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. This finding, however, arises from analyses that largely ignore the critical role of agriculture as an upstream sector in global production networks, with limited representations of sectoral and spatial linkages connecting local agricultural output to other sectors and regions. In this paper, I develop a multi-region multi-sector production network model that illustrates how heat shocks in agriculture can propagate to downstream sectors across countries by reducing supply availability and increasing intermediate input prices. This model motivates 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. Exploiting the differential geographic distribution and sensitivity to hot temperatures of crops across the world between 1975 and 2020, I construct a measure of agricultural heat exposure and show that it induces substantial losses to downstream sectors, across national borders, and beyond first degree linkages. Counterfactual exercises reveal that downstream aggregate losses are 31% greater than local losses that ignore such spatial and sectoral linkages. The analysis demonstrates the critical role of countries that are central to global production networks, suggesting that local benefits from adaptation in such regions can have substantial co-benefits downstream and in other locations.

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1 Introduction

Agriculture has long been considered the most vulnerable sector 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), establishing it as the main channel of macroeconomic climate impacts (Dell et al., 2012). 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 many downstream sectors (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).

Two main approaches predominate in the quantification of global climate damages. One approach empirically estimates the effect of local quasi-random variations in weather on GDP, which embeds some domestic sectoral linkages, but typically ignores spatial linkages (Burke et al., 2015; Kalkuhl and Wenz, 2020). A second approach structurally calibrates a spatial quantitative model that traces sectorally-disaggregated linkages through the economy relying on a set of assumptions on the structure of the economy and how climate affects it (Cruz and Rossi-Hansberg, 2021). Yet to date, the empirical consequences of accounting for spatial and sectoral linkages on aggregate economic impacts from climate change have yet to be assessed.

This paper quantifies the global economic losses induced by extreme heat 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 and input-output sectoral linkages between 1975 and 2020.

My analysis starts by showing four empirical facts that inform my theoretical model and empirical approach. First, in a global cross-country sample of value added for six sectors, extreme heat conditions negatively affect only agriculture.[2] This pattern echoes previous findings

[1] For example, Costinot et al. (2016) find that climate impacts on agriculture amount to a 0.26% reduction in global GDP when trade and crop production spatial patterns are allowed to adjust.

[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 (Carleton et al., 2022; Nath

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 build on a static multi-sector production network model where output is a function of intermediate inputs (Acemoglu et al., 2012), and extend it to an open-economy where I separately model agricultural production from other sectors and introduce local productivity shocks in the form of extreme heat that can transmit through input linkages. The objective of the model is two-fold. 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 direct 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 inducing a reduction in agricultural commodity supplies and increasing their prices, induces downstream sectors to reduce intermediate input demand, thus reducing their output.

Based on the empirical facts and on the theoretical model, I develop a reduced form specification 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 175 distinct plants with their differential sensitivity to maximum 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

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).

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, an additional degree day in domestic (respectively, foreign) heat in agriculture reduces the growth rate of value added by approximately 0.22% (0.16%). 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 domestic (foreign) agriculture heat is 0.28% (0.27%). 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 that does not affect sectors upstream. I empirically validate this hypothesis by showing that agriculture extreme heat 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 use the estimated parameters from the reduced form specification as the basis for two counterfactual exercises that showcase the importance of accounting for spatial and sectoral linkages in the quantification of the impact of global warming. 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 to aggregate

[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

value added losses in downstream sectors transmitted through input linkages to a baseline where extreme heat in agriculture stayed at its 1975-2000 average. While value added losses induced by local extreme heat in agriculture are spatially heterogeneous and concentrated in Africa and South Asia, input linkages amplify the aggregate impact of recent warming in agriculture by approximately 31%, with damages more homogeneously distributed across space.

Second, I compute the aggregate global impact of additional heat in each individual country. Annual global losses are larger when extreme heat occurs in countries with stronger supply chain interlinkages in the production network, such as China, the United States, India, France, and Brazil. For example, a one standard deviation increase in heat conditions in China leads to approximately global value added losses of 235 billion US$. Altogether, these countries are the major global agricultural producers (Costinot et al., 2016), indicating a strong positive relationship between the integration of a country in the production network and the global losses induced by heat shocks in that country.

This paper contributes to the literature on the macroeconomic impacts of climate change by bridging two complementary approaches that trade off plausibly exogenous variation with accounting for indirect effects across space and sectors. 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 national or sub-national GDP per capita (Akyapi et al., 2024; Burke et al., 2015; Burke and Tanutama, 2019; Dell et al., 2012; Kahn et al., 2021; Kalkuhl and Wenz, 2020; Kotz et al., 2021, 2024; Nath et al., 2024; Newell et al., 2021). 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 if the outcome responds to prices. For this reason, another approach is to run a time-series analysis of global spatially-averaged temperature on a global economic outcome (Berg et al., 2024; Bilal and Känzig, 2024), as suggested by Deschênes and Meng (2018). This approach embeds, by construction, all global spatial and sectoral linkages, but cannot disentangle the local effect from the spatial correlation structure of temperature and the role of trade linkages across sectors and space. This approach

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.

