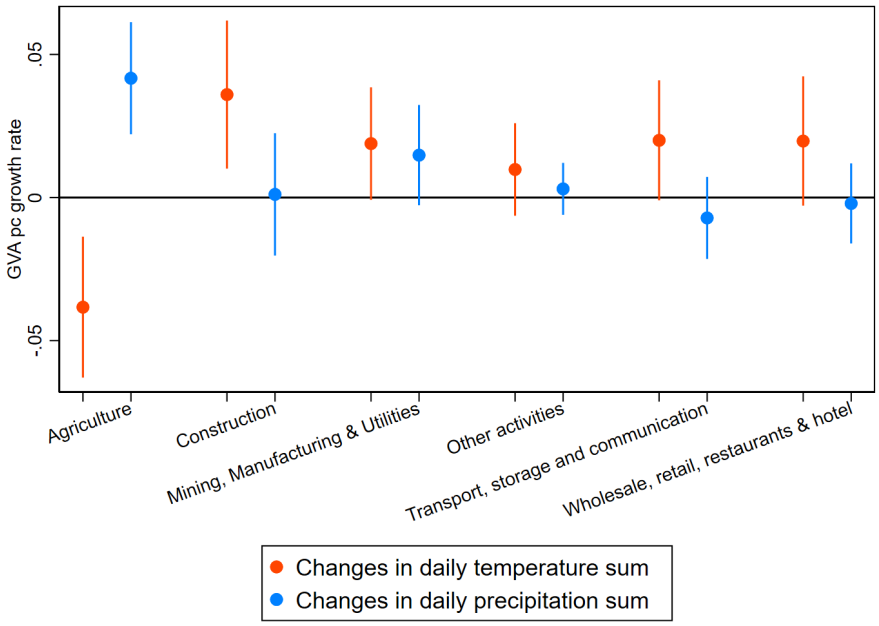
Notes: The figure shows the (standardized) coefficients associated with the response of bilateral sectoral interlinkages to heat shocks (measured as the number of days above the 95th percentile of the temperature distribution) in the period between 1970 and 2019. All sector-specific coefficients are 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.

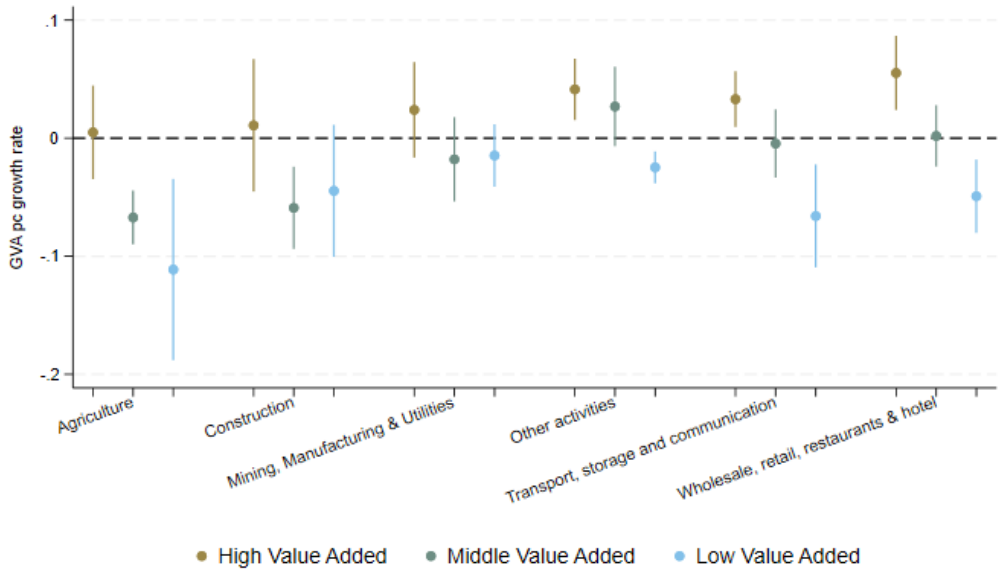
Figure A5. Sector-specific impact of annual temperature and precipitation changes



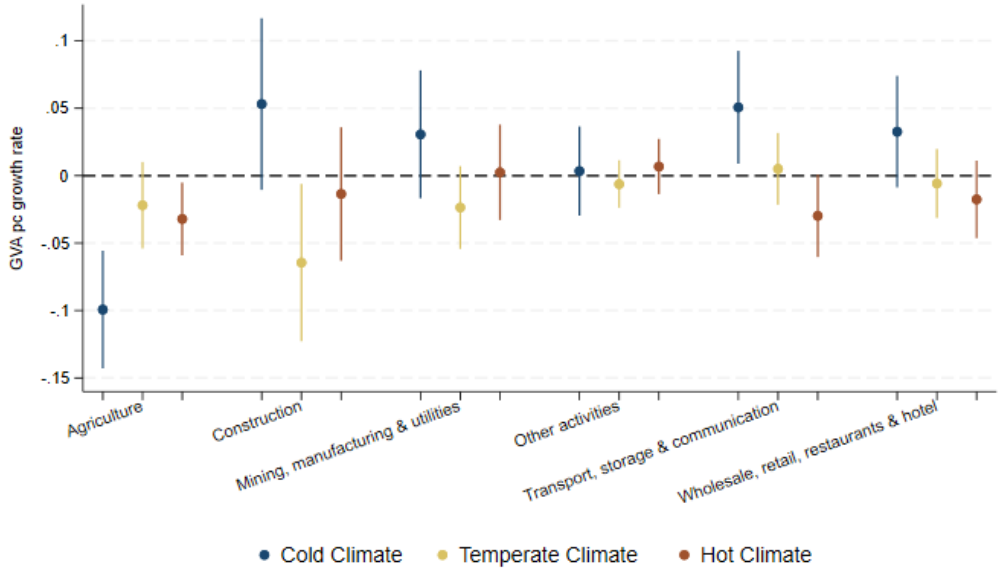
Notes: The figure shows the OLS coefficients associated with the response of sectoral GVA per capita growth rate to changes in the annual sum of average daily temperature. The regression controls for lagged sectoral GVA growth rate, country-sector, sector-year fixed effects. Bins represent the 90% confidence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

