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 extreme heat conditions that negatively affect the agricultural sector induce substantial losses to downstream sectors, which are non-responsive to local weather. Counterfactual scenarios reveal a threefold underestimation of global aggregate economic costs accounting for extreme heat in agriculture. The analysis also highlights centrality in the production network as a determinant of global losses.

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

JEL Classification: E23, E32, L14, O11, Q54, R15

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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 (Auffhammer, 2018; Hsiang, 2016), previous empirical studies examine the response of local aggregate measures of economic activity to isolated local weather shocks. In an increasingly interconnected world, intermediate inputs are a growing force of production networks and non-local weather shocks can affect output production through intermediate input availability. 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 sector-specific weather shocks propagate in the economy and beyond cross-national borders in international production networks by using cross-country global sector-level value added data combined with high-resolution weather data and input-output sectoral interlinkages. To show the importance of non-local weather shocks affecting sectoral production through intermediate input interlinkages, I formalize a model of production networks (Acemoglu et al., 2012; Carvalho and Tahbaz-Salehi, 2019). Weather shocks induce a reduction in the supplier's output and an increase in its output price, which leads customer sectors to reduce their demand for the intermediate input good and reduce their output accordingly.

My analysis starts by showing four empirical patterns that inform my empirical approach: (1) in a pooled multi-country sample of value added for six sectors across 183 countries between 1975 and 2020, extreme heat conditions negatively affect only the agriculture sector.[1] An additional degree day above optimal crop-specific growing conditions reduces agricultural per capita value added growth rate by 4.6% at the

[1]The other five sectors whose response to extreme heat is small and statistically indistinguishable from zero include: Mining, manufacturing and utilities; Construction; Wholesale, retail trade, restaurants, and hotels; Transport, storage, and communication; Other activities (including government and financial sector).

mean; (2) crop-weighted extreme heat shocks in the countries' agricultural sector are increasingly spatially correlated. Conventional quasi-experimental approaches estimating impacts of local temperature fluctuations neglect the interconnections among sectors and the spatial correlation structure of weather, leading to contraventions of common identifying assumptions, by violating the stable unit treatment value assumption. The other two empirical patterns make use of the input-output interlinkages from EORA26: (3) customer sectors' interlinkages with agriculture do not respond to extreme heat conditions, suggesting that the production network does not endogenously adjust to sector-specific temperature fluctuations; and (4) income does not explain differences in countries' ability to reduce their exposure to extreme heat in the upstream agricultural sectors.

Based on these patterns, I design an empirical methodology that examines how agricultural extreme heat conditions propagate through input-output interlinkages and affect other sectors' economic production domestically and abroad. I find that domestic and foreign extreme heat conditions in the agriculture sectors have a strong negative effect on downstream sectors' per capita value added growth rate. The magnitude of the indirect effect of network extreme heat shocks is substantial and comparable to the local effect of extreme heat on agricultural production. Results are stronger when accounting for the full propagation using the Leontief inverse matrix. These findings show input-output interlinkages with the agricultural sector as a new mechanism in the climate impact literature omitted in previous reduced-form attempts to quantify the economic cost of climate change.

Finally, I use the estimated parameters from the reduced-form specification as the basis of two counterfactual analyses. First, I quantify the contribution of input-output interlinkages between sectors to the average annual output loss due to recent warming from 2000 onwards. I consider a counterfactual world with no input-output linkages and with linearly trended daily temperatures from their baseline climate in 1970-2000. Accounting for network shocks, recent warming is responsible for an average annual output loss of 0.33%, compared to a 0.1% average loss 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 extreme heat occurs in countries with many supply chain interlinkages in the production networks, such as China, Brazil, France, India, and the United States, which are the major global agricultural exporters (Costinot et al., 2016).

Altogether, these findings provide evidence of the role of input-output sectoral interlinkages as an important mechanism for the propagation and amplification of extreme heat conditions in agriculture. 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 on macroeconomic impacts of climate change. A 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 location to estimate its effects on economic outcomes in a panel structure (Akyapi et al., 2024; 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., 2024; 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 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.,

[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).

2023), shocks can also propagate through production networks across geographically distant countries. 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, 2024), or after a localized single natural disaster such as the 2011 Japan earthquake (Boehm et al., 2019; Carvalho et al., 2021). Input-output linkages have been shown to matter for the economic cost of climate change in the US (Rudik et al., 2024). This paper contributes to the macroeconomic literature on the propagation of shocks by providing the first global estimate of the 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 and Section 4 uses them to establish a set of stylized facts that frame the analysis. Section 5 introduces the empirical approach. 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 static 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 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 indexed by $n \in \{1, ..., N\}$ (or m), each populated with J sectors indexed by

$j \in \{1, ..., J\}$ (or k). Production possibilities for sector j in region n are described by a constant returns-to-scale Cobb-Douglas technology whose inputs are capital and labor:

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

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

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

Traditionally, the reduced-form effect of temperature $\hat{\beta}$ on output per capita is estimated under the assumption that the residual variation in temperature is not correlated with the error term once absorbed unit- and time-specific unobserved heterogeneity.[3] The following section outlines a production network model where weather shocks propagate through the economy by altering input prices/quantities, and demand for intermediate inputs.

2.2 Weather shocks in a production network model

Idiosyncratic micro shocks can propagate through input-output production networks and impose substantial fluctuations at the aggregate level (Acemoglu et al., 2012; Carvalho et al., 2021). I present a simple model that is able to capture how weather shocks can propagate through the production network, affecting sectors not directly

[3] Identifying $\hat{\beta}$ also requires that the unit-specific capital-to-output ratio is constant. 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. 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.

hit by the shock (Acemoglu et al., 2016; Carvalho and Tahbaz-Salehi, 2019). The production process at each sector j 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 ($\omega_n^j + \sum_{j,m}^{J,N} \omega_{nm}^{jk} = 1$), such that

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

where x_{nm}^{jk} is the input from sector k in region m used in the production of good j in region n. The exponent $\omega_{nm}^{jk} \in [0, 1]$ represents the share of good k from region m in the total intermediate input use by sector j in region n, which can be equal to zero if it is not used. The larger ω_{nm}^{jk}, 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 j and k in two different regions n and m and assume for simplicity that the latter's output is the only intermediate input that sector j uses. Therefore, sector j's output (with lowercase letters indicating logs) is written as:

$$\begin{aligned} y_{nt}^j &= \underbrace{\log \bar{z}_n^j + \log \bar{z}_t^j + f(T_{nt}^j, \beta_j) + \omega_n^j \lambda k_n^j + \omega_n^j (1-\lambda) l_{nt}^j}_{\Xi_{nt}^j} + \omega_{nm}^{jk} \log \left(x_{nm}^{jk} \right) \\ &= \Xi_{nt}^j + \omega_{nm}^{jk} \left(\ldots + f(T_{mt}^j, \beta_j) + \ldots \right) \end{aligned} \tag{4}$$

Using Equation (2) to move from the first to the second line, this example showcases that a temperature shock would reduce input production k in region m and thus affect sector j's output in region n with elasticity ω_{nm}^{jk} due to the effect of temperatures on its suppliers. In particular, the increase in sector k's output price due to temperature changes induces sector j, which uses sector k's output in their input bundle, will reduce its demand for sector k's output, therefore reducing its own output.

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 j, which corresponds to the entries of the $(J \cdot N \times J \cdot N)$ input-output matrix $\mathbf{\Omega} = [\omega_{nm}^{jk}]$.[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 $\boldsymbol{L} = (\boldsymbol{I} - \mathbf{\Omega})^{-1}$, whose (j, k) elements denote the importance of sector k as a direct and indirect supplier to sector j. The inner product of elements ω in the input-output matrix $\mathbf{\Omega}$ (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 production (Section 3.1), weather (Section 3.2), and sectoral interlinkages (Section 3.3). Complementary secondary data are described in Appendix Section C.

[4] The assumption on the Cobb-Douglas production technology has two main implications. First, downstream effects emerge only in the case of supply-side shocks. Vice versa, upstream effects would be detected only in the case of demand shocks. Second, it 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.

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.[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). ERA-5 is available on a $0.25^{\circ} \times 0.25^{\circ}$ resolution grid ($\approx$ 28km at the Equator) from 1940 to the present. Crucial to the analysis is the construction of sectoral weather shocks. Below, I detail how I construct them.

Agricultural shock. First, I construct a measure of weather shock specific to the agricultural sector. Building on extensive prior literature, extreme heat exposure is quantitatively the most important weather determinant of yields (Schlenker and Roberts, 2009; Hultgren et al., 2022). I construct a measure that exploits the fact that locations grow different crops and are differentially exposed to changes in extreme temperatures and each crop is differentially sensitive to a change in extreme

[5] The final sample of countries and their frequency is reported in Appendix Table B2.

[6] The original data are available for seven sectors, including GVA in manufacturing (ISIC D). Unlike previous studies (Hsiang, 2010; Kunze, 2021), I consider mining, manufacturing and utilities (ISIC C-E) as one single sector, since value added across sectors is not additive.

[7] Appendix Table B1 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. 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.

heat exposure. First, I use the global geography of agricultural production from the Earthstat database (Monfreda et al., 2008). These land use data combine national, state, and county-level census statistics with a global data set of croplands to construct the area harvested for 175 crops at a 5 min (≈10 km) spatial resolution.

To capture crop-specific exposure to temperatures above which cumulative degree days are harmful, I use crop-specific temperature sensitivity from the UN FAO EcoCrop database. The EcoCrop data are compiled from expert surveys and textbooks and provide information on plants characteristics and crop environmental requirements for more than 2,000 plant species, including tolerance ranges for temperature and precipitation, soil pH, light intensity, and other soil characteristics. I use the crop-specific upper temperature threshold for optimal growing to compute the number of cumulative degree days that are harmful to a specific crop. For example, the harmful degree days for maize occur above 31°C. The use of crop-specific thresholds allays concerns on the spatial balance of the variation in extreme heat exposure used int the analysis. For instance, a spatially uniform threshold to compute extreme heat across locations and crops, e.g., 30°C, would completely mask Bolivia's exposure to above-optimal growing temperature conditions for quinoa (18°C), of which it is the leading world producer, and whose daily average temperature on agricultural lands was above 25°C only in 2% of the days in the sample.

Extending previous US-specific (Moscona and Sastry, 2023) and crop-specific global (Hsiao et al., 2024) efforts to measure agricultural extreme heat exposure, I construct a country-specific measure across crops k and grid cells g in country n, such that

$$ExtremeHeat_{nt} = \sum_k \sum_{g \in n} \frac{Area_{gk}}{\sum_k \sum_{g' \in n} Area_{g'k}} DegreeDays_{gt}(T_k^{max}) \tag{5}$$

where $DegreeDays_{gt}(T_k^{max})$ is the total number of degree days in excess of the crop-specific maximum optimal growing temperature T_k^{max} in grid cell g in year t, and $Area_{gk}$ is the fraction of grid cell g in country n growing crop k. To have a crop-weighted measure of extreme heat exposure at the country-level, I weigh crop-specific cumulative extreme heat exposure in a country by the total harvested area of each crop k in country n.

Other sector shocks. Unlike agriculture, production in other sectors is not linked to temperatures through specific geo-physical or agronomic relationships. Instead, output can be affected by weather variations through a variety of channels, including labor supply and productivity (Graff Zivin and Neidell, 2014; Rode et al., 2022), capital equipment (Zhang et al., 2018), and total factor productivity (Letta and Tol, 2019). To contrast sector-specific shocks with agricultural extreme heat exposure in the same country, I adopt a different approach to define abnormal hot temperatures.

Since the beginning of the reduced-form approaches to the output-temperature relationship, temperature has been used in levels (Dell et al., 2012). The non-stationarity of temperature levels, however, introduces concerns on the identification strategy (for a deeper discussion, see Appendix Section D). To construct an unexpected plausibly exogenous shock in temperature, I rely on people's climate beliefs being built upon long-run climatic conditions and adaptive responses based on their expectations (Shrader, 2021). I compute the annual number of days that belongs to the top 5^{th}-percentile of each grid-specific temperature distribution relative to a time-varying thirty-year long historical climate norm (Arguez et al., 2012). These events can be interpreted as abnormally hot shocks. Using this methodology, the measure is evenly distributed, and any abnormal realization is compared to the grid-specific climatic norm, in contrast to using absolute thresholds (e.g., number of days above 35°C), which only occur in certain areas of the world and might drive the variation used empirically without geo-physical justification.

