Propagation of extreme heat in agriculture across sectors and space

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Abstract

Agriculture is widely recognized as one of the sectors most vulnerable to extreme temperatures. Yet, crop losses are estimated to form only a modest share of aggregate macroeconomic damages from climate change, since agriculture accounts for a small share of global GDP. These estimates, however, arise from analyses that largely ignore the critical role of agriculture as an upstream sector in global production networks, including the sectoral and spatial linkages connecting local agricultural output to other sectors and regions. In this paper, I develop a novel reduced form method to incorporate input linkages between sectors and countries that I use to estimate the aggregate impacts of extreme heat in agriculture. A multi-region multi-sector production network model illustrates how extreme heat in agriculture can propagate to downstream sectors across countries by reducing supply availability and increasing intermediate input prices. Exploiting the granular spatial distribution and temperature sensitivity of 118 crops across the world, I construct a measure of local exposure to extreme heat in agriculture and show that it induces substantial losses to downstream sectors, across national borders, and beyond first degree linkages. Counterfactual exercises from a multi-region general equilibrium model reveal that input linkages account for approximately 43% of the total value added losses induced by recent warming in agriculture, with foreign linkages accounting for the majority of downstream losses. The analysis demonstrates that adaptation in agriculture to heat in regions that are central to global production networks can have substantial co-benefits downstream and in other locations.

JEL Classification: E23, E32, H23, L14, O11, Q51, Q54, R15

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1 Introduction

Agriculture has long been considered the sector most vulnerable to global warming. Given its exposure and sensitivity to weather fluctuations, the first studies estimating economic losses from climate change focused on this sector (Mendelsohn et al., 1994; Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009). Agriculture, however, only accounts for 10% of global GDP, implying that the global macroeconomic impacts of agricultural losses from climate change are often considered modest.[1] Nevertheless, agriculture is a critical upstream sector in the global economy, producing commodities that are directly or indirectly used in downstream sectors, ranging from cotton for the textile industry to rubber for the automotive industry (Antràs et al., 2012). In an increasingly interconnected world, local productivity shocks in agriculture can propagate through the economy and across space via trade in intermediate inputs (Farrokhi and Pellegrina, 2023). To date, however, the implications of such propagation on the aggregate economic impacts from climate change have yet to be assessed.

Two main approaches dominate in the quantification of global climate damages. One approach empirically estimates the effect of local quasi-random variations in temperature on GDP. By using an aggregate measure of economic output, this approach implicitly embeds domestic linkages across sectors, although typically failing to account for linkages across locations (e.g., Burke et al., 2015; Kalkuhl and Wenz, 2020). A second approach uses spatial quantitative models to trace sectorally-disaggregated linkages through the economy, but relies on a set of assumptions on the structure of the economy and its sensitivity to climate that are difficult to calibrate using real-world empirical data (Cruz and Rossi-Hansberg, 2024). Understanding the economic consequences of global climate change requires accounting for sectoral and spatial linkages, yet previous studies have either structurally modelled these linkages or empirically estimated the treatment effect of local temperatures.

This paper bridges these two approaches to quantify the global economic losses induced by extreme heat in agriculture accounting for linkages across sectors and space. I develop a reduced form representation of a class of spatial models that incorporates general equilibrium links in the form of intermediate input linkages between sectors and countries through model-consistent exposure shares, and use it to estimate the aggregate impacts of extreme heat in agriculture. To do so, I combine global country-level sectoral value added data with high-resolution daily temperatures, granular spatial variation in land use, agro-physical information

[1] For example, Costinot et al. (2016) find that climate impacts on agriculture amount to a 0.26% reduction in global GDP.

on growing temperatures for more than 100 agricultural commodities, and input-output sectoral linkages between 1975 and 2020.

My analysis starts by showing four empirical facts that inform my approach. First, in a global cross-country sample of value added for six sectors, extreme heat negatively affects only agriculture.[2] This pattern echoes previous findings that agriculture is the most vulnerable sector, and motivates my focus on this sector to study shock transmission through the economy. Second, the negative productivity effect of extreme heat on agriculture induces a short-lasting increase in agricultural commodity prices, which feeds into the transmission mechanism in my theoretical model. Third, extreme heat in agriculture is increasingly spatially correlated over time, underlining the importance of accounting for linkages across space in empirical analyses of temperature impacts. Fourth, downstream sectors do not alter their agricultural input expenditure shares in response to extreme heat shocks, suggesting limited adaptation in the form of spatial and sectoral adjustments in the global production network.

Armed with these empirical facts, I set out a general open-economy production network framework in which each country-sector produces with primary factors and intermediate inputs sourced across sectors and countries (Acemoglu et al., 2012), and in which local productivity shocks in the form of extreme heat transmit through input linkages. The framework serves three purposes. First, it highlights how traditional quasi-experimental research designs that estimate the effect of local weather on aggregate output ignore spatial linkages, deriving estimates by holding weather in other locations fixed. That is, the estimated (and projected) damages in a location due to *global* warming are computed under *local* warming, without accounting for simultaneous temperature increases elsewhere. Second, the model illustrates how agriculture-specific shocks in a location can propagate through input linkages not only to first degree downstream sectors, but also to the rest of the economy through higher degree linkages, which account for all sectoral and spatial interdependencies. Extreme heat, by reducing agricultural commodity supplies and increasing their prices, leads downstream sectors to reduce their demand for intermediate inputs, thereby reducing their output. Third, the framework makes explicit what a regression of sectoral value added on network-weighted heat exposure can and cannot recover, namely relative responses across sectors within a country-year rather than the level of aggregate losses, which is what motivates the quantitative model I turn to below.

Based on the empirical facts and on the theoretical model, I develop a reduced form spec-

[2]In the other five sectors the average effect is small and statistically indistinguishable from zero, but with substantial heterogeneity across climate and income, consistent with prior work (Nath et al., 2024). The other five sectors include: Mining, manufacturing and utilities; Construction; Wholesale, retail trade, restaurants, and hotels; Transport, storage, and communication; Other activities (including government and financial sector).

ification that integrates spatial and sectoral input linkages. A key empirical challenge lies in disentangling the direct effects of local heat on a sector from the indirect effect of heat propagating from agriculture. To address this challenge, I construct country-specific agricultural shock exposure metrics that combine the differential geographic distribution of crop areas for 118 distinct plants with their differential sensitivity to above optimal temperatures. The final metric is measured in degree days, which quantify the cumulative annual exposure of crops to temperatures above their optimal growing conditions. My econometric specification then relies on plausibly exogenous variation in extreme heat over time across sectors within country-years to identify both direct and indirect effects of extreme heat on sectoral value added. My approach builds on the popular "shift-share" design (Borusyak et al., 2022), using agriculture-by-location specific "shifters", driven by differential crop-specific heat sensitivities and crop acreage, that affect downstream sectors' value added via model-derived exposure "shares" through domestic and international input linkages, which are allowed to adjust endogenously.

My main analysis leads to three key findings. First, domestic and foreign extreme heat conditions in agriculture have a strong negative effect on the growth rate of downstream sectors' value added via first degree input linkages. On average across five downstream sectors, one additional degree day of heat exposure in domestic (respectively, foreign) agriculture reduces the growth rate of value added by approximately 0.18% (0.15%). Downstream sectors are heterogeneously affected, with damages concentrated in sectors like manufacturing, wholesale, retail, hotels, and restaurants, which directly rely on agricultural commodities, including unprocessed food crops, feed, fiber, and oil crops. Second, results are larger in magnitude when accounting for higher order linkages. The effect spreads further through the economy, affecting negatively other sectors, including construction, transport, storage, and communication. Accounting for higher order linkages, the average effect across downstream sectors for a one-degree day increase in heat in domestic (foreign) agriculture is 0.31% (0.26%). Third, as predicted by the theoretical model, I document that the direction of the propagation travels downstream from supplier to buyer sectors. Extreme heat is a (negative) productivity shock on agriculture, which can be interpreted as a supply-side shock propagating only downstream, not affecting sectors upstream. I empirically validate this hypothesis by showing that extreme heat in agriculture has a negligible and insignificant effect on upstream sectors. In additional robustness checks, I also show that the results cannot be rationalized by a distance-weighted exposure measure to heat, suggesting that spatial correlations do not confound the propagation effect through input linkages.

Finally, I build a quantitative general equilibrium model of the global production network,

which I calibrate to observed input-output linkages, discipline with the reduced form estimate of the direct effect of extreme heat on agriculture, and solve exactly, and I use it for two retrospective counterfactual exercises that quantify the importance of accounting for spatial and sectoral linkages in the measurement of climate damages. First, I quantify the contribution of input linkages to annual value added losses induced by recent warming from 2000 onwards.[3] I compare value added losses in agriculture induced by local heat and aggregate value added losses in downstream sectors transmitted through input linkages to a baseline where extreme heat in agriculture stayed at its 1975-2000 average. Expressed as a share of total value added, recent warming induces losses of 1.6% through the direct effect of local extreme heat on agriculture and a further 1.2% through losses transmitted to downstream sectors by input linkages, for a total loss of 2.8%. Input linkages therefore account for 43% of the total value added losses induced by recent warming in agriculture, and foreign linkages account for the majority (59%) of the downstream component. While value added losses induced by local extreme heat in agriculture are spatially heterogeneous and concentrated in the Sahel, North Africa, the Middle East, and South Asia, downstream losses are more homogeneously distributed across space and are sizable in countries with little local heat exposure.

Second, I compute the aggregate global impact of extreme heat in agriculture in each single country. Annual global losses are larger when extreme heat hits countries with stronger supply chain interlinkages in the production network, such as China, India, the United States, France, and Brazil. For example, a one standard deviation increase in heat conditions in China leads to global value added losses of approximately 21 billion US$ per year. Altogether, these countries are the major global agricultural producers (Costinot et al., 2016). The results indicate a strong positive relationship between how integrated and interconnected a country is in the production network and the global losses induced by heat shocks in that country. Summing all 183 counterfactuals across countries, annual global losses amount to approximately 189 billion US$.

This paper contributes to the literature on the macroeconomic impacts of climate change by bridging two complementary approaches that trade off identification with comprehensive measurement. A first approach relies on quasi-experimental variation in temperature in a given location in a panel data structure to estimate the effects of climate change on the growth rate of national or sub-national GDP (Akyapı et al., 2025; Burke et al., 2015; Burke and Tanutama,

[3]These counterfactuals use reduced form short-run elasticities to weather. For this reason, my counterfactual exercises focus on a retrospective quantification of the economic cost of recent warming, instead of a projection of future climate damages, where other long run adaptive margins (e.g., spatial adjustments in crop specialization patterns) might affect differences between short-run elasticities to weather and long-run elasticities to climate.

2019; Dell et al., 2012; Kahn et al., 2021; Kalkuhl and Wenz, 2020; Kotz et al., 2021; Nath et al., 2024; Newell et al., 2021). These reduced form panel fixed effects methods implicitly account for domestic sectoral linkages by studying the response of an aggregate measure of economic output. Sometimes they also account for spatial linkages either through the use of spatial lags (e.g., Kotz et al., 2024), or non-parametrically by exploiting variation in weather that is spatially uncorrelated through the use of time-varying fixed effects at broader spatial levels. Nevertheless, reduced form estimates from panel fixed effect models do not capture general equilibrium effects when outcomes respond to prices. For this reason, an alternative approach, suggested by Deschênes and Meng (2018) and adopted by Berg et al. (2024) and Bilal and Känzig (2026), exploits time-series variation in global spatially-averaged temperatures and global economic outcomes. This approach is appealing because, by construction, it embeds all global spatial and sectoral linkages. However, it cannot disentangle the local effect from the spatial correlation structure of temperatures or from trade and input linkages across sectors and regions. From a policy perspective, separating these three components is essential for adaptation policy design and loss and damage frameworks. From a research design perspective, this approach may fail to identify causal effects if other drivers of the global economy are changing over time in ways that are correlated with temperature changes.

A second method takes a spatial quantitative approach to quantify climate damages accounting for general equilibrium forces, including trade and spatial and sectoral reallocation of economic activities, through calibrated structural models.[4] In models that account for trade and crop specialization pattern adjustments, agriculture has only been considered a consumption good and not an intermediate input in other sectors' production (Costinot et al., 2016; Gouel and Laborde, 2021). The importance of agriculture has also been documented through consumption preferences characterized by non-homotheticity and low substitutability, although in a model without intermediate inputs (Nath, 2025). Rudik et al. (2024) show with a quantitative model that input linkages transmit climate shocks through the economy, but focus on within-state sectoral linkages in the US. In contrast, my paper develops and applies a reduced form approach to estimate global climate impacts accounting for sectoral and spatial input linkages, bridging the gap between the quasi-experimental approaches and structural spatial models of the economic activity under climate change. My approach allows for a flexible structure of

[4]Earlier contributions to this approach develop a computable general equilibrium (CGE) model, which simulates interactions between firms in multiple sectors using the Global Trade Analysis Project (GTAP) global economic model (Hertel, 1997). These models account for the indirect effects of climate damages beyond the sector and region where they occur, but quantify damages through calibrated simulations (Moore et al., 2017; Baldos et al., 2019).

spatial links and idiosyncratic shocks, and it does not require observing all trade costs before and after the shock (Donaldson and Hornbeck, 2016) nor calibrating parameters to match arbitrarily chosen distribution moments generated in the model with simulated shocks (Cruz, 2024). I then bring the two approaches together rather than choosing between them. The quantitative model of Section 7 is a multi-region production network in which agriculture enters as an intermediate input and not only as a consumption good, and its only estimated parameter is the sensitivity of agricultural productivity to heat, which I take from the reduced form. Relative to Rudik et al. (2024), the network is global rather than within-country; relative to Costinot et al. (2016) and Gouel and Laborde (2021), agricultural output feeds the rest of the economy; and relative to the calibrated spatial models discussed above, both the shock and the exposure weights are measured rather than assumed.

Besides spatial correlation in climate-induced productivity losses and absolute advantage as a channel for the global nature of climate change (Dingel et al., 2023), my paper shows that heat shocks can also propagate across sectors and geographically distant countries through production networks. Firm level studies quantify the role of input linkages as a mechanism for the propagation and amplification of natural disasters within the manufacturing sector in the US (Barrot and Sauvagnat, 2016) or after the 2011 Japan earthquake (Boehm et al., 2019; Carvalho et al., 2021). My paper shows that more frequent but less salient climate shocks driven by variation in extreme temperatures can transmit across sectors and countries. Recent studies have also explored firm adaptation in manufacturing production networks through shifts in the composition of their suppliers and diversification of sourcing locations in India (Castro-Vincenzi et al., 2024) and Pakistan (Balboni et al., 2024). My paper contributes to this growing literature adopting a macro perspective and documenting that cross-sectoral input linkages with agriculture are unresponsive to extreme heat conditions in this sector, leading these shocks to propagate downstream.

Altogether, my findings provide evidence of the importance of accounting for sectoral and spatial linkages when computing the impacts of extreme heat in agriculture. Without accounting for linkages across sectors and countries, the effects of extreme heat on agricultural production are concentrated locally in those countries whose share of agriculture in total value added is large. Trade can be an effective adaptation strategy to climate change that helps countries reduce their exposure to local shocks (Nath, 2025). At the same time, however, stronger input linkages make countries more interdependent and exposed to heat shocks that can propagate through these linkages, spreading local effects across sectors and countries. This result suggests

that local adaptation efforts might also have beneficial consequences in other locations.

2 Data

This section provides a summary of the main data sources used throughout the analysis. The final merged data set combines sector-level value added (Section 2.1) with weather (Section 2.2) and global country-sector interlinkages (Section 2.3). Complementary secondary data are described in Appendix Section D.

2.1 Sectoral value added data

The Economic Statistics Branch of the United Nations Statistical Division (UNSD, 2024) provides annual Gross Value Added (GVA) in constant 2015 US$ for 183 countries in the world from 1975 through 2020.[5] The data set categorizes sectors into six broad groups (with the International Standard Industrial Classification - ISIC - rev. 3.1 code in parentheses) and it 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]

These data present two main advantages. First, in contrast to previous work estimating macroeconomic damages to climate change globally (e.g., Dell et al., 2012; Burke et al., 2015; Nath et al., 2024), these data provide a more disaggregated sectoral breakdown categorizing the country's production in six sectors, as compared to the traditional tripartition into agriculture, manufacturing, and services. Calibrated structural models also articulate the economy often into agriculture and non-agriculture sectors (e.g., Costinot et al., 2016; Conte et al., 2021). In few exceptions, studies explicitly model the service sector (Nath, 2025; Rudik et al., 2024), or the construction and mining sectors (Casey et al., 2024).[8] Sectoral disaggregation is of

[5]The final sample of countries and their frequency are reported in Appendix Table C2.

[6]The original data include information for value added 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 C1 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.

[8]For a complete review of the sectoral heterogeneity in macro quantitative models quantifying climate damages, see Carleton et al. (2024).

paramount importance for two reasons. First, it informs which sectors are more vulnerable to temperature fluctuations, with first order relevance for policy implications. Second, since intermediate input use from agriculture can substantially differ along the supply-chain, sectoral disaggregation is crucial when tracing input linkages across sectors and countries, . For instance, industries in the manufacturing sector include "manufacture of food products and beverages", or "manufacture of wood and of products of wood and cork", which directly rely on intermediate inputs from agriculture. Conversely, the "retail sale of food, beverages and tobacco in specialized stores" industry in the wholesale, retail trade, restaurants, and hotels sector uses inputs from the agriculture sector to a smaller extent through first degree sectoral linkages, but more so at when accounting for higher order linkages through the food processing industry.

Second, sectoral production is measured in value added, which is equal to a sector's gross output (which consists of sales or receipts and other operating income, commodity taxes, and inventory change) minus its intermediate inputs (including both domestic and foreign sources). Using value added instead of gross output allows me to trace the role of shocks that affect local production from shocks that propagate through intermediate inputs. Although output could be affected by local weather through a variety of channels, including labor supply and productivity (Graff Zivin and Neidell, 2014), capital depreciation (Bakkensen and Barrage, 2018), and total factor productivity (Letta and Tol, 2019), the data do not allow me to disentangle which of these channels dominates the local response of value added to local weather. This is usually possible in firm level studies that disentangle the effect of temperature shocks through total factor productivity and local factor inputs, including capital and labor, although without allowing for the possibility of shocks to hit intermediate input availability, mostly due to data limitations (Zhang et al., 2018; Somanathan et al., 2021). Here, I investigate the propagation of temperature shocks over input-output linkages by observing both the production network and the shocks that I describe in the following sections, without having to rely on identifying assumptions for backing out the shocks from data.

2.2 Weather data

I construct daily average temperatures and total precipitation measures from the global reanalysis ERA-5 dataset compiled by the European Centre for Medium-Range Weather Forecasts (Muñoz Sabater, 2019). ERA-5 is available on a $0.25° \times 0.25°$ resolution grid ($\approx$ 28km at the Equator) at the hourly frequency from 1940 to the present. Reanalysis data combine climate model output with observational data from across the world into a globally complete dataset us-

ing the laws of physics and relying on information from weather stations and satellites, removing biases in measurement and creating a coherent, long-term record of past weather.[9]

A key empirical challenge in the parametric estimation of spillover effects of heat in agriculture transmitting through sectoral and spatial linkages lies in separating these from the direct effect of local heat on sectoral value added. In what follows, I detail how I construct country-specific shocks in agriculture, relying on temporal variation in daily temperatures combined with cross-sectional spatial variation in land use, as well as agro-physical information on the optimal growing temperatures for individual crops, and sector-country specific heat shocks that exploit the spatial distribution of population and of sectoral economic activity. This allows me to isolate a temperature shock that hits agricultural production, as based on crop sensitivity and exposure, but does not directly impact other sectors.

Heat shocks in agriculture. Crucial to the analysis is the construction of shocks specific to agriculture. Building on extensive prior literature, I focus on extreme heat exposure, which is quantitatively the most important weather determinant of agricultural yields (Schlenker and Roberts, 2009; Hultgren et al., 2025).

To construct a measure of extreme heat that contains orthogonal variation across sectors, I exploit the fact that locations grow different crops and each crop is differentially sensitive to extreme heat. Spatial variation in the global geography of crop areas comes 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 agricultural land coverage for 175 crops at a 5 arcmin (≈10 km) spatial resolution. The data are time-invariant and obtained as an average from multiple years between 1990 and 2003 to get a single representative value for circa the year 2000. By only relying on cross-sectional variation in the geography of crop acreage, this approach does not account for crop migration as an adaptive margin to changes in heat exposure. Three reasons justify this simplification. First, crop migration only occurs locally, with spatial patterns of production shifting to neighboring locations (Sloat et al., 2020). By aggregating the original spatial resolution of crop areas to match the spatial resolution of climate data (nine times coarser), I measure exposure of crop-specific agricultural land within each weather grid cell which thus accounts for crop migration within location. Second, around half of the crops in my sample, 84, are perennial, which suggests that spatial adjustments in

[9]The process undertaken by reanalyses data is called "data assimilation", which merges observational data with the physics-based global climate model. Despite partly relying on climate models, the use of reanalysis climate data for empirical analysis has been widely validated, particularly so in those regions where observations are sparse or of poor quality (Hogan and Schlenker, 2024).

crop specialization might be more limited than documented in previous work, which studies this margin of adaptation for annual crops (Costinot et al., 2016; Aragón et al., 2021; Gouel and Laborde, 2021). Third, in Appendix Section E, I empirically document that, for a subset of crops whose spatial distribution is available over time, accounting for spatial reallocation patterns does not substantially alter crop-specific extreme heat exposure.

To capture crop-specific exposure to harmful hot temperatures, I use crop-specific information on the optimal temperature for growing conditions from the UN FAO EcoCrop database. I construct a measure that combines the intensity and the length of exposure to extreme heat for each specific plant. The EcoCrop data are compiled from experts and provide information on plant characteristics and crop environmental requirements for each individual plant species, including tolerance ranges for temperature and precipitation, soil pH, light intensity, and other soil characteristics. The data set includes plant information for more than 150 agricultural commodities that can be broadly categorized into food crops (including fruits, cereals, grains, vegetables, nuts, spices), feed crops, fiber crops (e.g., agave, cotton, flax, hemp, and jute), oils and fats, ornamental crops, and industrial and secondary crops (including rubber and tobacco).

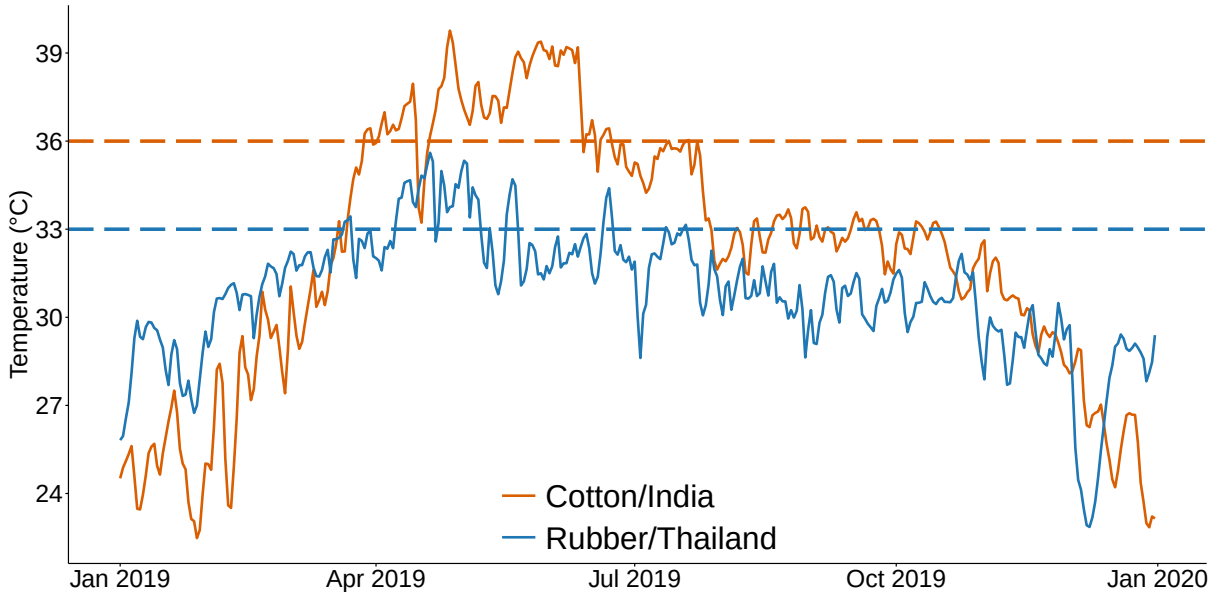
I use the crop-specific upper temperature threshold for optimal growing conditions to compute the cumulative number of degree days in a year during which temperatures exceed a threshold that is damaging to the plant growth. Appendix Figure A1 plots the distribution of optimal maximum growing temperatures for the 118 plants in my final sample.[10] For example, temperatures above 31°C are harmful for maize. Figure 1 illustrates graphically the importance of this approach with an example. A spatially uniform threshold to compute extreme heat across locations and crops, e.g., 30°C, would substantially overestimate India and Thailand exposure to above-optimal growing temperature conditions for two agricultural commodities they are leading world producers, cotton (36°C), and rubber (33°C).

Using the geographic and temperature sensitivity information for 118 crops, I expand on previous US-specific (Moscona and Sastry, 2023) and crop-specific (Hsiao et al., 2026) temperature exposure measures to construct a country-specific measure of extreme heat exposure in agriculture aggregating across crops c and grid cells g in country n, such that:

$$ExtremeHeat_{nt} = \sum_{c} \sum_{g \in n} \frac{Area_{gc}}{\sum_{c} \sum_{g' \in n} Area_{g'c}} DegreeDays_{gt}(T_c^{max}) \tag{1}$$

[10]Sample limitations are driven by data availability of the geography of crop acreage.

Figure 1. Temperatures in land growing cotton and rubber in India and Thailand



Notes: The figure shows daily average temperatures in 2019 in India and Thailand weighted by fraction of crop land in each grid cell that respectively grows cotton and rubber. Dashed lines show the maximum optimal growing temperature for cotton in orange (36°C, ≈ 97°F) and for rubber in blue (33°C, ≈ 91°F).

where $DegreeDays_{gt}(T_c^{max})$ is the total number of degree days above the crop-specific optimal growing temperature T_c^{max} in grid cell g in year t, and $Area_{gc}$ is the fraction of grid cell g in country n growing crop c. To have a crop-weighted cumulative measure of extreme heat exposure at the country-level, I sum crop-specific cumulative extreme heat exposure weighted by the relative importance of each crop c in country n in terms of land where it is grown.

Heat shocks in other sectors. Unlike agriculture, production in other sectors is not linked to temperatures through specific geo-physical or agronomic relationships. Output can be affected by temperatures through a variety of channels, including labor productivity, capital damages, and health. For this reason, I construct a grid-specific measure of abnormal heat exposure using deviations of temperatures from their historical norms.