Figure A6. Heterogeneity in the GVA response to heat shocks

(a) Value Added terciles



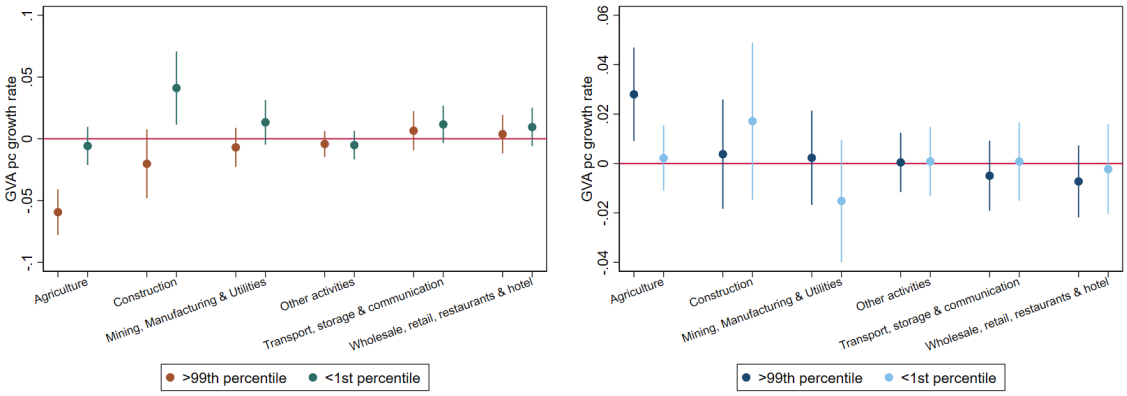
(b) Climate terciles



Notes: The figure shows the (standardized) coefficients associated with the response of sectoral GVA per capita growth rate to heat shocks (defined as the number of days above the 95th percentile) by income terciles of average sectoral value addded and climate terciles of 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 1st and 99th percentiles

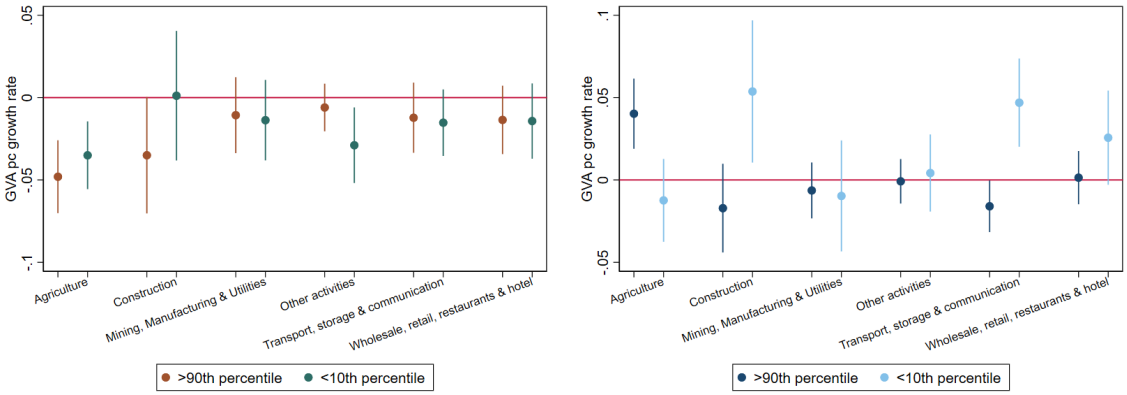
(a) Hot and cold temperature shocks (b) Wet and dry precipitation shocks



Notes: The figure shows the (standardized) regression estimates for the country-average number of days above the 99th and below the 1st 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 10th and 90th percentiles

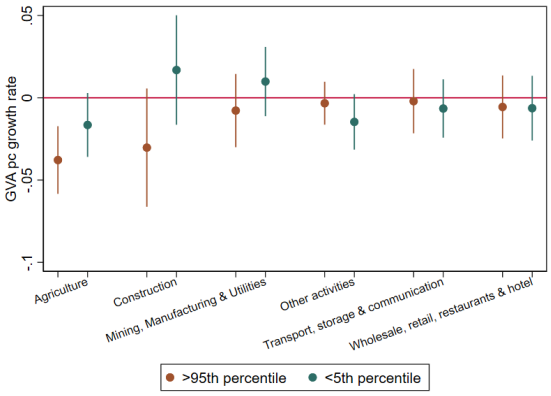
(a) Hot and cold temperature shocks (b) Wet and dry precipitation shocks



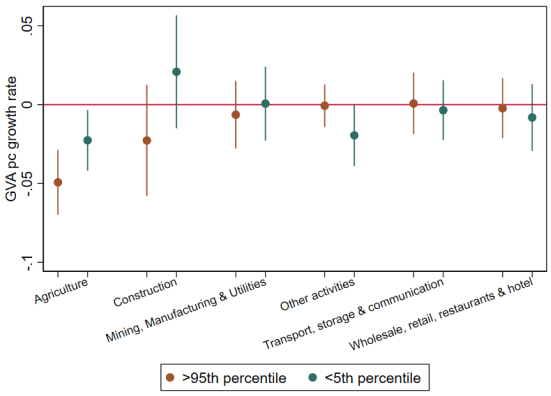
Notes: The figure shows the (standardized) regression estimates for the country-average number of days above the 90th and below the 10th percentile of the daily distribution in temperature (Panel (a)) and in precipitation (Panel (b)). All sector-specific coefficients are estimated jointly in a stacked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

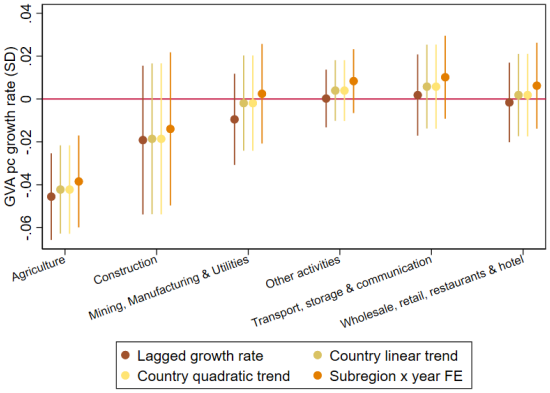
(a) Balanced panel



(b) Excluding "large" countries



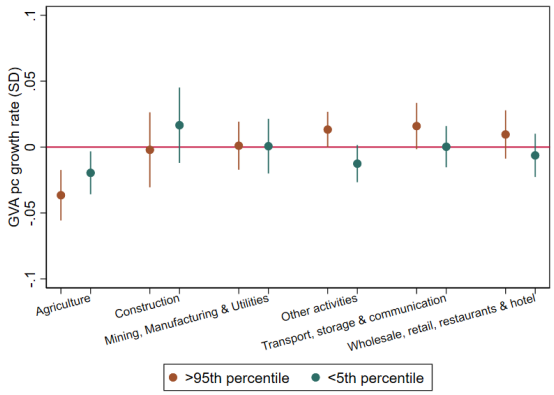
(c) Heat shocks - Additional controls and FE