To construct a measure of weather exposure for the average individual in a country, after taking any nonlinear transformation at the grid cell level, I average grid cell values across space using time-invariant population weights from the 2000 Landscan dataset (Bright and Coleman, 2001) and accounting for fractional grid cells that partially fall within a country (Hsiang, 2016). To obtain sectoral variation in weather conditions within a country, I rely on the sub-national geographic distribution of sectoral activities (Appendix Section C provides additional details on the data sources).

3.3 Production network

I use Input-Output (IO) data from EORA26 (Kanemoto et al., 2011; Lenzen et al., 2012) 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.[8] I examine the propagation of weather shocks through a 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.

Construction of network shocks. I construct shocks to agriculture that propagate through input-output interlinkages accounting for the geographic location and position in the supply 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 using entries from the inter-country IO tables with different weights 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.[9]

From the perspective of sector j in country n, agricultural downstream shocks are weighted by

$$\omega^{j,Ag}_{n,m,\tau} = \frac{\overline{input}_{Ag,m\tau \to jn\tau}}{\sum\limits_{kf \in \Theta_{jn}} \overline{input}_{jn\tau \to kf\tau}} \tag{6}$$

i.e., the average ratio of the inputs of j in country n produced by the agriculture sector (Ag) in country m over total inputs supplied to its set of customer sector-

[8] Appendix Table B3 maps the 26 EORA sectors to the six sectors described in Section 3.1.

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

countries Θ_{jn} over the previous five years τ for each decade. These weights reflect the inputs sector-country jn needs from the agriculture sector in country m to produce one output unit. Conversely, the weights associated with agricultural upstream shocks are constructed as

$$\widehat{\omega}^{j,Ag}_{n,m,\tau} = \frac{\overline{input}_{jn\tau \to Ag,m\tau}}{\sum\limits_{lf \in \hat{\Theta}_{jn}} \overline{input}_{jn\tau \to lf\tau}} \tag{7}$$

i.e., the ratio of the inputs of sector-country jn to the agriculture sector (Ag) in country m over the total inputs supplied to its set of customers Θ_{jn}. These upstream weights reflect the importance of each the agriculture sector in country m for the sector-country of interest jn. There are four different network shocks: downstream domestic (DnD), upstream domestic (UpD), downstream foreign (DnF), and upstream foreign (UpF), constructed as follows:

$$NetworkShock^{DnD}_{j,n,t} = \omega^{j,Ag}_{n,n,\tau} ExtremeHeat_{nt} \tag{8}$$

$$NetworkShock^{UpD}_{j,n,t} = \widehat{\omega}^{j,Ag}_{n,n,\tau} ExtremeHeat_{nt} \tag{9}$$

$$NetworkShock^{DnF}_{j,n,t} = \sum_{m \neq n} \omega^{j,Ag}_{n,m,\tau} ExtremeHeat_{mt} \tag{10}$$

$$NetworkShock^{UpF}_{j,n,t} = \sum_{m \neq n} \widehat{\omega}^{j,Ag}_{n,m,\tau} ExtremeHeat_{mt} \tag{11}$$

where $ExtremeHeat_{mt}$ measures the crop-weighted extreme heat conditions on agricultural land in country m in year t.

4 Empirical Patterns

I begin the analysis by bringing together the data presented in Section 3 to document four key empirical facts about i) global patterns of extreme heat conditions, ii) the relationship between local extreme heat and sectoral production, and iii) and iv) on the potential endogeneity of the production network. Together, these facts help frame the subsequent empirical approach that introduces the role of sectoral interlinkages as a transmission channel of agricultural heat exposure to sectoral economic production domestically and abroad.

Pattern 1: Local extreme heat reduces agriculture value added. To validate my measure of extreme heat exposure, I estimate the sectoral response in per capita GVA growth rate to local extreme heat conditions. Differently than previous cross-country 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, such that:

$$\Delta \log(GVA)_{jnt} = f_j(\mathbf{W}_{nt}) + \alpha_{jn} + \mu_{jt} + \varepsilon_{jnt} \tag{12}$$

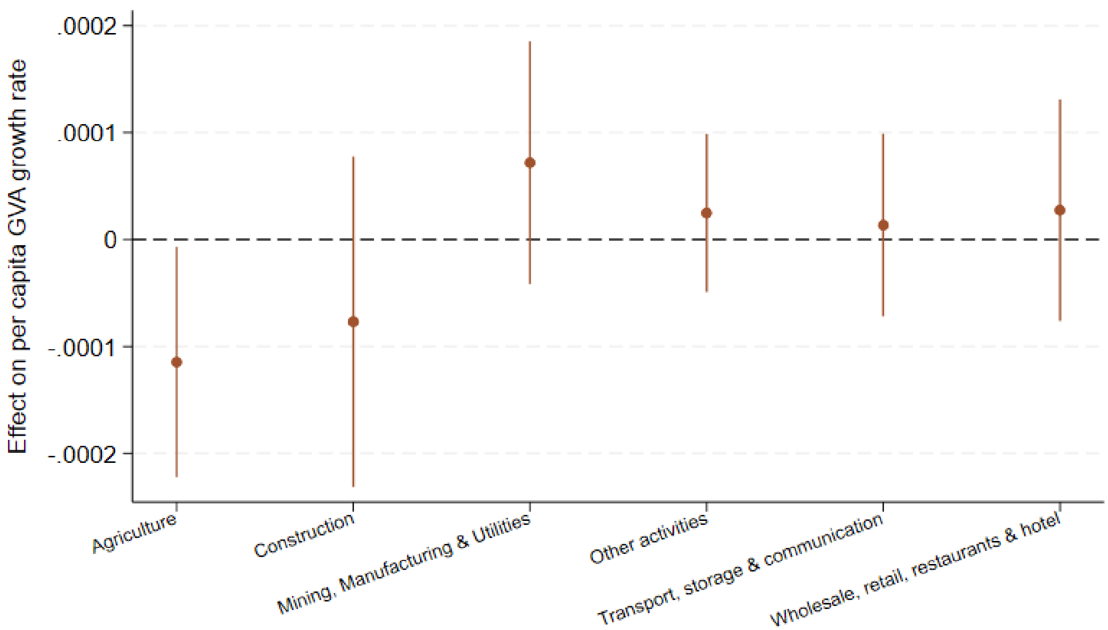
where I regress the growth rate of GVA per capita in sector j in country n in year t (approximated by the first difference in logarithms) on a sector-specific function of weather variables $\mathbf{W}$ in country n in year t, which includes extreme heat and a second order polynomial of total precipitation. Country-sector α_{jn} fixed effects 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, and sector-year μ_{jt} fixed effects capture year-specific worldwide shocks, such as El Niño events or global recessions, and shocks to specific sectors (e.g. agricultural commodity price shocks).[10] Equation (12) 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 (Hsiang, 2016).

Figure 1 shows the sector-specific coefficients associated with local extreme heat conditions on sectoral per capita gross value added growth rate. An additional degree day in the extreme heat measure constructed in Equation (5) ($\approx 1\%$ at the sample

[10] 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).

mean) reduces the agricultural growth rate by 4.6% at the mean. All other five sectors do not respond to extreme heat, with the effect very small in magnitude and statistically indistinguishable from zero. Together, these estimates indicate that extreme heat exposure has substantial negative effects on agricultural value added and does not significantly affect any other sector's production. In Appendix Section E, I describe the heterogeneous effects of local extreme heat by adaptation potential as measured by income and climate.[11]

Figure 1. Effect on local extreme heat on sectoral per capita value added growth rate



Notes: The figure shows the regression estimates for the country-average number of degree days for the agricultural sector and country-sector average number of days above the 95^{th} percentile of the daily distribution in temperature. All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects and allowing for sector-specific response to a quadratic functional form in precipitation. Bins represent the 95% confidence intervals around point estimates. 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.

[11] I find a comparable and quantitatively similar result with the measure of abnormal heat shocks constructed using the number of days above the 95^{th} percentile of the daily distribution in temperature (Appendix Figure A4). Appendix Figure A5 plots the response in agricultural value added per capita growth rate to changes in terciles or quintiles of the extreme heat distribution. Results are 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 A6).

Pattern 2: Extreme heat shocks are increasingly spatially correlated. A first empirical fact relates to the geography of the measure of extreme heat for the agricultural sector. I measure the global spatial correlation of extreme heat exposure in each year t using Moran's I, a statistics for spatial autocorrelation that ranges from -1 to 1:

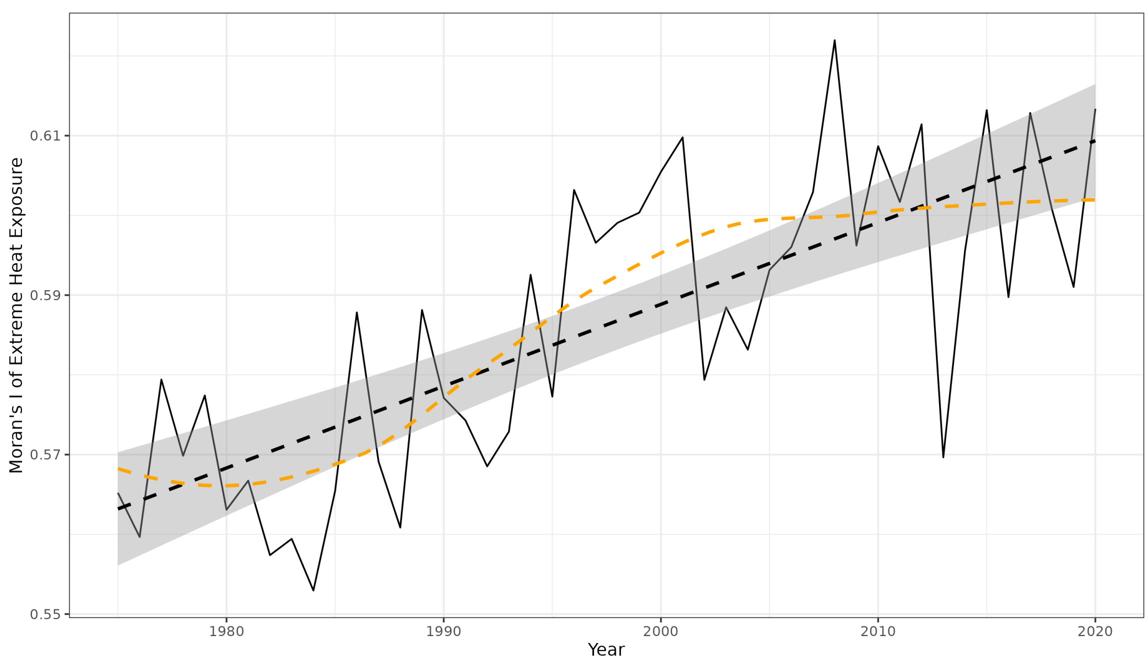
$$I_t \equiv \frac{N}{\sum_n \sum_{m \neq n} a_{nm}} \frac{\sum_n \sum_{m \neq n} a_{nm} \left(EH_{nt} - \overline{EH_t}\right) \left(EH_{mt} - \overline{EH_t}\right)}{\sum_\ell \left(EH_{\ell t} - \overline{EH_t}\right)^2} \tag{13}$$

where N is the number of countries, $a_{nm} = a_{mn}$ is a (symmetric) spatial weight that depends on the distance between countries n and m, and $\overline{EH_t}$ is the world average extreme heat exposure in year t across countries as constructed in Equation (5). Figure 2 plots the time series of the Moran's I statistics. In the 45 years in the sample, the Moran's I ranges from 0.55 to 0.62 with an average equal 0.59 and a strong positive trend over time. This fact suggests that, despite crop-specific temperature thresholds, extreme heat exposure is spatially correlated across countries and increasingly so over time, indicating that crop specialization patterns might also follow a similar spatial structure (Dingel et al., 2023).