This measure has two major benefits over previous measures. First, it allows for non-linearity while preserving unidimensionality. Since early reduced form approaches assessing the GDP-temperature relationship, temperature has been used in levels (Dell et al., 2012). The non-stationarity of temperature levels, however, introduces concerns for the identification strategy that first-differenced temperature would allay, only if introduced linearly (for a detailed discussion and mathematical proofs, see Appendix Section G). Previous work, however, has documented substantial non-linearities in the relationship between temperature and out-

put (e.g., Burke et al., 2015). To preserve non-linearities while avoiding econometric pitfalls, I construct deviations of temperature counting the cumulative number of degree days above the 95^{th}-percentile of each grid-specific 30-year long temperature distribution. I do so in two ways. Firstly, I construct a distribution across the twelve months in each year; secondly, I construct a month-specific distribution to account for month-specific deviations, e.g., temperatures in January 2000 are compared to the 95^{th}-percentile of temperatures in January between 1970 and 1999 in a given location.

Second, using temperature deviations from their historical norms allows for an implicit model of adaptation. Using a baseline climate of 30 years is consistent with assuming that individuals form climate beliefs over this time length and any deviations from it would constitute unexpected idiosyncratic shocks. To allay concerns on the arbitrariness of the cut-off, I test for the robustness of the results using the 90^{th} and 99^{th} percentile as alternative cut-offs (Carleton et al., 2024). Furthermore, although 30 years is the traditional length over which climate is generally computed in climate science (Arguez et al., 2012), I construct alternative measures of abnormal heat exposure with respect to a 20-year and a 40-year long historical norm. This approach also allows me to test for the speed of adaptation (the shorter the interval, the faster individuals treat higher temperatures as the new norm).

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 variation without geo-physical justifications. To construct a measure of weather exposure for the average individual in a country, after taking any non-linear 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 collect data from National Statistics Offices on the sub-national geographic distribution of sectoral economic activities (Appendix Section D provides additional details on the data sources).[11]

In additional robustness checks, I also construct an alternative measure of heat shocks, following Nath et al. (2024). The approach relies on projecting the temperature in each country

[11] Like in the case of the spatial geography of land use, a time-invariant measure for population distribution and sectoral activity implies that this approach does not account for human migration (Cai et al., 2016) or sectoral reallocation (Rudik et al., 2024), which could be important adaptation margins. Nevertheless, these adaptive margins entail ex ante decisions. In this paper, I focus on short run elasticities that do not capture any long run adaptation decision.

on its own lags and interact them with country mean temperature to allow the dynamics to vary across climates. I implement this approach at the sectoral level accounting for all possible two-way fixed effects, country-year, sector-year, and country-sector, and use the innovation in this non-linear regression as the temperature shock.[12]

2.3 Production network

The definition of sectoral and spatial input linkages is crucial to my analysis. 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 a sequence of global bilateral input-output tables that record final and intermediate goods shipments at basic prices (i.e., the amount a producer receives for a unit of a good or service, minus any taxes and plus any subsidies) across countries for 26 sectors from 1970.[13]

Construction of sectoral linkages across space. To investigate whether and how shocks in agriculture propagate to other sectors and countries through input-output interlinkages, I account for the geographic location and the position in the supply chain of the origin of the shock. First, I distinguish between shocks to agriculture 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 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 sector 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. I allow for the production network to slowly evolve, wherein input linkages are averaged over a five-year lagged period every five years (e.g., I use average linkages between 1970 and 1974 for period between

[12]The temperature shock τ_{jnt} is defined as the innovation to temperature in the equation

$$T_{jnt} = \sum_{p=1}^{5} \gamma_{jp} T_{jn,t-p} + \sum_{p=1}^{5} \delta_{jp} T_{jn,t-p} \times \overline{T}_{jn} + \alpha_{jn} + \mu_{nt} + \nu_{jt} + \tau_{jnt}, \tag{2}$$

where T_{jnt} is temperature in sector j in country n in year t, $\overline{T}_{jnt}$, is the country mean temperature in the sample, and I include up to 5 lags in temperature. The second summation term allows the coefficients on lagged temperature to vary with country mean temperature. The residuals from this regression $\widehat{\tau_{jnt}}$ are the temperature shocks that I use in additional robustness checks.

[13]The dataset contains the richest information in terms of geographic, temporal and sectoral disaggregation for input-output interlinkages, which makes it preferable over alternative datasets, including WIOD and EXIOBASE. The EORA26 respects national account definitions of final and intermediate goods and is consistent with standard macro aggregates. Appendix Table C3 maps the 26 EORA sectors to the six sectors described in Section 2.1.

1975 and 1979), so as to smooth annual variation and to account for the intensification of inter-sectoral and inter-national production linkages over time with more interconnected global supply chains.

From the perspective of sector j in country n, I construct weights associated with shocks in agriculture using the downstream linkages with the agricultural sector in country m, such that

$$\omega_{m,\tau}^{j,n} = \frac{\overline{input}_{m,\tau \to jn\tau}}{\overline{sales}_{jn\tau}}, \qquad \overline{sales}_{jn\tau} = \sum_{kf \in \Theta_{jn}} \overline{input}_{jn\tau \to kf\tau} + \overline{final}_{jn\tau}, \tag{3}$$

i.e., the value of the intermediate inputs that sector j in country n sources from agriculture in country m, divided by the gross output of jn, averaged over the previous five years τ. A sector's output can in turn be used as an input by other sectors or consumed as a final good, so the denominator sums sales to the set of customer sector-countries Θ_{jn} and sales to final use $\overline{final}_{jn\tau}$. In other words, these weights represent the share of a dollar of output of sector-country jn that is spent on agricultural inputs from country m, which is exactly the direct cost share $\omega_{Ag,m}^{j,n}$ of the theoretical framework in Section 4. Because the denominator is gross output rather than intermediate sales alone, the rows of $\mathbf{\Omega}$ sum to less than one wherever value added is positive, so the Leontief inverse $(\mathbf{I} - \mathbf{\Omega})^{-1}$ that I use below is well defined and has non-negative entries. [14]

Appendix Figure A5 displays the inter-sectoral linkages (i.e., the full Ω matrix of ω sector-by-country interlinkages) averaged across countries and time. Agriculture is the most upstream sector and, on average, downstream interlinkages with agriculture are larger than with any other sector. This result resonates with the "upstreamness" measure in Antràs et al. (2012) and Fally (2012), constructed as the average position of an industry's output in the value chain in terms of distance from final use.[15] There is, however, substantial heterogeneity across sectors. Manufacturing has much stronger first order linkages with agriculture (0.317) than the transport, storage, and communication sector (0.043, which does not include agricultural storage), reflecting different use of agricultural commodities as an intermediate input in the production process in

[14] In robustness checks, I use upstream linkages between agriculture and sector j, which are constructed as

$$\widehat{\omega}_{m,\tau}^{j,n} = \frac{\overline{input}_{jn\tau \to ,m\tau}}{\sum_{lf \in \hat{\Theta}_{jn}} \overline{input}_{jn\tau \to lf\tau}}, \tag{4}$$

i.e., intermediate inputs of sector-country jn to the agriculture sector in country m over the total inputs supplied to its set of customers Θ_{jn}. These upstream weights reflect the importance of the agriculture sector in country m as a customer for the sector-country of interest jn.

[15] Antràs et al. (2012) construct the upstreamness measure for industries in the manufacturing sector in the United States, but in complementary analysis they show using global trade flows from 2002 that the mean value of upstreamness for the agriculture sector is 2.84, while it is 2.10 for manufacturing industries.

each of these sectors.

Appendix Figure A6 shows the empirical distribution of the first order linkages with agriculture across sectors by five-year period. The distributions are noticeably skewed, with heavy right tails. These skewed distributions are indicative of the presence of agricultural commodities that are general purpose inputs used by many other sectors and of the presence of major agricultural suppliers to sectors that produce the general purpose inputs. I return to the latter point when studying counterfactuals in the propagation of shocks in Section 7.4. These distributions, however, do not considerably vary over time, suggesting that linkages have been relatively stable, with the average varying between 0.38 in 2005 and 0.52 in 2015.

Construction of network shocks. I combine the country-specific measures of extreme heat in agriculture with sectoral linkages to construct two measures of network shocks that differ by location and supply chain position. Downstream shocks Dn are constructed for domestic, Dom, and foreign, Fgn, agriculture as follows (upstream shocks are symmetric but differ by using upstream weights $\widehat{\omega}^{j,Ag}_{n,m,\tau}$ in Equation (4)):

$$NetworkShock^{Dn,Dom}_{j,n,t} = \omega^{j,n}_{n,\tau} ExtremeHeat_{nt} \tag{5}$$

$$NetworkShock^{Dn,Fgn}_{j,n,t} = \sum_{m \neq n} \omega^{j,n}_{m,\tau} ExtremeHeat_{mt} \tag{6}$$

where $ExtremeHeat_{nt}$ measures the crop-weighted extreme heat conditions in agriculture in country n in year t, as defined in Equation (1). These metrics resemble a "shift-share" approach since the sum of extreme heat conditions is weighted by pre-shock sector-country exposure shares. Indirect exposure of sector j in country n to extreme heat in agriculture in m depends on sector-country input linkages $\omega^{j,n}_{m,\tau}$, which are computed in the pre-shock period τ, averaging the five-year linkages prior to the shock.

The measures in Equations (5) and (6) capture the exposure to extreme heat shocks in agriculture of immediate downstream industries that use agricultural commodities as intermediate inputs. Agricultural commodities in the sample include a wide range of crops that enter in the production processes of several downstream sectors. Intuitively, cereals, fruits, vegetables, spices, oils and fats are essential for the food and beverage manufacturing industry. Other types of agricultural commodities include fiber crops (such as cotton, kapok, flax, hemp, ramie) used in the textile and apparel industry, oil crops (including sunflower, soybean, canola, palm, sesame, coconut) used for oilseed processing, fats and oils refining and blending, ornamental plants used

in plant wholesale and retail of ornamental plants (lavender, peppermint, rosemary), herbs and spices (such as basil, thyme, sage, mint, chive), tobacco product manufacturing, crops for pharmaceutical, medicinal, cosmetic, and personal care products (including coconut, aloe vera, olive, safflower, sesame, chamomile, jojoba), rubber and latex products for the automotive industry, and crops for paper and packaging products (including bamboo, hemp, agave, flax).

The transmission of heat shocks may not be limited to first degree linkages but can ripple down through higher order linkages to sectors that are not or only partially directly connected with agriculture. A negative productivity shock in agriculture will reduce commodity output and increase its price, adversely impacting all of the sectors that purchase inputs from agriculture. This direct impact will be further augmented in competitive equilibrium because these first-round-affected sectors will change their production and prices, creating indirect negative effects on other customer industries that might not rely directly on agriculture inputs. Examples of these industries include automotive components, packaging industries, construction material, home decor and landscaping industries, clothing and apparel industries, therapeutic and wellness industries, and cosmetics and personal care products. To account for higher order linkages, I compute the Leontief inverse matrix, $\boldsymbol{L} = (\boldsymbol{I} - \boldsymbol{\Omega})^{-1} = \sum_{r=0}^{\infty} \boldsymbol{\Omega}^r$, which summarizes the sector-specific "technical coefficients" of the shock propagation through a power series representation of the Leontief inverse (Leontief, 1970). The technical coefficients capture all direct and indirect sectoral interdependencies with agriculture and allow me to capture the total aggregate effect of heat shocks in agriculture through the production network. This intuition is formally derived in the model in Section 4.

3 Empirical facts

I begin the analysis by bringing together the data presented in Section 2 to document four key empirical facts about the relationship between local extreme heat and i) sectoral value added; ii) agriculture prices; iii) global patterns of extreme heat conditions; and iv) the production network potential endogenous adjustments of the production network in response to weather variation. Together, these facts allow me to characterize the main features of my theoretical model and build the subsequent empirical approach, which introduces sectoral and spatial linkages as a transmission channel of extreme heat in agriculture to sectoral economic production.

Fact 1: Local extreme heat reduces agricultural value added. To empirically establish the sector-specific sensitivity to heat, I estimate the response to local extreme heat conditions

in growth rate of sectoral value added. Differently than previous cross-country evidence on the channels through which weather shocks impact sectoral outcomes (Acevedo et al., 2020; Dell et al., 2012), I jointly estimate sector-specific response functions in a pooled, multi-country multi-sector sample. This model allows me to directly compare the different response functions across sectors estimated in a single econometric specification of the form:

$$\Delta \log(value\ added)_{jnt} = \beta_j ExtremeHeat_{jnt} + \mathbf{W}'_{jnt}\delta_j + \alpha_{jn} + \lambda_{jt} + \mu_{nt} + \varepsilon_{jnt} \tag{7}$$

where I regress the growth rate of value added in sector j in country n in year t (approximated by the first difference in logarithms) on a sector-specific extreme heat measure j in country n in year t, and control for a second order polynomial of total precipitation $\mathbf{W}_{jnt}$. Country-sector fixed effects α_{jn} 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. Sector-year fixed effects λ_{jt} capture shocks to specific sectors (e.g., agricultural commodity price shocks), while country-year fixed effects μ_{nt} account for time-varying differences across countries, but also country-specific differential impacts of larger scale shocks, including El Niño events or economic recessions. The full set of two-way fixed effects means that my estimates only exploit variation across sectors within country-years and are not driven by any country-specific or sector-specific trends, or differences in sector specialization across countries. Therefore, this empirical strategy exploits the differential exposure of country-sector pairs to plausibly exogenous variation in extreme heat over time, drawing on differential geographic distribution of crops, population, and sectoral economic activities.[16] Standard errors are clustered at the country level to account for spatial correlation of the error terms across sectors and over time within a country.

Figure 2 shows the sector-specific coefficients associated with local extreme heat conditions on growth rate of sectoral value added. On average, an additional degree day in the extreme heat measure constructed in Equation (1) ($\approx 1\%$ at the sample mean) reduces the growth rate of agricultural value added by 0.76%. 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.[17]. These average

[16] I do not include any other time-varying determinants of sectoral production - such as investments or capital stocks - since they are endogenous to weather and may thus introduce bias in the estimates because of the "bad controls" problem (Dell et al., 2014).

[17] Results are robust to estimating the baseline equation in a balanced panel, excluding large countries (i.e.,

treatment effects mask heterogeneous effects of local extreme heat by adaptation potential as measured by income and climate (Carleton et al., 2022). I describe the results in Appendix Section H. I find that sectors that rely on outdoor activities such as construction, transport, storage and communication, benefit from hotter days in colder climates. Finally, to allay concerns that differences in shock construction explain heterogeneous sectoral responses, I also construct a measure of abnormal heat exposure in agriculture that is directly analogous to the metric used for all other sectors. This measure weighs exposure to daily temperatures above the grid-cell specific 95^{th} percentile by agricultural land coverage in each grid cell (Ramankutty et al., 2010). I find comparable and quantitatively similar results, with agriculture being the only affected sector (Appendix Figure B3). I also estimate the specification using the alternative measure of temperature shocks from Equation (2). Also in this case, agriculture is the only sector affected by temperature shocks (Appendix Figure B4). Finally, I explore whether extreme heat has any long-lasting impact on growth rate of value added by estimating a dynamic event study, but I only uncover contemporaneous impacts (Appendix Figure B5).

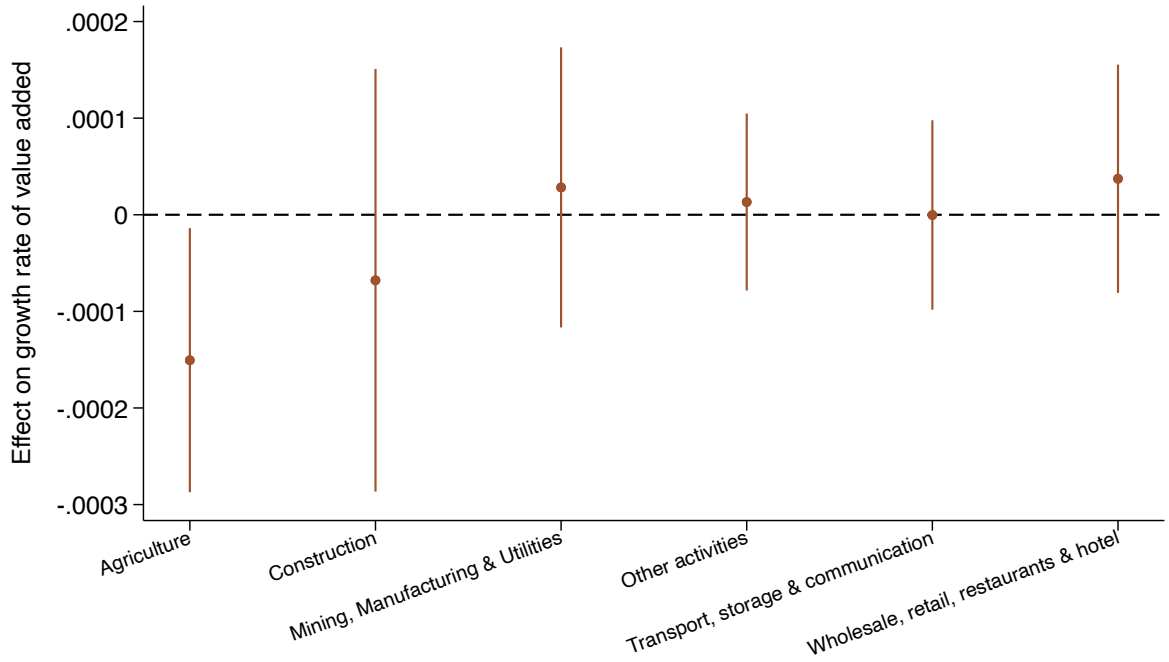
The empirical finding that agriculture is the only sector for which value added responds to heat resonates with previous micro (Nath, 2025) and macro findings (Dell et al., 2012; Acevedo et al., 2020; Nath et al., 2024). Temperature-induced damages to agriculture are substantially larger than those on non-agricultural sectors.[18] The confidence intervals on the effects of extreme heat on other sectors, however, cannot entirely rule out moderate impacts, which are more visible in the heterogeneity analysis by climate and income that I study in Appendix Section H. In particular, the construction sector might experience benefits from extreme heat in cold climates and losses in temperate and hot climates. This finding is consistent with previous research that underlines this sector's vulnerability to climate through damages to investment productivity (Casey et al., 2024). Overall, this finding indicates the importance of accounting for sectoral heterogeneity when estimating or calibrating damage functions in climate impact studies so as to inform direct sector-specific investments in climate policies. Previous work has documented heterogeneous effects of temperature on economic output across locations depending on their sectoral composition (Nath, 2025; Cruz, 2024), however, these studies often limit their approach to contrasting agriculture with the rest of the economy, neglecting further sectoral heterogeneity

Brazil, China, India, Russia, US), controlling for lagged growth, and to alternative specifications (linear and quadratic country-specific trends, sub-region-year fixed effects) (Appendix Figure B1). Results are also robust when altering the threshold to construct abnormal heat (90^{th} or 99^{th}) percentile, computing the distribution separately for each grid-month instead of for each grid-year, and altering the length of the climate distribution (20-year or 30-year) (Appendix Figure B2).

[18] Appendix Figure B6 plots the response of growth rate of agricultural value added to changes in terciles or quintiles of the extreme heat distribution.

combined with climate and income heterogeneity. Yet to date, most studies calibrating damage functions do not incorporate sectoral heterogeneity in their structural models (Cruz and Rossi-Hansberg, 2024; Bilal and Rossi-Hansberg, 2023).

Figure 2. Effect on local extreme heat on growth rate of sectoral value added

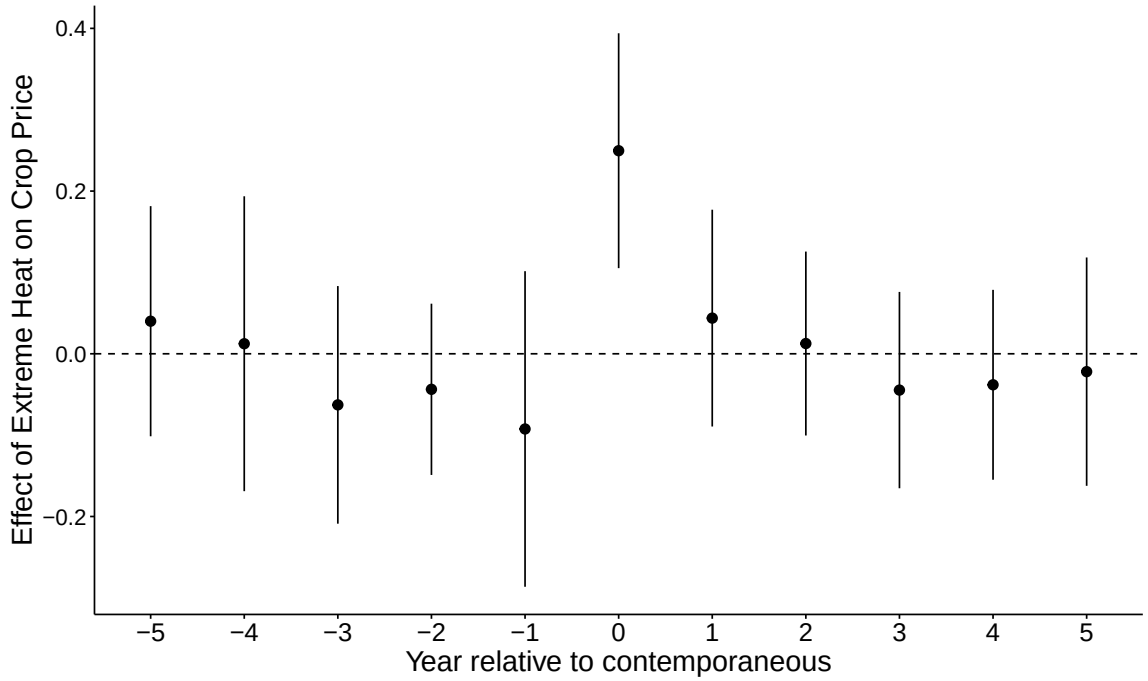


Notes: The figure shows the coefficients associated with the sector-specific extreme heat exposure in a regression where the outcome is the growth rate in sectoral value added, as detailed in Equation (7). All sector-specific coefficients are estimated jointly in a regression model fully saturated with country-sector, sector-year, and country-year fixed effects and allowing for sector-specific response to a quadratic functional form in precipitation. Vertical lines represent the 95% confidence intervals around point estimates. Standard errors are clustered at the country level.

Fact 2: Extreme heat induces a short-lasting increase in crop prices. Negative effects of extreme heat on agricultural value added combine a price and a quantity effect. To disentangle how much of the local response in supply is driven by changes in price and quantities, I use FAO crop price data measured in current US$ per tonne. In a crop-country level distributed lag model, I estimate the response of crop prices to cumulative exposure to extreme heat conditions above the crop-specific maximum optimal growing temperature over land cultivating that crop in the country, accounting for five lags and leads. Figure 3 shows a substantial price increase induced by heat conditions that, however, is not persistent over time. Only extreme heat during year t increases crop prices, with the effect vanishing after one year. Appendix Table C4 reports

the tabular results in a country-crop panel regression that only accounts for contemporaneous heat. The empirical finding documented here provides the source of propagation of extreme heat conditions in agriculture throughout the economy that the theoretical model in Section 4 builds upon. Extreme heat in agriculture reduces sectoral value added and increases commodity prices, inducing downstream sectors to decrease their demand for the intermediary inputs and consequently leading to a reduction in the production of downstream goods.

Figure 3. Dynamic price effect of extreme heat



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

Fact 3: Extreme heat shocks are increasingly spatially correlated. The third empirical pattern relates to the geography of extreme heat exposure (EH) in agriculture around the world. I measure the global spatial correlation of extreme heat in each year t using Moran's I (Dingel et al., 2023), a statistic for spatial autocorrelation that indicates how similar or dissimilar the values of a variable are across locations in a geographic space:

$$I_t \equiv \frac{N}{\sum_n \sum_{m \neq n} a_{nm}} \frac{\sum_n \sum_{m \neq n} a_{nm} \left(EH_{nt} - \overline{EH_t}\right) \left(EH_{mt} - \overline{EH_t}\right)}{\sum_\ell \left(EH_{\ell t} - \overline{EH_t}\right)^2} \tag{8}$$

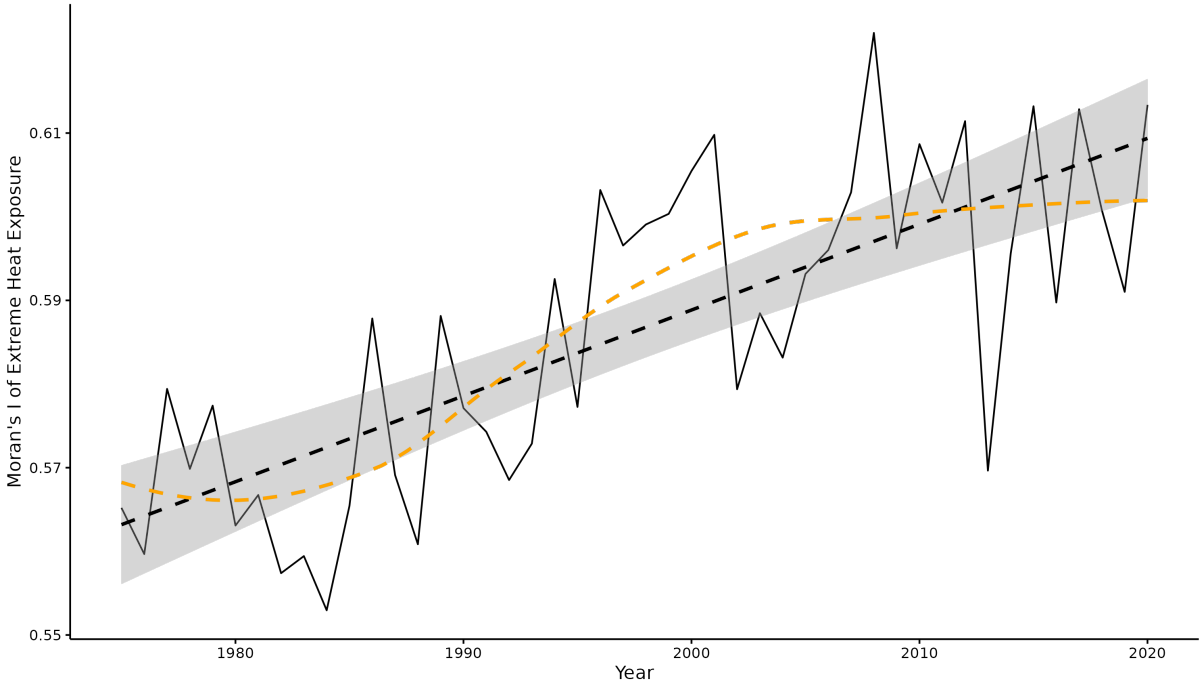
where N is the number of countries, $a_{nm} = a_{mn}$ is a (symmetric) spatial weight that depends on the distance between countries n and m, and $\overline{EH_t}$ is the world average extreme heat exposure in year t across countries. Moran's I values range from -1 to 1. A value equal to 1 indicates that similar values of extreme heat cluster together in space, high values are surrounded by high values and low values by low values, while a negative statistics would indicate that extreme heat values are surrounded by low values, and vice versa. Figure 4 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, in spite of crop-specific temperature thresholds, extreme heat exposure is spatially correlated across countries and increasingly so over time, indicating that crop specialization patterns also follow a similar spatial structure (Dingel et al., 2023).