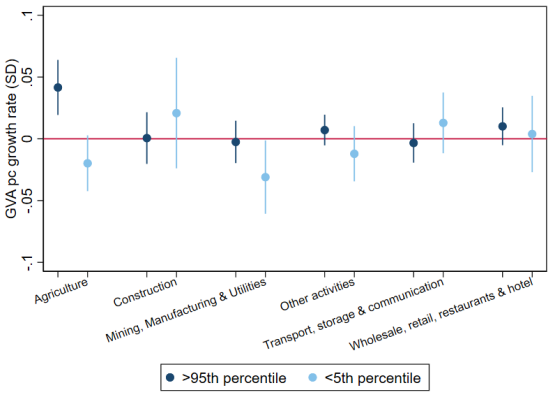
Notes: The figure shows the (standardized) regression estimates for the country-average number of days above the 95th and below the 5th percentile of the daily distribution in temperature using a sector-country balanced panel (Panel (a)), excluding large countries (Brazil, China, India, Russia, US) (Panel (b)), and for days above the 95th 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 5th and 95th percentiles

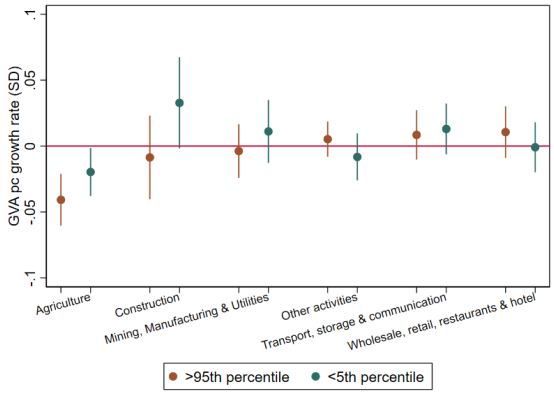
(a) Temperature - 20-year



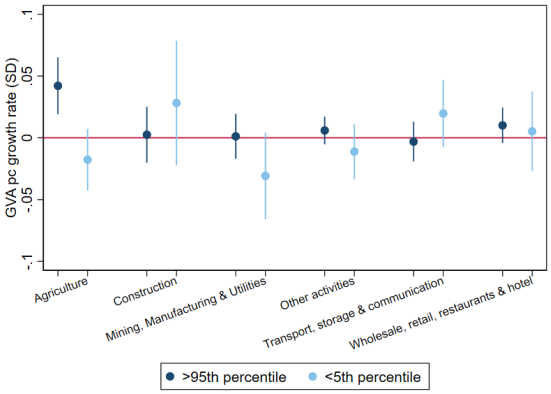
(b) Precipitation - 20-year



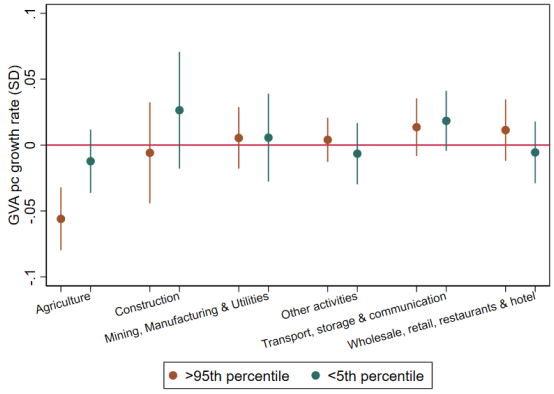
(c) Temperature - 30-year



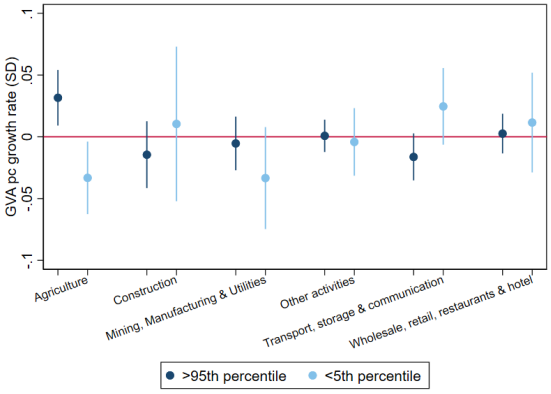
(d) Precipitation - 30-year



(e) Temperature - 40-year



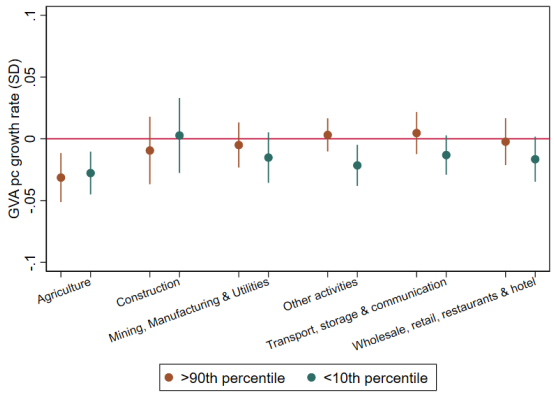
(f) Precipitation - 40-year



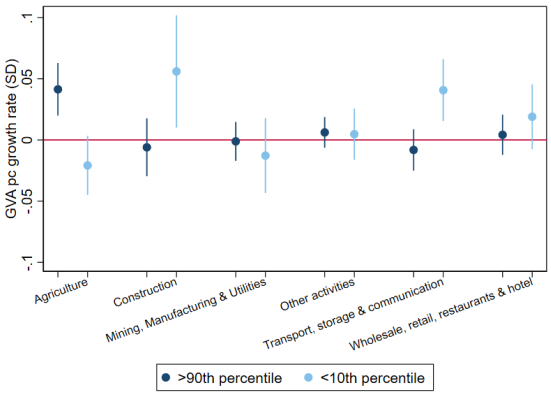
Notes: The figure shows the (standardized) regression coefficients on the number of days above the 90th and below the 10th percentile of the daily distribution in temperature (Panels (a-c-e)) and in precipitation (Panels (b-d-f)) using time-varying distributions (respectively, 20-year, 30-year and 40-year). 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 A11. Abnormal weather realizations from time-varying climate norms using 10th and 90th percentiles