The spatial correlation structure of extreme heat exposure is an additional aggravating factor to well-documented agricultural losses induced by extreme temperatures. Trade costs lead to stronger trade relationships with neighboring countries rather than distant ones (Chaney, 2018). In spite of accounting for differential crop composition of agricultural production across countries, this empirical result suggests that a country experiencing reduced yields due to increases in temperatures is likely to be near other similarly affected countries. This spatial correlation pattern diminishes the potential adaptive role of international trade compared to scenarios where shocks are not spatially correlated.

Furthermore, local temperature fluctuations have been used in quasi-experimental studies that inform climate impact projections (e.g., Burke et al., 2015). In this literature, the effect of local temperatures on an economic outcome is traditionally estimated using quasi-random variation implicitly holding temperatures in other locations fixed. Climate change's global impact is then computed as the sum of projected local impacts, which, however, hold fixed the spatial structure of temperature and thus correspond to considering many scenarios in which in each scenario only one location experiences warming. Two approaches so far account for the global nature of climate change, in which all locations experience warming simultaneously: cereal productivity depending on spatial correlation induced by global climatic phenomena (Dingel et al., 2023) and controlling for spillovers from neighbouring regions using a spatial-lag model (Kotz et al., 2024). In either cases, incorporating changes in the spatial correlation exacerbates global welfare inequality and losses induced by changes in climate conditions.

Figure 2. Spatial Correlation of Extreme Heat Exposure



Notes: Figure shows the time series evolution between 1975 and 2020 of the Moran's I Statistic computed as in Equation (2) for the Extreme Heat Exposure constructed in Equation (5). The dashed black line represents the linear fit with the 95% confidence intervals displayed in the gray shaded areas (the coefficient on the linear trend is equal to 0.001, with standard error equal to 0.0001), and the dashed orange line is a local polynomial.

Pattern 3: Downstream agricultural sectoral interlinkages do not respond to extreme heat. One potential concern is that the input-output network described in Section 3.3 is endogenous to the extreme heat. Countries may endogenously respond to extreme heat conditions that hit the agricultural sector by altering sectoral interlinkages and thus the production network structure. A productivity shock to agriculture may result in a reallocation of resources across sectors in the economy. In a perfectly competitive efficient closed-economy with Cobb-Douglas preferences and technologies, a sector's Domar weight (i.e., the sales share of a sector with respect to the economy's output) is a sufficient statistic for how shocks to that sector impact aggregate output.[12]

Previous empirical evidence documents that at the micro level, firms systematically respond to changes in weather conditions by altering their location choice, their supply partners and their characteristics (Balboni et al., 2023; Castro-Vincenzi et al., 2024; Pankratz and Schiller, 2024). For example, firms may relocate to safer locations, shift purchases towards suppliers in less exposed regions and use less exposed routes. Such endogenous changes in the production network can, in turn, significantly alter the economy's response to exogenous disturbances. To examine whether the production network endogenously adjusts in response to weather shocks, I exploit the time-varying nature of the IO matrix and estimate the following specification:

$$IO^{Ag,j}_{n,m,t} = f_{j,\ell}(\mathbf{W}_{Ag,t}) + \alpha_{jnm} + \mu_{jmt} + \varepsilon_{jnmt} \tag{14}$$

where the outcome variable $IO^{j,Ag}_{n,m,t}$ is the (log) ratio of inputs that sector j in country m sources from the agricultural sector in country n in year t over the total inputs sourced by sector-country (j, m).[13] I exploit inter-annual variation in extreme heat conditions and precipitation in the agricultural sector in country n to test for within country-pair-sector changes in intermediate inputs sourced from the agricul-

[12]This result is commonly know as Hulten's theorem (Hulten, 1978). Although versions of Hulten's theorem continue to hold in open-economies, the sales shares are no longer such universal sufficient statistics (Baqaee and Farhi, 2024).

[13]Sector-specific density distribution of the sectoral interlinkages with agriculture are reported in Appendix Figure A3.

tural sector in country n. The specification accounts for country-pair-sector α_{inm} and customer country-sector by year μ_{imt} fixed effects (which effectively also accounts for weather conditions in the customer country). To allow for heterogeneous elasticities of substitution, I estimate sector-specific response functions to extreme heat and precipitation conditions and allow elasticities to differ also by location ℓ of the agricultural sector (either domestic or foreign).

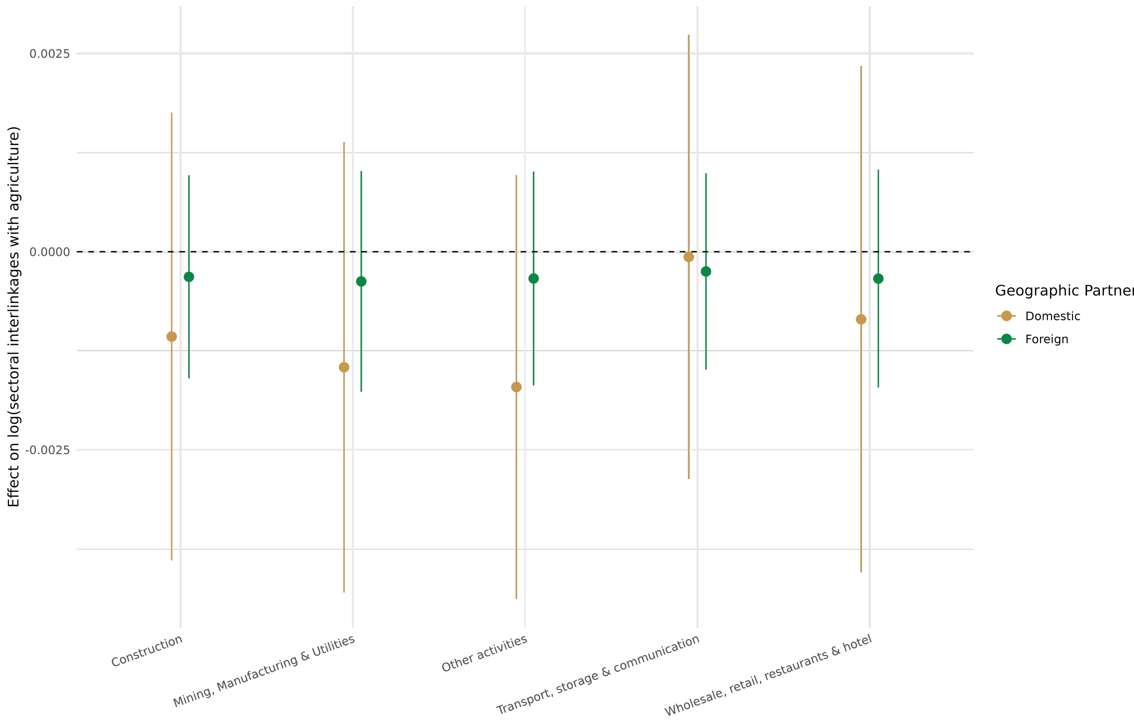
Figure 3 reports the sector-location specific coefficients associated with extreme heat on the sectoral interlinkages with agriculture. The ten coefficients are small and not statistically significant at any conventional level, suggesting that the sectors do not endogenously respond to extreme heat in their agricultural trade partners by altering their expenditure shares providing suggestive evidence of the stickiness of production processes.[14] As previously conjectured (Carvalho and Tahbaz-Salehi, 2019), this fact suggests that the Cobb-Douglas model may serve as a good approximation at the sector level, in contrast with previous micro level evidence on firms' ability to substitute inputs and trading patterns in response to idiosyncratic shocks.

Pattern 4: Downstream exposure to extreme heat in agriculture does not vary systematically across countries with different GDP per capita. Income is one of the most important factors governing the economics of climate adaptation (Carleton et al., 2022). High-income countries have less binding budget constraints, which could in turn facilitate adaptive behavior and make them less affected by temperature. While this result holds for the economic output response to local weather fluctuations (Dell et al., 2012), I document that downstream exposure to extreme heat in agricultural has been relatively constant over the past forty years.

As Fact 3 establishes that sectors do not substantially differ in response to agricultural extreme heat, I pool exposure to agricultural extreme heat conditions across sectors in a country and divide the global sample in three sub-samples based on

[14] Kunze (2021) also documents a small and negligible shift of sectoral interlinkages in response to tropical cyclones.

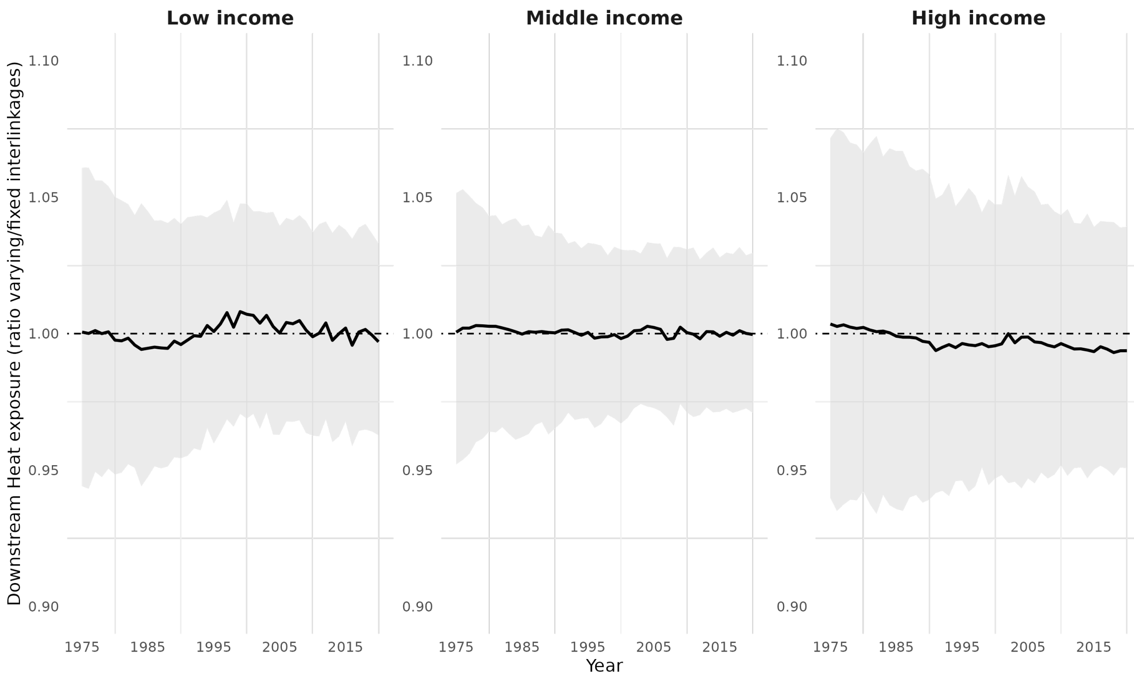
Figure 3. Response of downstream sectoral interlinkages with agriculture to extreme heat



Notes: The figure shows the sector-location specific coefficients associated with extreme heat on agriculture in a regression where the outcome variable is the log of the ratio of inputs that a sector (in the x-axis) sources from the agricultural sector over the total inputs sourced by each sector-country. All coefficients are estimated jointly in a stacked regression model saturated with country-pair-sector and country-sector-year fixed effects and sector-location specific coefficients on linear and squared term of total precipitation. Bins represent the 95% confidence intervals around point estimates. Standard errors are clustered at the country level.

terciles of income. I construct downstream heat exposure in two ways. First, I measure a country's exposure to extreme heat allowing the production network to evolve over time and constructing sectoral interlinkages which vary yearly. Second, I construct downstream extreme heat exposure using a time-invariant production network where sectoral interlinkages are constructed from the earliest available five-year period of input-output linkages (1970 to 1974). The ratio between these two measures of downstream heat exposure indicates whether countries have been able to reduce their exposure to downstream non-local extreme heat conditions conditional on their income class. Figure 4 shows a relatively stable and flat ratio statistically indistinguishable from one, suggesting that, differently than in the case of response to local extreme heat, income does not explain differences in downstream exposure to extreme heat.

Figure 4. Downstream exposure to agricultural extreme heat by income terciles



Notes: Each panel in the figure displays the average (black solid line) ratio of downstream heat exposure computed between a production network where sectoral interlinkages are varying annually and one where sectoral interlinkages are fixed in time averaged between 1970 and 1974 for each income tercile. Income terciles are defined averaging for the whole 45-year time period the log of per capita GDP using data from the World Bank's World Development Indicators. The gray shaded areas represent the 95% confidence intervals.