may also not identify causal effects if other drivers of the global economy are changing over time and 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] Agriculture has only been considered a consumption good and not an intermediate input in other sectors' production in models that account for trade and crop specialization pattern adjustments (Costinot et al., 2016; Gouel and Laborde, 2021). The importance of agriculture has also been documented through consumption preferences characterised by non-homotheticity and low substitutability, although in a model without intermediate inputs (Nath, 2020). Rudik et al. (2024) show with a macro quantitative model that input linkages transmit climate shocks through the economy, but focus on within-state sectoral linkages in the US. To the extent that some of these models include sectoral or spatial interdependencies, they do so through the structure of a model, which allows for welfare calculations. 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 approach and structural spatial models of the economic activity under climate change. My approach allows for a flexible structure of spatial links and idiosyncratic shocks, and it does not require observing all trade costs before and after the shock nor calibrating parameters to match distribution moments generated in the model with simulated shocks.

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

[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).

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 are unresponsive to extreme heat conditions, leading to downstream amplification of these shocks.

Altogether, these 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, 2020). At the same time, however, stronger input linkages make countries more interdependent and exposed to heat shocks that can propagate through these linkages, amplifying 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 to empirically test the hypothesis that heat shocks affect sectoral production and propagate through input-output interlinkages. To do so, I combine data on sector-level value added (Section 2.1), 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

The Economic Statistics Branch of the United Nations Statistical Division (UNSD, 2024) provides 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 (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

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

[6] The original data comprise 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.

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 (Dell et al., 2012; Burke et al., 2015; Nath et al., 2024), these data provide a more disaggregated sectoral breakdown articulating the country's production in six sectors (compared to the traditional tripartition into agriculture, manufacturing, and services). Structurally calibrated models also articulate the economy often into agriculture and non-agriculture sectors (Costinot et al., 2016; Conte et al., 2021). In few exceptions, studies explicitly model the service sector (Nath, 2020; Rudik et al., 2024), or the construction and mining sectors (Casey et al., 2024).[8] Sectoral disaggregation is of paramount importance when tracing input linkages across sectors and countries, since intermediate input use from agriculture can substantially differ along the supply-chain. 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 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 sectoral value added instead of gross output allows me to disentangle the channel of the shock between local and 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; Rode et al., 2022), 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 al-

[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).

lowing 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 realizations

I compute daily average temperatures and total precipitation 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 model data with observations from across the world into a globally complete and consistent dataset using the laws of physics and rely on information from weather stations, satellites and sondes, removing biases in measurement and creating a coherent, long-term record of past weather.[9]

A key empirical challenge in the parametric estimation of spillover effects of heat shocks lies in separating the local direct effect of heat from the indirect effect of heat in agriculture transmitting through sectoral and spatial linkages. In what follows, I detail how I construct sector-country specific shocks, by relying on temporal variation in temperatures, combined with spatial variation in land use, population distribution, and sub-national sectoral economic activity, and of agro-physical information on the maximum optimal growing temperature conditions for individual plant species.

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., 2022).

To construct a measure of extreme heat exposure, I exploit the fact that locations grow different crops and each crop is differentially sensitive to extreme heat. I use the global geography of crop areas 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

[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).

to construct the agricultural land coverage for 175 crops at a 5 min ($\approx$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 using a time-invariant measure for the spatial geography of crop acreage, this approach does not account for crop migration as an adaptive margin to changes in heat exposure. Three main reasons allay potential concerns on omitting this margin of adaptation. First, crop migration is a spatial adjustment that occurs mostly locally (Sloat et al., 2020). By aggregating the original spatial resolution of agricultural land to match the spatial resolution of climate data (which is nine times larger), I implicitly account for crop migration and crop spatial adjustment patterns that occur within the weather grid cell. Second, around half of the crops in my sample, 84, are perennial, which suggests that spatial adjustments in 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.