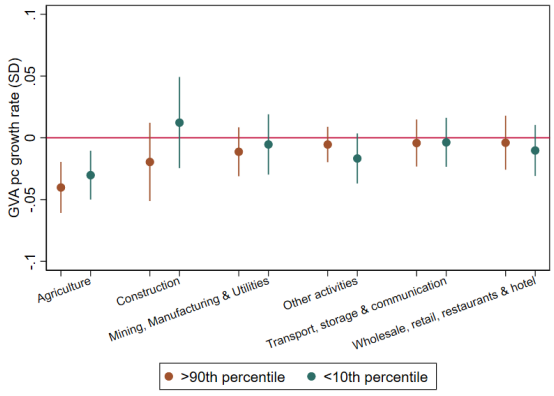
(a) Temperature - 20-year



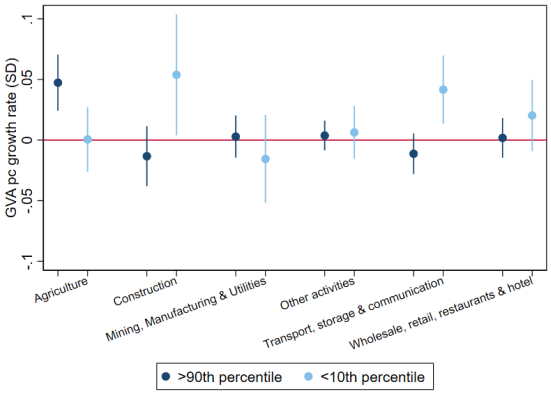
(b) Precipitation - 20-year



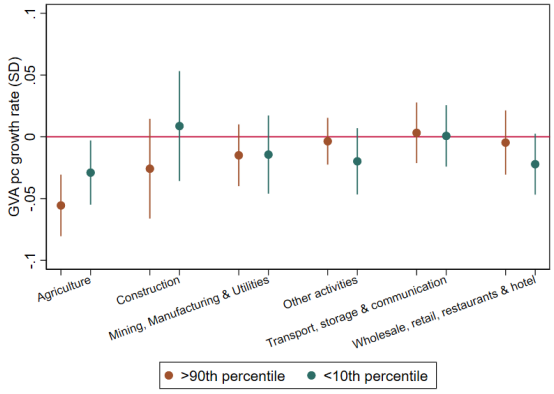
(c) Temperature - 30-year



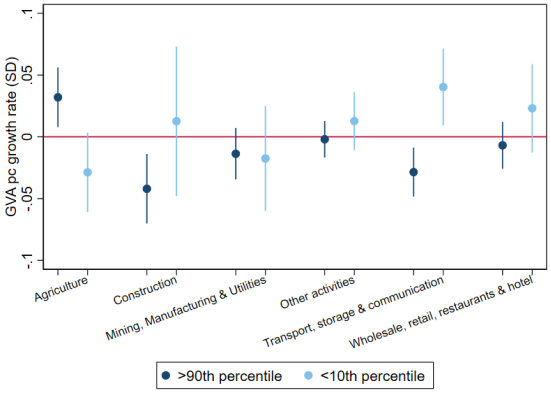
(d) Precipitation - 30-year



(e) Temperature - 40-year



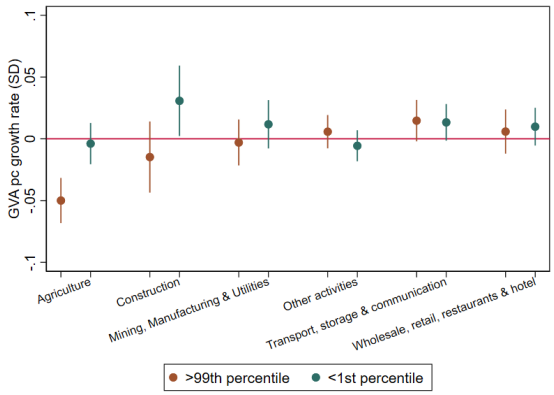
(f) Precipitation - 40-year



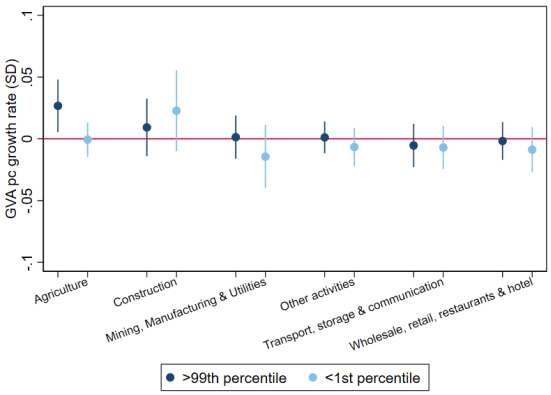
Notes: The figure shows the (standardized) regression coefficients on the number of days above the 90th and below the 10th percentile of the daily distribution in temperature (Panels (a-c-e)) and in precipitation (Panels (b-d-f)) using time-varying distributions (respectively, 20-year, 30-year and 40-year).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