The spatial correlation structure of extreme heat exposure is an additional aggravating factor to previously 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 lower agricultural output in a country due to increases in temperatures is likely to be spatially correlated and neighboring countries are likely to be similarly affected. This spatial correlation pattern might diminish the potential adaptive role of international trade compared to scenarios where shocks are not spatially correlated (Cruz and Rossi-Hansberg, 2024).

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 economic output is traditionally estimated using quasi-random variation implicitly holding temperatures in other locations fixed. Climate change global impacts are 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 only one location experiences warming in each scenario. Two empirical approaches so far account for the global nature of climate change, in which all locations experience warming simultaneously: a number of studies accounts for spillovers from neighbouring regions using a spatial-lag model (e.g., Kotz et al., 2024), while Dingel et al. (2023) integrate the general-equilibrium effect of spatial correlated shocks induced by global climatic phenomena on cereal productivity. In either cases,

incorporating changes in the spatial correlation exacerbates global welfare inequality and losses induced by changes in climate conditions.

Figure 4. Spatial Correlation of Extreme Heat Exposure



Notes: The figure shows the time series evolution between 1975 and 2020 of the Moran's I Statistic computed as in Equation (4) for the Extreme Heat Exposure constructed in Equation (1). 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.

Fact 4: Downstream linkages with agriculture do not respond to extreme heat. Countries may react to extreme heat conditions that hit the agricultural sector by altering sectoral interlinkages and thus the production network structure. In other words, the production network described in Section 2.3 might be endogenous to extreme heat. A productivity shock to agriculture may result in a reallocation of resources across sectors in the economy, altering expenditure shares of agriculture from specific locations hit by the shock.

Previous micro level empirical evidence documents that firms systematically respond to changes in weather conditions by altering their location choice, their supply partner composition and characteristics (Balboni et al., 2024; 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. A similar result is documented with changes in intranational trade patterns of crops in the US (Dall'Erba et al., 2021). These 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 heat in agriculture, I exploit the time-varying nature of the input-output matrix and estimate the following specification:

$$IO^{j}_{n,m,t} = \beta_{j,\ell} ExtremeHeat_{n(\ell),t} + \alpha_{jnm} + \mu_{jmt} + \varepsilon_{jnmt} \tag{9}$$

where the outcome variable $IO^{j}_{n,m,t}$ is the (log) of intermediate inputs share that sector j in country m sources from agriculture in country n in year t.[19] I exploit inter-annual variation in extreme heat conditions in the agricultural sector in country n to test for within country-pair-sector changes in intermediate inputs sourced from the agricultural sector. The specification accounts for country-pair-sector α_{jnm} and customer country-sector by year μ_{jmt} fixed effects (which effectively also accounts for weather conditions and any other time-varying shock in the downstream sector-country). To allow for heterogeneous elasticities of substitution, I estimate sector-specific response functions to extreme heat and allow elasticities to differ also by location ℓ of the agricultural sector (either domestic or foreign).

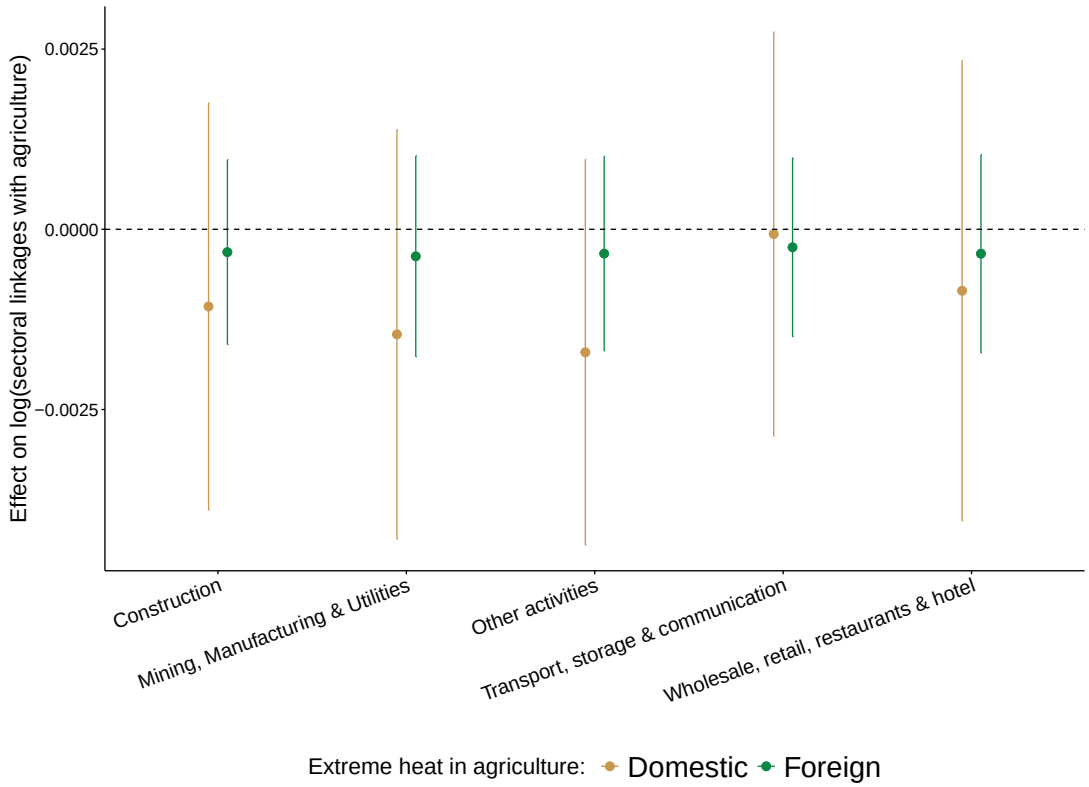
Figure 5 reports the sector-location specific coefficients associated with extreme heat on the sectoral interlinkages with agriculture. The ten coefficients on domestic and foreign extreme heat in agriculture for five downstream sectors are small and not statistically significant at any conventional level. This pattern suggests that sectors do not endogenously respond to extreme heat in agriculture by altering their expenditure shares, providing suggestive evidence of the stickiness of production processes.[20] This fact suggests that a model where expenditure shares are independent of the realization of productivity shocks as in a 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. I also explore whether a country's ability to diversify extreme heat exposure from agriculture linkages differs by income groups. 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

[19] Sector-specific density distribution of the downstream sectoral linkages with agriculture are reported in Appendix Figure B7.

[20] Kunze (2021) also documents a small and negligible shift of sectoral interlinkages in response to cyclones. In contrast, input linkages have been shown to have elastic responses after trade shocks including the NAFTA (Caliendo and Parro, 2015) and the 2018 trade war (Fajgelbaum et al., 2020; Handley et al., 2024).

by temperature. While this result holds for the response of economic output to local weather fluctuations (Dell et al., 2012, and Appendix Section H), I document that downstream exposure to extreme heat in agriculture has been relatively constant over the past 40 years across income groups. The ratio in downstream exposure to extreme heat in agriculture between time-varying and time-invariant linkages has been relatively flat and statistically indistinguishable from one across income classes (Appendix Figure B8). A ratio that is not statistically distinguishable from one indicates that countries did not alter their input linkages compared to the baseline linkages in 1970-1974 in such a way to reduce extreme heat exposure in the agricultural sectors they source inputs from. This result suggests that, differently than in the case of local extreme heat responses, income does not explain differences in downstream exposure to extreme heat.

Figure 5. Response of downstream sector-specific input linkages to extreme heat in agriculture



Notes: The figure shows the sector-specific coefficients associated with extreme heat in domestic and foreign agriculture obtained from Equation (9). 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 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. Vertical lines represent the 95% confidence intervals around point estimates. Standard errors are clustered at the country level.

Together, these four facts inform the theoretical model and the empirical approach in multiple ways. These facts indicate that local extreme heat reduces agricultural value added and increases agricultural commodity prices. This pattern motivates the focus of the analysis on local shocks in extreme heat conditions in agriculture and how they can propagate through the economy via price increases through input linkages between agricultural and downstream sectors, emphasizing the broad-reaching consequences of climate-induced disruptions in agriculture. Furthermore, I observe that extreme heat shocks are becoming increasingly spatially correlated, indicating the necessity of accounting for spatial dependencies in my empirical analysis to capture the broader economic impacts. Despite the significant effects of heat shocks on agriculture, downstream sectoral interlinkages are not responsive. This observation aligns with the characteristics of a Cobb-Douglas production technology where expenditure shares are fixed. This result informs my theoretical approach to obtain model-derived sectoral exposure shares to upstream supply-side shocks through a shift-share approach with quasi-randomly assigned shocks. In the next section, I present a theoretical model that rationalizes the importance of sectoral and spatial interlinkages in climate damage quantification and then bring this model to the empirical estimation.

4 Theoretical framework

Motivated by the evidence above, I set out a general framework for the propagation of productivity shocks through a global production network. The framework serves three purposes. It makes explicit the object that a regression of sectoral value added on network-weighted heat exposure recovers, it identifies the features of the data that this object requires, and it delimits what such a regression can and cannot deliver. In Appendix Section F, I describe the more traditional conceptual framework adopted to derive empirical estimates of the effect of local weather shocks on local economic output. That approach derives temperature-related productivity shocks from a Cobb-Douglas production function that relies solely on local factor inputs, labor and capital, so that extreme heat is a Hicks-neutral productivity shock which reduces local economic output. When that framework is taken to the data, temperature shocks in other sectors and countries are absorbed in the error term. Sectoral and spatial linkages, combined with the spatial correlation structure of temperature shocks documented in Fact 3, can then introduce bias in the estimates.

Setup. The world economy consists of N countries indexed by $n \in \{1, ..., N\}$ (or m) and $J+1$ sectors: one agricultural sector, denoted Ag, and J other sectors indexed by $i \in \{1, ..., J\}$ (or j). The unit of analysis is a country-sector (i, n), that is, sector i located in country n. Each country-sector is a competitive producer operating a constant returns to scale technology

$$Y_{in} = A_{in}\, F_{in}\left(L_{in}, \{X^{i,n}_{j,m}\}_{j,m}\right), \tag{10}$$

where L_{in} denotes the primary factors supplied locally (labor and, in agriculture, land), $X^{i,n}_{j,m}$ is the quantity of the good produced by sector j in country m and used as an intermediate input by sector i in country n, and A_{in} is a Hicks-neutral productivity shifter. Beyond constant returns to scale, I leave F_{in} unrestricted. It nests Cobb-Douglas, Leontief, and any nested constant elasticity of substitution structure, and it imposes no restriction on how readily producers substitute between labor and intermediate inputs, across supplying sectors, or across supplying countries. Goods are differentiated by country of origin, so that the output of a given sector sourced from different countries consists of distinct varieties: international trade enters through the same input structure as domestic sourcing. Households in each country supply labor inelastically, own the factors of production, and consume the $J+1$ goods. Markets are competitive and the equilibrium allocation is efficient. The framework is the open-economy counterpart of the standard multi-sector production network (Acemoglu et al., 2012; Carvalho and Tahbaz-Salehi, 2019), in which inputs can be sourced across countries as well as across sectors.

The production network is summarized by the matrix $\mathbf{\Omega} = [\omega^{i,n}_{j,m}]$ of direct cost shares, where $\omega^{i,n}_{j,m} = p_{jm}X^{i,n}_{j,m}/(p_{in}Y_{in})$ is the share of the sales of country-sector (i,n) spent on inputs purchased from country-sector (j,m), evaluated at the observed equilibrium. Their empirical counterparts are constructed from the inter-country input-output tables described in Section 2.3, as in Equation (3). Extreme heat enters as a Hicks-neutral productivity shock. In agriculture it operates through crop yields, $d\log A_{Ag,m} < 0$, as documented in Fact 1 and Fact 2. In the other sectors it operates through own-sector local heat, $d\log A_{i,n}$, whose average effect Fact 1 shows to be small and statistically indistinguishable from zero.

First-order propagation. Consider a vector of productivity shocks $d\log \mathbf{A}$ and log-linearize the equilibrium around the observed allocation. Cost minimization and market clearing imply that the output response of any country-sector is a weighted sum of the productivity shocks occurring anywhere in the world economy,

$$d\log Y_{in} = \sum_{j,m} \psi^{i,n}_{j,m}\, d\log A_{jm}, \qquad \mathbf{\Psi} \equiv (\mathbf{I}-\mathbf{\Omega})^{-1} = \mathbf{I} + \mathbf{\Omega} + \mathbf{\Omega}^2 + \cdots, \tag{11}$$

where $\psi^{i,n}_{j,m}$ is the $\big((i,n),(j,m)\big)$ entry of the Leontief inverse $\mathbf{\Psi}$ (Hulten, 1978). While $\omega^{i,n}_{j,m}$ records the inputs from (j,m) that (i,n) purchases directly, $\psi^{i,n}_{j,m}$ records total requirements: the direct purchases plus the inputs from (j,m) embodied in every other input that (i,n) buys,

at every round of the power series expansion.

Three features of Equation (11) organize the empirical analysis that follows. First, only observed cost shares enter. The weights $\psi_{j,m}^{i,n}$ are functions of $\mathbf{\Omega}$ alone, which is measured directly in the input-output data. Second, no elasticity of substitution appears in the expression. How much a heat shock in a distant agricultural sector moves the output of a downstream producer depends, in Equation (11), on how intensively that producer relies on agricultural inputs, directly and indirectly, and not on how easily it could substitute away from them. Third, it is worth being precise about the sense in which that is an approximation. The expression is exact under Cobb-Douglas technologies, in which cost shares are invariant to the realization of the shocks. Away from Cobb-Douglas, the elasticities of substitution wash out of the response of aggregate output to a first order, which is the content of Hulten's theorem, and enter only at second order (Baqaee and Farhi, 2019). For the disaggregated output of an individual country-sector, which is the object I take to the data, the claim is weaker: expenditure shares reallocate at first order whenever an elasticity departs from one, so Equation (11) omits a reallocation term proportional to that departure. That term is endogenous and is not a function of observable input-output shares alone, which is why no reduced form built on fixed exposure weights can recover it. Fact 4 supplies the empirical discipline on the omitted term: agricultural expenditure shares in downstream sectors do not measurably respond to extreme heat at the horizons I study, so the fixed-share expression is a reasonable description of the data at the sector level, and the quantitative model of Section 7 specifies the elasticities explicitly and quantifies what the fixed-share approximation leaves out.[21]

Specializing Equation (11) to shocks that originate in agriculture, and separating the country in which the downstream producer is located from the rest of the world, gives

$$d\log Y_{in} = \underbrace{\psi_{Ag,n}^{i,n}\, d\log A_{Ag,n}}_{\text{domestic}} + \underbrace{\sum_{m\neq n} \psi_{Ag,m}^{i,n}\, d\log A_{Ag,m}}_{\text{foreign}}. \tag{12}$$

Equation (12) is the theoretical counterpart of the estimating equation of Section 5. Two producers located in the same country and facing the same set of agricultural heat shocks around the world respond differently to the extent that their total agricultural requirements $\psi_{Ag,m}^{i,n}$ differ, and the expression separates exposure that runs through domestic agriculture from

[21] Under Cobb-Douglas technologies the same Leontief inverse delivers the exact response of unit costs and prices, $d\log p_{in} = -\sum_{j,m} \psi_{j,m}^{i,n}\, d\log A_{jm}$, taking world nominal value added as the numeraire, under which nominal sales and factor prices are unchanged. This is the price channel documented in Fact 2 and the mechanism through which extreme heat in agriculture reaches downstream producers.

exposure that runs through foreign agriculture.[22]

Direction of propagation. A negative productivity shock in agriculture propagates downstream, from supplier to buyer, and not upstream. The shock reaches other producers through the price of agricultural goods: extreme heat lowers agricultural productivity and raises the price of agricultural commodities, as Fact 2 documents, and that price increase passes into the unit costs of every sector that uses agricultural inputs, directly or indirectly, reducing its output. In the opposite direction, agriculture is a customer of other sectors, and a heat shock has two offsetting effects on its demand for inputs. Agricultural output falls, which reduces the physical quantity of inputs the sector requires, while the agricultural price rises, which increases the revenue available to pay for them. Under Cobb-Douglas technologies the two effects cancel exactly, since nominal expenditure on each input is a fixed share of sales, and the shock transmits nothing to upstream suppliers through this channel. This is a statement about the channel and not about the supplier: a sector that sells to agriculture is still affected by an agricultural heat shock to the extent that it uses agricultural inputs itself, directly or indirectly, and the size of that effect is governed by its own total requirements $\psi^{i,n}_{Ag,m}$. Away from Cobb-Douglas the cancellation is imperfect, and the residual upstream effect is governed by the departure of the elasticities of substitution from one. The prediction that a supply-side shock travels downstream and not upstream therefore provides a test of the framework, which I implement in Section 6 by constructing exposure measures from upstream rather than downstream linkages, as in Equation (4). Because upstream and downstream intensity are correlated across sectors, the sharper version of the test estimates the upstream coefficient conditional on downstream exposure.

What the reduced form identifies. Equation (12) maps directly into a regression of sectoral value added growth on network-weighted heat exposure, which I set out in Section 5. Two properties of that mapping are worth stating before the estimation, because together they define the role of the reduced form and of the quantitative model in Section 7.

First, the regression identifies relative responses across country-sectors, not the level of aggregate losses. My specification includes country-year fixed effects, which is what allows me to separate exposure through input linkages from the spatially correlated component of extreme

[22]The estimation uses value added rather than gross output as the outcome, and the mapping between the two deserves care. Under exact double deflation and Cobb-Douglas technologies, a producer's substitution towards cheaper inputs offsets the change in its input prices, and measured real value added responds only to own-sector productivity. Sectoral value added in the UN national accounts is not double-deflated for many countries in my sample, so it does move with intermediate input prices, and the coefficients below should be read as responses of measured value added. Away from Cobb-Douglas, when inputs are complements, value added responds to upstream productivity even under double deflation. The quantitative model of Section 7 computes value added directly from the solved equilibrium and so is not subject to this ambiguity.

heat and from any other country-wide shock. The same fixed effects, however, absorb the general equilibrium response that is common to all sectors within a country-year, including the movements in factor prices and in the aggregate price index that a global agricultural shock induces. The estimated coefficients are therefore differences in exposure, and the common component is the "missing intercept" familiar from the literature on the general equilibrium effects of local shocks (see, e.g., Chodorow-Reich, 2020; Adao et al., 2026). Recovering the level requires solving the model rather than reading it off the regression.[23]

Second, the regression is by construction linear in exposure and holds the exposure weights fixed at their pre-period values, so it is silent about the reallocation term. A linear specification recovers the average pass-through of exposure into output. Whether a network with limited substitutability amplifies aggregate losses beyond the fixed-share accounting in Equation (11) depends on the elasticities of substitution, which do not appear in that expression at all. Quantifying amplification requires a model in which those elasticities are specified and the equilibrium is solved rather than linearized.

Both limitations motivate Section 7, where I embed the framework of this section in a fully specified multi-region multi-sector general equilibrium model, calibrate it to the observed global production network, discipline the sensitivity of agricultural productivity to heat with the reduced-form estimate of Fact 1, and solve it exactly.

5 Empirical approach

In this section, I use the data described in Section 2, the empirical facts in Section 3, and the theoretical notions in Section 4 to derive an empirical specification that considers input linkages from agriculture to other sectors across space. My research design builds upon the conventional methodology adopted in quasi-experimental approaches that typically estimate local direct effects, ignoring spatial linkages (e.g., Dell et al., 2012; Burke et al., 2015). This traditional approach implicitly assumes that residual variation in local weather is orthogonal to variations in weather elsewhere. The potential outcomes of one observation, however, may vary with the treatment assignment of other units through input linkages and through the spatial correlation of shocks. Therefore, when there are upstream and downstream relationships across space as those modelled here, spatial considerations become of first-order relevance. These

[23] In open economies the sales shares of individual producers are no longer universal sufficient statistics for the aggregate response (Baqaee and Farhi, 2024), which is a further reason to recover the level by solving the model rather than by aggregating the estimated coefficients with observed Domar weights.

challenges may result in violations of common identifying assumptions, including the stable unit treatment value assumption (SUTVA). The SUTVA rules out that extreme heat in agriculture can differentially affect expected outcomes in other countries.

To account for sectoral and spatial linkages, I design an econometric specification that builds on the traditional quasi-experimental approach, also adopted in Equation (7), but I introduce a parametric measure of *network* shocks to evaluate the differential effect of extreme heat conditions in agriculture across sectors on value added domestically and abroad. The specification is the sample analogue of the model's first-order prediction in Equation (12): it regresses the growth rate of real value added on own-sector local heat and on extreme heat in agriculture weighted by pre-period total requirements from agriculture, separately for domestic and foreign agriculture. For sector i in country n in year t, the estimating equation is written as follows

$$\begin{aligned}\Delta \log(\text{Value Added})_{int} = \beta_i^{Local} \, LocalHeat_{int} + \gamma_i^{Dom} \left(\psi_{Ag,n,\tau}^{i,n} \, AgriHeat_{nt} \right) \\ + \gamma_i^{Fgn} \left(\sum_{m \neq n} \psi_{Ag,m,\tau}^{i,n} \, AgriHeat_{mt} \right) + \mathbf{W}'_{int} \delta_i \\ + \rho_t \, \bar{\psi}_{Ag,\tau}^{i,n} + \alpha_{in} + \lambda_{it} + \mu_{nt} + \eta_{int},\end{aligned} \tag{13}$$

where I regress the growth rate of value added in sector i in country n in year t for all five downstream sectors in the economy on own-sector local extreme heat $LocalHeat_{int}$ and on exposure to extreme heat in domestic and foreign agriculture.[24] The term $AgriHeat_{mt}$ is the crop-weighted measure of extreme heat conditions in agriculture in country m in year t constructed in Equation (1), where it is denoted $ExtremeHeat_{mt}$, and it is the shifter of the research design. The term $LocalHeat_{int}$ is the sector-specific local heat measure of Equation (7), denoted $ExtremeHeat_{jnt}$ there. The weight $\psi_{Ag,m,\tau}^{i,n}$ is the total requirement of agricultural inputs from country m per unit of output of sector i in country n, taken from the Leontief inverse of the input-output matrix and averaged over the five-year period τ preceding the shock, so that it is the empirical counterpart of the total-requirements share $\psi_{Ag,m}^{i,n}$ of Equation (12). The term $\bar{\psi}_{Ag,\tau}^{i,n} = \sum_m \psi_{Ag,m,\tau}^{i,n}$ is the sector-country sum of exposure shares, which I interact with year indicators and include as the incomplete-shares control of Borusyak et al. (2022). The specification also accounts for a second order polynomial of total precipitation in $\mathbf{W}_{int}$, and for a full set of two-way fixed effects at the country-sector α_{in}, sector-year λ_{it}, and country-year μ_{nt} level. The two-way fixed effects mean that my estimates only exploit variation across sectors

[24] The estimation sample does not account for agriculture since local and domestic network shocks would be collinear up to a constant.

within country-years. As a result, they absorb country-specific or sector-specific trends, or any differences in baseline sector specialization across countries. For a given country-year, sectors differ only in how exposed they are, through input linkages, to extreme heat in domestic and in foreign agriculture.

Equation (13) is written in the notation of the theoretical framework, and it restates the network shocks constructed in Section 2. The downstream sector index i used here is the index j used there; the two exposure terms are $NetworkShock_{int}^{Dn,Dom}$ and $NetworkShock_{int}^{Dn,Fgn}$ of Equations (5) and (6); and $\psi_{Ag,m,\tau}^{i,n}$ is the total-requirements counterpart of the first-degree share $\omega_{m,\tau}^{j,n}$ of Equation (3). Equation (13) is displayed with the total-requirements weights ψ; the first-degree specification replaces every $\psi_{Ag,m,\tau}^{i,n}$ with the direct share $\omega_{m,\tau}^{j,n}$ of Equation (3) and is otherwise identical. Section 6 reports results under both weighting schemes: the first-degree shares first, for comparability with the prior literature, which has typically proxied network exposure with direct input shares, and then the total-requirements shares, which capture the full set of direct and indirect requirements and which Equation (11) identifies as the relevant first-order exposure. Because Equation (13) is the sample analogue of Equation (12), it inherits the status of that expression: it is exact under Cobb-Douglas technologies and, for small shocks, a first-order approximation under any constant returns technology, with an omitted term that scales with the response of the expenditure shares, which Fact 4 shows to be small. What it does not deliver, as discussed in Section 4, is the level of aggregate losses or the second-order term.

This approach relies on the differential exposure of country-sector pairs to plausibly exogenous variation in extreme heat over time both locally, used to identify β_i^{Local}, and in domestic and foreign agriculture, used to identify γ_i^{Dom} and γ_i^{Fgn}. This research design is in nature similar to a shift-share (or "Bartik") approach. The network shocks are constructed as a sum of a set of shocks, extreme heat in agriculture, weighted by input-output interlinkages as exposure share weights. Although the empirical facts in Section 3 suggest that downstream interlinkages do not endogenously adjust in response to extreme heat in agriculture, this assumption is not necessary for the identification of the effect of network shocks, which only relies on the quasi-random assignment of extreme heat (Borusyak et al., 2022). Identification and consistency of the γ's can therefore be satisfied in a setting where shocks are as-good-as-randomly assigned, mutually uncorrelated, large in number, and sufficiently dispersed in terms of their average exposure.

One of these conditions deserves scrutiny in this setting. The shocks are not mutually uncorrelated across origins: Fact 3 shows that extreme heat in agriculture has a Moran's I of

about 0.59 that rises over the sample, so the effective number of independent shocks is smaller than the 183 countries that supply them. Country-year fixed effects absorb the component of the shock vector that is common within a country-year, which removes the bulk of that correlation from the identifying variation, but they do not render the remaining shocks independent. This matters for inference rather than for consistency. Since the exposure of each observation is a weighted average of shocks originating in all 183 countries, clustering at the level of the country in which the exposed sector is located does not address correlation across the shocks themselves, and I therefore read the reported standard errors as a lower bound on sampling uncertainty.

The identification of local direct and network extreme heat shocks faces two major challenges. First, it is crucial to isolate extreme heat conditions in agriculture that propagate through the production network from the effect of local heat conditions. I address this challenge constructing sector-specific heat shocks, as detailed in Section 2. This allows me to isolate extreme heat conditions that affect agriculture based on crop sensitivity and exposure and affect the downstream sectors only by way of intermediate input linkages. I conduct a number of diagnostics tests in support of this hypothesis. Appendix Figure A2 displays the residual variation in extreme heat in agriculture conditional on country and year fixed effects and highlighting the variation for China, India, and the United States. Appendix Figure A3 displays the empirical residual variation in extreme heat exposure in manufacturing for the 183 countries over the sample period considered, conditional on country and year fixed effects. Most importantly, I compare the residual variation in extreme heat exposure in agriculture with heat shocks in any of the other five sectors and find no statistically significant relationship between these two measures (Appendix Figure A4). This result allays potential concerns on the collinearity of the sector-specific measures of heat exposure and implies the existence of independent sector-specific variation.