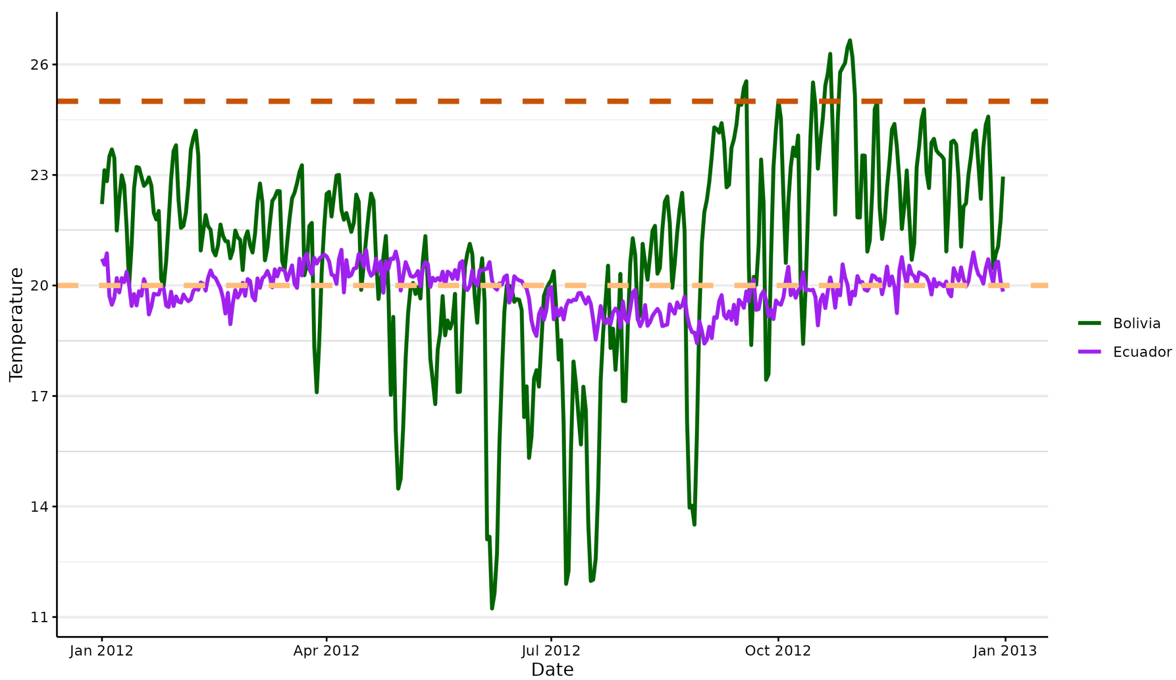
To capture crop-specific exposure to harmful temperatures, I use crop-specific temperature sensitivity from the UN FAO EcoCrop database to construct a measure of killing degree days which combines the intensity and the length of exposure to extreme heat for each specific plant. The EcoCrop data are compiled from expert surveys and textbooks and provide information on plants 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 categorised 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. The use of crop-specific temperature thresholds allays concerns on the imbalance of the spatial variation in extreme heat exposure in the

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

analysis. Figure 1 illustrates this concept graphically with an example. A spatially uniform threshold to compute extreme heat across locations and crops, e.g., 30°C, would completely mask Bolivia's and Ecuador's exposure to above-optimal growing temperature conditions for quinoa (20°C), of which these countries are the leading world producers but whose daily average temperature on agricultural land growing quinoa is above 25°C only in 2% of the days in the sample.

Figure 1. Daily temperatures in agricultural land growing quinoa in Ecuador and Bolivia



Notes: The figure shows the daily average temperatures in 2012 across grid cells in Bolivia and Ecuador where quinoa is grown. These countries are the leading world producers of quinoa, whose maximum optimal growing temperature according to EcoCop data is 20°C (dashed line in orange). Using a uniform cut-off across crops and locations to define extreme heat, e.g., 25°C (dashed line in red), would entirely mask Ecuador's exposure to above-optimal temperature growing conditions and substantially underestimate Bolivia's exposure.

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., 2024) efforts and construct a country-specific agriculture extreme heat exposure measure aggregating across crops c and grid cells g in country n, such that:

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

where $DegreeDays_{gt}(T_c^{max})$ is the total number of degree days above the crop-specific maximum 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 in a country weighted by the total area of each crop c in country n. Appendix Figure A2 displays the empirical residual variation in extreme heat exposure for the 183 countries over the sample period considered, conditional on country- and year- fixed effects.

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 temperature through a variety of channels, including labor productivity, capital damages, and health outcomes. 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 previously adopted measures. First, it allows for non-linearity while preserving unidimensionality. Since the beginning of the reduced form approaches to the GDP-temperature relationship, temperature has been used in levels (Dell et al., 2012). The non-stationarity of temperature levels, however, introduces concerns on the identification strategy 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 output (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. This is done in two ways. First, I construct a distribution across the twelve months in each year; second, 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 deviations of temperature and precipitation from their respective historical norms allows for an implicit model for adaptation. Using a baseline climate of thirty years is equivalent to 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. Furthermore, although thirty 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] 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 also 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.

In additional robustness checks, I also construct an alternative measure of heat shocks. The approach relies on projecting the temperature in each country on its own lags and interact them with country mean temperature to allow the dynamics to vary across climates (Nath et al., 2024). 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]

[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.

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

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

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

2.3 Production network

The definition of sectoral and spatial linkages is crucial to my analysis. For this purpose, 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 across countries for 26 sectors from 1970.[13]

Construction of sectoral linkages across space. To measure shocks in agriculture that propagate through input-output interlinkages, I account for the geographic location and position in the supply chain of the origin of the shock. First, I distinguish between shocks originating in the same country, *domestic*, and those originating in others, *foreign*. Second, I classify network shocks into downstream and upstream using entries from the inter-country IO tables with different weights depending on the relative importance of agricultural intermediate inputs, respectively, as a supplier or customer of the sector of interest. From the perspective of the sector of interest, downstream shocks originate in agriculture as a supplier 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 construct a slowly adjusting production network, where input-output interlinkages are averaged over a five-year lag for each five-year period to smooth annual variation and to account for the intensification of inter-sectoral production linkages over time with more fragmented global supply chains and intensive use of intermediate inputs.