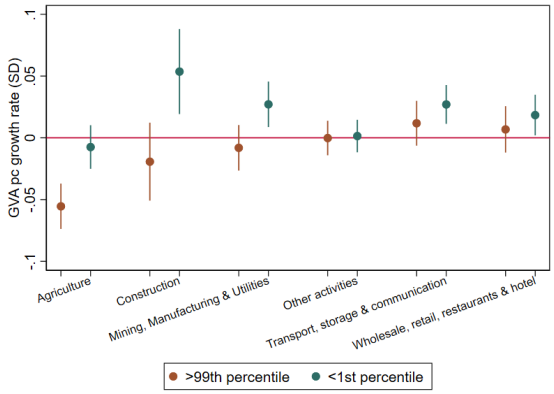
(a) Temperature - 20-year



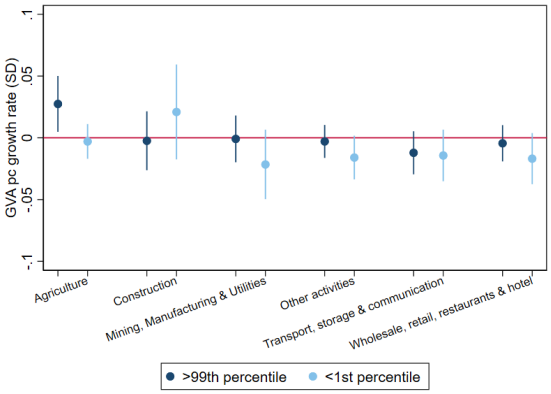
(b) Precipitation - 20-year



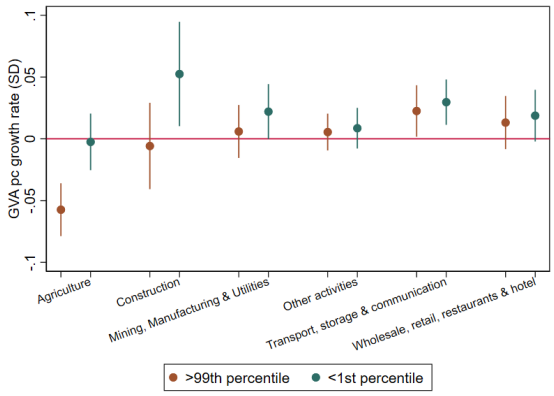
(c) Temperature - 30-year



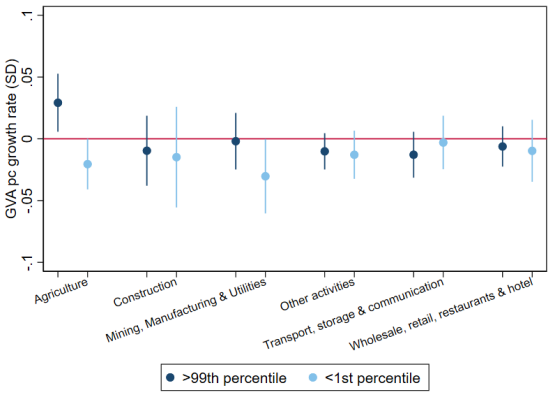
(d) Precipitation - 30-year



(e) Temperature - 40-year



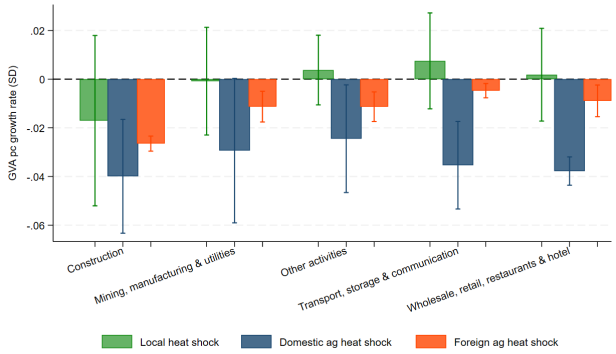
(f) Precipitation - 40-year



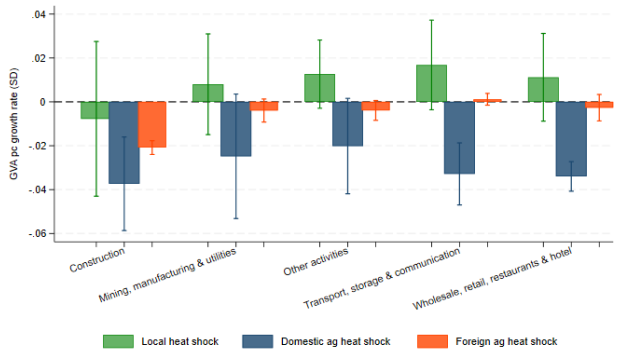
Notes: The figure shows the (standardized) regression coefficients on the number of days above the 99th and below the 1st percentile of the daily distribution in temperature (Panels (a-c-e)) and in precipitation (Panels (b-d-f)) using time-varying distributions (respectively, 20-year, 30-year and 40-year). 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. Robustness: Alternative specifications

(a) Region-by-year FE



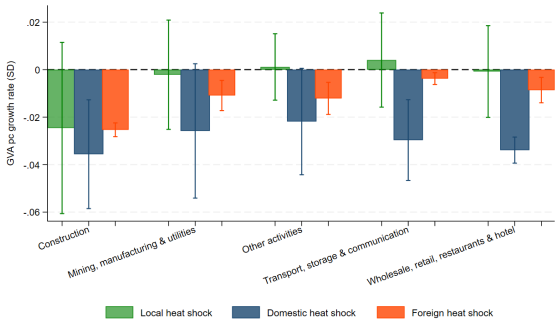
(b) Continent-by-year FE



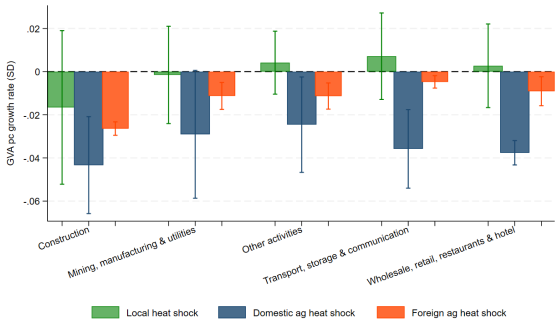
Notes: The figure shows the (standardized) sector-specific coefficients associated with direct shocks and domestic and foreign shocks, using the average number of days above the 95th percentile of the daily temperature distribution. All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects and accounting for sector-specific responses to temperature realizations below the 5th percentile and sector-specific responses to precipitation realizations below the 5th and above the 95th percentile. Panel (a) accounts for region-by-year fixed effects, Panel (b) accounts for continent-by-year fixed effectsBins represent the 90% confidence intervals.