Together, these four facts on the local response of agriculture production to extreme conditions, together with the spatial correlation of extreme heat and limited evidence of production network adaptation across sectors and income terciles, motivate the empirical strategy that I adopt in the next sections to rationalize the importance of trade interlinkages in climate damage quantification.

5 Empirical Approach

The baseline empirical approach builds on the conventional methodology adopted in quasi-experimental climate impact studies and it introduces a parametric measure of spillovers to analyze how extreme heat conditions in agriculture affect sectoral economic production domestically and abroad.

The traditional fixed-effect model (e.g., Dell et al., 2012; Burke et al., 2015) typically estimates local direct effects of temperatures but ignores spatial linkages, by implicitly assuming that the residual variation in weather is orthogonal to variations in weather elsewhere. Estimates obtained from traditional equations in the style of Equation (12) may thus be biased when omitting trade linkages across observational units by 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.

To introduce a new impact channel of weather shocks rippling through the supply chain via sectoral interlinkages, I design an econometric specification that builds on Equation (12), but parametrically accounts for *network* shocks:

$$\Delta \log(GVA)_{jnt} = f_j(\mathbf{W}_{n(j)t}; \beta_j) + \sum_{\ell \in \{D;F\}} \gamma_{j,\ell} NetworkShock_{jnt}^{Dn,\ell} + \alpha_{jn} + \mu_{jt} + \eta_{jnt} \quad (15)$$

where I regress the growth rate of GVA per capita in sector j in country n in year t for all five sectors in the economy except agriculture on a sector-specific function of local weather conditions $\mathbf{W}$ in country n in year t, including abnormal hot days and a second order polynomial of total precipitation. Most importantly, the specification includes a measure of $NetworkShock_{jnt}^{\ell}$, defined as extreme heat conditions in agriculture weighted by downstream interdependence of sector j with the agricultural sector in geographic location ℓ (where $\ell \in$ {Domestic; Foreign}). The specification also accounts for country-sector α_{jn} and sector-year μ_{jt} fixed effects.

This approach aims at quantifying the impact on sectoral production of trade-induced exposure to harmful extreme heat conditions in agriculture. As formulated in the theoretical framework and supported by the empirical evidence, extreme heat reduces agricultural productivity. By only considering the *direct* impact of local weather conditions on a given sector, one is omitting the amplification and transmission of these shocks due to the intersectoral reliance. A negligible or null effect of local weather conditions on a given sector may be amplified by extreme heat conditions hitting agricultural sectors around the world with strong commercial interlinkages with that sector. The effect would ripple down to downstream customer sectors that then use agricultural inputs less intensively and thus reduce their own production.

6 Heat shocks in a production network

In this section, I report the results from the estimation of Equation (15) that quantifies the propagation of extreme heat on agriculture across the economy through the production network. Figure 5 displays the coefficients associated with local and downstream agricultural *network* heat shocks decomposed into domestic and foreign.

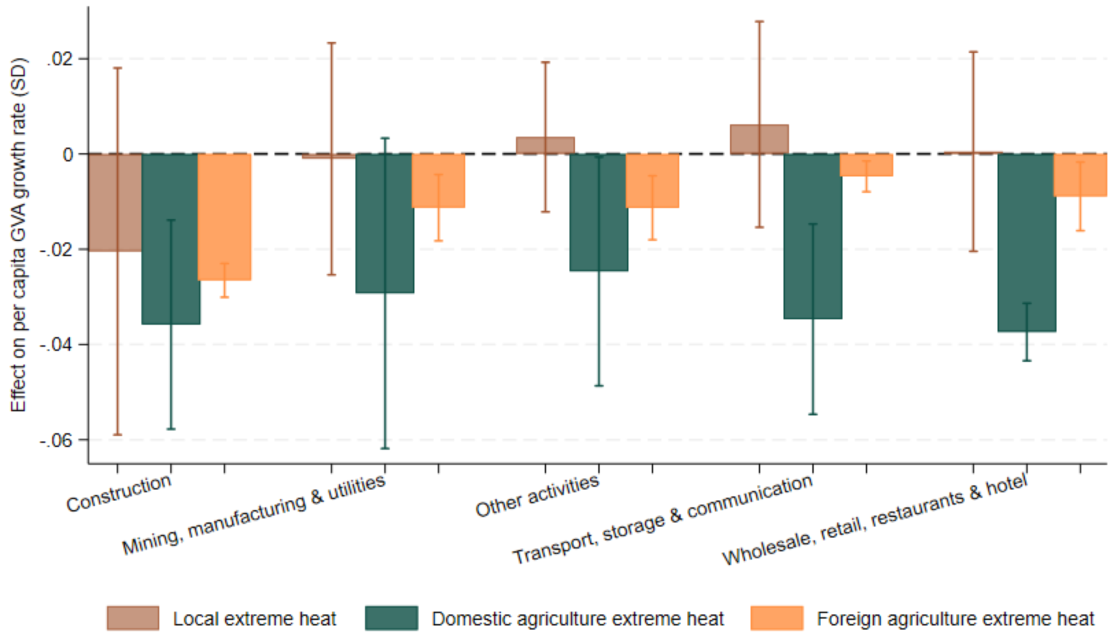
Starting from the coefficients on local extreme heat, the estimated effect on all sectors is not statistically distinguishable from zero. Both domestic and foreign extreme heat conditions in agriculture have a negative and sizable effect on economic production in all the five sectors of the economy. Aggregating domestic and foreign estimates, the magnitude of network shocks is substantially larger for the construction sector, which relies heavily on various inputs from agriculture (e.g., timber, bamboo, straw and hay, natural fibers, plant-based binders, soil and gravel, biofuels, geotextiles) and produces investment goods, more vulnerable to climate change than e.g. the retail sector, which primarily produces consumption services (Casey et al., 2024).

The theoretical model in Section 2 suggests that the reduction in the production of downstream sector goods is attributable to changes in upstream good prices which induce customer sectors to decrease their demand for such goods. Nevertheless, the potential heat-induced price distortion has not been quantified yet. I use FAO crop price to empirically validate this hypothesis. Appendix Table B4 reports the results in a country-crop panel regression of crop prices on a crop-specific degree day measure computed as the average exposure to crop-specific maximum optimal growing temperature thresholds on land cultivating a given crop and a second order degree polynomial of total precipitation. In line with the theoretical framework, an increase in extreme heat conditions substantially increases crop prices. The price distortion induced by heat conditions, however, is not persistent. A dynamic event study estimation shows that only extreme heat at time t increase crop prices, with the effect vanishing after one year (Appendix Figure A7).

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 the agriculture sector. The statistical and economic significance of foreign network shocks suggests that also geographically distant weather fluctuations matter through trade interlinkages. Second, agriculture-specific extreme heat conditions are amplified in the economy through input-output interlinkages, affecting other sectors beyond agriculture and also 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.

To address potential concerns on spatially correlated patterns in extreme heat, I exploit local variation in extreme heat uncorrelated with contemporaneous weather elsewhere within the same region, by accounting for year-specific fixed effects at the regional level (Deschênes and Meng, 2018) (Appendix Figure A8). Results are also robust to estimating the equation with country-specific linear trends, using a balanced panel, and excluding large countries As a test for the validity of the Cobb-Douglas production function assumed in Section 2, Appendix Figure A9 shows that agriculture

Figure 5. Local and downstream agricultural extreme heat on sectoral production

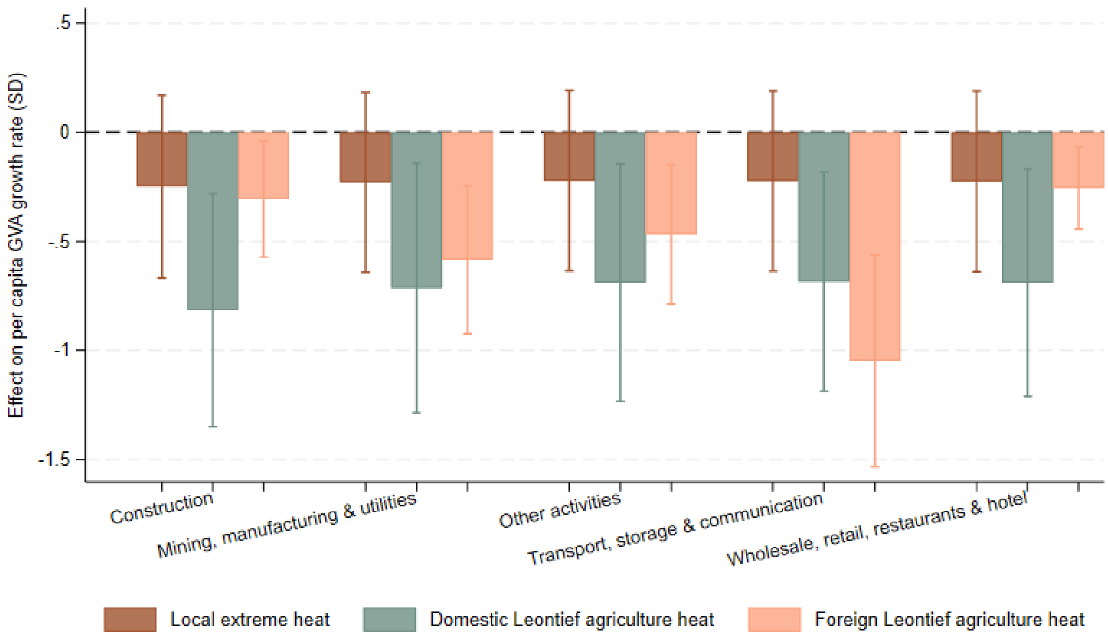


Notes: Bars represent the (standardized) sector-specific coefficients associated with local shocks and domestic and foreign downstream shocks, using the extreme heat exposure measure constructed as in Equation (5). Domestic and foreign downstream shocks are constructed respectively as in Equations (8) and (10). The specification jointly estimates all sector-specific coefficients in a stacked regression model fully saturated with country-sector and sector-year fixed effects and sector-specific responses to a second-order polynomial of total precipitation. Bins represent the 95% confidence intervals with standard errors clustered at the country level.

extreme heat does not propagate upstream, as a demand-side shocks would do, but only downstream, confirming the interpretation of extreme heat in agriculture as a supply-side productivity shock.

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 6. 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.

Figure 6. Sector-specific response to agriculture extreme heat 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 95$^{\text{th}}$ percentile of the daily temperature distribution weighted by the Leontief inverse matrix obtained from the downstream sectoral interlinkages obtained as in Section 3.3. 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 5$^{\text{th}}$ percentile and sector-specific responses to precipitation realizations below the 5$^{\text{th}}$ and above the 95$^{\text{th}}$ percentile. Bins represent the 95% confidence intervals with standard errors clustered at the country level.

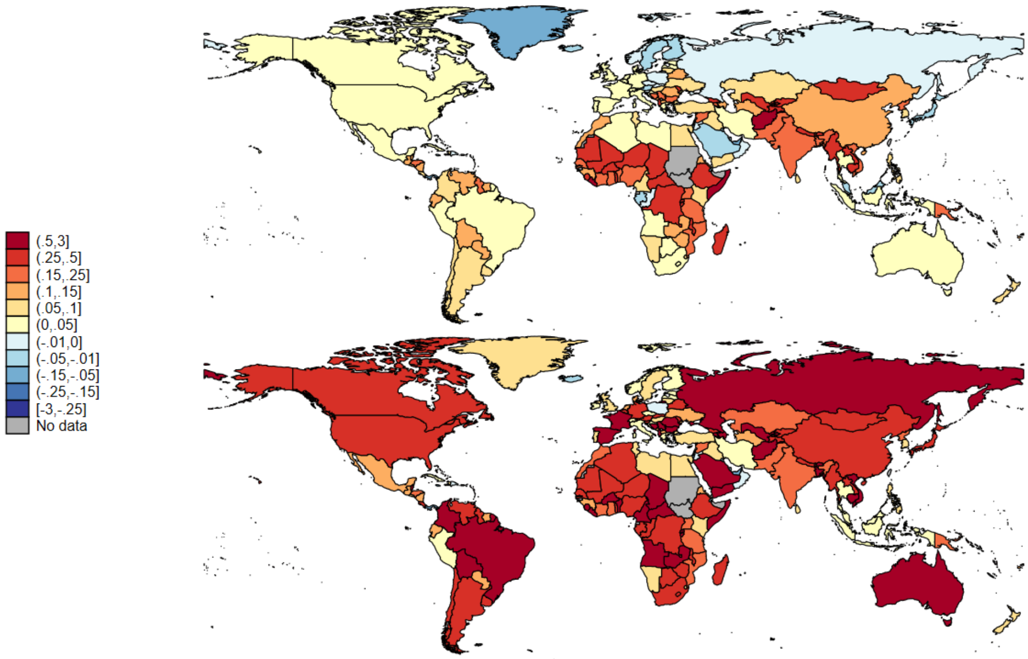
7 Counterfactuals: Cost of recent warming in a production network

To assess the economic importance of the propagation of extreme heat in agriculture through production networks, I perform two counterfactual analyses. First, I compare the differential sectoral output losses/benefits as a result of recent historical warming. Prior research quantifies and projects the impact of temperature increases assuming a counterfactual with no further warming (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 F for additional details).