From the perspective of sector j in country n, I construct downstream linkages with the agricultural sector in country m such that

$$\omega_{m,\tau}^{j,n} = \frac{\overline{input}_{m,\tau \to jn\tau}}{\sum\limits_{kf \in \Theta_{jn}} \overline{input}_{jn\tau \to kf\tau}} \tag{3}$$

i.e., intermediate inputs used by sector j in country n sourced from agriculture in country m over total inputs supplied to its set of customer sector-countries Θ_{jn} averaged over the previous five years τ. These weights represent the share of intermediate inputs that sector-

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, EXIOBASE. This framework 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.

country jn sources from the agriculture sector in country m to produce one dollar's worth unit of its output. A sector's output can in turn be both used as an input for other sectors or consumed as a final good, hence the denominator embeds both inputs and value added for sector-country jn.[14]

Appendix Figure A5 displays the inter-sectoral linkages (i.e., the full Ω matrix) averaged across countries and time. Agriculture is the most upstream sector and, on average, downstream interlinkages are larger from agriculture than from 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 (0.48) than the transport, storage, and communication (0.08, which does not include agricultural storage), reflecting different use of agricultural output as an intermediate in the production process in 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. In particular, I return to the latter points when studying counterfactuals in the propagation of shocks in Section 7. These distributions, however, do not considerably vary over time, suggesting that linkages have been relatively stable over time, with the average varying between 0.38 in 2000 and 2005 and 0.52 in 2015.

Construction of network shocks. I combine the country-specific measure 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 Dom are constructed for domestic agriculture Dn and foreign agriculture Fgn as follows (upstream shocks are symmetric but

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

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

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 each the agriculture sector in country m for the sector-country of interest jn.

[15] Antràs et al. (2012) focus on 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.

differ by using upstream weights $\widehat{\omega}^{j,Ag}_{n,m,\tau}$ from 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 $ExtremeHeat_{mt}$ measures the crop-weighted extreme heat conditions in agriculture in country m in year t, as defined in Equation (1). These metrics resemble a "shift-share" approach since shocks in extreme heat are summed 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 input linkage $\omega^{j,n}$, which are computed in the pre-shock period τ, averaging the five-year linkages prior to the shock.

This measure captures the exposure to extreme heat shocks in agriculture of immediate downstream industries that use agricultural commodities as intermediate inputs. Agricultural commodities in my sample include a wide range of crops that enter in the production processes of several downstream sectors. Cereals, fruits, vegetables, spices, oils and fats are essential for the food and beverage manufacturing industry. Fiber crops are used in the textile and apparel industry. Other examples of downstream use of agricultural commodities include oilseed processing, fats and oils refining and blending, plant wholesale and retail, tobacco product manufacturing, pharmaceutical and medicinal products, cosmetic and personal care products, rubber and latex products, and paper and packaging products.

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 are directly connected with agriculture. Section 4 theoretically formalizes what I briefly summarize here to provide an intuition. A negative productivity shock in agriculture will reduce its production and increase its price. This will adversely impact all of the sectors that purchase inputs from agriculture, but 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 cosmetics and personal care products, automotive components, packaging industries, construction material, home decor and landscaping industries, clothing and apparel industries, therapeutic and wellness industries.

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.

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, and ii) agriculture prices; iii) global patterns of extreme heat conditions, 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 agricultural heat exposure to sectoral economic production.

Fact 1: Local extreme heat reduces agriculture value added. To validate my measure of extreme heat exposure, I estimate the response to local extreme heat conditions in growth rate of sectoral value added per capita. Differently than previous cross-country evidence on the channels of the impact of weather shocks on sectoral outcomes (Acevedo et al., 2020; Dell et al., 2012), I estimate sector-specific response functions in a pooled, multi-country multi-sector sample. This model allows me to jointly estimate sector-specific responses to extreme heat and compare the different response functions in an econometric specification of the form:

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

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 α_{jn} fixed effects account for unobserved heterogeneity that influences countries' average sectoral growth rates, such as history, culture, or topography and time-invariant sectoral compositions of national output. Sector-year λ_{jt} fixed effects capture shocks to specific sectors (e.g. agricultural commodity price shocks), while country-year μ_{nt} fixed effects 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 in the same country over time.

Figure 2 shows the sector-specific coefficients associated with local extreme heat conditions on growth rate of sectoral value added. An additional degree day in the extreme heat measure constructed in Equation (1) ($\approx 1\%$ at the sample mean) reduces the growth rate of agriculture value added by 0.76% at the mean. All other five sectors do not respond to extreme heat, with the effect very small in magnitude and statistically indistinguishable from zero. Together, these estimates indicate that extreme heat exposure has substantial negative effects on agricultural value added and does not significantly affect any other sector's production.[17]. These average treatment effects mask heterogeneous effects of local extreme heat by adaptation potential as measured by income and climate (Carleton et al., 2022), which I describe in Appendix Section H. Finally, to allay concerns that differences in shock construction explain heterogeneous sectoral responses, I also construct a similar measure of abnormal heat exposure in agriculture as for the 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 find contemporaneous impacts (Appendix Figure B5).

This empirical fact resonates with previous micro (Nath, 2020) and macro findings (Dell

[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 (Dell et al., 2014).