Figure A14. Robustness: Domestic and foreign agricultural heat shocks

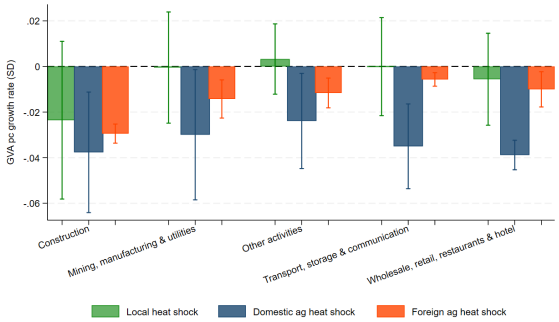
(a) Balanced panel



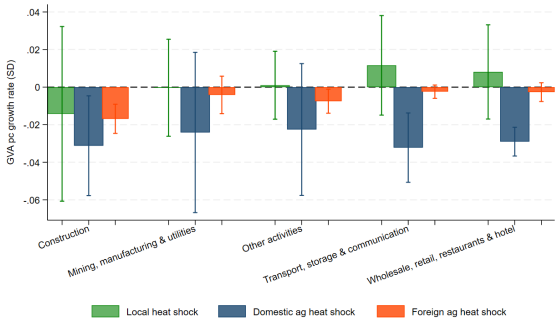
(b) Excluding "large" countries



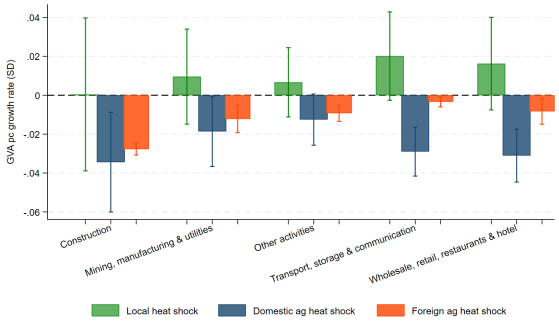
(c) Using 90th percentile



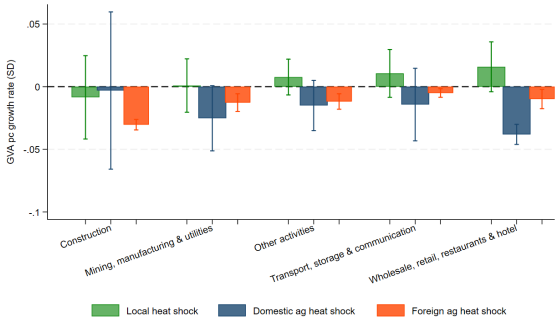
(d) Using 99th percentile



(e) Time-invariant production network

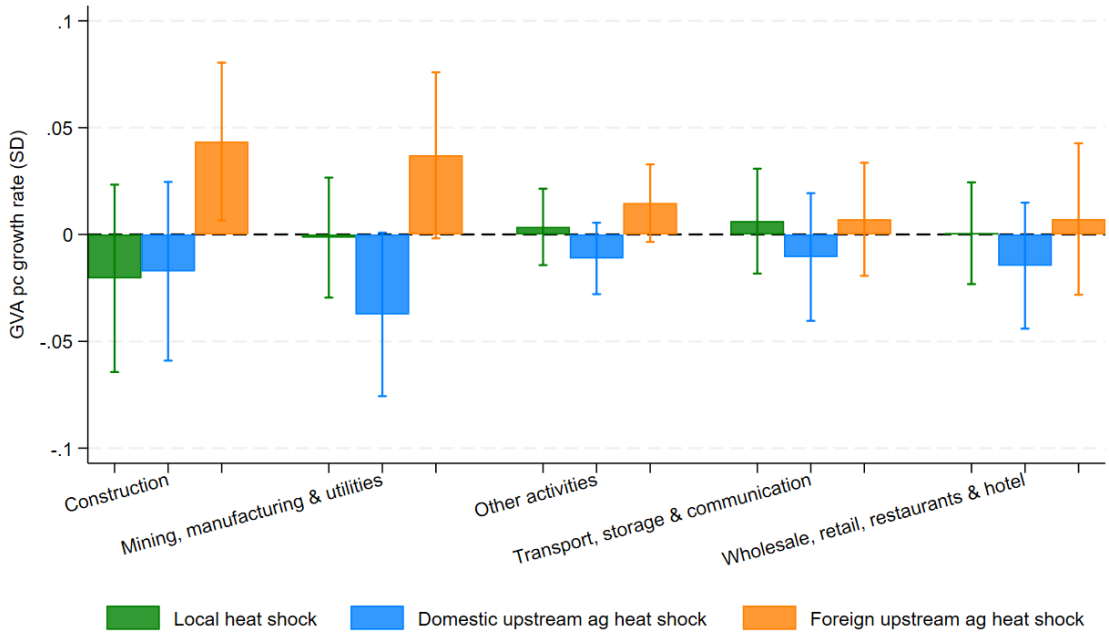


(f) 30-y MA climate norm



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 90th and the 99th percentile to construct heat shocks. Panel (f) uses a time-invariant production network constructed using the average of the first available five years of input-output interlinkages. Bins represent the 90% confidence intervals around point estimates.

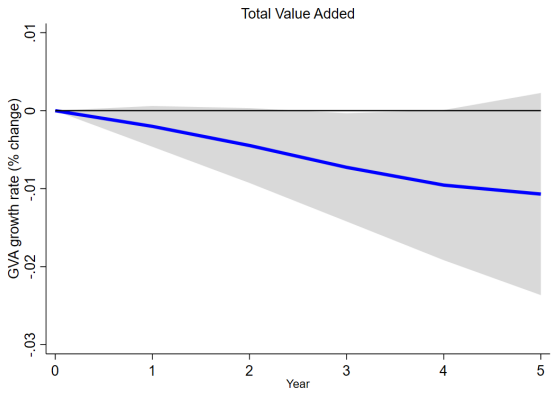
Figure A15. Local and upstream agricultural heat shocks on sectoral production



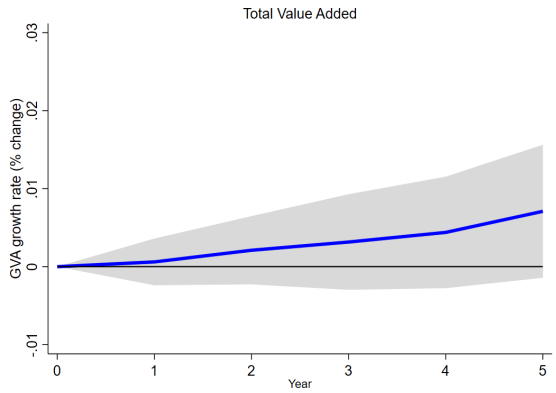
Notes: Bars represent the (standardized) sector-specific coefficients associated with direct shocks and domestic and foreign upstream shocks, using the average number of days above the 95th percentile of the daily temperature distribution. Domestic upstream shocks are constructed as the average weather shock in agriculture in the same country as the sector of interest weighted by the upstream interdependence with each sector. Symmetrically, foreign upstream shocks are constructed as the average weather shock in the agriculture sector abroad weighted by the upstream interdependence with each sector. 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 5th percentile and sector-specific responses to precipitation realizations below the 5th and above the 95th percentile. Bins represent the 95% confidence intervals with standard errors clustered at the country level.