Omitting shocks in the agricultural sector partners substantially underestimates the losses due to recent warming (Appendix Figure A11). 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 7).

In a second exercise, I quantify the macroeconomic impact of an increase in one degree day in extreme heat conditions in a region or country from 2000 onwards. Figure 8 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

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



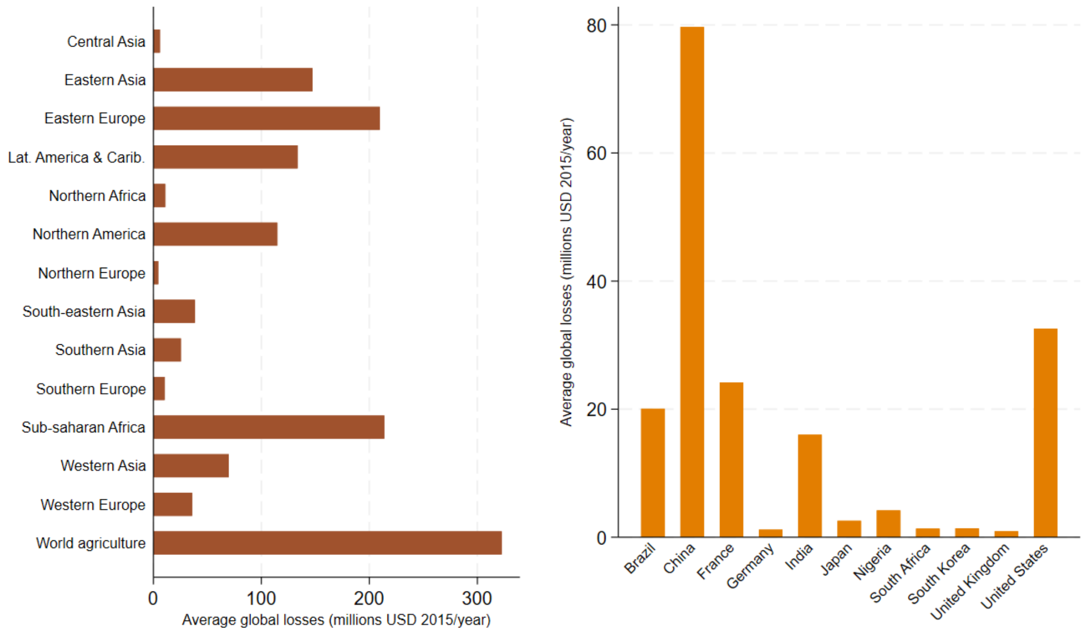
Notes: The figure shows the average annual losses (in red) and gains (in blue) in per capita GVA (%) compared to a counterfactual daily temperature evolved linearly from the trend estimated over the period 1970-2000. Sector-specific damages are weighted by the average sectoral share of total GVA between 1996 and 2000. The world map above only accounts for sector-specific local extreme heat conditions. The world map below accounts for indirect extreme heat in agriculture using sector-specific semi-elasticities from bootstrapping 1000 times the underlying panel estimates of Equation (15), 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 A11, Table B5 reports the sector-specific losses significant at 95% level estimated with 1000 bootstrap replications with replacement.

damages on local economic production. An alternative mechanism could be explained by a scale effect since these regions have the largest number of countries contemporaneously shocked. For this reason, I also compute average annual global losses if one single country experiences an additional hot day (right-hand side of Figure 8). 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$).[15] These losses are

[15] Together, these five countries make up more than 45% of world crop output (Costinot et al., 2016).

sizable since they are obtained for an increase by one in the extreme heat measure of degree days. Hot days have substantially increased over the time period considered. For example, the decadal average number of degree-days in China in the 1970s was 16.4 degree days/year and reached 23.3 degree days/year in the 2010s. Similarly, extreme heat conditions in Brazil increased from 21.22 degree days/year to 40.6 degree days/year and from 41.1 degree days/year to 55.7 days/year in the US.

Figure 8. Average annual global losses due to an additional degree day in extreme heat in agriculture 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 degree day in agricultural extreme heat conditions in the sub-region (resp. country) reported in the y-axis (x-axis), using sector-specific semi-elasticities from Equation (15), 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 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 at the sector level across the world and generates substantial fluctuations in sectoral production. Downstream 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 extreme heat conditions. In particular, sectors at later stages of the supply chain are negatively impacted by supply-side agricultural heat shocks that propagate downstream. In light of the negative impact of indirect extreme heat conditions in agriculture on other sectors, these findings suggest that climate damages may be larger than indicated by standard empirical approaches and integrated assessment models that do not account for trade interlinkages.

The findings point to the structure of sectoral production network linkages as a key driver of aggregate fluctuations induced by extreme heat. In particular, they indicate that even if most sectors with the exception of agriculture are sheltered from local 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 extreme heat conditions in agriculture may lead to approximately a threefold underestimation of the effect of recent warming around the world (0.1% vis-à-vis 0.33% of per capita GVA 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 when experience more extreme heat conditions.

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 local extreme heat condition depends on climate and income. There is, however, little evidence of countries' ability to reduce their exposure to upstream extreme heat in agriculture. The analysis does not explicitly model adaptive investments, technological change, or other agriculture-specific adaptive responses (e.g. irrigation) that may heterogeneously affect the response functions and reduce climate damage. Moreover, crop-specific extreme heat conditions are computed over agricultural land that do not allow for crop specialization adjustments, a crucial adaptive margin that can help mitigate climate damages (Costinot et al., 2016). Accounting for this and other adaptive margins may alter the propagation of extreme heat conditions in agriculture in countries that are more sheltered.

Second, the transmission of weather shocks is studied through the relative importance of trade partners in input-output interlinkages in a Cobb-Douglas economy. Productivity shocks in agriculture may impact the output of other sectors via two distinct channels. First, the resulting increase in the impacted sector's good price adversely affects sectors that rely on that good as intermediate input for production. Second, extreme heat conditions may also lead to reallocation of resources across sectors depending on the elasticities of substitution across inputs. The input specificity and different elasticities of substitution would lead to the impact of agricultural productivity shock to not remain confined to downstream sectors (Barrot and Sauvagnat, 2016). This channel has only been documented at the firm level, and although I find evidence consistent with the Cobb-Douglas model being a good approximation at the sector level, other additional layers of heterogeneity could shed light on the exact channel of transmission of agriculture extreme heat conditions through the economy.

Third, the analysis is mostly silent about agents' climate beliefs and expectation formation processes. Despite the use of implicit and explicit models of adaptation accounting for long-run climate, income and adjustments in sectoral interlinkages, adaptive behavior reflects agents' perceptions 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, modelling the learning process about underlying weather risk from weather shock realizations and adaptive responses.

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Appendix

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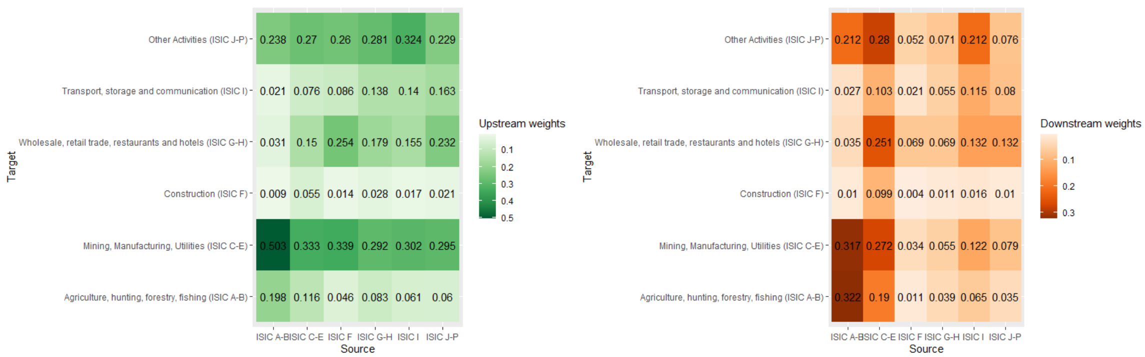
A Additional figures

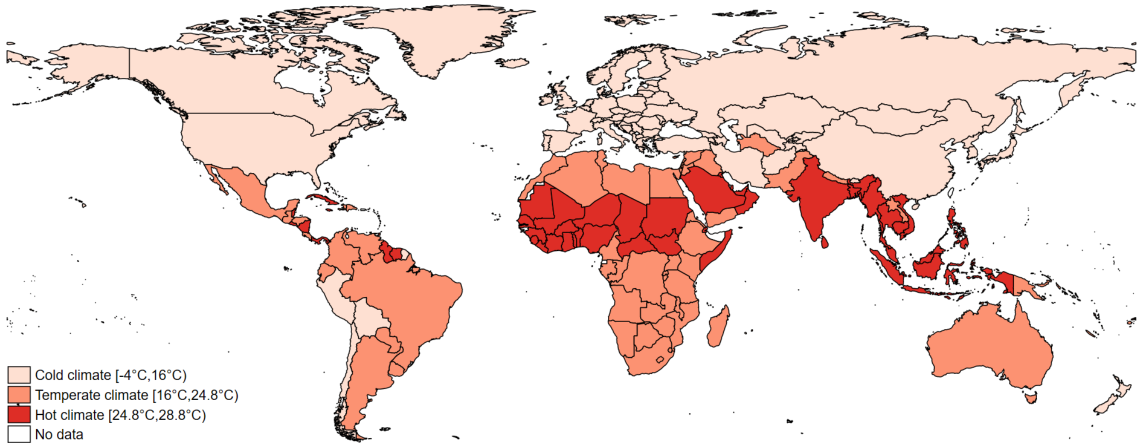
Figure A1. Average upstream and downstream weights across countries

(a) Upstream (b) Downstream



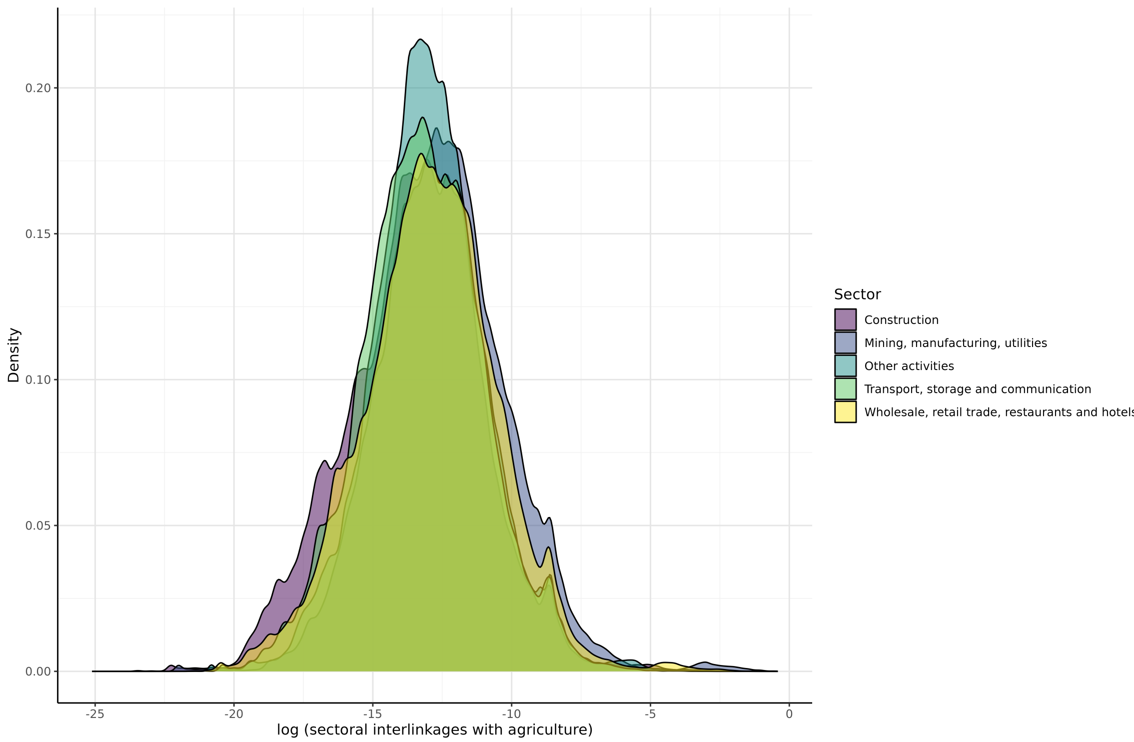
Notes: The figure shows the average upstream and downstream weights across countries by sector. Upstream and downstream weights are constructed from the perspective of Source sectors on the x-axis.