A second empirical challenge for identification is that the sum of exposure shares is not constant, that is, $\bar{\psi}^{i,n}_{Ag,\tau}$ varies across sectors and countries over time. In this case, even if shocks are uncorrelated and quasi-randomly assigned, the estimator will also leverage non-experimental variation in the shares, in addition to quasi-experimental variation in extreme heat conditions. Even when extreme heat is random, sector-countries with higher total agricultural requirements $\bar{\psi}^{i,n}_{Ag,\tau}$ will have systematically different values of the network shocks, leading to bias if they also have different unobservables. To address this challenge, I include the sum of exposure shares $\bar{\psi}^{i,n}_{Ag,\tau}$, interacted with year indicators, directly in Equation (13) (Borusyak et al., 2022). This approach isolates quasi-experimental variation in extreme heat in agriculture conditional on sector-country exposure shares. As a result, my approach does not rely on conventional

assumptions of independent or clustered data that would be inconsistent with the shift-share data structure when the shocks are considered random variables. Instead, domestic and foreign heat shocks are as-good-as-randomly assigned conditional on exposure weights.

This approach aims at quantifying the impact of trade-induced exposure to harmful extreme heat conditions in agriculture on sectoral value added. 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 transmission of these shocks due to the intersectoral reliance. A sector that shows no response to local weather conditions may nevertheless lose value added when extreme heat hits agricultural sectors around the world with strong commercial interlinkages with that sector. The effect would ripple down to downstream customer sectors that use agricultural inputs less intensively in response to increases in agricultural prices, thus reducing their own production.

With respect to previous approaches that account for sectoral and spatial linkages, there are a number of advantages of using Equation (13) for the aggregate and differential effect of extreme heat in agriculture. First, this specification links in a transparent way the shock's impact in general equilibrium to exposure measures and reduced form effects (direct and indirect). The model-consistent empirical driver of my approach is a significant departure from the traditional approach of computing the shock's general equilibrium impacts using calibrated spatial models in quantitative frameworks with calibrated spatial links (Redding and Rossi-Hansberg, 2017). Second, my approach remains valid under a flexible structure of spatial links and idiosyncratic shocks. This flexibility is in contrast with previous approaches, e.g., the "market access" (Donaldson and Hornbeck, 2016), which is an endogenous variable obtained from solving the general equilibrium model under restrictive assumptions on the spatial links in the economy and that requires observing all trade costs before and after the shock. Last, my empirical strategy is distinct from an indirect inference procedure that calibrates parameters to match arbitrarily chosen moments generated in the model with simulated shocks (Farrokhi and Pellegrina, 2023). This procedure may yield biased estimates of the reduced form semi-elasticities if the chosen moments are not closely related to the model-implied relationship. In contrast, my approach is not subject to this concern because it is derived from the model's predictions for the impact of the observed shock. The indirect inference exercise planned in Section 7 is disciplined in the same way: its auxiliary moments are not arbitrary, but the model's own reduced-form general equilibrium elasticities.

Importantly, country-year fixed effects in my specification isolate any residual variation in

extreme heat that is not spatially correlated across countries. This approach allows me to separate the effect of extreme heat exposure through input linkages from the unobserved spatial correlation in shocks across countries. To further allay any concern that input linkages embed linkages across space and are simply a proxy for the underlying correlation of heat shocks, I construct a gravity-based measure of spatial exposure to extreme heat in country n

$$SpatialHeat_{nt} \equiv \sum_{m \neq n} \frac{D_{mn}^{-\delta}}{\sum_{o \neq n} D_{on}^{-\delta}} ExtremeHeat_{mt}, \tag{14}$$

where D_{mn} is the bilateral distance between the population centroids of country n and m. The specification has a "gravity" structure in the sense that $SpatialHeat$ is higher if country n is closer to a country m exposed to higher extreme heat. The parameter δ controls how much indirect exposure declines with distance and I use the typical estimate of the trade elasticity by setting $\delta = 5$. In additional robustness checks, I replace country-year fixed effects with this measure that captures the spatial differential effect of heat exposure. This measure, at the cost of stronger identifying assumptions without country-year fixed effects, captures the net effect of spatial shock transmission.

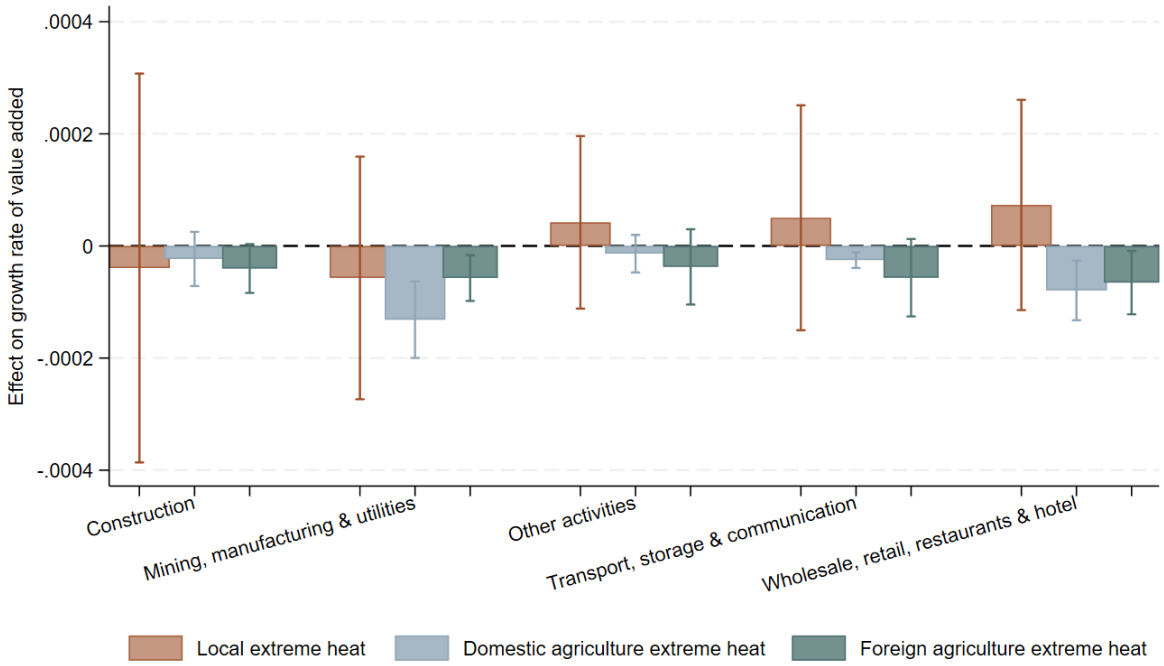
6 Extreme heat across sectors and space

In this section, I report the results from the estimation of Equation (13) that quantifies the propagation of extreme heat on agriculture across the economy through the production network. I begin with the first-degree weighting scheme, in which the exposure weights are the direct input shares $\omega_{m,\tau}^{j,n}$ of Equation (3), since this is the exposure measure that the prior literature has used, and I turn below to the total-requirements weights $\psi_{Ag,m,\tau}^{i,n}$ that Section 4 identifies as the first-order relevant object. Figure 6 displays the 15 jointly estimated coefficients, three for each of the five sectors, associated with local extreme heat conditions and downstream exposure to extreme heat in domestic and foreign agriculture.

Starting from the effect of local extreme heat on the growth rate of sectoral value added, the coefficients are not statistically distinguishable from zero for any of the five sectors. I then turn to the coefficients associated with extreme heat conditions in domestic and foreign agriculture. The coefficients measuring the differential impact of exposure to extreme heat in agriculture on the growth rate of downstream sectoral value added are negative, indicating that local extreme heat in agriculture propagates to downstream sectors reducing their growth rate. For downstream sectors that heavily rely on agricultural goods as intermediate input, such as

mining, manufacturing, and utilities, and wholesale, retail, restaurants and hotels, the effect is more pronounced and statistically significant for extreme heat in both domestic and foreign agriculture, suggesting that extreme heat in agriculture propagates both across sectors and space. On average, one degree day of extreme heat exposure in domestic (foreign) agriculture reduces the growth rate of manufacturing value added by 0.47% (0.15%). Similarly, one degree day of extreme heat exposure in domestic (foreign) agriculture reduces the growth rate of wholesale, retail, restaurants and hotels value added by 0.26% (0.21%).

Figure 6. Effect of local heat and downstream exposure to extreme heat in agriculture on sectoral value added



Notes: Bars represent the sector-specific coefficients associated with local extreme heat and with extreme heat in domestic and foreign agriculture obtained estimating Equation (13). Extreme heat in agriculture is constructed as in Equation (1). Domestic and foreign agriculture extreme heat metrics are constructed respectively as in Equations (5) and (6), using the first-degree exposure weights $\omega_{m,\tau}^{j,n}$ of Equation (3). The specification jointly estimates all sector-specific coefficients in a regression model that accounts for country-sector, sector-year, country-year fixed effects and sector-specific second-order polynomial of total precipitation and sum of exposure shares. Vertical lines represent the 95% confidence intervals with standard errors clustered at the country level. Tabular results are reported in Appendix Table C5.

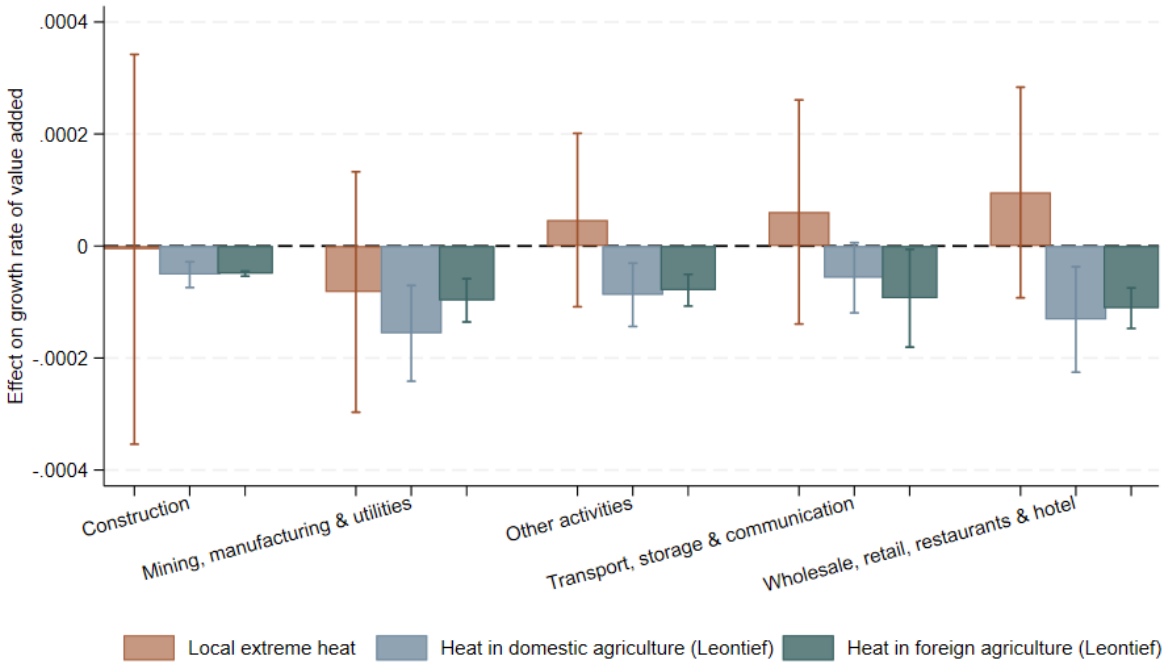
Altogether, these findings have two consequences in the interpretation of previous temperature-output relationships. First, from a methodological perspective, sector-specific estimates that

only account for local weather conditions 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. This is visible when comparing point estimates of local heat in Figures 2 and 6. While the estimates are noisy and imprecisely estimated, the magnitude of the coefficients indicates a potential downward bias in the estimates obtained without accounting for extreme heat in agriculture across space. In particular, the statistical and economic significance of extreme heat in foreign agriculture suggests that also geographically distant weather fluctuations matter through input linkages. Second, from an economic perspective, extreme heat conditions in agriculture are transmitted through the production network, affecting other sectors beyond agriculture and beyond national borders. As a result, recent estimates on the economic damage of temperature increases may have been underestimated due to the omission of this propagation channel. On average, across the five downstream sectors, one degree day of extreme heat in domestic (foreign) agriculture reduces the sectoral growth rate by 0.18% (0.15%). This result indicates a substantial underestimation of the total economic cost imposed by extreme heat exposure in agriculture via intermediate input linkages. When only considering the semi-elasticities of the growth rate of sectoral value added, the average effect across sector is 0.03%.

Beyond first degree sectoral interlinkages. The analysis has so far relied on first degree input linkages in the production network. These are not the weights that the framework of Section 4 calls for: Equation (11) shows that the first-order exposure of a producer to a distant agricultural shock is its total requirement of agricultural inputs, direct and indirect, and not the share it buys directly. To account for the full transmission of shocks over the network, I therefore construct the Leontief inverse matrix, which summarizes the sector-specific technical coefficients of the shock propagation through a power series representation of input linkages. By taking the inner product of extreme heat in agriculture and the Leontief inverse matrix, I obtain measures of extreme heat conditions in agriculture that take full inter-sectoral relations into account. I estimate a specification using the resulting vector of shocks of extreme heat in agriculture and report the coefficients in Figure 7. By taking into account the full direct and indirect linkages of downstream sectors with agriculture, all sectors are negatively affected by extreme heat in both domestic and foreign agriculture. The effect of extreme heat in agriculture percolates downstream to final goods and service sectors such as construction, other activities, and transport, storage, and communication. The effects are also larger in magnitude than first degree input linkages. At the mean, the effect of one degree day of heat exposure in domestic (foreign) agriculture reduces growth rate of manufacturing value added by 0.56% (0.35%). Sim-

ilarly, extreme heat in domestic (foreign) agriculture reduces growth rate of wholesale, retail, restaurants and hotels value added by 0.43% (0.36%). On average, across the five downstream sectors, a one-degree day increase in exposure to extreme heat in domestic (foreign) agriculture reduces the sectoral growth rate by 0.31% (0.26%).

Figure 7. Sector-specific response to extreme heat in agriculture accounting for higher degree linkages



Notes: Bars represent the sector-specific coefficients associated with local extreme heat shocks and extreme heat in domestic and foreign agriculture. Domestic and foreign downstream shocks are constructed respectively as in Equations (5) and (6), with extreme heat in agriculture constructed as in Equation (1) and the exposure weights given by the total requirements $\psi^{i,n}_{Ag,m,\tau}$ from the Leontief inverse of the downstream sectoral interlinkages of Section 2.3. The specification jointly estimates all sector-specific coefficients in a regression model that accounts for country-sector, sector-year, country-year fixed effects and sector-specific second-order polynomial of total precipitation and sum of exposure shares. Vertical lines represent the 95% confidence intervals with standard errors clustered at the country level. Tabular results are reported in Appendix Table C6.

Propagation over time. The estimates indicate that extreme heat in agriculture propagates across sectors and countries with a contemporaneous short-run negative effect on the growth rate of value added in downstream sectors. It might be, however, that the effects of extreme heat on agricultural production may take up to one year to manifest in downstream sectors, particularly in those furthest away in the supply chain from direct agricultural inputs. This delayed impact

might occur for two reasons. First, the structure of the crop calendar complicates the alignment of agricultural impacts with the calendar year, as growing seasons can extend across two years. As a result, the cumulative negative effect of extreme heat on agricultural output may only become evident at the conclusion of the growing season, which may not coincide with the timing of value added measurements in national accounts. Second, in downstream sectors, the impact of extreme heat in a given year may only emerge in subsequent years due to the lag in the processing and distribution of agricultural goods. An alternative hypothesis, however, is that if agricultural production rebounds the year following an extreme heat shock, there might be no negative effect on downstream sectors in the following year. This dynamic effect could be further reinforced by the availability of agricultural inventories, which allow agricultural producers to smooth shocks (Roberts and Schlenker, 2013). To empirically test which of these two mechanisms dominate, I estimate the baseline regression including a one-year lagged measure of local heat and of extreme heat in domestic and foreign agriculture. Appendix Figure B9 displays the six coefficients on contemporaneous and lagged local and network heat impacts for each of the five sectors. Local extreme heat is never statistically significant, however, an interesting pattern emerges for extreme heat in domestic and foreign agriculture. They both have a negative and statistically significant impact on most sectors, with the effect larger in magnitude on lagged shocks, in particular for sectors further downstream. This result suggest that the cumulative effect of extreme heat exposure in domestic and foreign agriculture is larger once we account for lags in the response of the growth rate of value added in downstream sectors.

Robustness. I consider a number of robustness and placebo tests to ascertain the stability and validity of my findings. I conduct these exercises for both first degree linkages and for the Leontief linkages. First, I estimate the baseline specification including country-specific quadratic time trends and country-sector specifics quadratic time trends, respectively. These two additional controls flexibly account for country-specific and country-sector time-trending covariates allowing these covariates to influence different countries (demographic trends) or country-sectors in different ways (e.g., country-specific trends in agricultural innovations, manufacturing input use, sectoral labor supply trends). Since the outcome variable is the derivative of value added, quadratic country-(sector) specific time trends permit growth rates to evolve nonlinearly over time, allowing to account for country-(sector) specific cubic polynomials in value added levels. Secondly, the exclusion of certain countries does not substantially affect my baseline estimate. A potential concern is that certain countries may overinfluence my estimates and thus drive my findings. Using a balanced sector-country sample, excluding certain large countries (China,

India, Russia, United States), or the 10% coldest or hottest countries, does not substantially change my baseline findings (Appendix Figures B10 and B11).

Upstream propagation. As a test of the directional prediction of the framework in Section 4, under which a supply-side shock propagates downstream while the upstream channel cancels exactly under Cobb-Douglas technologies, I construct a measure of exposure to extreme heat weighted by upstream linkages with agriculture. Since extreme heat is a supply-side shock that reduces agricultural output and increases its prices and thus percolates to downstream sector as a input shock, my theoretical model predicts that the effect should only manifest downstream. I empirically validate this hypothesis testing whether extreme heat propagates upstream. Appendix Figures B12 and B13 show that extreme heat exposure in agriculture does not propagate upstream neither using first order linkages nor using the linkages obtained from the Leontief inverse matrix. This result suggests that extreme heat in agriculture behaves as a supply-side productivity shock that only propagates downstream. The ten coefficients on extreme heat in domestic and foreign agriculture are very close to zero in magnitude and not statistically significant. Since upstream and downstream intensity are correlated across sectors, the upstream-only specification is a weaker test than the one that includes both exposure measures jointly, and I read the null as evidence on the direction of propagation conditional on that caveat.

Distance-weighted extreme heat. In an additional robustness check, I introduce the distance-weighted measure of $SpatialHeat$ constructed in Equation (14) to examine whether input linkages capture the same variation in the spatial correlation structure of shocks. Dingel et al. (2023) and Neal (2023) demonstrate the importance of accounting for spatial linkages in the estimation of global climate damages. I empirically test whether my approach confounds the role of spatial correlation, but find that the distance-weighted measure $SpatialHeat$ is not statistically significant at any conventional level, and controlling for it in my baseline specification does not substantially alter the magnitude of the input-weighted network shocks (Appendix Figure B14). This result suggests that distance-weighted exposure to extreme heat does not capture the effect identified by extreme heat conditions in agriculture transmitting through input linkages.

7 A quantitative model of agriculture in the global production network

7.1 From reduced form to quantification

The estimates of Section 6 identify how much more one country-sector loses than another, in the same country and year, when extreme heat hits agriculture. Section 4 explains why this is the object the regression recovers, and why on its own it is not an estimate of the aggregate cost of warming. To move from relative responses to levels, I embed the framework of Section 4 in a fully specified multi-region multi-sector general equilibrium model, calibrate it to the observed global production network, and solve it exactly.

The model delivers three objects the regression cannot. First, it recovers the level of aggregate losses. The general equilibrium response common to all sectors within a country-year, which the fixed effects absorb, is restored once the model is solved: factor prices, sectoral prices, and the allocation of labor across sectors all adjust, and the missing intercept becomes a computed quantity rather than a nuisance parameter (see, e.g., Chodorow-Reich, 2020; Adao et al., 2026). Second, it decomposes those losses into the part that originates in agriculture itself and the part that reaches other sectors through input linkages, which is the quantity of interest for this paper. Third, it supports counterfactuals in which the vector of agricultural heat shocks is changed and the world economy is re-solved. Because the sensitivity of agricultural productivity to heat is disciplined by short-run panel estimates, I restrict attention throughout to retrospective counterfactuals.

7.2 Model

Agriculture. Agriculture in country n aggregates many crops c, each produced with land and labor as perfect complements, following Costinot et al. (2016), and each subject to its own heat-sensitive productivity term A_{cn}:

$$Y_{Ag,n} = \prod_c Q_{cn}^{b_{cn}}, \qquad Q_{cn} = A_{cn} \min\left\{H_{cn}, L_{cn}\right\}, \tag{15}$$

where H_{cn} is the land and L_{cn} the labor allocated to crop c in country n, and the weights b_{cn} are country-specific crop value shares summing to one. Extreme heat enters the model only through the crop productivities A_{cn}. The country-specific composition of the agricultural basket and the crop-specific temperature thresholds described in Section 2.2 therefore determine how

much a given temperature realization lowers agricultural productivity in each country, mirroring the construction of $AgriHeat_{nt}$ in Equation (1); the model weights crops by value shares while the exposure measure weights by cropped area. Two departures from Costinot et al. (2016) are worth stating. The land and labor complementarity is theirs: in their notation a parcel combines hectares with workers in fixed proportions, and I keep that structure. The crop aggregator is not. They combine crops through a constant elasticity of substitution demand system and allocate land across crops through a Fréchet discrete choice, so that comparative advantage across crops evolves as productivities change, which is the adaptation margin their paper is built to measure. I aggregate crops with fixed value shares b_{cn}, which holds the crop mix constant. That margin is therefore shut down in the model as well as in the exposure measure of Section 2.2, and both omissions push in the same direction, toward overstating the losses I compute. Relatedly, because land and labor are perfect complements within a crop and the land endowment is fixed and always used, agricultural employment is pinned by the land endowment, so the labor mobility assumed below operates across the non-agricultural sectors. Costinot et al. (2016) avoid this by letting parcels stand idle when the value of their marginal product falls below the wage bill; allowing idle land is the natural way to reopen the margin.

Non-agricultural sectors. Production outside agriculture has a nested constant elasticity of substitution structure with three elasticities,

$$\begin{aligned} Y_{in} &= A_{in}\left[\alpha_i^{1/\sigma} L_{in}^{\frac{\sigma-1}{\sigma}} + (1-\alpha_i)^{1/\sigma} X_{in}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \\ X_{in} &= \mathrm{CES}_\theta\left(\{X_j^{i,n}\}_j\right), \qquad X_j^{i,n} = \mathrm{CES}_\varepsilon\left(\{X_{j,m}^{i,n}\}_m\right). \end{aligned} \tag{16}$$

The outer nest, governed by σ, determines how readily a producer substitutes labor for the bundle of intermediate inputs. The middle nest, governed by θ, determines substitution across supplying sectors, for instance between cotton and machinery. The inner nest, governed by ε, determines substitution across countries of origin within a supplying sector, for instance between Indian and Pakistani cotton, and is the Armington elasticity that governs trade.

Demand and equilibrium. The representative household in country n has Cobb-Douglas preferences over the $J+1$ sectoral bundles, with expenditure shares β_i, and combines origins within each bundle with the same Armington elasticity ε:

$$U_n = \prod_i C_{in}^{\beta_i}, \qquad C_{in} = \mathrm{CES}_\varepsilon\left(\{c_m^{i,n}\}_m\right). \tag{17}$$

The equilibrium is competitive and efficient. Labor is supplied inelastically, is mobile across

sectors within a country, and is immobile across countries. Land is specific to agriculture and mobile across crops. Prices, wages, and the rental rate on land adjust to clear all goods and factor markets. The structure follows the open-economy production network of Baqaee and Farhi (2019) and Baqaee and Farhi (2024); a self-contained appendix with the full equilibrium system and the solution algorithm is in preparation for the next version of the paper.

7.3 Taking the model to the data

Table 1 summarizes the parameters, which fall into three groups.

The first group consists of the three substitution elasticities, which I calibrate from the literature. I set $\sigma = 0.6$, the aggregate elasticity of substitution between capital and labor in US manufacturing estimated by Oberfield and Raval (2021), which I adopt as a benchmark for substitutability between the primary factor bundle and intermediate inputs. The nest it measures is not the nest I need, so I treat σ as a calibrated benchmark rather than an estimate; reporting how the results move with it is part of the sensitivity analysis planned for the next iteration. I set $\theta = 0.1$ following Atalay (2017); what matters for the results is not the precise value but that the elasticity across supplying sectors lies well below one, which is Atalay's central finding and a rejection of the Cobb-Douglas benchmark across inputs. I set the Armington elasticity across origins to $\varepsilon = 4$, which corresponds to a trade elasticity of $\varepsilon - 1 = 3$. Simonovska and Waugh (2014) estimate a trade elasticity of approximately 4, which would correspond to $\varepsilon = 5$, so my choice implies marginally less substitution across origins than their estimate and, if anything, raises the transmission of foreign agricultural shocks.

The second group consists of the shares, which I match to the data rather than estimate. The input-output linkages $\omega_{j,m}^{i,n}$, the labor shares α_i, and the final-demand shares β_i all come from EORA26, averaged over the five-year period 1970-1974, so that the calibrated network predates the estimation window and is not itself a function of the heat realizations I study. The crop composition of the agricultural basket, b_{cn}, comes from FAO crop value shares. The labor and final-demand shares are country-specific in the calibration, so α_i and β_i in Equations (16) and (17) should be read as α_{in} and β_{in}, with the country index suppressed in the equations for readability. Setting the constant elasticity of substitution share parameters equal to the observed expenditure shares, with base prices normalized to one, implies that the model reproduces the pre-shock allocation exactly by construction. Using the 1970-1974 network rather than a contemporaneous one keeps the calibration exogenous to the shocks I study, but it also understates the linkage channel, since Section 2.3 documents that input linkages with agriculture intensified

over the sample.

The third group consists of a single estimated parameter: the sensitivity of agricultural productivity to extreme heat. I choose it so that the agricultural value added response of the solved model reproduces the reduced-form estimate of Fact 1. Because the event study in Appendix Figure B5 recovers only contemporaneous effects, I treat the estimated growth response as a one-time level effect rather than as a permanent change in the growth rate.

I solve the model exactly, with a nested fixed point on prices and factor allocations, rather than log-linearizing it. This matters for the exercises that follow: the solved equilibrium retains the higher-order terms that the first-order expression in Equation (11) omits. Any amplification those terms generate is conditional on the calibrated elasticities, so the results below focus on the incidence decomposition, and I defer amplification magnitudes to the iteration of the paper in which the elasticities are estimated.