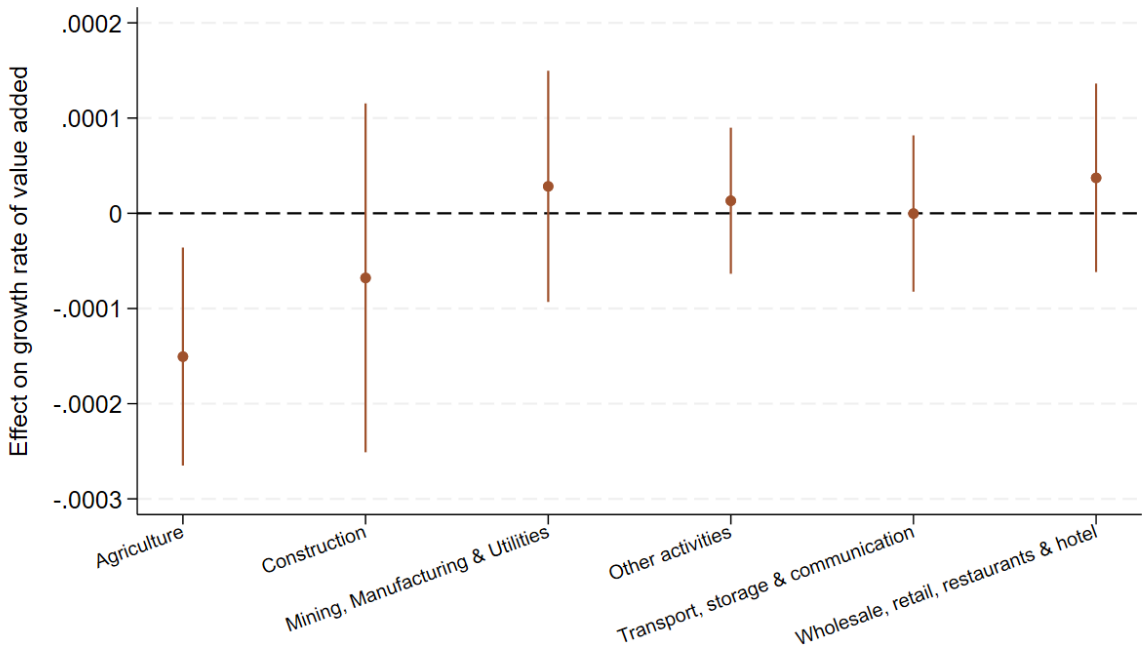
[17] Results are robust to estimating the baseline equation in a balanced panel, excluding large countries (i.e., Brazil, China, India, Russia, US), controlling for lagged growth, and to alternative specifications (linear and quadratic country-specific trends, sub-region-year fixed effects) (Appendix 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).

et al., 2012; Acevedo et al., 2020; Nath et al., 2024). Temperature-induced damages on agriculture are substantially larger than impacts on non-agricultural sector.[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 losses induced by extreme heat, which would be consistent with this sector's vulnerability because of investment good production rather than consumption services that, for example, the retail sector produces (Casey et al., 2024). Overall, this fact indicates the importance to account for sectoral heterogeneity when estimating or calibrating damage functions in climate impact studies. Previous work has documented heterogeneous effects of temperature on economic output across locations depending on their sectoral composition (Nath, 2020; Cruz, 2021), however, these studies often limit their approach to contrasting agriculture to the rest of the economy, neglecting further sectoral heterogeneity combined with climate and income heterogeneity. Yet to date, most studies calibrating damage functions do not incorporate sectoral heterogeneity in their models (Cruz and Rossi-Hansberg, 2021; Bilal and Rossi-Hansberg, 2023).

Fact 2: Extreme heat induces a short-lasting increase in crop prices. Negative effects of extreme heat on agriculture 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 dollars per ton. In a crop-country-year event study specification, 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, and 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 at time t increases crop prices, with the effect vanishing after one year. Appendix Table C4 reports the results in a country-crop panel regression. The empirical pattern documented here is the source of the propagation of extreme heat in agriculture throughout the economy that the theoretical model in Section 4 builds upon. Extreme heat in agriculture reduces crop supply and increases their prices, inducing downstream sectors to decrease their demand for the intermediary inputs and consequently leading to a reduction in the production of downstream goods.

[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.