Figure A2. Countries in the sample by climatic zone



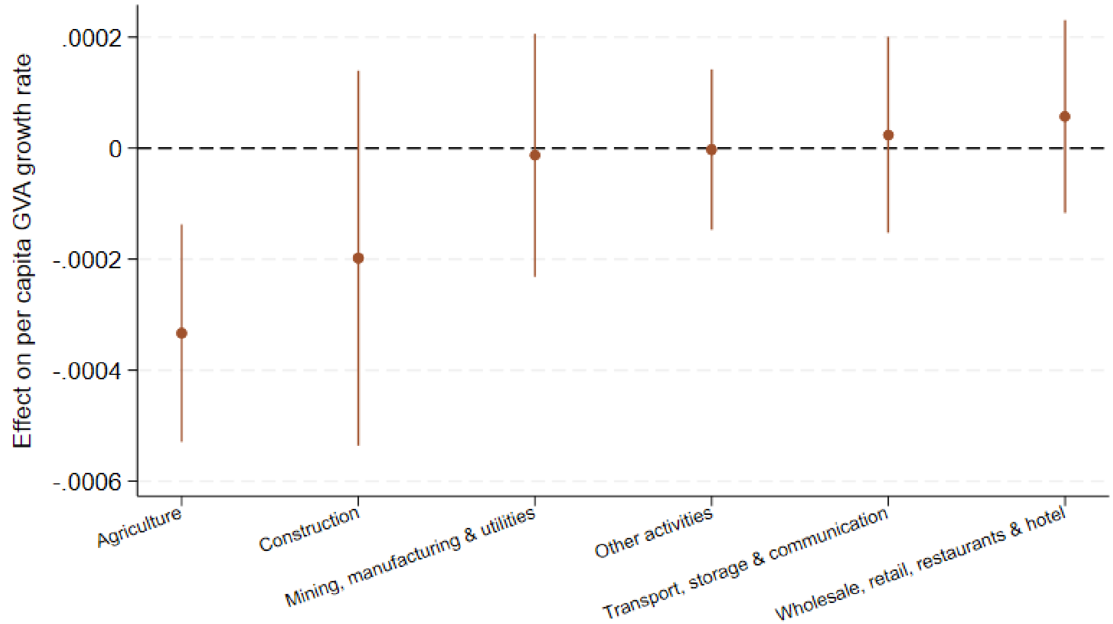
Notes: The map represents the countries in the sample divided by climatic zones, defined as terciles of the average annual temperature from 1975 through 2020. The classification is implemented in order to compute heterogeneous treatment effects as reported in Figure E1.

Figure A3. Sectoral density function of intermediate input interlinkages with agriculture



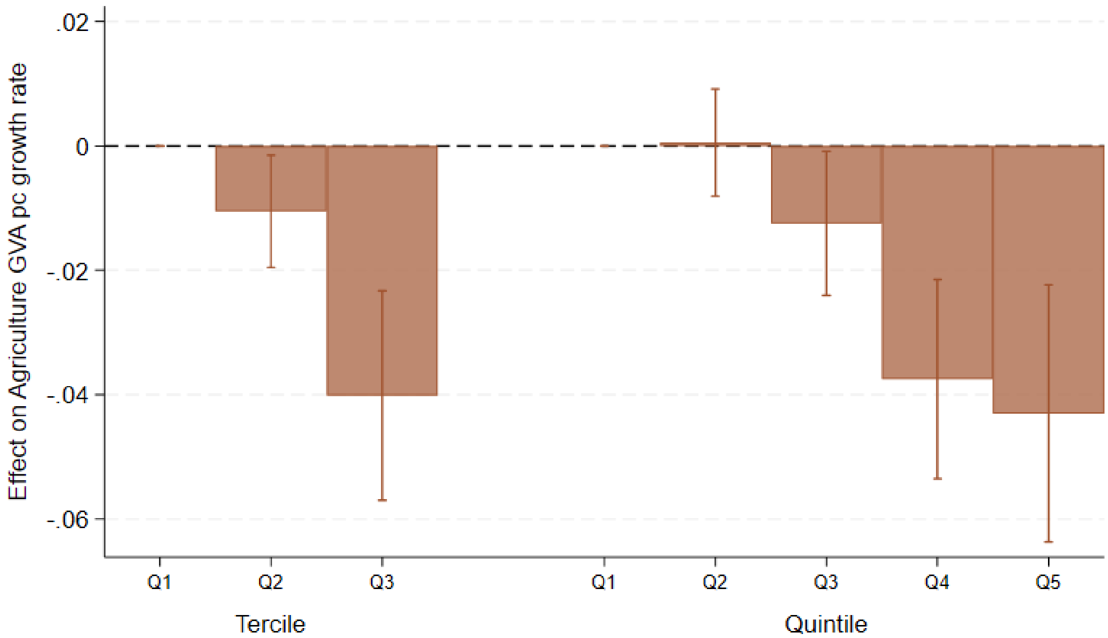
Notes: The figure plots the sector-specific density distribution of the (log) of interlinkages with agriculture used as outcome variable in the regression equation (14).

Figure A4. Effect on local abnormal hot days on sectoral per capita value added growth rate



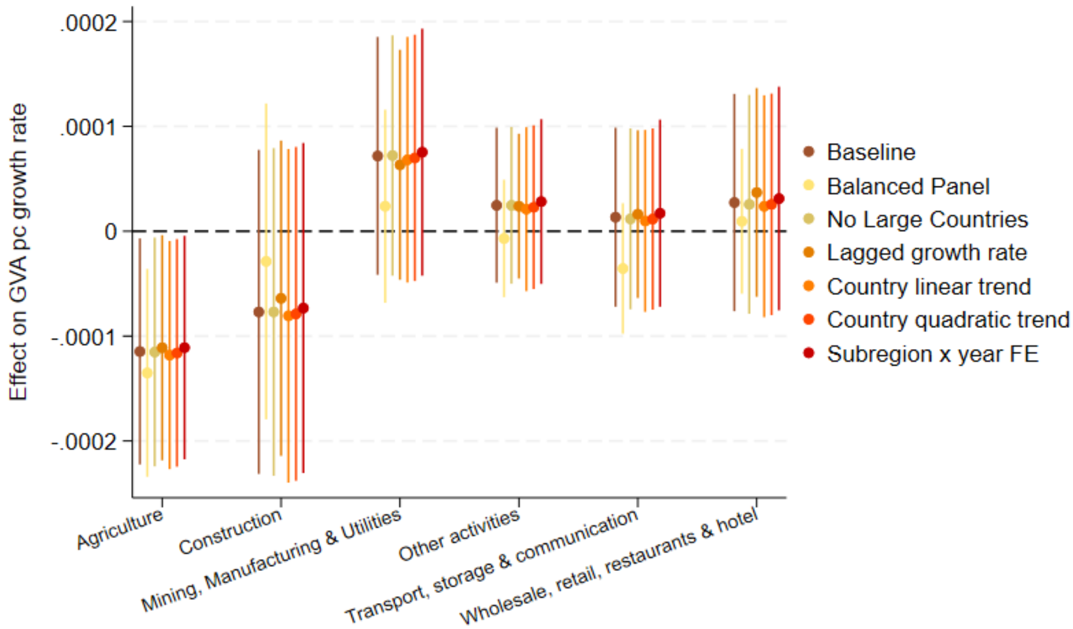
Notes: The figure shows the regression estimates for the country-average number of days above the 95^{th} percentile of the daily distribution in temperature (Panel (a)). All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year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

Figure A5. Extreme Heat on Agriculture Value Added



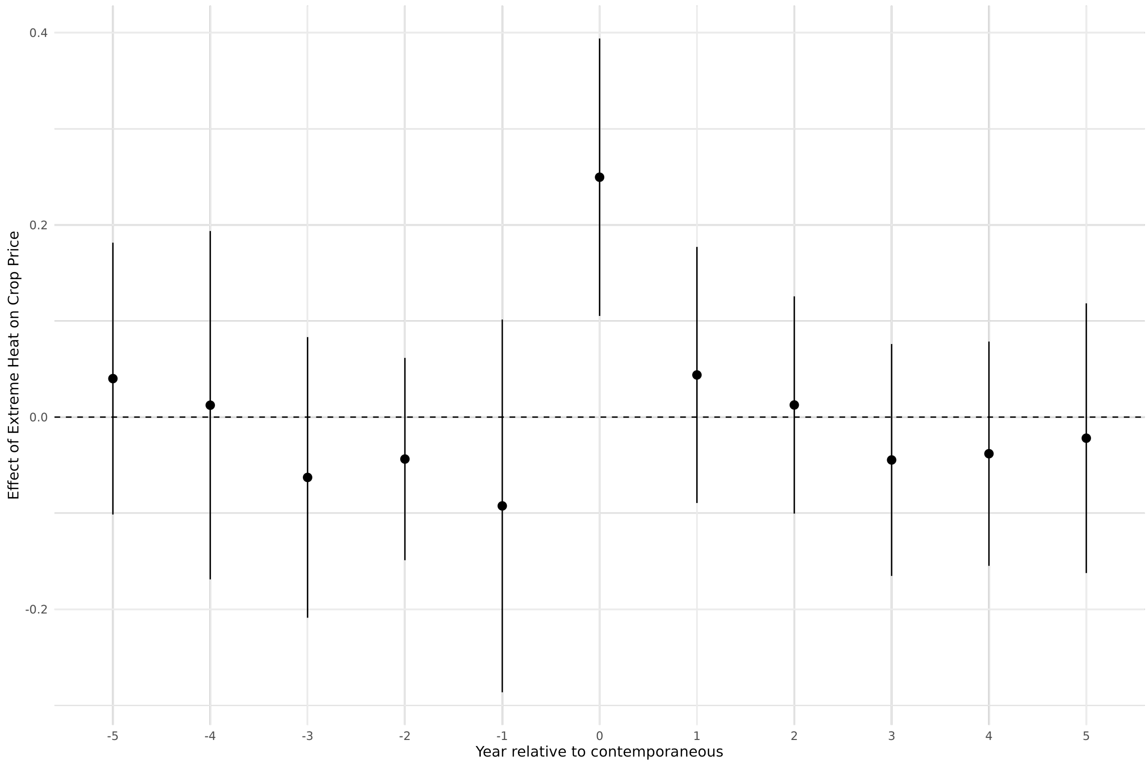
Notes: The figure shows the regression estimates for the measure of extreme heat (degree days) constructed as in Equation (5) on the agricultural GVA per capita growth rate and categorized by terciles or quintiles. Each set of bars corresponds to the estimates from a single regression which accounts for linear and quadratic terms of precipitation, and country and year fixed effects. Bins represent the 95% confidence intervals around point estimates. Standard errors are clustered at the country level.