Two extensions are in progress. First, rather than calibrating all of the substitution elasticities, I discipline the elasticity across supplying sectors, θ, directly from the reduced-form coefficients by indirect inference: Equation (13) is estimated on data simulated from the solved model, and θ is chosen so that the simulated spillover coefficients match their empirical counterparts, holding σ and ε at their calibrated values. The auxiliary moments in this procedure are not arbitrarily selected, since they are the model's own reduced-form general equilibrium elasticities; the cross-origin elasticity ε is not separately identified by this design, because the foreign exposure measure aggregates across origins. Second, the spillover coefficients that are not targeted in the calibration serve as validation, in the sense that a well-specified model should reproduce the sign and the cross-sector ranking of coefficients it was not asked to fit. In the results reported below the elasticities are calibrated, so I treat the decomposition as conditional on that calibration.

7.4 Counterfactuals

I use the solved model for two retrospective exercises. Since the elasticity of agricultural productivity to heat is disciplined by short-run panel estimates, my counterfactual exercises focus on a retrospective quantification of the economic cost of recent warming, instead of a projection of future climate damages. For this reason, I abstain from applying estimates based on past exogenous short-run changes in extreme heat to future long-term output changes due to climate change, which would require accounting for possible adaptations in anticipation of future climate change (Carleton et al., 2024). Both exercises change only the vector of agricultural productivity

Table 1. Parameters of the quantitative model

Parameter	Source
Calibrated	
$\sigma = 0.6$ (primary factors vs. intermediate inputs)	Oberfield and Raval (2021), benchmark
$\theta = 0.1$ (across supplying sectors)	Atalay (2017)
$\varepsilon = 4$ (across countries of origin)	Simonovska and Waugh (2014)
Matched to data	
$\omega_{j,m}^{i,n}$ (input-output linkages)	EORA26, 1970-1974
α_i (labor shares)	EORA26, 1970-1974
β_i (final-demand shares)	EORA26, 1970-1974
b_{cn} (crop composition of the agricultural basket)	FAO
Estimated	
Sensitivity of agricultural productivity to extreme heat	Fact 1

Notes: The elasticity ε is an Armington elasticity of substitution across countries of origin, corresponding to a trade elasticity of $\varepsilon - 1 = 3$; Simonovska and Waugh (2014) estimate a trade elasticity of approximately 4, which would correspond to $\varepsilon = 5$. The value of σ is the aggregate capital-labor elasticity estimated by Oberfield and Raval (2021) for US manufacturing, adopted here as a benchmark for the primary-factor versus intermediate-input nest rather than as a direct estimate of that nest. The value of θ is taken as a benchmark below one rather than as a tightly estimated point: what the results require is that substitution across supplying sectors be limited, which is the finding of Atalay (2017). Input-output linkages, labor shares, and final-demand shares are five-year averages over 1970-1974, which precede the estimation window; the labor and final-demand shares are country-specific. The sensitivity of agricultural productivity to extreme heat is chosen so that the agricultural response of the solved model reproduces the reduced-form estimate of Fact 1 in Section 3.

shocks, holding every other feature of the calibrated economy fixed.

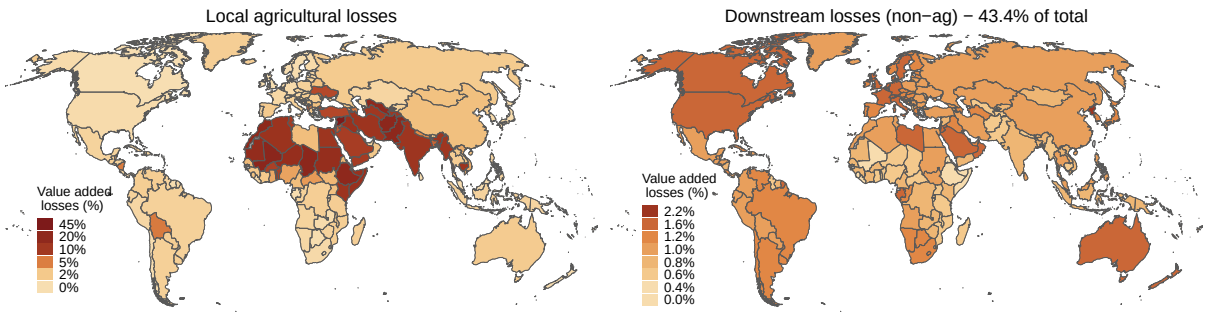
The cost of recent warming. In the first exercise, the shock is the observed change in exposure to extreme heat in agriculture between 2001-2020 and the 1975-2000 baseline. Averaged across countries, crop-weighted extreme heat rose from 71 to 90 degree days, an increase of 19 degree days, or 27%. I translate this change into a vector of crop productivity shocks $\{d \log A_{cn}\}$ using the estimated heat sensitivity, feed it into the model, and solve for the new equilibrium.

Figure 8 reports the resulting annual value added losses, expressed throughout as a percentage of total (all-sector) value added. The left panel displays direct losses in agriculture from local extreme heat; the right panel displays losses in non-agricultural sectors that reach them through input linkages. Direct agricultural losses amount to 1.6%, downstream losses to 1.2%, and total losses to 2.8%. Input linkages therefore account for 43% of the total value added losses caused by recent warming in agriculture. The two panels differ markedly in their geography. Direct losses concentrate in the Sahel, North Africa, the Middle East, and South Asia, where agriculture is both heat-exposed and a large share of value added. Downstream losses are more evenly spread, and they are sizable in countries with little local heat exposure, because a coun-

try's downstream loss depends on how intensively its producers rely on agricultural inputs and on where those inputs are grown, rather than on its own climate.

Decomposing downstream losses by the origin of the agricultural input makes this explicit. Domestic linkages, through which a country's own agricultural shock reaches its own downstream sectors, account for 41% of downstream losses; foreign linkages account for the remaining 59%. Transmission through international input linkages is thus the larger of the two channels, and a substantial share of the losses caused by extreme heat in agriculture lands in countries that experienced little of that heat. This is not in tension with the larger domestic coefficients in Section 6: per degree day of heat at a given origin, the response to domestic agricultural heat is stronger, but the foreign exposure of a country-sector aggregates shocks from all other origins, so the foreign channel carries more of the aggregate incidence.

Figure 8. Annual value added losses (%) induced by recent warming in agriculture



Notes: The figure shows annual value added losses (%) obtained by solving the quantitative model under the observed 2001-2020 exposure to extreme heat in agriculture and comparing it to a counterfactual in which exposure had remained at its 1975-2000 baseline average (an increase of 19 degree days on average, or 27%). The left map displays direct losses in agricultural value added from local extreme heat. The right map displays losses in the five non-agricultural sectors reaching them through domestic and foreign input linkages. Country-level losses are value-added-weighted sums of sectoral losses. Note the different scales in the two panels.

Network position and the origin of the shock. In the second exercise, I ask how much of a single country's agricultural heat shock the rest of the world absorbs. I simulate 183 counterfactuals in which one country at a time experiences a one standard deviation increase in extreme heat in agriculture, measured against the observed global annual distribution of crop-weighted extreme heat, holding heat in every other country at its baseline, and I solve the world economy and record global value added losses for each.

Figure 9 reports the ten largest. Global losses are largest when the shock hits China, at approximately 21 billion US$ per year, followed by India at approximately 17 billion US$ per year. Summing across all 183 single-country counterfactuals gives approximately 189 billion US$ per year; because the solved model is nonlinear, this sum summarizes the 183 separate exercises rather than the loss from one simultaneous global shock, and the gap between the two is itself a measure of the curvature the network introduces. The ranking tracks a country's position in the production network rather than the size of its own agricultural losses. Brazil, China, France, India, and the United States, which together account for more than 45% of world crop output (Costinot et al., 2016), are also the origins whose shocks generate the largest losses elsewhere in the world.

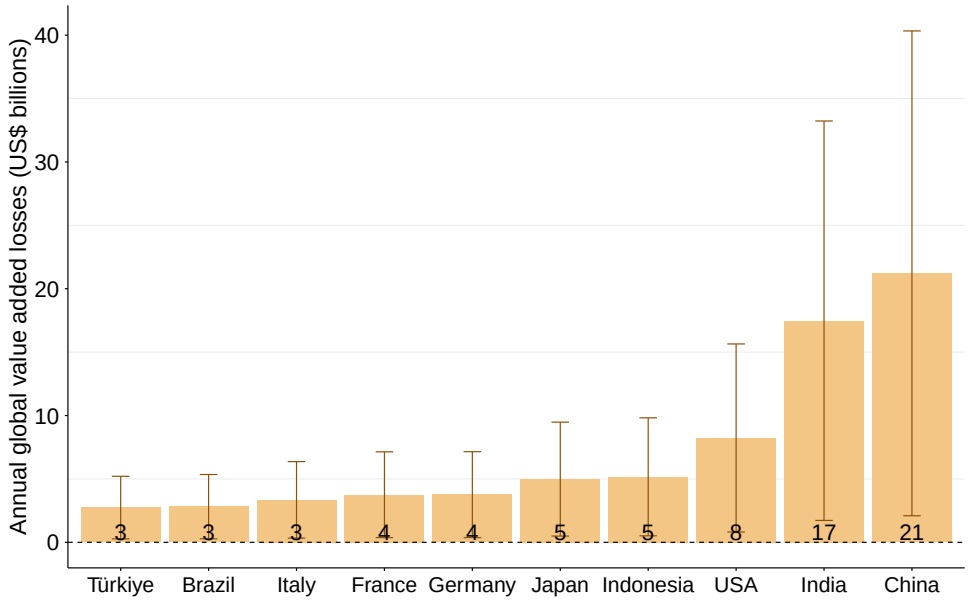
This exercise is likewise a decomposition of the input-linkage channel rather than a damage estimate: it holds constant everything except agricultural productivity in a single country, and it measures how much of that shock is transmitted abroad through trade in intermediate inputs. Read that way, it carries a direct implication for adaptation policy. The returns to reducing heat sensitivity in agriculture are not confined to the country that makes the investment, and they are largest where the agricultural sector is most deeply embedded in the global production network. Appendix Figures I1 and I2 report total losses by country and the cross-country distribution of local and downstream losses.

8 Conclusion

Recent studies have pushed forward the frontier for an accurate estimation of aggregate economic losses induced by climate for an adequate quantification of the total economic impact of climate change (Bilal and Känzig, 2026; Nath et al., 2024). This paper contributes to this effort by shedding light on a new potential component of climate damages, arising from the propagation of extreme heat in agriculture through production networks across sectors and countries. Complementing firm level evidence on the spillover effects of natural disaster shocks, I build on prior research on production networks to quantify the economic cost of global warming. The methodology is applied to global production networks constructed from input-output sectoral interlinkages and sectoral value added data combined with high-resolution daily temperatures between 1975 and 2020.

The analysis reveals that input linkages work as a transmission mechanism of extreme heat

Figure 9. Annual global value added losses from a one standard deviation increase in extreme heat in agriculture in a single country (in x-axis)



Notes: The figure shows annual global value added losses (2015 US$ billions) obtained by solving the quantitative model when the country reported in the x-axis experiences a one standard deviation increase in extreme heat in agriculture and every other country remains at its baseline exposure. Brown bars indicate the 95% confidence intervals.

conditions in agriculture across countries, generating substantial fluctuations in sectoral value added. Downstream sectors, including manufacturing, mining, utilities, and wholesale, retail, restaurants, and hotel that are unresponsive to local heat suffer from substantial economic losses due to the interdependence of their production process with domestic and foreign agricultural production exposed to extreme heat. 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 quantitative models that do not account for input linkages.

The findings point to the structure of sectoral production network linkages as a key driver of aggregate fluctuations induced by extreme heat in agriculture. In particular, they indicate that even if most sectors with the exception of agriculture are sheltered from local weather fluctuations, the potential propagation of the impacts on agriculture along the economy's production network can impact them, thus resulting in movements in macroeconomic aggregates. Using the reduced form estimate of the direct agricultural response to discipline a calibrated general equilibrium model of the global production network, I show that input linkages account for ap-

proximately 43% of the total value added losses induced by recent warming in agriculture, with foreign linkages accounting for the majority of downstream losses. Global losses are sizable even for just a single country experiencing extreme heat if the country is strongly interconnected in the global production network. This is the case for China, India, the United States, France, and Brazil. A one standard deviation increase in extreme heat in agriculture in China alone lowers global value added by approximately 21 billion US$ per year.

Several important avenues remain open to future research. First, the analysis provides modest but suggestive evidence of adaptation. In particular, the effect of local extreme heat conditions depends on climate and income. My analysis, however, cannot reject the hypothesis of little to modest evidence of countries' ability to reduce their exposure to extreme heat in agriculture by adjusting input linkages. My approach does not explicitly model adaptive investments, technological change, or other agriculture-specific adaptive responses (e.g., irrigation) or production process strategies (e.g., inventories) that may heterogeneously affect the response functions and reduce climate damage. As an example, crop-specific extreme heat conditions are computed over a time-invariant measure of agricultural land that does not allow for crop specialization adjustments, a crucial adaptive margin that can help mitigate climate damages (Costinot et al., 2016). Although my analysis cannot reject differential extreme heat exposure in agriculture in a country by varying the geographic distribution of crop acreage over time, accounting for these margins may alter the propagation patterns of extreme heat conditions. Related to these long run adjustments to climate, the analysis is also mostly silent about agents' climate beliefs and expectations, which explain adaptation (Shrader, 2021; Zappalà, 2024). Although my analysis accounts for implicit models of adaptation by using different time frames to compute anomalies in local extreme heat exposure for other sectors, I leave to future research accounting for heterogeneous beliefs and expectations in production networks and supply-chain relationships, modelling the learning process about climate risk from weather realizations and their spatial correlation structure.

Second, the reduced form analysis studies the transmission of weather shocks through observed input-output interlinkages, an approach that is exact under Cobb-Douglas technologies and that, away from Cobb-Douglas, omits a reallocation term scaling with the departure of the substitution elasticities from one. The quantitative model relaxes this restriction by specifying elasticities of substitution between primary factors and intermediate inputs, across supplying sectors, and across countries of origin, but in the present version of the paper those elasticities are calibrated from the literature. When inputs are complements, limited substitutability can

amplify aggregate losses beyond the fixed-share accounting, and reallocation can partially transmit supply shocks upstream, a channel so far documented only at the firm level. Estimating the elasticity across supplying sectors directly from the reduced form coefficients, and quantifying the amplification it implies, is the object of ongoing work and the natural next step of this project.

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Appendix

"Propagation of extreme heat in agriculture across sectors and space"

Guglielmo Zappalà

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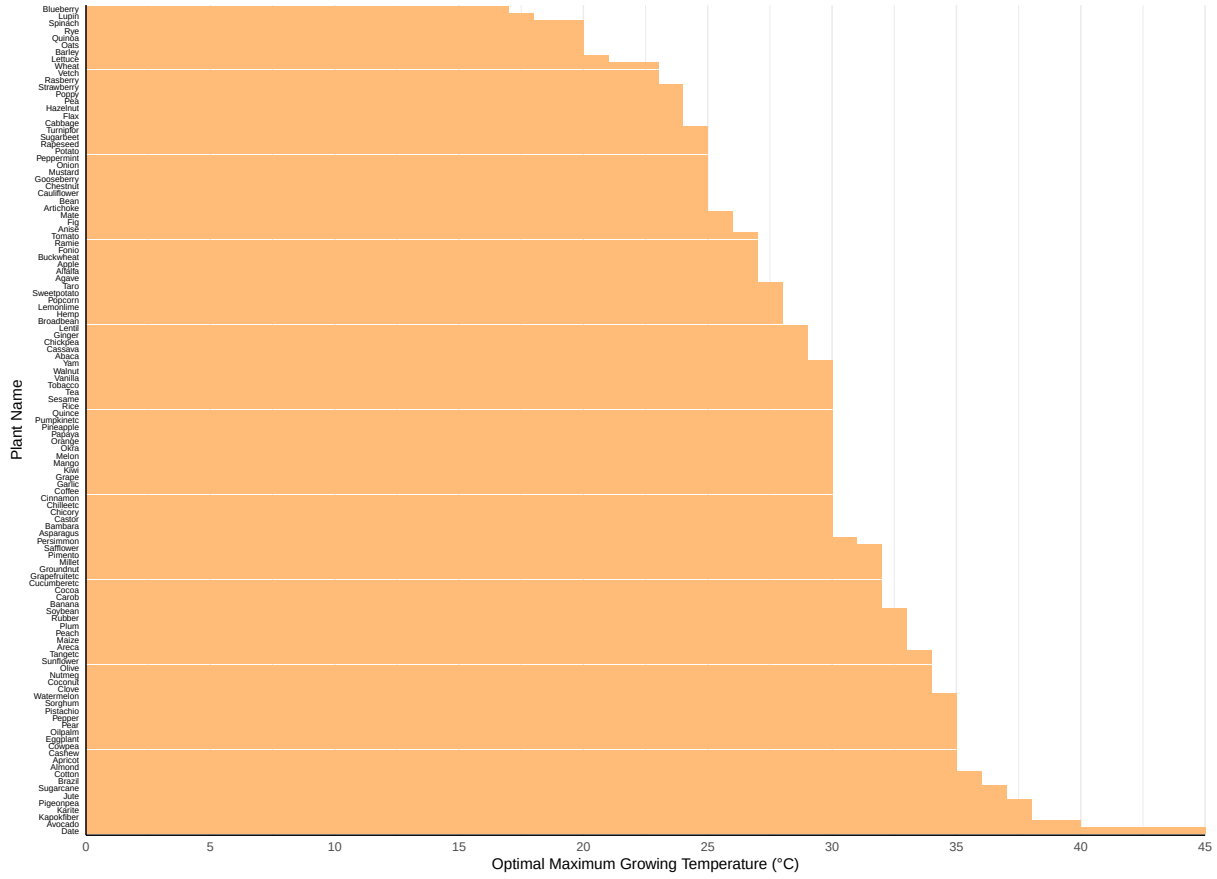
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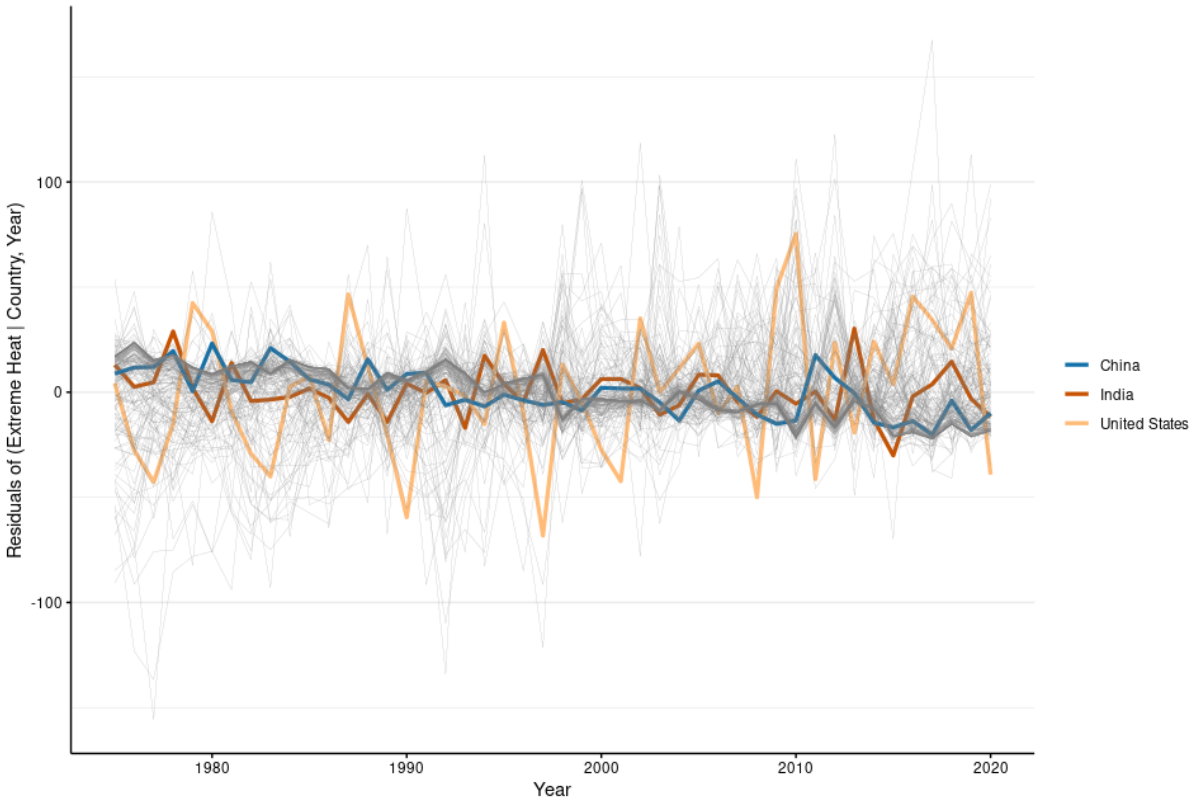
A Additional figures - Descriptive Statistics

Figure A1. Crops and optimal maximum growing temperature



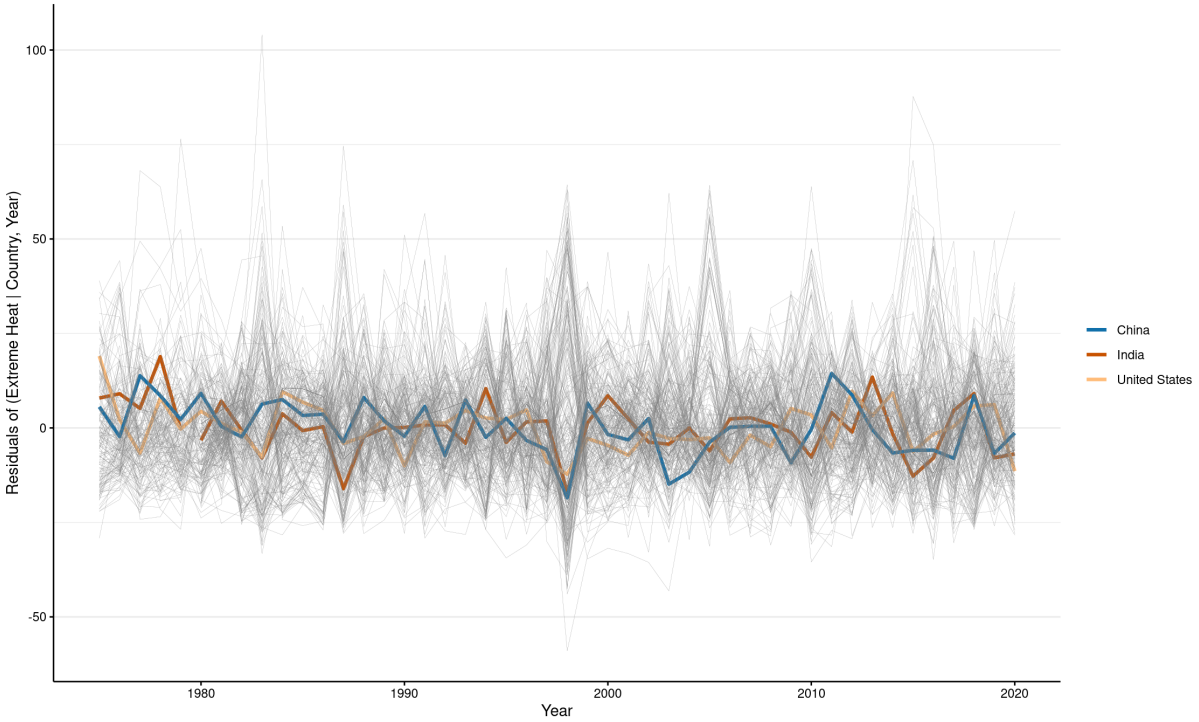
Notes: The figure shows the optimal maximum growing temperature for the 118 plant species in my final sample, as reported in the FAO EcoCrop (UN FAO, 2024).

Figure A2. Residuals in extreme heat exposure in agriculture



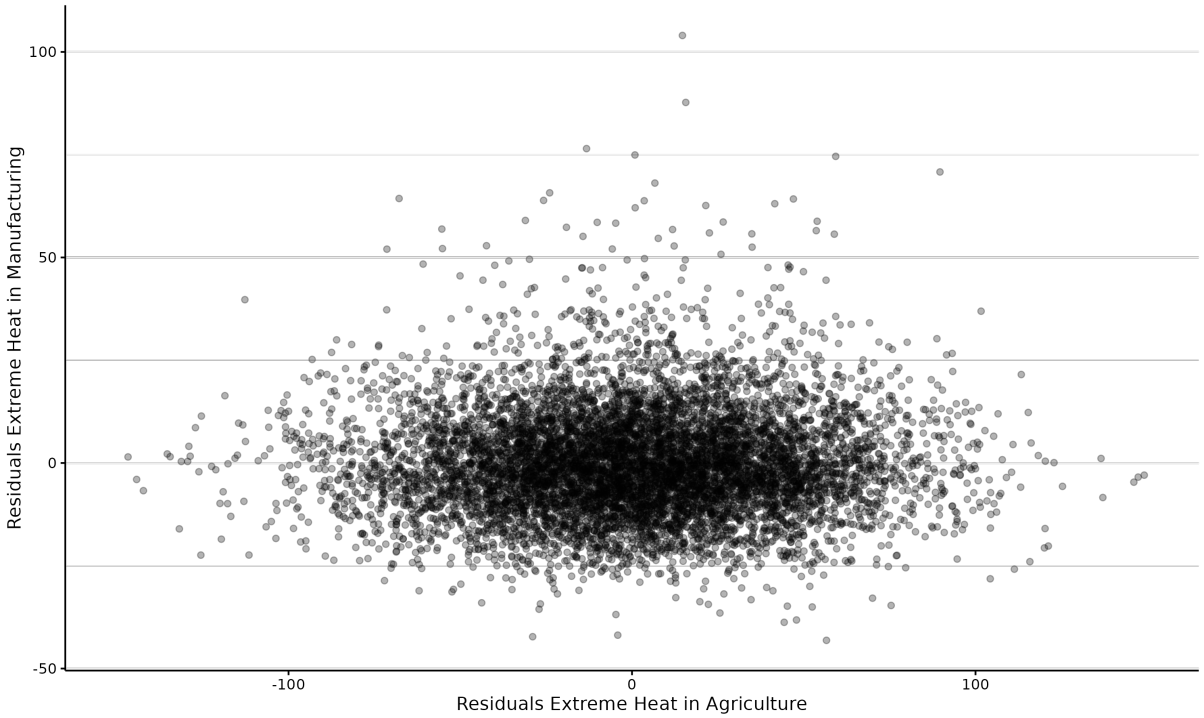
Notes: The figure shows the residuals in extreme heat exposure in agriculture obtained from a regression projecting extreme heat on country and year fixed effects.