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



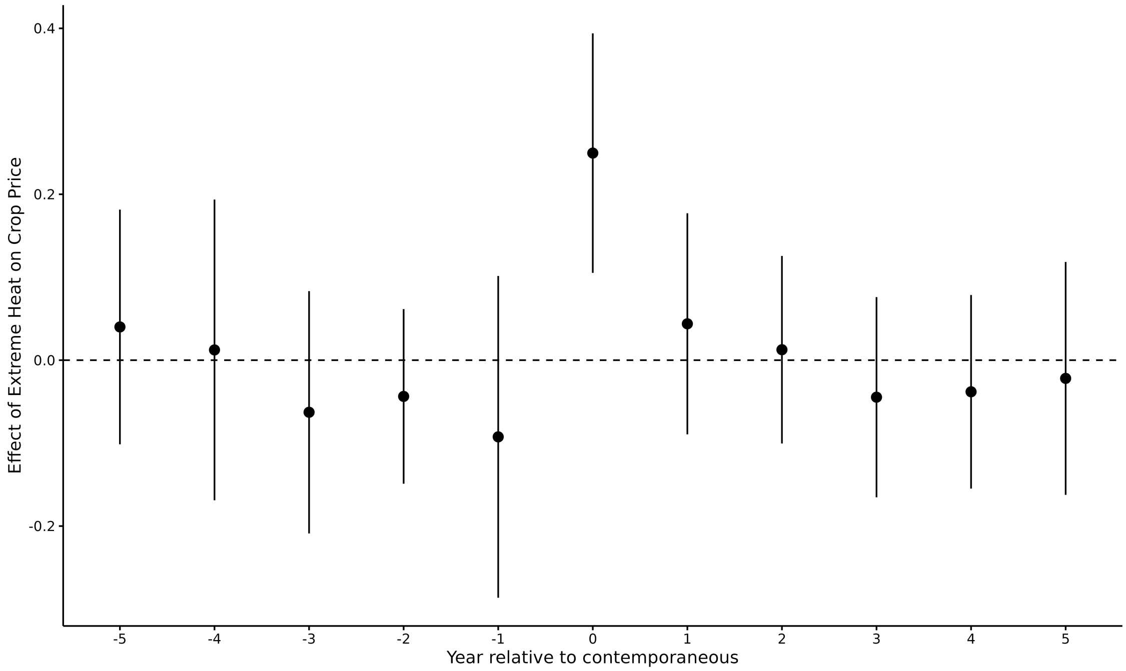
Notes: The figure shows the regression estimates for the country-average number of degree days in the extreme heat exposure for the agricultural sector (constructed as in Equation (1)) and country-sector average number of days above the 95$^{\text{th}}$ percentile of the daily distribution in temperature. All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects and allowing for sector-specific response to a quadratic functional form in precipitation. Bins represent the 95% confidence intervals around point estimates. Standard errors are clustered at the country level.

Fact 3: Extreme heat shocks are increasingly spatially correlated. The third empirical pattern relates to the geography of extreme heat exposure (EH) for the agricultural sector around the world. I measure the global spatial correlation of extreme heat in each year t using Moran's I, a statistics for spatial autocorrelation that 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

Figure 3. Dynamic price effect of extreme heat



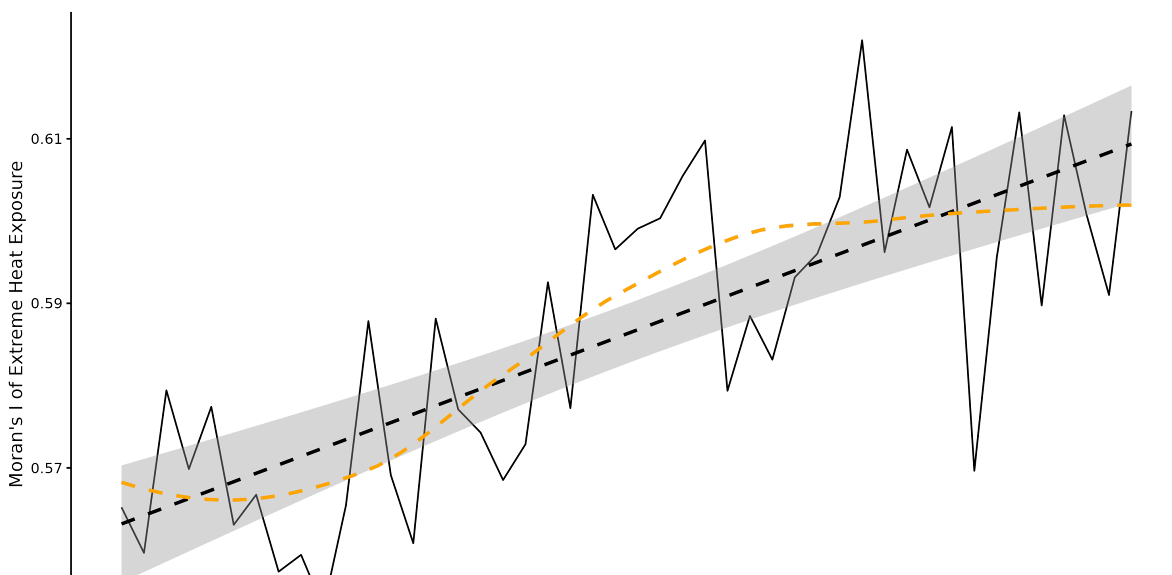
Notes: The figure reports the regression coefficients on crop-specific extreme heat from an event study specification where the outcome variable is the crop price (in $/tonne) from UN FAOStat Crop Price (see Appendix Section D for additional details on the data source). The specification includes five 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. Bins represent the 95% confidence intervals with standard errors clustered at the country-level.

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 a country experiencing reduced yields due to increases in temperatures is likely to be near other similarly affected countries. This spatial correlation pattern might diminish the potential adaptive role of international trade compared to scenarios where shocks are not spatially correlated.