Figure A6. Robustness: Response to local extreme heat



Notes: The figure shows the regression estimates for the country-average number of degree days of extreme heat using a sector-country balanced panel; excluding large countries (Brazil, China, India, Russia, US); including lagged growth rate; including country-specific linear trends; including linear and quadratic country-specific trends; including subregion-by-year fixed effects. 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. Subregions 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.

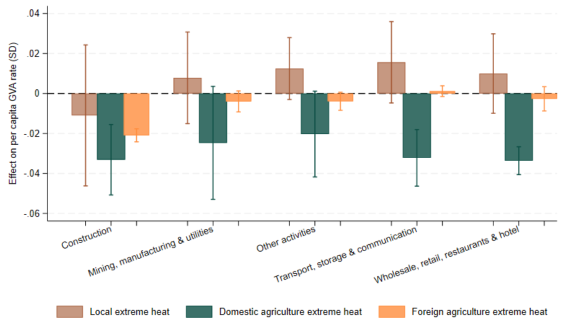
Figure A7. Dynamic Price Effect of Extreme Heat



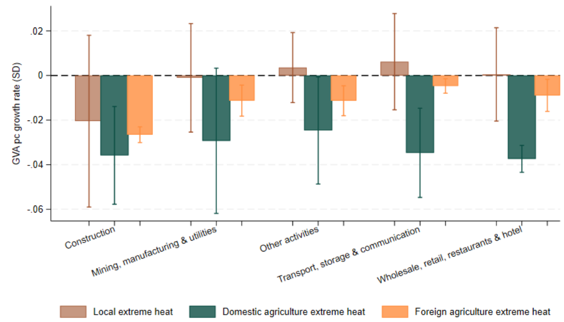
Notes: The figure reports the regression coefficients on extreme heat on an event study specification where the outcome variable is the crop price (in $/tonne) from UN FAOStat Crop Price (see Appendix Section C for additional details on the data source). The specification includes five leads and lags of extreme heat exposure controls for a second order polynomial in precipitation, country-crop, crop-year fixed effects and a linear country-specific trend. Bins represent the 95% confidence intervals with standard errors clustered at the country-level.

Figure A8. Robustness: Alternative specifications

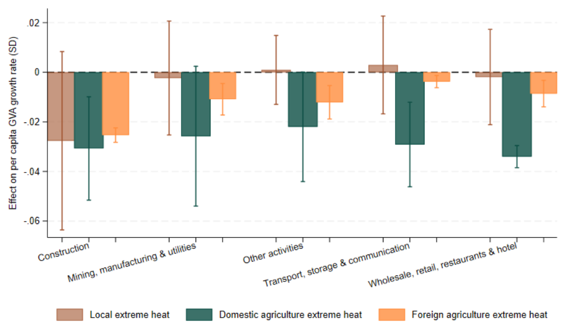
(a) Subregion-by-year FE



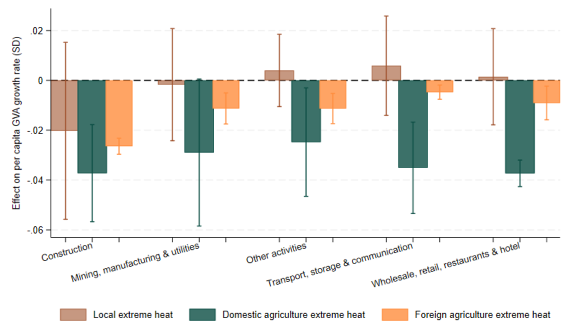
(b) Country-specific linear trend



(c) Balanced panel

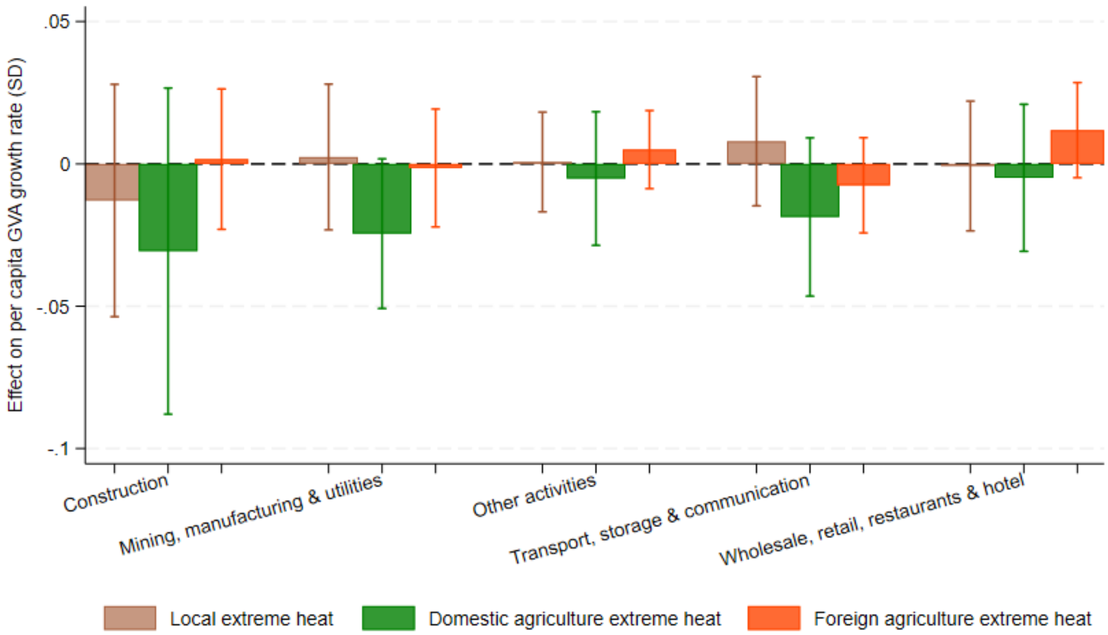


(d) Excluding "large" countries



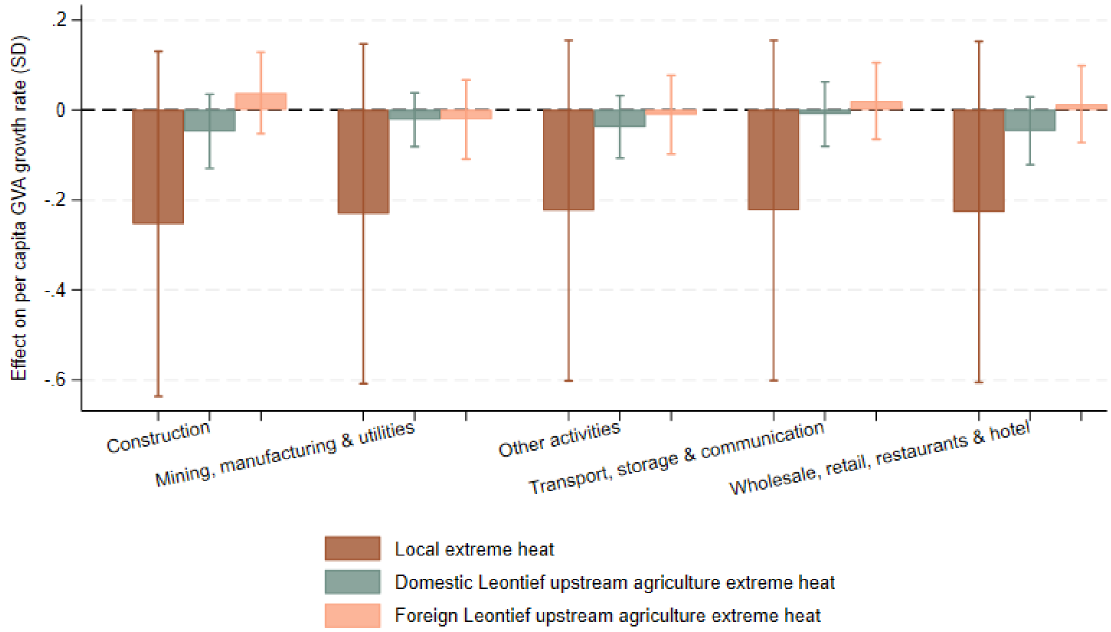
Notes: The figure shows the (standardized) sector-specific coefficients associated with local extreme heat and domestic and foreign downstream agricultural heat shocks, Panel (a) shows the estimates accounting for subregion-year FE; Panel (b) accounts for country-specific linear trends; Panel (c) uses sector-country balanced panel; Panel (d) excludes large countries (Brazil, China, India, Russia, US). Bins represent the 95% confidence intervals around point estimates. Subregions 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.

Figure A9. Local and upstream agricultural extreme heat on sectoral production



Notes: Bars represent the (standardized) sector-specific coefficients associated with local shocks and domestic and foreign downstream shocks, using the extreme heat exposure measure constructed as in Equation (5). Domestic and foreign downstream shocks are constructed respectively as in Equations (9) and (11). The specification jointly estimates all sector-specific coefficients in a stacked regression model fully saturated with country-sector and sector-year fixed effects and sector-specific responses to a second-order polynomial of total precipitation. Bins represent the 95% confidence intervals with standard errors clustered at the country level.

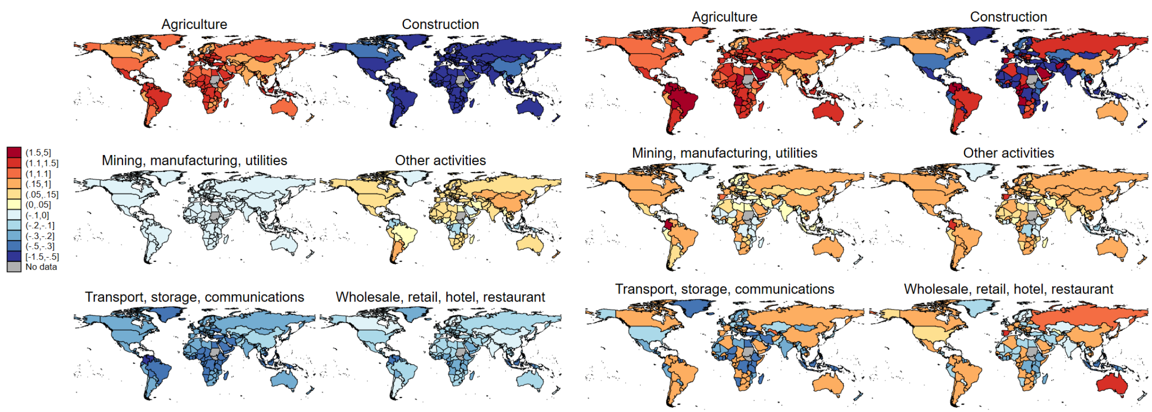
Figure A10. Local and upstream agricultural extreme heat on sectoral production in a Leontief matrix



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 95$^{\text{th}}$ 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 5$^{\text{th}}$ percentile and sector-specific responses to precipitation realizations below the 5$^{\text{th}}$ and above the 95$^{\text{th}}$ percentile. Bins represent the 95% confidence intervals with standard errors clustered at the country level.

Figure A11. 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 (15), 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 B5 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 B1. 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 B2. 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 B3. 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 B4. Effect of extreme heat on crop prices

	Crop Price (USD/Tonne)		(log) Crop Price (USD/Tonne)	
	(1)	(2)	(3)	(4)
Degree Days	0.4114**	0.2875***	0.0007***	0.0002*
	(0.2078)	(0.0825)	(0.0002)	(0.0001)
Total Precipitation	1,196.6	435.0	0.4562	-0.7051
	(992.6)	(838.0)	(1.207)	(0.5697)
Total Precipitation^2	-412,342.2	-156,285.3	-853.8	233.7
	(328,287.8)	(248,919.6)	(1,026.4)	(269.8)
Observations	96,266	96,266	96,265	96,265
Outcome mean	834.15	834.15	6.1182	6.1182
Crop-Country fixed effects	✓	✓	✓	✓
Crop-Year fixed effects	✓	✓	✓	✓
Country-specific linear trends		✓		✓

Notes: Degree Days is a crop-specific extreme heat exposure in $°C \times days/year$ for each country-crop combination around the world computed as the average exposure to extreme temperatures in degree-days (using maximum optimal growing temperature thresholds from FAO EcoCrop) on land cultivating a given crop (from Monfreda et al. (2008)). Total Precipitation is measured in metres.