Figure A3. Residuals in heat shocks in manufacturing



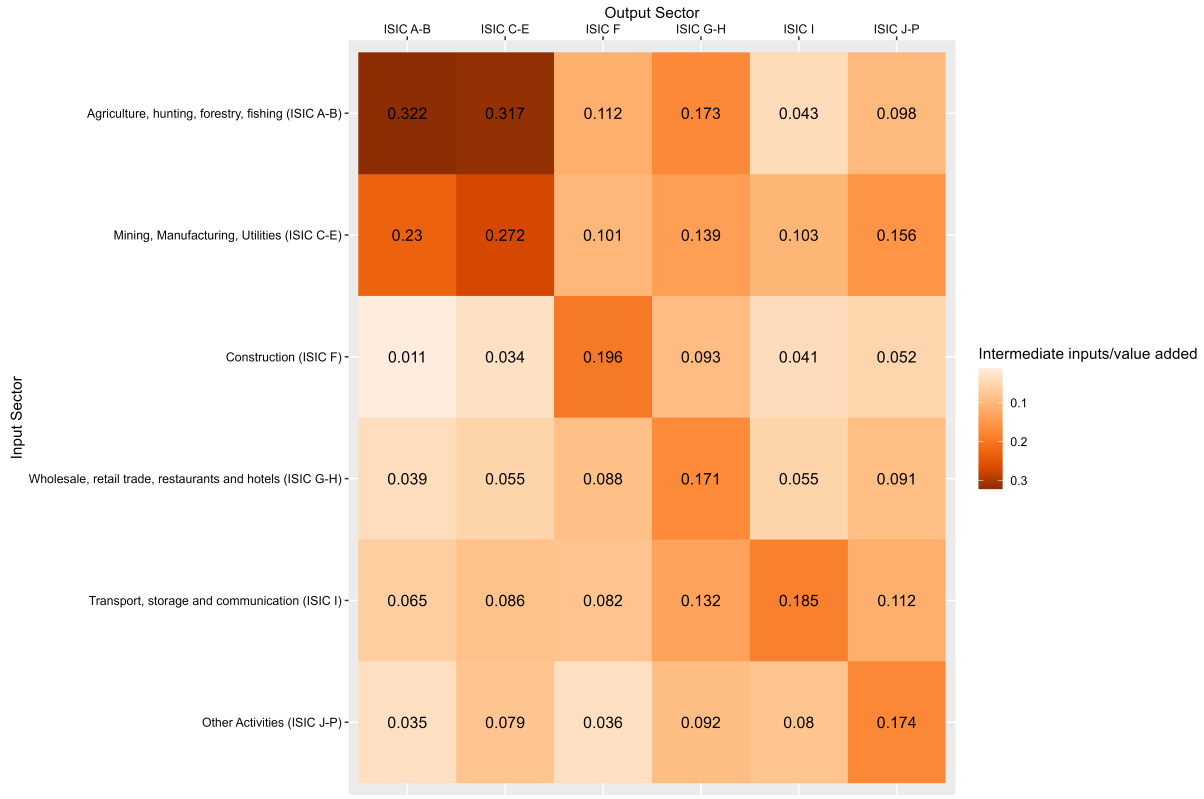
Notes: The figure shows the residuals in extreme heat exposure in manufacturing obtained from a regression projecting extreme heat on country and year fixed effects.

Figure A4. Scatter plot of residuals in agricultural and manufacturing sectors



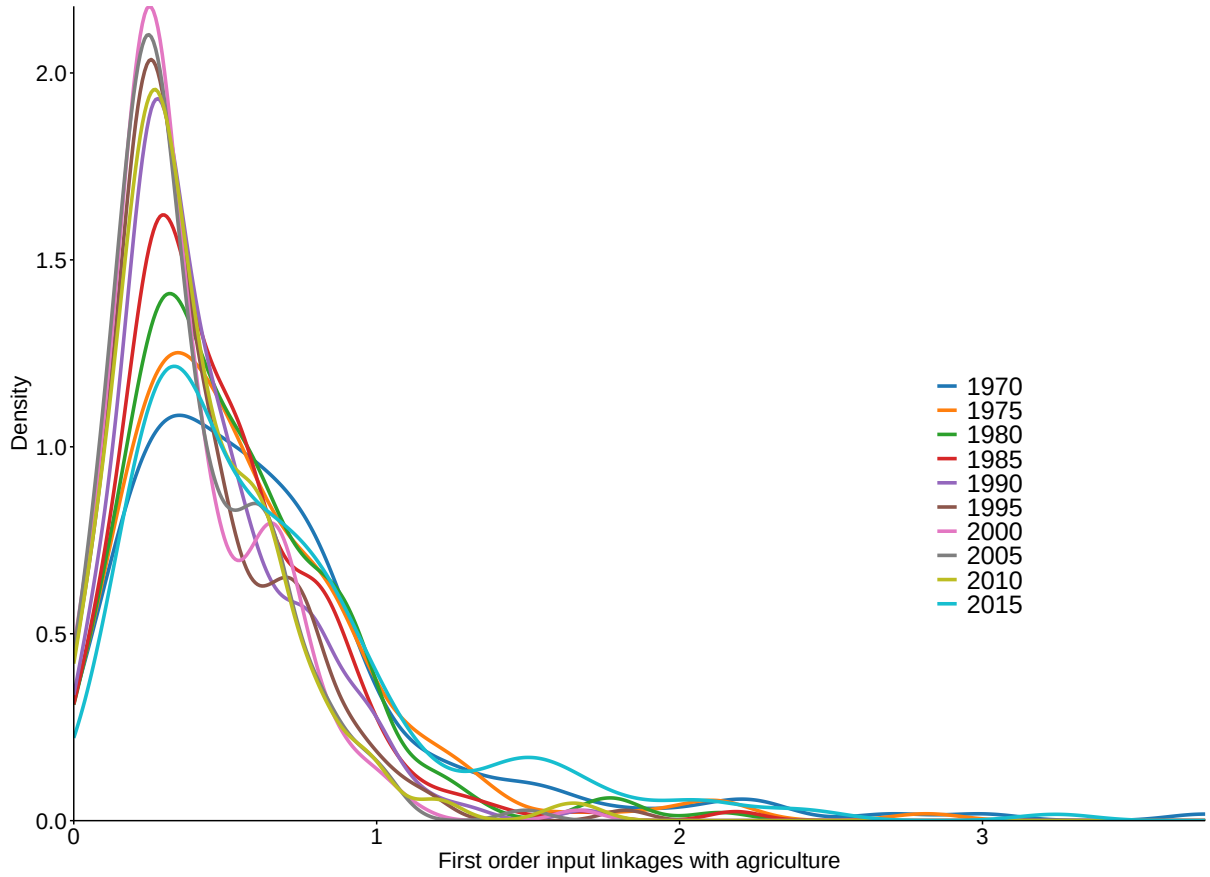
Notes: The figure shows the scatter plot of the residuals in extreme heat in agriculture and in manufacturing obtained after conditioning on country- and year- fixed effects. The relationship between the residuals in the final sample is not statistically different from zero (p-value equal to 0.61).

Figure A5. Average downstream linkages across countries and times



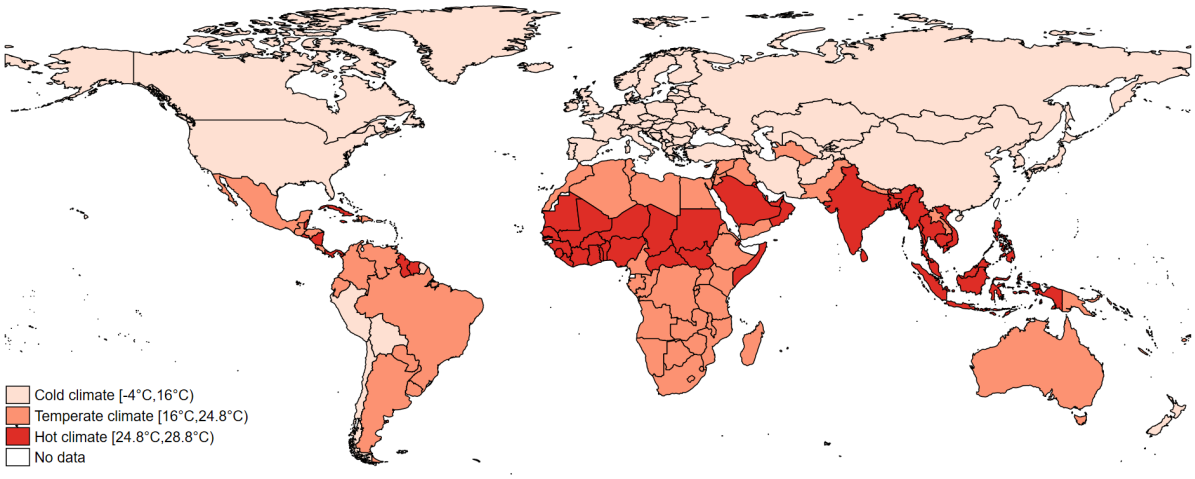
Notes: The figure shows the average downstream input linkages across countries and over time computed as the share of intermediate inputs that input sector (in rows) provides to output sector (in columns) over total value added. Intermediate inputs are computed in basic prices from EORA26.

Figure A6. Density distribution of first order degree linkages of agriculture



Notes: The figure shows the empirical density distribution of the first order outdegree of each agriculture sector in the world across years (each year represents the average of the following five years, e.g., 1970 indicates the average linkages between 1970 and 1974).

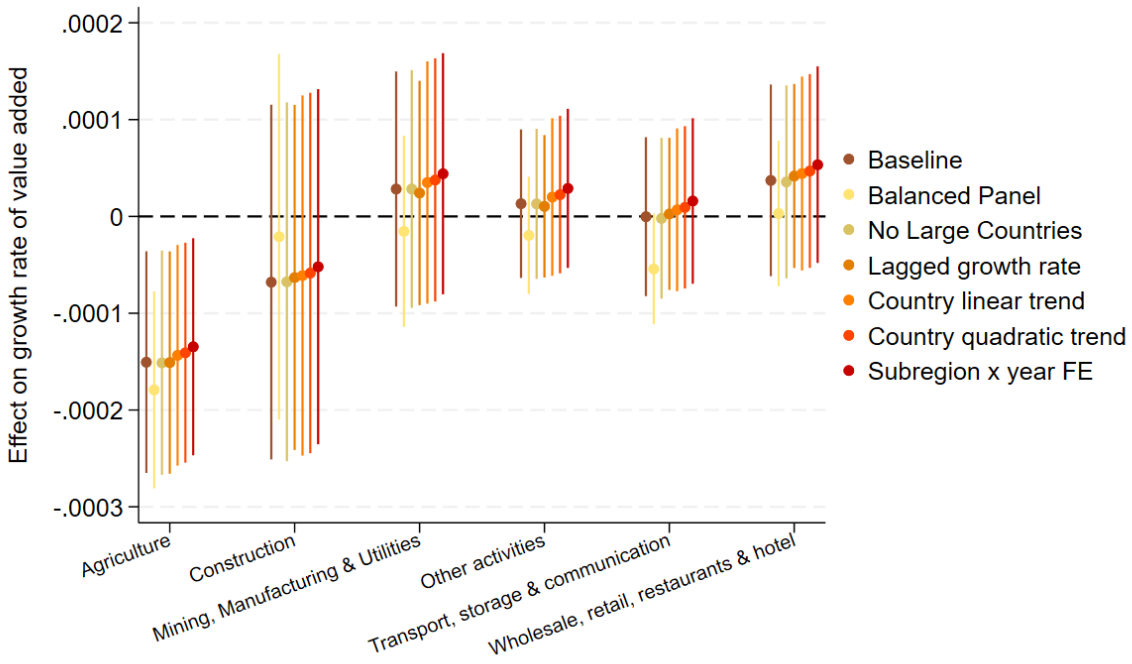
Figure A7. Countries in the sample by climatic zone



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 Appendix Figure H1.

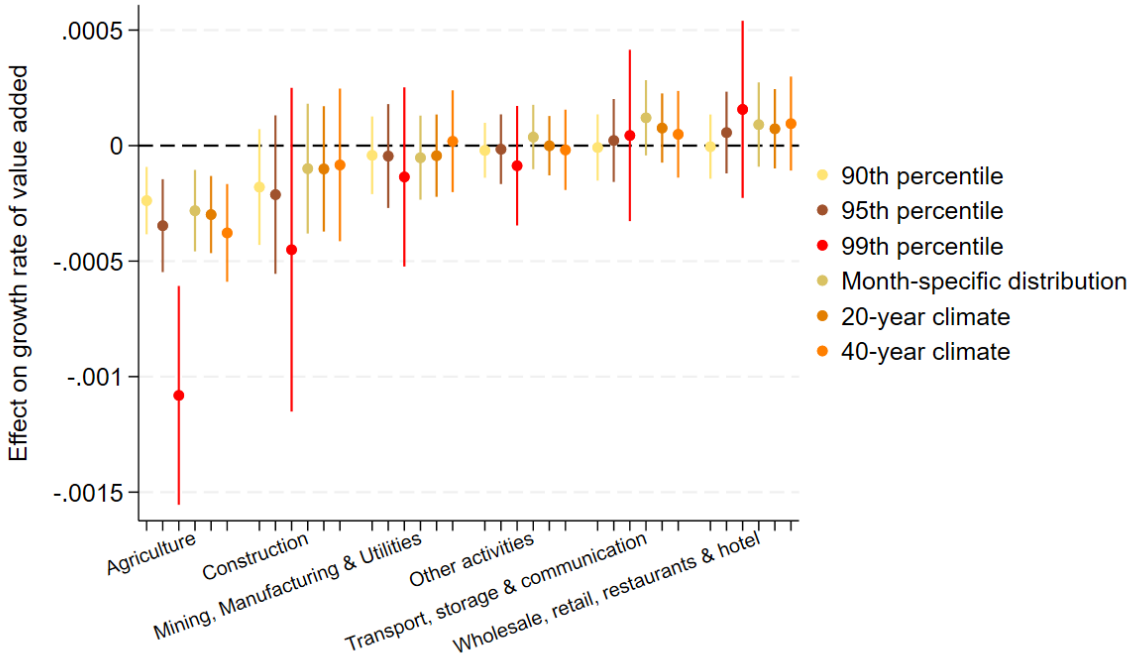
B Additional figures - Robustness and additional results

Figure B1. Robustness 1: Response to local extreme heat



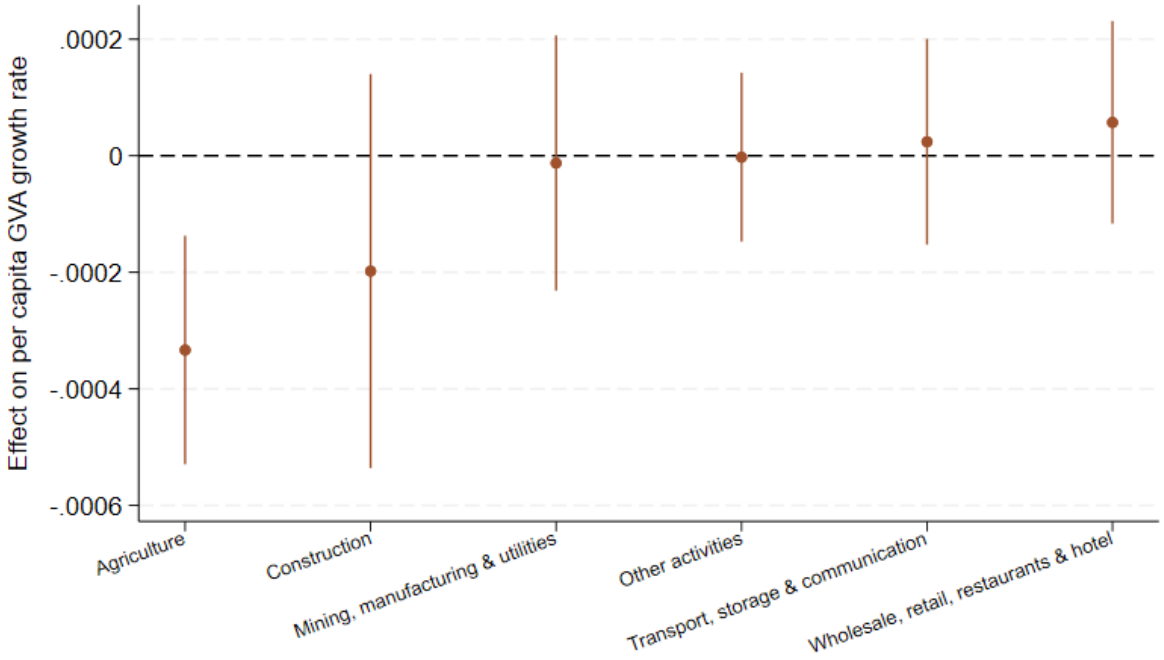
Notes: The figure shows the regression estimates for the country-average number of degree days of extreme heat using a sector-country balanced panel; excluding large countries (Brazil, China, India, Russia, US); including lagged growth rate; including country-specific linear trends; including linear and quadratic country-specific trends; including subregion-by-year fixed effects. All sector-specific coefficients are estimated jointly in a regression model fully saturated with country-sector and sector-year fixed effects. Vertical lines 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 B2. Robustness 2: Response to local extreme heat



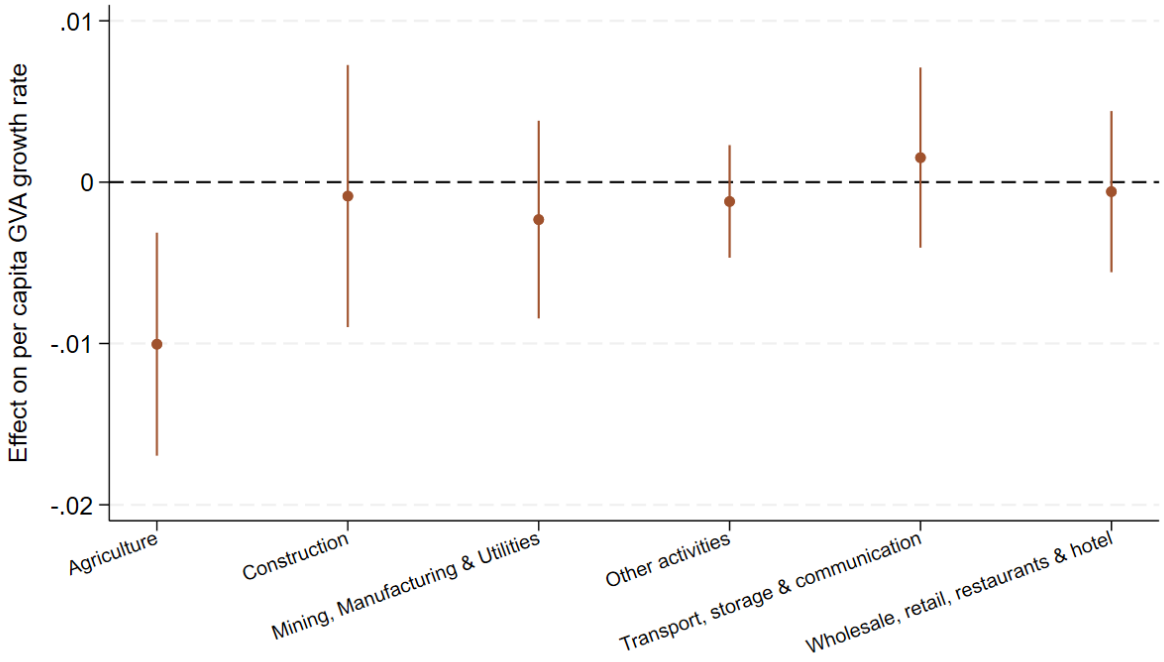
Notes: The figure shows the regression estimates constructing the extreme heat exposure differently: I use different percentiles of the grid-specific distribution (90, 95 - the baseline - and 99); I construct heat exposure relative to the 95th percentile of each grid-month specific distribution of temperature in the previous 30 years and relative to the 95th percentile of each grid-year specific distribution of temperature in the previous 20 or 40 years.

Figure B3. Effect of local abnormal hot days on growth rate of sectoral value added



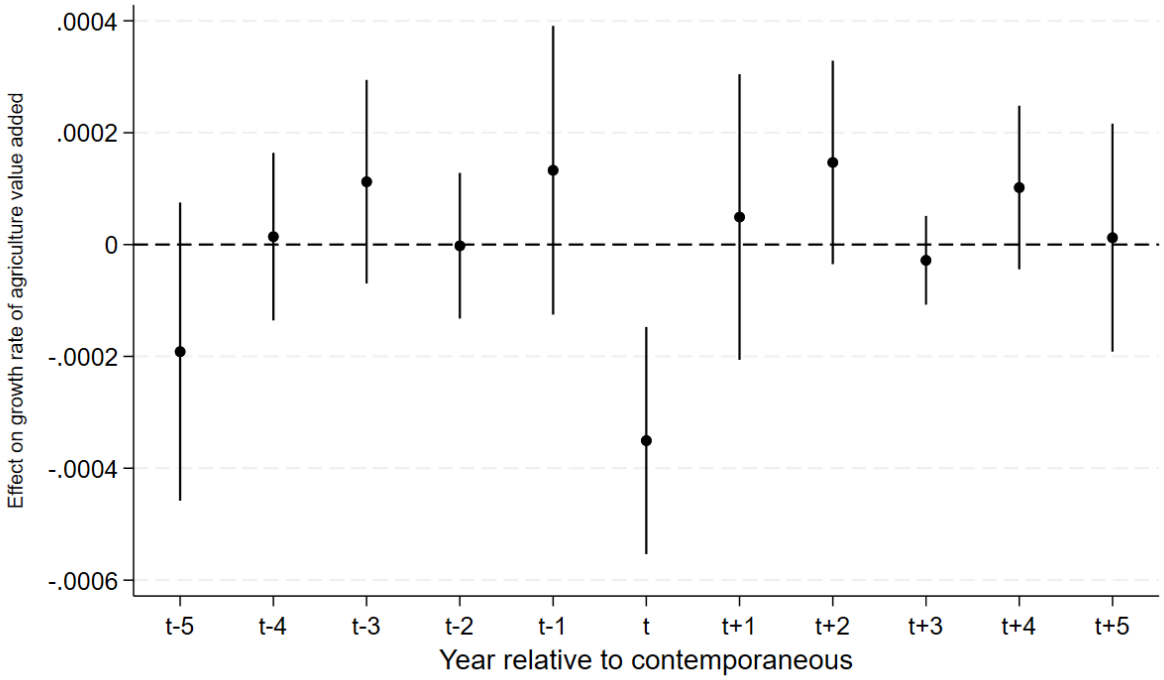
Notes: The figure shows the regression estimates for the country-average number of days above the 95$^{\text{th}}$ percentile of the daily distribution in temperature. All sector-specific coefficients are estimated jointly in a regression model fully saturated with country-sector and sector-year fixed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

Figure B4. Effect of temperature shocks on growth rate of sectoral value added



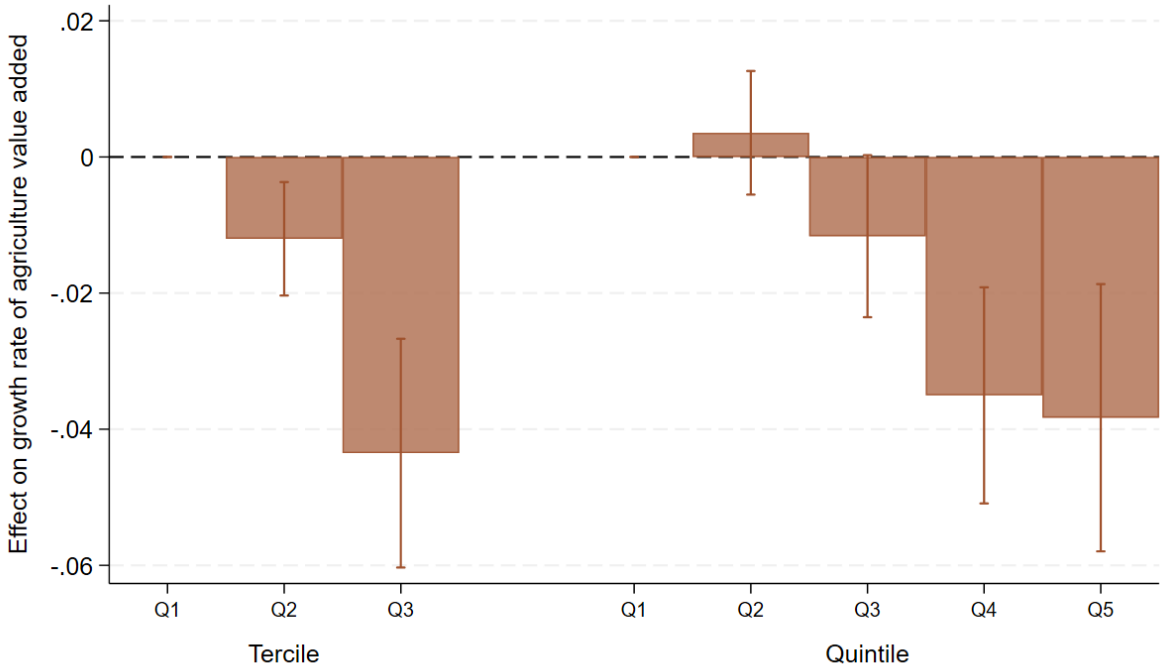
Notes: The figure shows the regression estimates of the temperature shocks constructed as in Equation (2). All sector-specific coefficients are estimated jointly in a regression model fully saturated with country-sector and sector-year fixed effects and controlling for a sector-specific second order polynomial in total precipitation. Vertical lines represent the 95% confidence intervals around point estimates. Standard errors are clustered at the country level.

Figure B5. Dynamic effect on local extreme heat on growth rate of sectoral value added



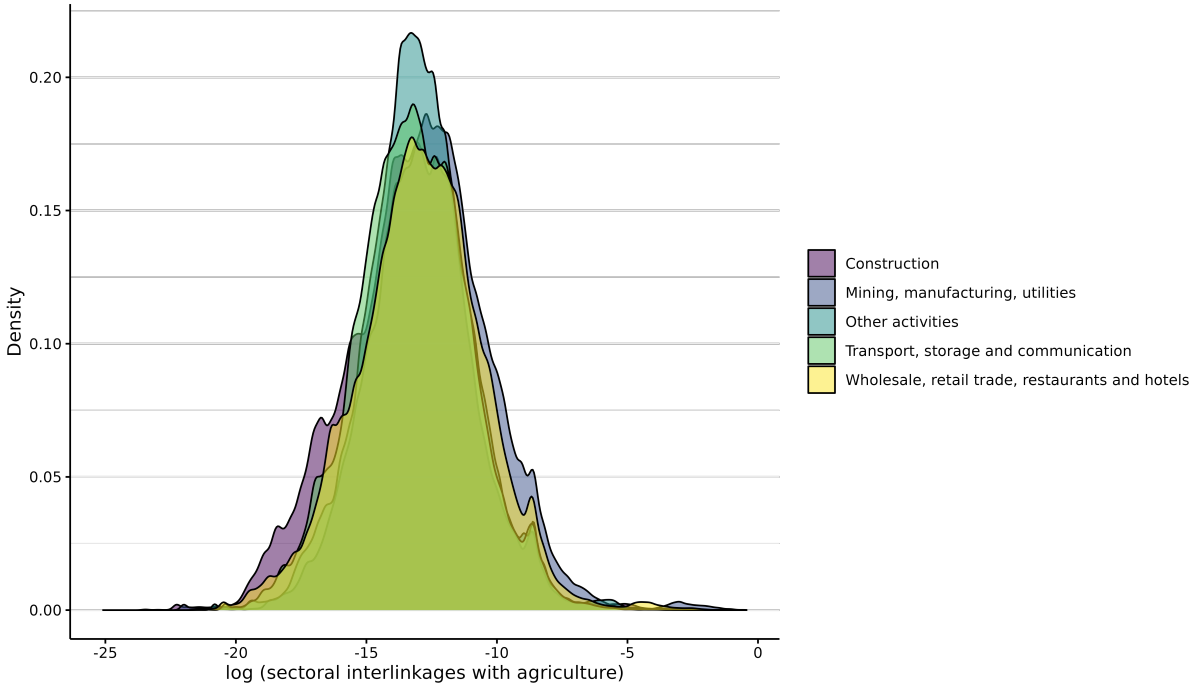
Notes: The figure shows the regression estimates of the temperature shocks constructed as in Equation (2). All sector-specific coefficients are estimated jointly in a regression model fully saturated with country-sector and sector-year fixed effects and controlling for a sector-specific second order polynomial in total precipitation. Vertical lines represent the 95% confidence intervals around point estimates. Standard errors are clustered at the country level.