Furthermore, local temperature fluctuations have been used in quasi-experimental studies that inform climate impact projections (e.g., Burke et al., 2015). In this literature, the effect of local temperatures on economic output is traditionally estimated using quasi-random variation implicitly holding temperatures in other locations fixed. Climate change's global impact is then computed as the sum of projected local impacts, which, however, hold fixed the spatial structure of temperature and thus correspond to considering many scenarios in which 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 respond 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.[19] 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.

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. Such endogenous changes in the production network can, in turn, significantly alter the economy's response to exogenous disturbances. To examine whether the production network endogenously adjusts in response to 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) intermediate inputs share that sector j in country m sources from the agricultural sector in country n in year t.[20] 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 agricultural heat for five downstream sectors are small and not statistically significant at any conventional

[19] An additional channel that my approach does not account for is sectoral reallocation driven by temperatures (Nath, 2020; Conte et al., 2021; Cruz and Rossi-Hansberg, 2021). Nevertheless, agriculture consumption enters consumers' utility function accounting for low substitutability and non-homotheticity, a pattern that I also document at the production stage in my model.

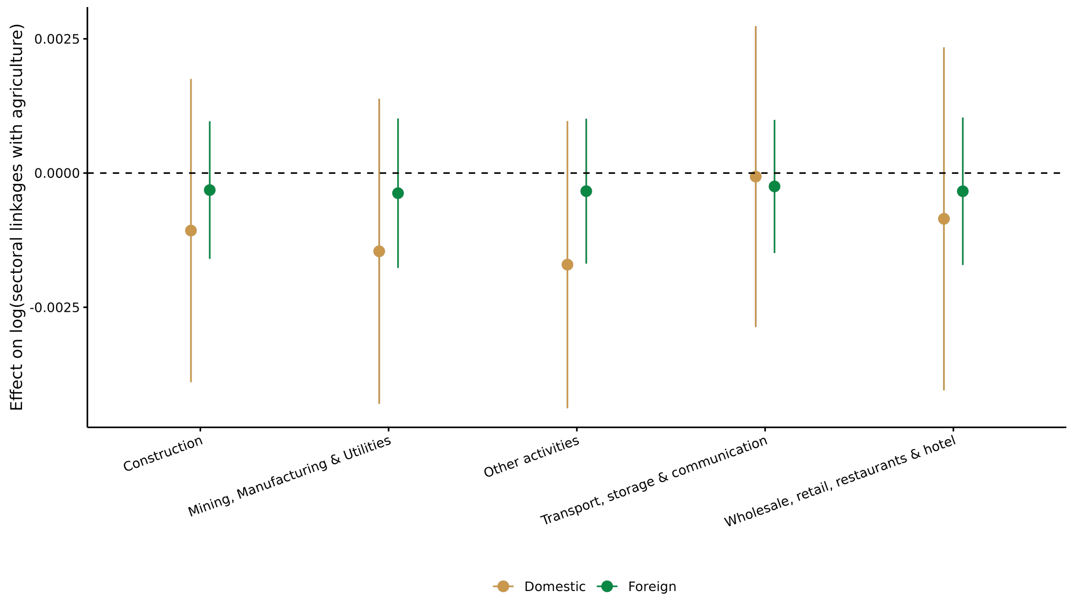
[20] Sector-specific density distribution of the downstream sectoral linkages with agriculture are reported in Appendix Figure B7.

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.[21] 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 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 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 forty years across income groups. The ratio in downstream exposure to agriculture extreme heat between time-varying and time-invariant linkages has been relatively flat and statistically indistinguishable from one across income classes (Appendix Figure B8). 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.

Together, these four facts inform the theoretical model and the empirical approach in multiple ways. These facts indicate that extreme heat reduces agricultural value added and increases crop prices. This pattern suggests that agricultural shocks 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

[21] 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., 2023).

Figure 5. Response of downstream sectoral interlinkages to extreme heat in agriculture



Notes: The figure shows the sector specific coefficients associated with extreme heat on 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 stacked regression model saturated with country-pair-sector and country-sector-year fixed effects and sector-location specific coefficients on linear and squared term of total precipitation. Bins represent the 95% confidence intervals around point estimates. Standard errors are clustered at the country level.

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 propose a simple static production network model where sectors use intermediate inputs from agriculture and other sectors in the economy. This model is able to capture how extreme heat shocks can propagate through the production network, affecting sectors that are exposed to the shock through input linkages (Acemoglu et al., 2012; Carvalho and Tahbaz-Salehi, 2019). In Appendix Section F, I describe the traditional conceptual framework adopted to derive empirical estimates of the effect of local weather shocks on local economic output. This traditional approach derives temperature-related productivity shocks from a Cobb-Douglas production function where the only inputs are labor and capital.

Here, I introduce a production network where output uses intermediate inputs and use this model to show that the effect of extreme heat shocks can be expressed in its reduced form in terms of each sector-country exposure shares to the shock.

Informed by the previous sections, I incorporate differences in factor-intensity between the agricultural sector and the other non-agricultural sectors. I consider a multi-sector multi-region model consisting of N regions indexed by $n \in \{1, ..., N\}$ (or m), each populated with $J+1$ sectors indexed by $j \in \{1, ..., J\}$ (or k), and the $J+1^{th}$ sector is agriculture, denoted as Ag.