Table B5. 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]

Country	Sector	Average loss	95% CI
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]

Country	Sector	Average loss	95% CI
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 (15), where indirect shocks are constructed with a time-varying production network that uses the first five-year average input-output interlinkages for each decade.

C Additional data sources

Sub-national sectoral activity. To obtain geographic variation in sectoral exposure to weather conditions within a country, I rely on the geographic distribution of sectoral activities. This information is available for 41 countries around the world, including Europe, Brazil, Canada, China, and United States. For each country, I consider the first available five years of sectoral production to construct a measure of sub-national geographic distribution of sectoral activities. I use these measure as a weight to aggregate nationally sub-national measures of weather exposure. Below, I describe each data source in detail.

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).

State-level sectoral data for Brazil are taken from the Brazilian Institute of Geography and Statistics, which displays information since 2003 for 15 economic services: agriculture, industry (extraction industries; transformation industries; and electricity and gas), construction, trade and transportation (trade; transport, storage and communications; hotels and restaurants; and information and communication), finance (financial activities; real estate; and professional activities) and government and other services (public administration and defense; education and health; and other services).

Sectoral value added data across provinces for Canada is obtained from the Statistics of Canada, which provides information since 2001 according to the NAICS standard in chained 2012 U.S. dollar.

Value added data across states for China are taken from the Macro Economy Statistics Yearbook. As for value added, the dataset comprises nine sectors, including agriculture, wholesale and retail, hotels and catering and transport, storage and post.

For the United States, data at the state level come from the Bureau of Economic Analysis. Information is reported since 1997 according to the NAICS standard.

Crop prices. Data on domestic crop prices come from the UN FAOSTAT domain on Agricultural Producer Prices and Producer Price Index (expressed in USD/Tonne), which reports official national level data received from FAO Members on annual prices their farmers obtain from 1991 to 2020 for 160 countries and for about 262 products. I match crop names to $DegreeDays$ measures at the crop level computed using the UN FAO EcoCrop database and the agricultural land where each crop is grown in each country as explained in Section 3.

D Reduced-form approach to the climate-output relationship

Kahn et al. (2021) review the three main approaches that study the climate-output 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. In an attempt to deal with the non-stationarity issue of trended temperatures, a recently often implemented alternative is to use changes in temperature levels (Akyapi et al., 2024; 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.

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. To allow for the non-linear effect of temperature changes while dealing with the non-stationarity issue of trended temperatures, 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

$$\Delta y_{nt} = \alpha_n + \delta_t + \lambda \Delta T_{nt} + \psi \Delta [T_{nt}^2] + \varepsilon_{nt} \tag{D.16}$$

which uses the growth rate of log-differences of real GDP per capita of country n 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), α_n is the country-specific fixed effect and δ_t is the time-specific fixed effect. Motivated by empirical evidence on the temperatures being trended, I assume that

$$T_{nt} = a_{T_n} + b_{T_n} t + \nu_{T_{nt}} \tag{D.17}$$

where, in line with historical evidence, $b_{T_n} > 0$, and $\mathbb{E}(\nu_{T_{n;t}}) = 0$ and $\mathbb{E}(\nu^2_{T_{n;t}}) = \sigma^2_{T_n}$. Substituting Equation (D.17) in Equation (D.16) and taking expectations yields

$$\mathbb{E}(\Delta y_{nt}) = \mathbb{E}(\delta_t) + \alpha_n + b_{T_n}[\lambda + 2\psi a_{T_n}] + 2\psi b^2_{T_n} t \tag{D.18}$$

To ensure that $\mathbb{E}(\Delta y_{nt})$ 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 $2\psi b^2_{T_n} t = 0$ for all n. 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 (D.16), such that it becomes

$$\Delta y_{nrt} = \alpha_{nr} + \delta_{rt} + \lambda \Delta T_{nrt} + \psi \Delta [T^2_{nrt}] + \varepsilon_{nrt} \tag{D.19}$$

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

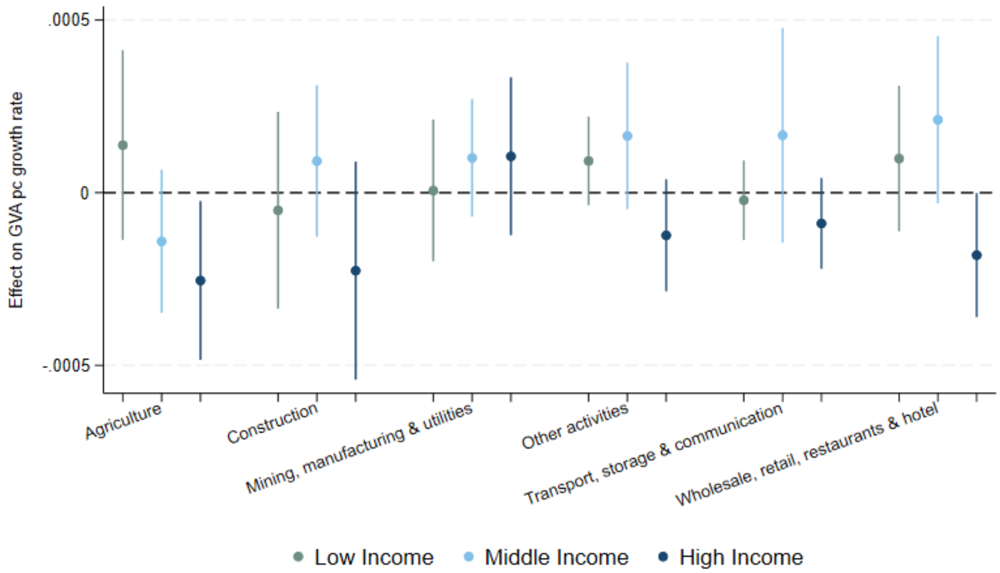
E Heterogeneous effects of local extreme heat across adaptation potential

The impact of extreme heat 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 hotter climate may differentially incentivize adaptive investments as returns to adaptation would be relatively higher for more frequent temperature changes. I estimate heterogeneous temperature-value added relationships by interacting the vector of temperature and precipitation coefficients with income and climate terciles from long-run average income and temperature (Appendix Figure A2 shows the sample composition) (Carleton et al., 2022).

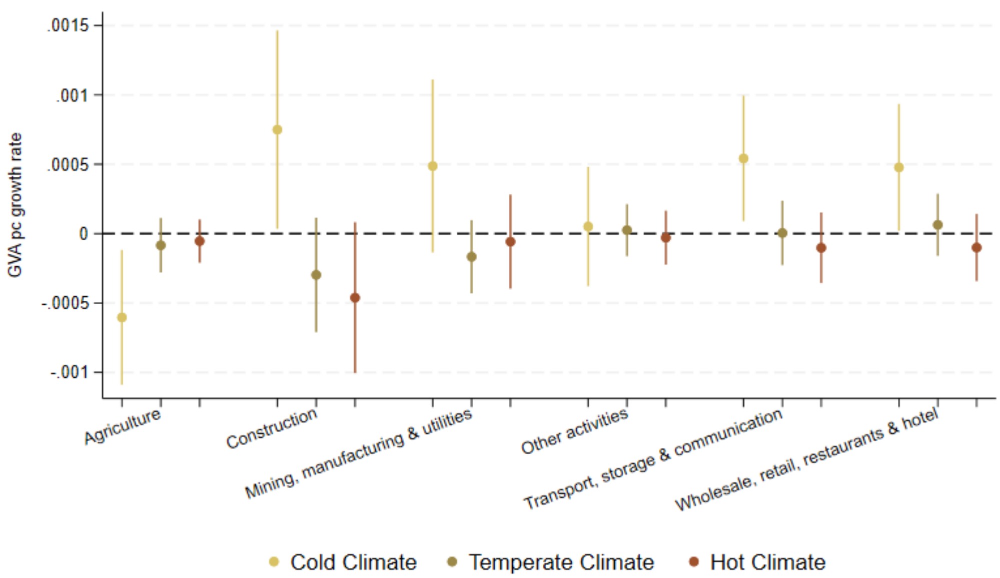
Appendix Figure E1 graphically presents the coefficient associated with heat shocks interacted with income and climate terciles. Although there is no substantial heterogeneity in the response of other sectors to extreme heat conditions, with the estimated coefficients that are never statistically distinguishable from zero, the response of the agricultural sector is heterogeneous across the income gradient. Agricultural value added becomes is more sensitive to extreme heat as income rises. This result, perhaps surprising at first, could be explained by differences in improved technologies, infrastructure, or insurance that influence producer strategies. Similarly, I document that countries adapt to higher temperatures across crops such that agricultural value added is sheltered from the impact of extreme heat in temperature and hot climate countries and negatively affected in cold countries.

Figure E1. Income and climate heterogeneity in GVA response to extreme heat

(a) Income terciles



(b) Climate terciles



Notes: The figure shows the coefficients associated with the response of sectoral GVA per capita growth rate to extreme heat by income using long-run average per capita GDP and average temperature. All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects and controlling for a second order polynomial in precipitation. Bins represent the 95% confidence intervals with standard errors clustered at the country-level.

F 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 local abnormal days and domestic and foreign agriculture extreme heat 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 $T_{dmnt} = \alpha_n + \lambda_{dm} + \beta_n t + \varepsilon_{dnct}$ on the 1970-2000 sample, where T_{dmct} is the average temperature in day d in month m in year t in country n. I obtain country-specific historical trends in daily temperature exploiting within day-month variation between 1970 and 2000 and use $\hat{\beta}_n$ to construct a counterfactual daily temperature $\tilde{T}_{dmnt}$ between 2001 and 2020 that is then used to compute the counterfactual extreme heat measure. 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 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.

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 extreme heat in agriculture both domestic and abroad:

$$g_{jnt}^{local} = \widehat{\beta}_j (ExtremeHeat_{nt} - \widetilde{ExtremeHeat}_{nt}) \tag{F.20}$$

$$
\begin{aligned}
g_{jnt}^{global} &= (\widehat{\beta}_j ExtremeHeat_{nt} + \sum_{\ell \in \{D;F\}} \widehat{\gamma}_{j,\ell} NetworkShock_{jnt}^{Dn,\ell}) \\
&- (\widehat{\beta}_j \widetilde{ExtremeHeat}_{nt} + \sum_{\ell \in \{D;F\}} \widehat{\gamma}_{j,\ell} \widetilde{NetworkShock}_{jnt}^{Dn,\ell})
\end{aligned}
\tag{F.21}
$$

where $ExtremeHeat_{nt}$ is the observed extreme heat measure constructed in Equation (5), $\widetilde{ExtremeHeat}_{nt}$ is the counterfactual predicted extreme heat measure had the 1970-2000 temperature mean evolved linearly, and similarly for $NetworkShock$, which is constructed as detailed in Equations (8) and (10), and the counterfactual predicted $\widetilde{NetworkShock}$ is constructed using the extreme heat measures using counterfactual temperatures that evolved linearly from the 1970-2000 trend. $\widehat{\beta_j}$'s are the sector-specific estimates for the effect of local extreme heat, and $\widehat{\gamma_{j,\ell}}$ are the sector-specific domestic and foreign semi-elasticities to downstream agricultural extreme heat exposure on the sectoral growth rate obtained from bootstrapping 1000 times the underlying panel estimates from Equation (15). I compute sector j's counterfactual value added levels in year t omitting and accounting for indirect shocks

$$
\hat{Y}_{jnt}^{p} = Y_{ict-1} + y_{jnt} + g_{jnt}^{p} \tag{F.22}
$$

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

$$
\%\overline{\text{LOSS}}_{jn}^{p} = \frac{1}{T} \sum_{t=2001}^{2020} \frac{e^{\hat{Y}_{jnt}^{p}} - e^{Y_{jnt}}}{e^{Y_{jnt}}} \tag{F.23}
$$

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 A11).

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

$$
\%\overline{\text{LOSS}}_{n}^{p} = \sum_{j}^{J} \%\lambda_{jn} \overline{\text{LOSS}}_{jn}^{p} \tag{F.24}
$$

where λ_{jn} is the baseline five-year average share of total GVA of sector j in country n between 1996 and 2000. The country-level losses omitting and accounting for indirect heat shocks are reported in Figure 7.