Figure B6. Quantiles of Extreme Heat on Agricultural Value Added



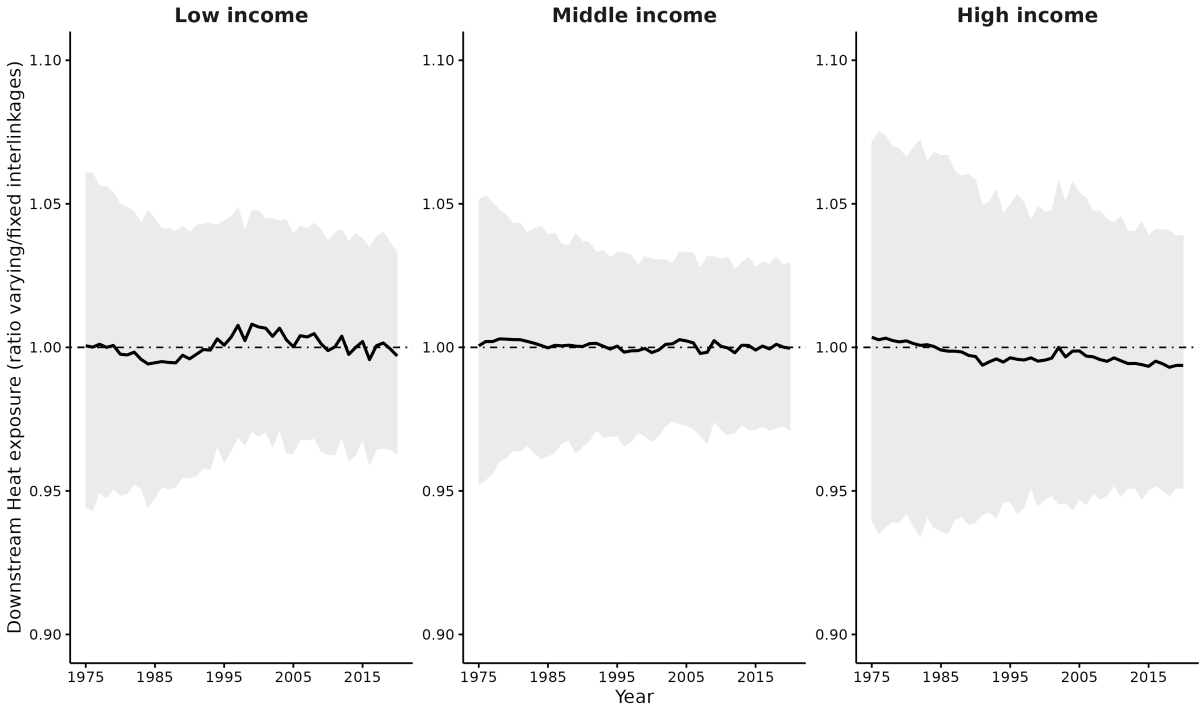
Notes: The figure shows the regression estimates for the measure of extreme heat (degree days) constructed as in Equation (1) on the growth rate of agricultural value added and categorized by terciles or quintiles. Each set of bars corresponds to the estimates from a single regression which accounts for linear and quadratic terms of precipitation, and country and year fixed effects. Vertical lines represent the 95% confidence intervals around point estimates. Standard errors are clustered at the country level.

Figure B7. Density function of intermediate input interlinkages with agriculture by sector



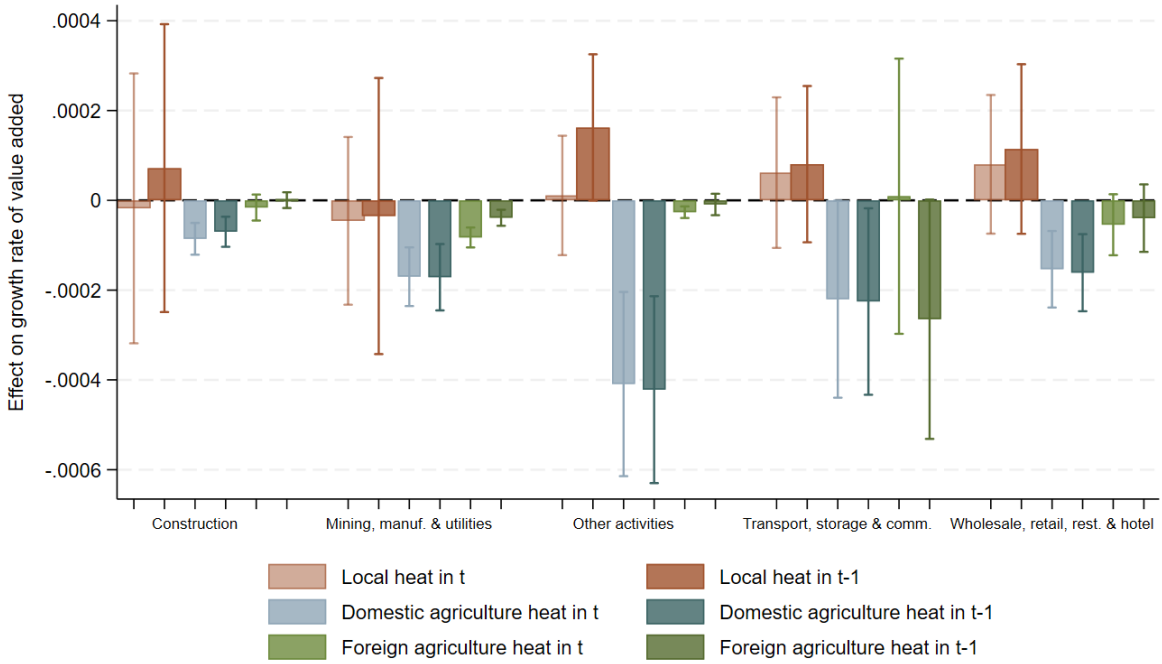
Notes: The figure plots the sector-specific density distribution of the (log) of interlinkages with agriculture used as outcome variable in Equation (9).

Figure B8. Downstream exposure to extreme heat in agriculture by income terciles



Notes: Each panel in the figure displays the income tercile-specific 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. As Fact 4 establishes that sectors do not substantially differ in response to extreme heat in agriculture, I pool downstream exposure to extreme heat conditions across sectors in a country and divide the global sample by terciles of income. 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. 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 annually. 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). A ratio between these two measures of downstream heat exposure below one would indicate that countries have been able to reduce their exposure to downstream non-local extreme heat conditions. The gray shaded areas represent the 95% confidence intervals.

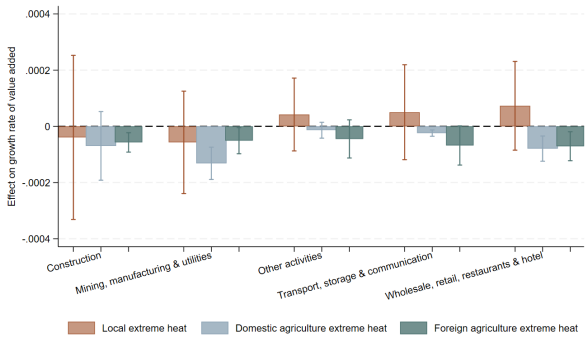
Figure B9. Contemporaneous and lagged response to extreme heat conditions in agriculture accounting for higher order linkages



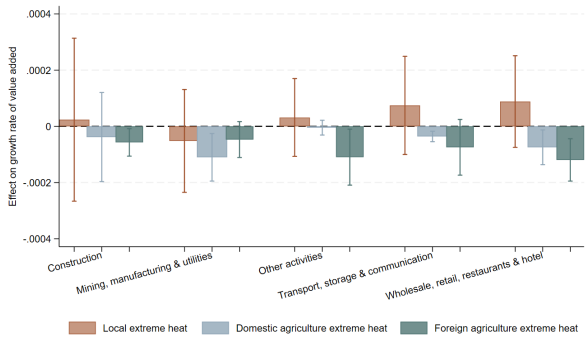
Notes: Bars represent the sector-specific coefficients associated with contemporaneous and one-year lagged local extreme heat shocks and extreme heat in domestic and foreign agriculture constructed using the extreme heat exposure measure constructed as in Equation (1). Domestic and foreign downstream shocks are constructed respectively as in Equations (5) and (6), with sectoral interlinkages obtained from the Leontief inverse matrix obtained from the downstream sectoral interlinkages obtained as in Section 2.3. The specification jointly estimates all sector-specific coefficients in a regression model that accounts for country-sector, sector-year, country-year fixed effects and sector-specific second-order polynomial of total precipitation and sum of exposure shares. Vertical lines represent the 95% confidence intervals with standard errors clustered at the country level.

Figure B10. Robustness: Alternative specifications for first degree linkages

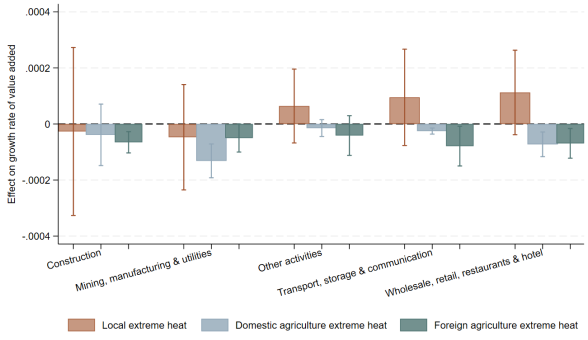
(a) Country quadratic time trends



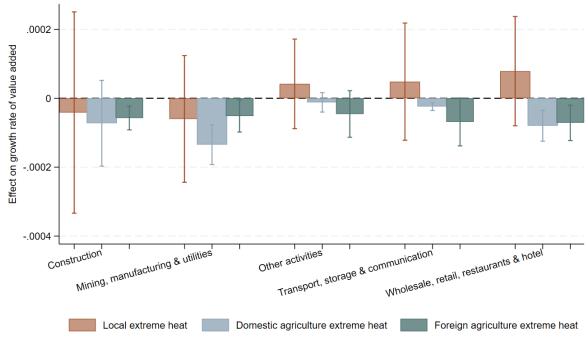
(b) Country-sector quadratic time trends



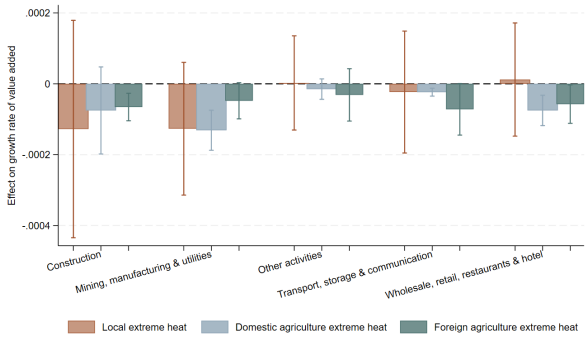
(c) Balanced panel



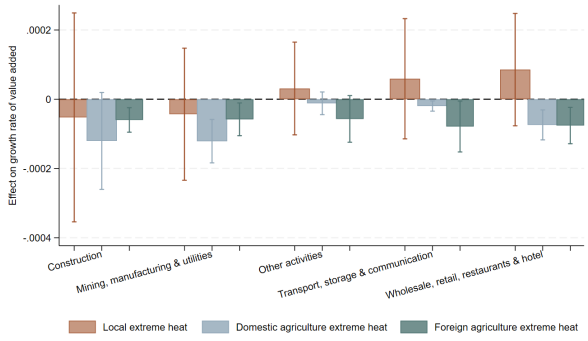
(d) Excluding "large" countries



(e) Exclude 10% coldest



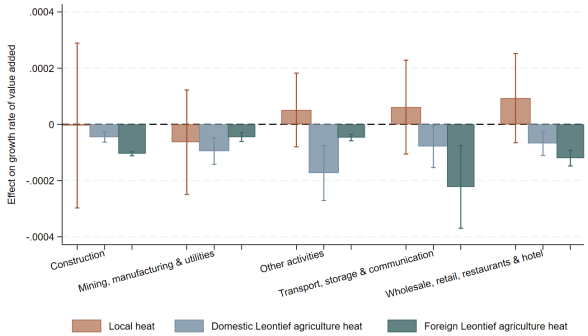
(f) Exclude 10% hottest



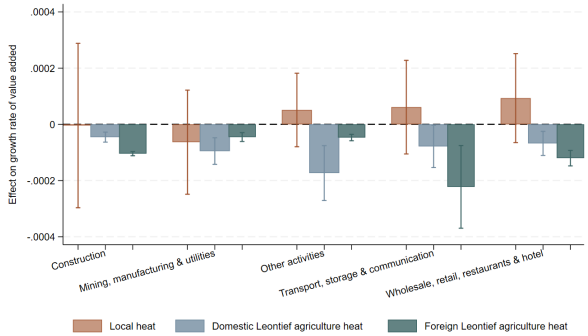
Notes: The figure shows the sector-specific coefficients associated with local extreme heat and domestic and foreign extreme heat in agriculture. Panel (a) shows the estimates accounting for country-specific quadratic time trends; Panel (b) accounts for country-sector specific quadratic time trends; Panel (c) uses sector-country balanced panel; Panel (d) excludes large countries (China, India, Russia, US); Panel (e) excludes the 10% coldest countries based on mean temperature in the 45 years considered; Panel (f) excludes the 10% hottest countries based on mean temperature in the 45 years considered. Vertical lines represent the 95% confidence intervals around point estimates with standard errors clustered at the country level.

Figure B11. Robustness: Alternative specifications for Leontief matrix

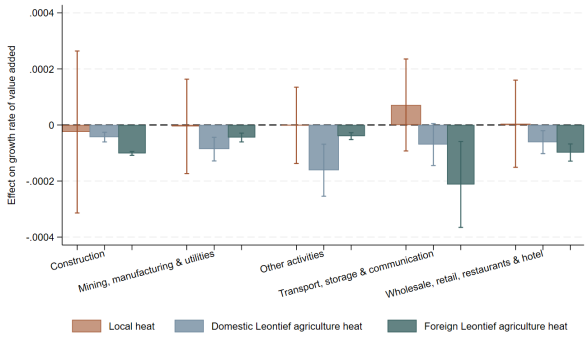
(a) Country quadratic time trends



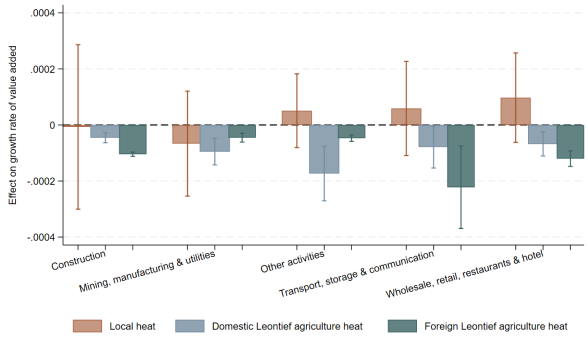
(b) Country-sector quadratic time trends



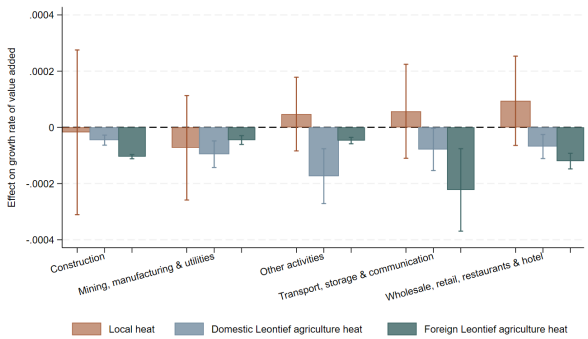
(c) Balanced panel



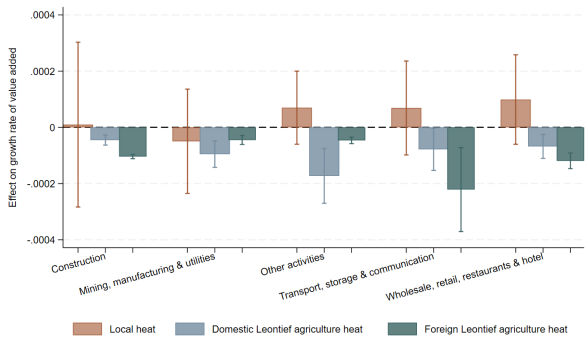
(d) Excluding "large" countries



(e) Exclude 10% coldest

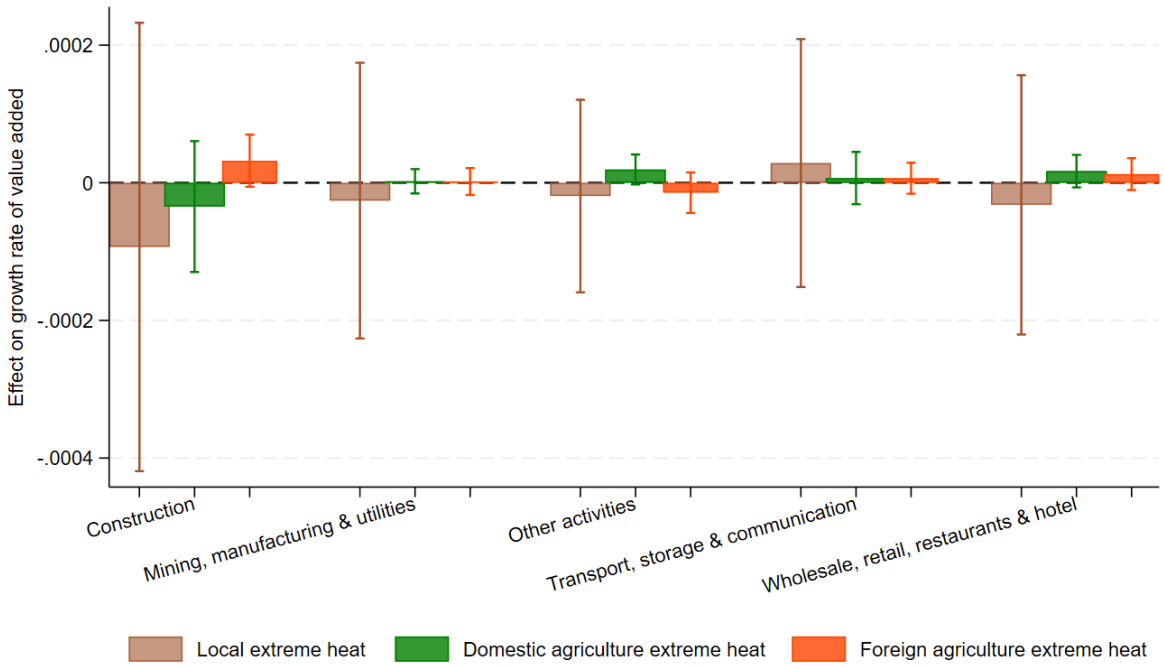


(f) Exclude 10% hottest



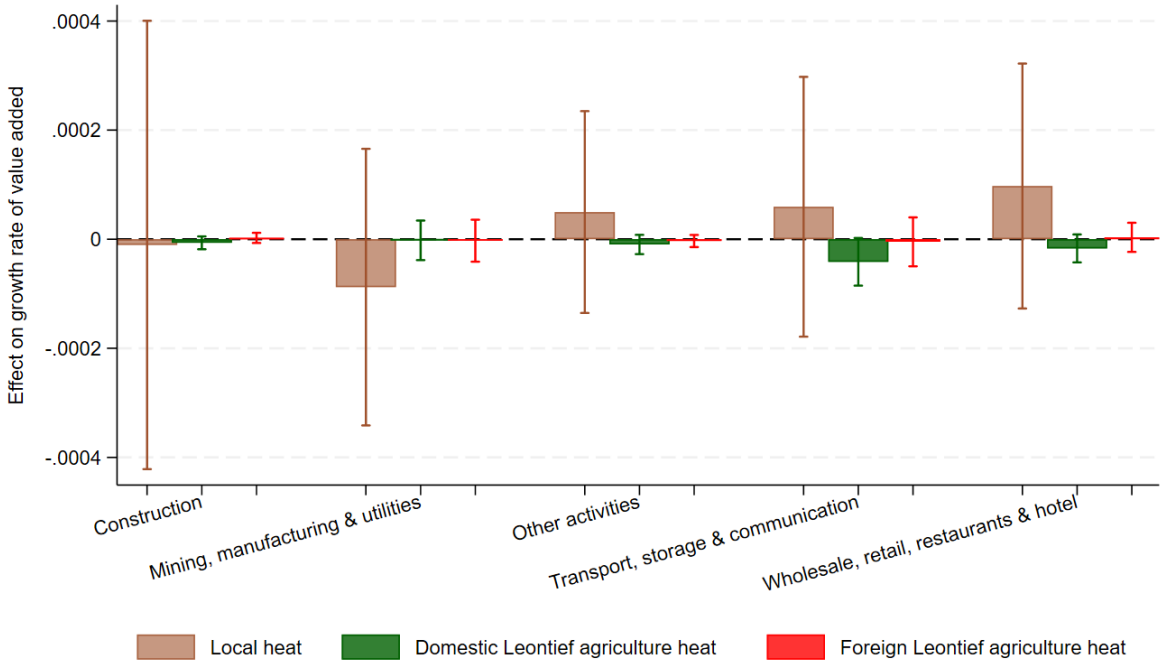
Notes: The figure shows the sector-specific coefficients associated with local extreme heat and domestic and foreign extreme heat in agriculture using the Leontief inverse matrix. Panel (a) shows the estimates accounting for country-specific quadratic time trends; Panel (b) accounts for country-sector specific quadratic time trends; Panel (c) uses sector-country balanced panel; Panel (d) excludes large countries (China, India, Russia, US); Panel (e) excludes the 10% coldest countries based on mean temperature in the 45 years considered; Panel (f) excludes the 10% hottest countries based on mean temperature in the 45 years considered. Vertical lines represent the 95% confidence intervals around point estimates with standard errors clustered at the country level.

Figure B12. Local and upstream agricultural extreme heat on sectoral production



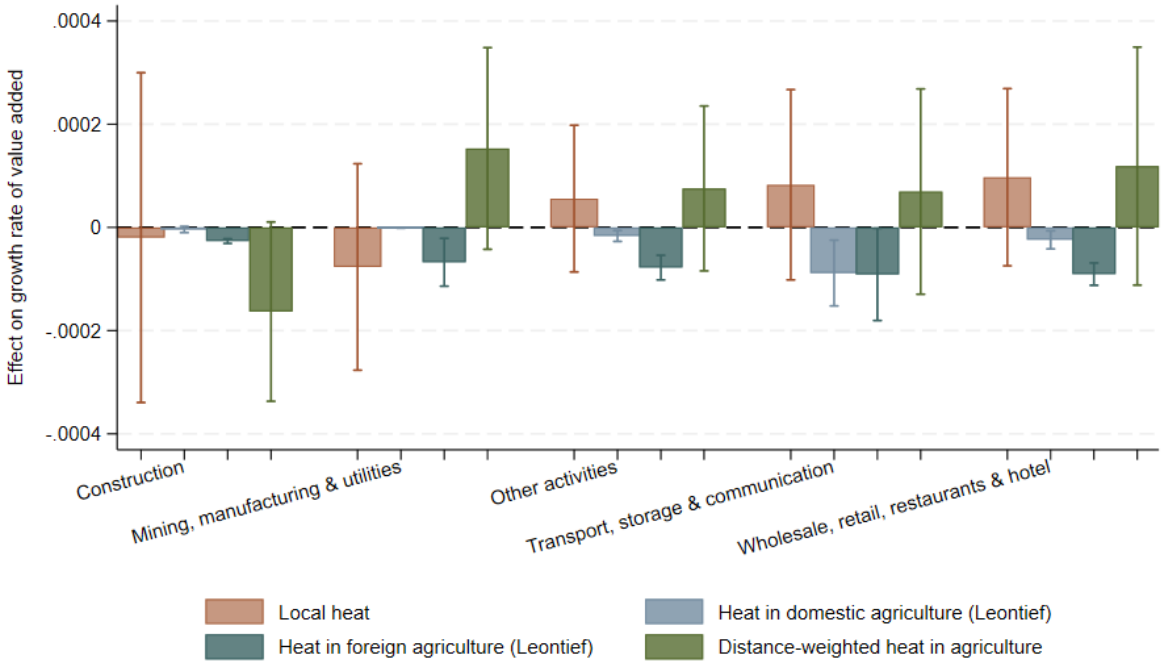
Notes: Bars represent the sector-specific coefficients associated with local shocks and domestic and foreign upstream shocks, using the extreme heat exposure measure constructed as in Equation (1). The specification jointly estimates all sector-specific coefficients in a regression model that accounts for country-sector, sector-year, country-year fixed effects and sector-specific second-order polynomial of total precipitation and sum of exposure shares. Vertical lines represent the 95% confidence intervals with standard errors clustered at the country level.