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

(a) Domestic heat shock

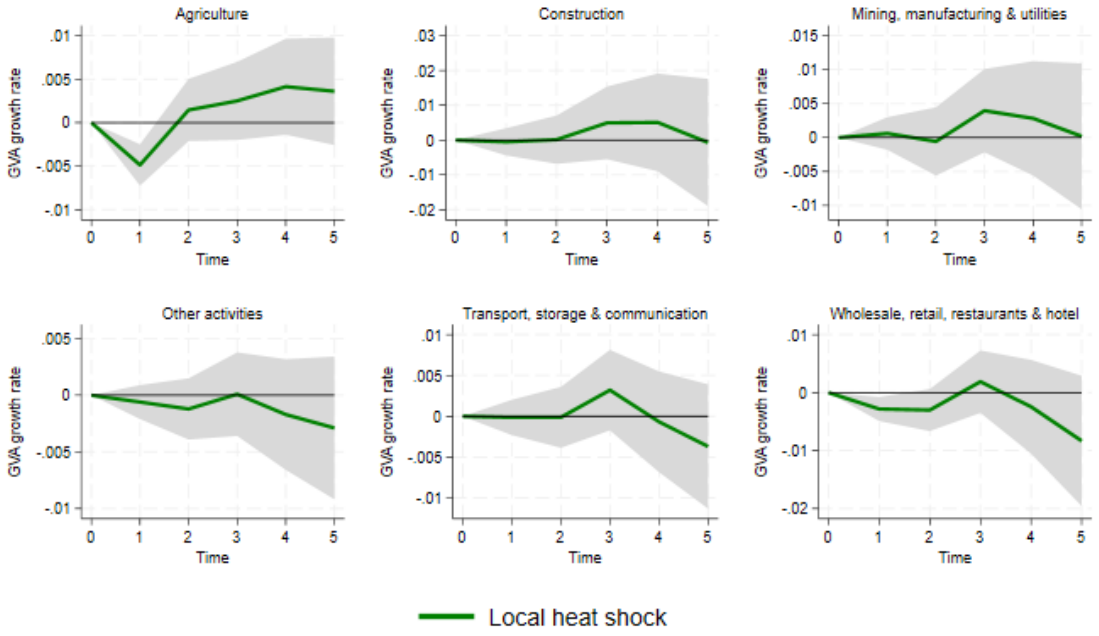


(b) Foreign heat shock



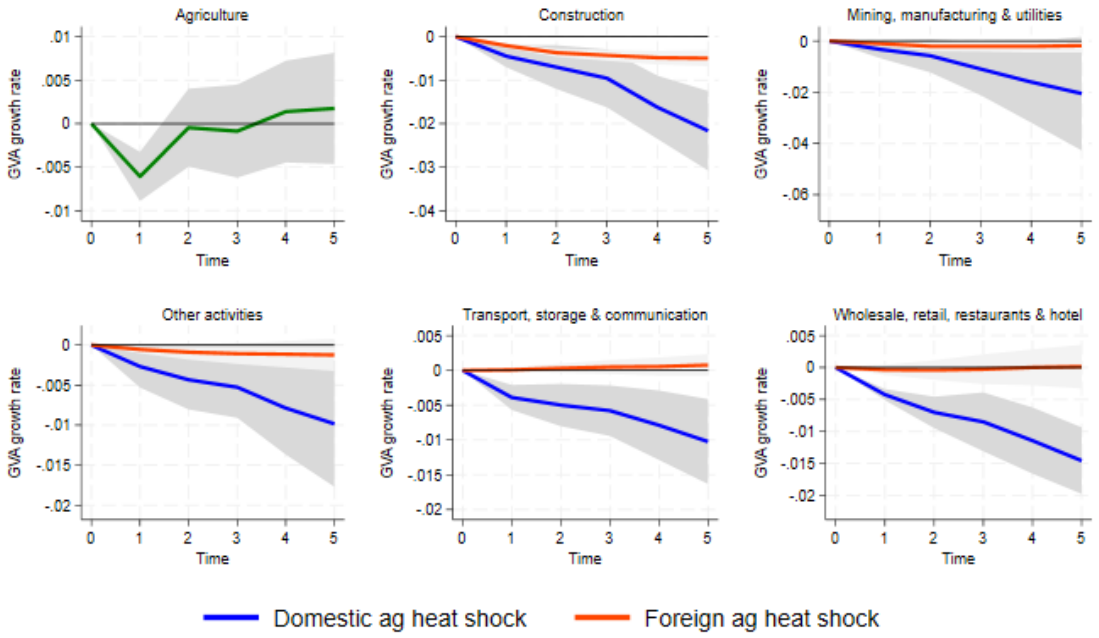
Notes: Panels show the impulse response function of per capita total value added growth rate to a 1 SD increase in heat shocks estimated in a stacked regression model with country and year fixed effects and accounting for cold temperature shocks (below the 5th percentile) and precipitation realizations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