Figure B13. Local and upstream agricultural extreme heat on sectoral production in a Leontief matrix



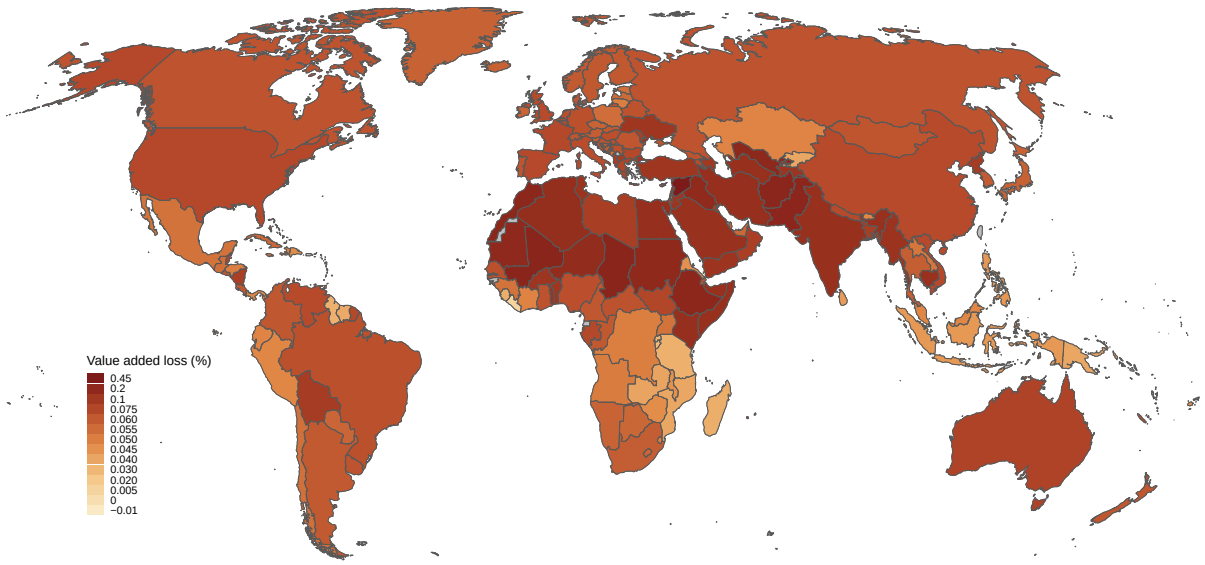
Notes: Bars represent the sector-specific coefficients associated with direct shocks and domestic and foreign upstream shocks, using the average number of days above the 95$^{\text{th}}$ percentile of the daily temperature distribution. Domestic upstream shocks are constructed as the average weather 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 regression model that accounts for country-sector, sector-year, country-year fixed effects and sector-specific second-order polynomial of total precipitation and sum of exposure shares. Vertical lines represent the 95% confidence intervals with standard errors clustered at the country level.

Figure B14. Controlling for distance-weighted measure of extreme heat in agriculture



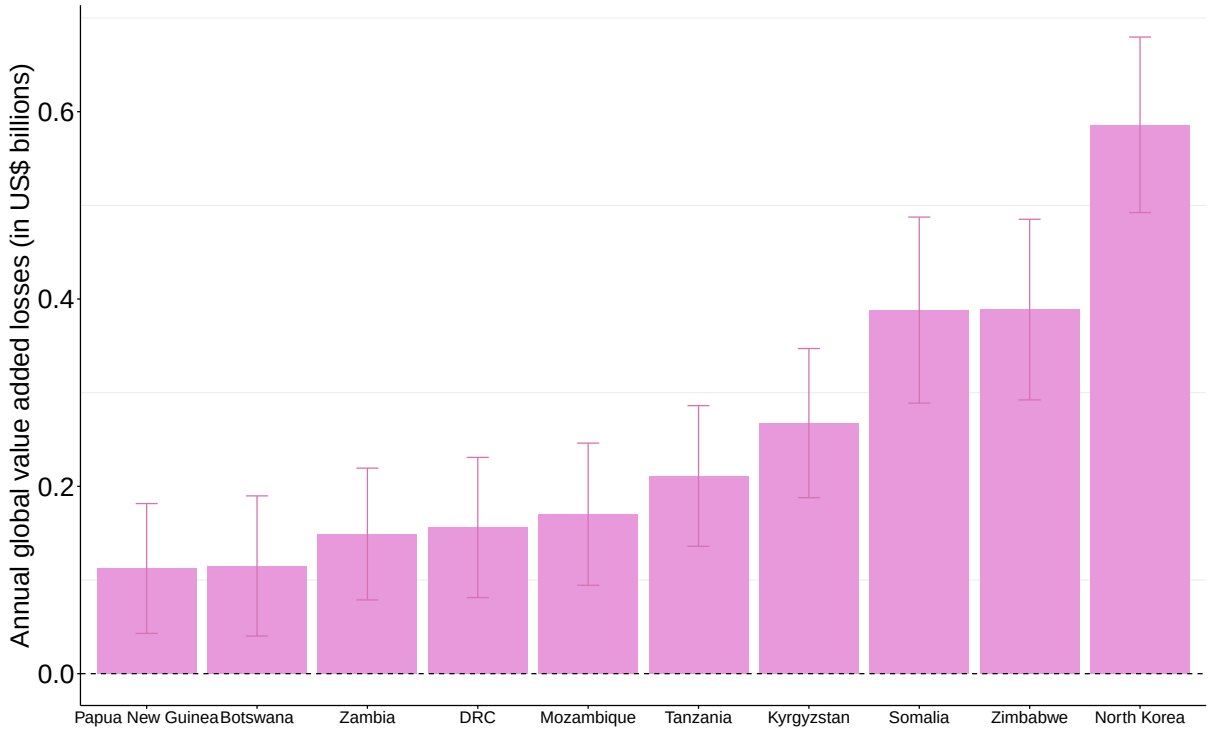
Notes: Bars represent the sector-specific coefficients associated with local shocks and domestic and foreign agriculture shocks, and a gravity-based measure of indirect exposure to extreme heat where I use the typical estimates of the trade elasticity $\delta = 5$ to obtain the weighted average of extreme heat by distance across countries. I construct the extreme heat exposure as in Equation (1). The specification jointly estimates all sector-specific coefficients in a regression model that accounts for country-sector, sector-year fixed effects, and sector-specific second-order polynomial of total precipitation and sum of exposure shares. Vertical lines represent the 95% confidence intervals with standard errors clustered at the country level.

Figure B15. Aggregate annual value added losses (%) induced by recent warming (2001-2020)



Notes: The figure shows the total annual losses in value added (%) between 2001 and 2020 aggregating value added losses in agriculture induced by local extreme heat and downstream value added losses induced by extreme heat in domestic and foreign agriculture, compared to a counterfactual where extreme heat in agriculture had remained at 1975-2000 baseline averages. The sector-specific semi-elasticities are obtained from bootstrapping 1000 times the underlying panel estimates of Equation (13) with replacement.

Figure B16. Annual global value added losses accounting for input linkages for a standard deviation increase in extreme heat in agriculture in a country (in x-axis)



Notes: The figure shows the annual global value added losses in 2015$ billions for a one standard deviation increase in extreme heat in agriculture in each country reported in the x-axis. Estimates are obtained using sector-specific semi-elasticities from Equation (13) and aggregating across sectors and countries to obtain average annual global losses. Purple bins indicate the 95% confidence intervals obtained from 1000 bootstrap replications with replacement. These ten countries represent the ten cases in which global value added losses are smallest but significant at the 95% level.

C Additional tables

Table C1. Summary statistics on sectoral GVA growth rate

	N	mean	SD	min	max
(log) Value added	36,079	21.901	2.424	13.560	30.016
Growth rate of value added	36,079	0.033	0.125	-3.267	2.608
Sector					
Agriculture, hunting, forestry, fishing (ISIC A-B)	7,351	0.027	0.104	-1.691	0.745
Construction (ISIC F)	7,345	0.029	0.169	-3.267	2.608
Mining, Manufacturing, Utilities (ISIC C-E)	7,351	0.027	0.130	-3.099	2.466
Other Activities (ISIC J-P)	7,351	0.034	0.087	-1.567	1.237
Transport, storage and communication (ISIC I)	7,306	0.042	0.111	-2.567	2.067
Wholesale, retail trade, restaurants and hotels (ISIC G-H)	6,726	0.030	0.109	-1.609	1.546
Number of countries	183				
Number of sectors	6				
Number of years per country-sector		44.381	4.647	31	46

Table C2. 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 C3. 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 C4. 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 $^{\circ}C \times days/year$ 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 C5. Effect of local heat and downstream exposure to extreme heat in agriculture on sectoral value added

	Construction (1)	Mining, manufacturing & utilities (2)	Other activities) (3)	Transport, storage & communication (4)	Wholesale, retail, restaurants & hotel (5)
Local extreme heat	-0.0000393	-0.0000570	0.0000422	0.0000503	0.0000732
	(0.000176)	(0.000110)	(0.0000780)	(0.000102)	(0.0000950)
Domestic agriculture extreme heat	-0.0000232	-0.000132***	-0.0000138	-0.0000252***	-0.0000793***
	(0.0000245)	(0.0000346)	(0.0000170)	(0.00000714)	(0.0000270)
Foreign agriculture extreme heat	-0.0000402*	-0.0000572***	-0.0000373	-0.0000567	-0.0000654**
	(0.0000221)	(0.0000208)	(0.0000340)	(0.0000350)	(0.0000286)
Sector-specific quadratic precipitation	✓	✓	✓	✓	✓
Exposure share sums	✓	✓	✓	✓	✓
Sector-Country fixed effects	✓	✓	✓	✓	✓
Country-Year fixed effects	✓	✓	✓	✓	✓
Sector-Year fixed effects	✓	✓	✓	✓	✓
Mean outcome	0.0290103	0.0274871	0.0345063	0.042939	0.0304112
N	36079				
adj. R^2	0.335				

Notes: Table reports the OLS estimates of one single regression estimating 15 coefficients (Equation (13)),, including the effect of local extreme heat and the indirect effect of extreme heat in domestic and foreign agriculture via exposure through intermediate inputs with downstream sectors. This is the tabular version of Figure 6. The regression controls for a second-order polynomial in total precipitation, and exposure share of each sector with domestic agriculture and the sum of exposure shares with foreign agriculture. Standard errors are clustered at the country-level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C6. Effect of local heat and downstream exposure to extreme heat in agriculture on sectoral value added accounting for higher degree linkages

	Construction (1)	Mining, manufacturing & utilities (2)	Other activities) (3)	Transport, storage & communication (4)	Wholesale, retail, restaurants & hotel (5)
Local extreme heat	-0.00000586	-0.0000821	0.0000464	0.0000608	0.0000956
	(0.000176)	(0.000109)	(0.0000785)	(0.000101)	(0.0000952)
Domestic Leontief agriculture extreme heat	-0.0000605***	-0.000156***	-0.0000871***	-0.0000567*	-0.000131***
	(0.0000137)	(0.0000433)	(0.0000286)	(0.0000317)	(0.0000477)
Foreign Leontief agriculture extreme heat	-0.0000493***	-0.0000970***	-0.0000789***	-0.0000933**	-0.000111***
	(0.00000229)	(0.0000196)	(0.0000144)	(0.0000442)	(0.0000184)
Sector-specific quadratic precipitation	✓	✓	✓	✓	✓
Exposure share sums	✓	✓	✓	✓	✓
Sector-Country fixed effects	✓	✓	✓	✓	✓
Country-Year fixed effects	✓	✓	✓	✓	✓
Sector-Year fixed effects	✓	✓	✓	✓	✓
Mean outcome	0.0290103	0.0274871	0.0345063	0.042939	0.0304112
N	36079				
adj. R^2	0.334				

Notes: Table reports the OLS estimates of one single regression estimating 15 coefficients (Equation (13)), including the effect of local extreme heat and the indirect effect of extreme heat in domestic and foreign agriculture via exposure through intermediate inputs with downstream sectors. This is the tabular version of Figure 7. The regression controls for a second-order polynomial in total precipitation, and exposure share of each sector with domestic agriculture and the sum of exposure shares with foreign agriculture. Standard errors are clustered at the country-level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

D Additional data sources

The empirical analysis and additional empirical facts rely on a set of complementary secondary data, which I describe below.

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. Agriculture Producer Prices are prices received by farmers for primary crops, live animals and livestock primary products as collected at the point of initial sale (prices paid at the farm-gate). 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 2.

Crop acreage over time. To study crop adjustments in space I use the Spatial Production Allocation Model (SPAM) (International Food Policy Research Institute, 2019, 2024). In particular, I use the first and last available year, respectively 2000 and 2020 that contain information on the physical area for 12 crops at a 5min spatial resolution. Physical area is measured in a hectare and represents the actual area where a crop is grown, not counting how often production was harvested from it. Physical area is calculated for each production system and crop, and the sum of all physical areas of the four production systems constitute the total physical area for that crop. Appendix Section E explains how I use the data.

E Extreme heat in agriculture accounting for crop spatial adjustments

In this section, I empirically show the negligible consequences of accounting for spatial reallocation patterns of crop acreage. To do so, I rely on the availability of the spatial distribution of cropland in 2000 and 2020 (International Food Policy Research Institute, 2019, 2024) for 12 crops and construct extreme heat exposure at the country-level for the year 2010 as explained in Section 2.2, using the crop-specific maximum optimal growing temperature to compute extreme heat exposure and weighting by cropland coverage in the two different years.

Table E1 shows the balance test results testing for difference in means in extreme heat exposure in 2010 for each of the 12 crops in the sample (N indicates the number of countries where exposure is non-zero). I cannot reject the null hypothesis that on average the extreme heat exposure measures are statistically equivalent using different years to measure crop acreage.

Table E1. T-test for extreme heat exposure using crop geographic distribution in 2000 and 2020

	Extreme Heat by Crop (degree days in 2010)			
Crop	Crop acreage in 2000	Crop acreage in 2020	p-value	N
Barley	955.46	989.34	0.324	124
Bean	524.63	507.04	0.342	130
Cassava	86.49	89.12	0.685	85
Cotton	11.38	8.06	0.239	44
Groundnut	55.37	50.54	0.360	85
Maize	46.56	45.19	0.675	82
Rice	97.72	103.80	0.164	113
Sorghum	24.38	26.95	0.543	55
Soybean	47.47	40.14	0.198	54
Sugarbeet	236.66	232.34	0.882	65
Sugarcane	10.49	13.64	0.475	19
Wheat	680.95	694.27	0.506	137

F Local output 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 (Dell et al., 2012; Burke et al., 2015). To match this section with the model described in the main text, I consider an economy with N regions indexed by $n \in \{1, ..., N\}$ (or m), each populated with J sectors indexed by $j \in \{1, ..., J\}$ (or k). Although empirically we usually observe sectors and countries for multiple years, here I consider a static version for simplicity. 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:

$$Y_n^j = \mathcal{Z}_n^j (K_n^j)^{\lambda} (L_n^j)^{1-\lambda} \tag{F.1}$$

where total factor productivity $\mathcal{Z}_n^j$ is a product of two components: (i) a region-sector specific component $\overline{z}_n^j$, (ii) an exponential vector of temperature effects T_n^j with sector-specific elasticities β_j. Taking the log and rearranging in terms of output per worker, one obtains:

$$\log \frac{Y_n^j}{L_n^j} = \frac{1}{1-\lambda} [\log \overline{z}_n^j + f(T_n^j, \beta_j)] + \frac{\lambda}{1-\lambda} \log \left(\frac{K_n^j}{Y_n^j} \right) \tag{F.2}$$

In this static setting, 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 sector-region specific unobserved heterogeneity. This simple framework serves as an example to show that weather conditions T_n^k or T_m^j, i.e., temperature conditions in other sectors k in the same country n or in the same sector j in other countries m do not enter in the production function for Y_n^j. When this is taken to the data, these variables are absorbed in the error term. Linkages across sectors and space through the spatial correlation structure of temperature shocks and through the use of intermediate inputs suggest that the empirical approach using only local variation in temperature on local output might suffer from omitted variable bias.

G Reduced form GDP-temperature regressions with temperature in first-difference

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 (Akyapı et al., 2025; 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. This is because the first difference in temperature effectively removes any information on the temperature levels. Therefore, a change in 2°C temperature will have the same effect regardless of the temperature level. A workaround to this shortcoming proposed by Kalkuhl and Wenz (2020) is to interact the change in temperature ΔT_{nt} with temperature levels T_{nt}, which, however, re-introduces trends in the regression, therefore biasing the coefficient on the interaction term.

Here, I discuss another approach implemented in the literature which is to include higher order polynomials of first-differenced temperature as main regressors (as in Ortiz-Bobea et al. (2021)). This approach allows for non-linear effect of temperature changes while dealing with the non-stationarity issue of trended temperatures. Without loss of generality, the estimating equation considering only a second-order polynomial of differenced temperature is written as

$$\Delta y_{nt} = \alpha_n + \delta_t + \lambda \Delta T_{nt} + \psi \Delta [T_{nt}^2] + \varepsilon_{nt} \tag{G.1}$$

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

$$T_{nt} = a_{T_n} + b_{T_n} t + \nu_{T_{nt}} \tag{G.2}$$

where, in line with historical evidence, $b_{T_n} > 0$, and $\mathbb{E}(\nu_{T_{n;t}}) = 0$ and $\mathbb{E}(\nu_{T_{n;t}}^2) = \sigma_{T_n}^2$.

Substituting Equation (G.2) in Equation (G.1) and taking expectations yields

$$\mathbb{E}(\Delta y_{nt}) = \mathbb{E}(\delta_t) + \alpha_n + b_{T_n}[\lambda + 2\psi a_{T_n}] + 2\psi b_{T_n}^2 t \tag{G.3}$$

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 $2\psi b_{T_n}^2 t = 0$ 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 (G.1), such that it becomes

$$\Delta y_{nrt} = \alpha_{nr} + \delta_{rt} + \lambda \Delta T_{nrt} + \psi \Delta[T_{nrt}^2] + \varepsilon_{nrt} \tag{G.4}$$

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. $\delta_{rt} + \psi \bar{b}_{Tr}^2 t = 0$, for all r, where $\bar{b}_{Tr}^2 = \frac{1}{n}\sum_{n=1}^{n_r} b_{T_{n,r}}^2$. The use of this fixed effects, besides not necessarily tackling this issue, comes at the cost of drastically increasing the signal-to-noise ratio in the remaining variation in weather (Fisher et al., 2012).

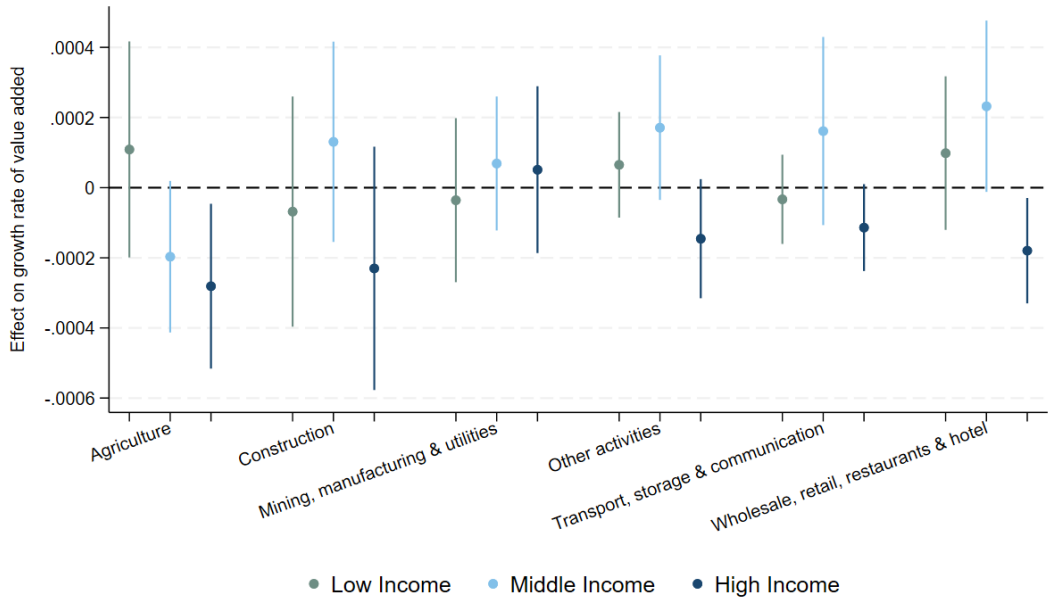
H Heterogeneous effects of local extreme heat across adaptation potential

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 A7 shows the sample composition) (Carleton et al., 2022).

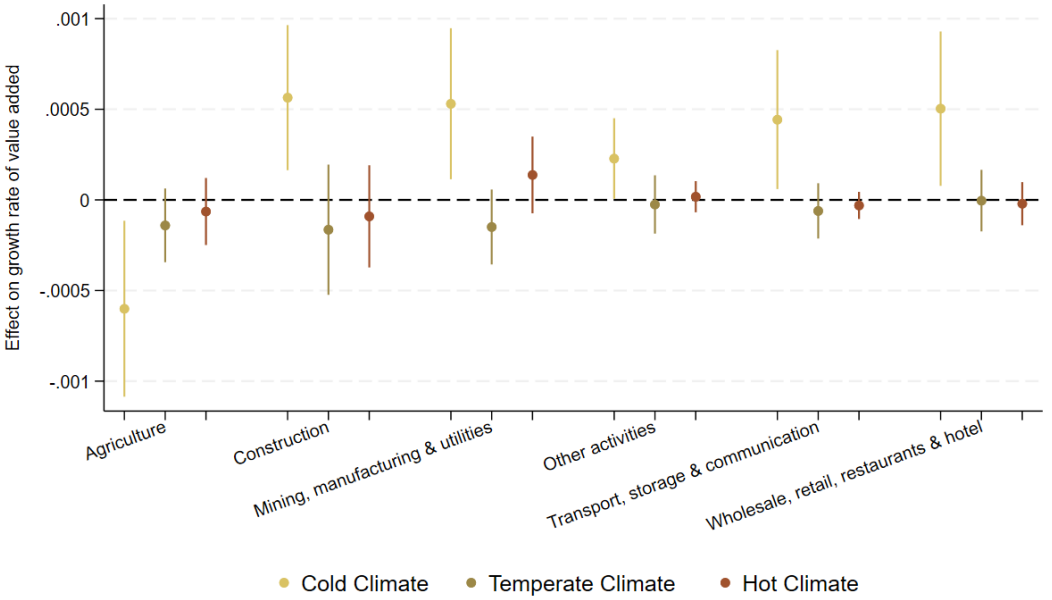
Appendix Figure H1 graphically presents the coefficient associated with heat shocks interacted with income and climate terciles. Starting from heterogeneity by income, agricultural value added becomes more sensitive to extreme heat as income rises. This result, perhaps surprising at first, could be explained by differences in improved technologies, infrastructure, or insurance that influence producer strategies (Hultgren et al., 2025). There is not substantial heterogeneity in the response of other sectors to extreme heat conditions by income, with the estimated coefficients that are never statistically distinguishable from zero. 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 temperate and hot countries and negatively affected in cold countries. Conversely, there is considerable heterogeneity in the sectoral response to extreme heat by climate. In particular, the manufacturing and service sectors benefit from hotter conditions in cold countries, whereas these sectors do not respond in hot and temperate countries.

Figure H1. Income and climate heterogeneity in GVA response to extreme heat

(a) Income terciles



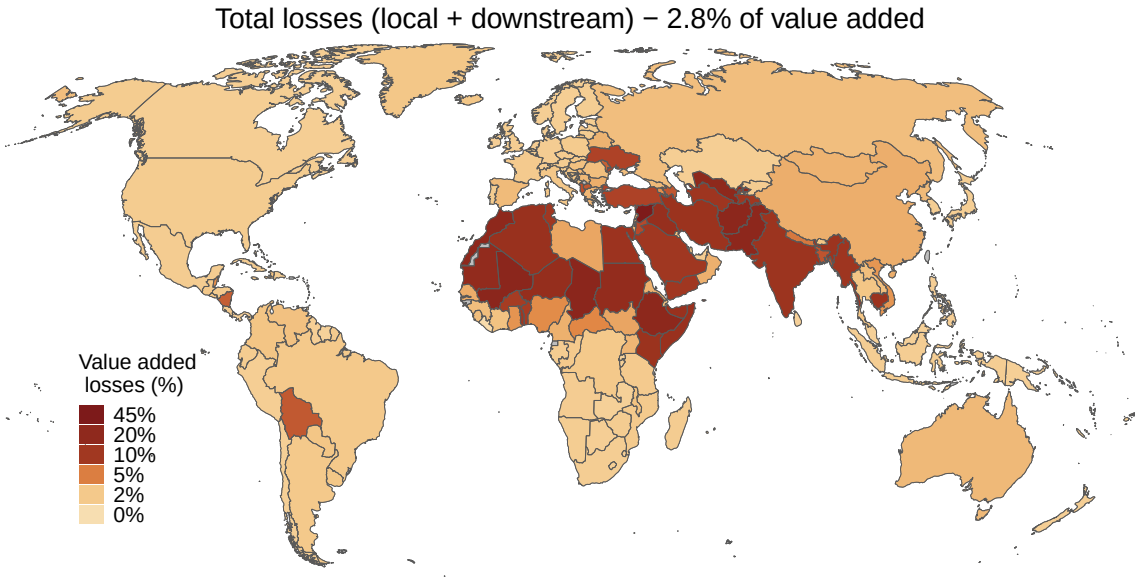
(b) Climate terciles



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

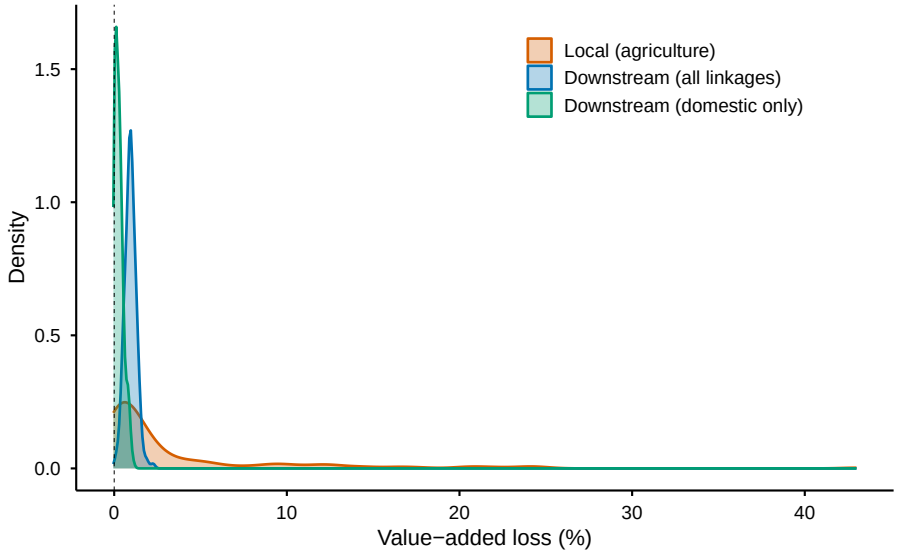
I Additional figures for the quantitative model

Figure I1. Total annual value added losses (%) induced by recent warming in agriculture



Notes: The figure shows total annual value added losses (%) by country obtained by solving the quantitative model under the observed 2001-2020 exposure to extreme heat in agriculture, compared to a counterfactual in which exposure had remained at its 1975-2000 baseline average. Total losses are the sum of direct agricultural losses from local extreme heat and downstream losses transmitted through domestic and foreign input linkages, as displayed separately in Figure 8.

Figure I2. Distribution of local and downstream value added losses across countries



Notes: The figure shows the cross-country density of annual value added losses (%) from the quantitative model under recent warming: direct losses in agriculture from local extreme heat, downstream losses transmitted through all input linkages, and downstream losses transmitted through domestic linkages only. Direct agricultural losses are an order of magnitude larger than downstream losses for the most exposed countries, while downstream losses are more evenly distributed across countries.