Figure A17. Local projections of local heat shocks on sectoral value added



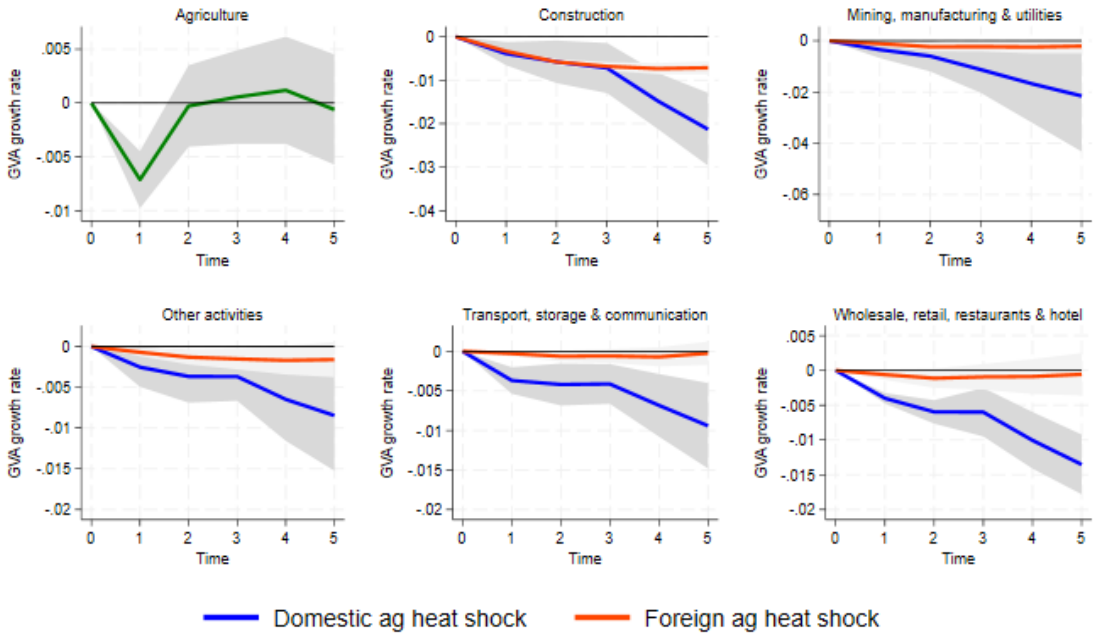
Notes: Panels show the sector-specific impulse response function of sectoral per capita GVA growth rate to a 1 SD increase in heat shocks estimated in a stacked regression model fully saturated with country-sector and sector-year fixed effects and accounting for sector-specific responses to domestic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

Figure A18. Local projections of domestic and foreign agricultural heat shocks on sectoral production. Continent-sector-year FE.



Notes: Panels show the sector-specific impulse response function of sectoral per capita GVA growth rate to a 1 SD increase in domestic and foreign agricultural heat 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 cold temperature shocks (below the 5th percentile) and to precipitation realizations below the 5th and above the 95th percentile. Horizon 0 is the year of the shock. Shaded areas represent the 90% confidence intervals with standard errors clustered at the country-level.

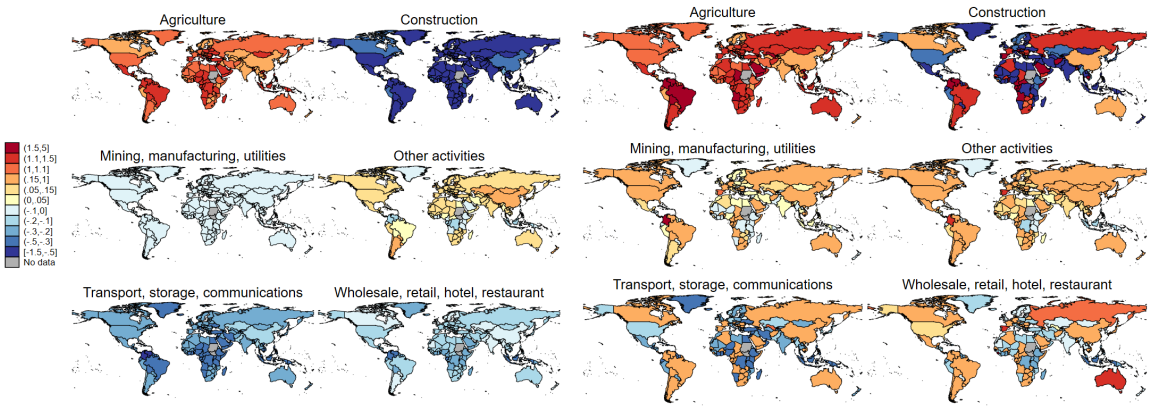
Figure A19. Local projections of domestic and foreign agricultural heat shocks on sectoral production. Continent-sector linear trends.



Notes: Panels show the sector-specific impulse response function of sectoral per capita GVA growth rate to a 1 SD increase in domestic and foreign agricultural heat 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 cold temperature shocks (below the 5th percentile) and to precipitation realizations below the 5th and above the 95th 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 A20. 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 heat 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 A8 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. 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 A5. 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 A6. 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 A7. 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 A8. 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 Reduced-form approach to the climate-output relationship

Kahn et al. (2021) review the three main approaches that study the climate-economy relationship in reduced form in the literature (Dell et al., 2012; Burke et al., 2015; Kalkuhl and 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 (as in Ortiz-Bobea et al. (2021)). Without loss of generality, the estimating equation considering only a second-order polynomial of differenced temperature is written as

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

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

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

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

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

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 $2\psi b^2_{T_i} t = 0$ 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 (C.1), such that it becomes

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

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. $\delta_{rt} + \psi \bar{b}^2_{Tr} t = 0$, for all r, where $\bar{b}^2_{Tr} = \frac{1}{n} \sum_{i=1}^{n_r} b^2_{T_{i,r}}$.

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-invariant production network

To test for robustness, I construct alternative weights for sectoral-interlinkages for which weather shocks affect economic production via a pre-determined exogenous production network. To do so, I retain the average of the first available five years of input-output sectoral interlinkages (i.e., 1970-1974) such that the downstream weights are constructed as

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

and upstream weights are constructed as

$$\widehat{\omega}_{i,c,j,m} = \frac{\overline{input}_{ic \to jm}}{\sum\limits_{lf \in \Theta_{ic}} \overline{input}_{ic \to lf}} \tag{E.2}$$

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

F 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 A5 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 A6), which translates into a 284% decrease with respect to the sample average (0.002). The effect is large but comparable to previous estimates on the effect of heat waves and tropical cyclones on agricultural growth rates (Miller et al., 2021; Kunze, 2021). In contrast, agriculture benefits from more precipitation, as documented in prior literature (Deschênes and Greenstone, 2007; Schlenker and 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 A7 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 the 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). In contrast, production in other sectors does not respond to changes in precipitation, except for the transportation sector which benefits from drier conditions.

G Quantifying the 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 and 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 estimated trend over the period 1970-2000, and distinguish between omitting and accounting for weather shocks in trade partners:

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

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

where T_{ict}^{95} is the observed number of days above 95th 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 95th 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

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

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

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

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 A20).

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

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

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.