Agricultural sector. I begin by characterizing the agricultural sector. I adopt a parsimonious representation at a micro disaggregated level equivalent to a grid cell g in country n to represent the richness of the micro level data used in the empirical analysis, while keeping the model transparent. For this reason, I abstract from modelling fields and assume that labor and parcels of land are the only inputs in the production of each crop c and are perfect complements (Costinot et al., 2016). By combining $H_n^c(g)$ workers and $L_n^c(g)$ hectares of arable land for crop c in grid cell g, a representative farm can produce

$$q_n^c(g) = Z_n^c(g) \min\{H_n(g), L_n^c(g)\} \tag{10}$$

where $Z_n^c(g)$ denotes the total factor productivity of grid cell g in country n allocated to crop c, which embeds an exponential vector of Hicks-neutral productivity extreme heat shocks $EH_n^c(g)$ that is crop-grid specific and unobserved crop and grid specific technological heterogeneity. The temperature productivity shocks account for differential geographic distribution and differential heat sensitivity of crops c across grid cells g in country n. Total agricultural output in country n is therefore

$$Q_n(EH_n) = \sum_g \sum_c q_n^c(g) \tag{11}$$

where exogenous variation in the vector of crop-grid temperature-related productivity shocks T_n affects negatively agricultural output, increasing its price.[22]

Non-agricultural sectors. In each of the J non-agricultural sectors in region n, a representative competitive firm produces good j with production possibilities described by a constant

[22] As previously discussed, I abstract from potential endogenous input adjustments. Previous micro level studies document that farmers adjust inputs, including planted are and labor use, and change crop mix as a short-term mechanism to attenuate the effect of extreme heat on agricultural output (Aragón et al., 2021). Nevertheless, while is documented only for annual crops, a large share of my crop data cover perennial crops. Moreover, I show that crop-specific planted area exposure to extreme heat conditions does not significantly vary over time (Appendix Section E).

returns-to-scale Cobb-Douglas technology whose inputs are capital, labor, and, most importantly, intermediate inputs. The output in sector j in country n is given by

$$Y_n^j = \mathcal{Z}_n^j [(\mathcal{K}_n^j)^\lambda (H_n^j)^{1-\lambda}]^{1-\omega_n^j} X_n^{j\,\omega_n^j} \tag{12}$$

where total factor productivity $\mathcal{Z}_n^j$ is a product of two components: (i) a region-sector unobserved specific component $\overline{z}_n^j$, and (ii) an exponential vector of Hicks-neutral productivity temperature-related shocks T_n^j with sector-specific elasticities β_j.[23] There are three types of inputs: K_n^j is capital and H_n^j is the amount of labor hired by firms in sector j in region n, and, most importantly, intermediate inputs X_n^j. To keep the model simple, all production technologies have the same capital intensity λ, however, I allow the intensity intermediate input use ω_n^j to be sector-region specific.

The production function in non-agricultural sectors has a nested constant elasticity of substitution (CES) structure. It is useful to unpack the composite bundle of intermediate inputs X one step at a time. Differently than previous multi-sectoral production network models (Carvalho and Tahbaz-Salehi, 2019), I introduce two key margins of heterogeneity to distinguish spatial and sectoral linkages. I distinguish between domestic and foreign inputs, and between agricultural and non-agricultural inputs, to isolate different propagation patterns depending on the origin sector of the shock. First, each aggregate sector k production is a Cobb-Douglas aggregation of inputs produced in other regions m and domestically, where respectively X_k represents an aggregation of the intermediate inputs from J sectors in the economy, and Q_m represents the agricultural production aggregated across crop commodities c in region m. Second, intermediate input bundle is aggregated across $J+1$ sectors in a CES aggregate of inputs with elasticity of substitution ξ_n^j, such that

$$X_n^j = \left(\underbrace{\sum_k^J \omega_{k,n}^{\frac{1}{\xi_n^j}} X_{k,n}^{\frac{\xi_n^j - 1}{\xi_n^j}} + \omega_{Ag,n}^{\frac{1}{\xi_n^j}} Q_n^{\frac{\xi_n^j - 1}{\xi_n^j}}}_{\text{Domestic input linkages}} + \underbrace{\sum_{m \neq n} \left(\sum_k^J \omega_{k,m}^{\frac{1}{\xi_n^j}} X_{k,m}^{\frac{\xi_n^j - 1}{\xi_n^j}} + \omega_{Ag,m}^{\frac{1}{\xi_n^j}} Q_m^{\frac{\xi_n^j - 1}{\xi_n^j}} \right)}_{\text{Foreign input linkages}} \right)^{\frac{\xi_n^j}{\xi_n^j - 1}} \tag{13}$$

where ξ_n^j is the sector-region specific elasticity of substitution between different intermediate goods, and $\omega_n^j + \sum_{m \in N} \left(\sum_k \omega_{k,m} + \omega_{Ag,m} \right) = 1$. The coefficient $\omega_{k,m}^{j,n} (\forall k \in \{J+1\})$

[23] I assume that sector-specific temperature productivity shock are mutually uncorrelated, sufficiently dispersed in terms of their average exposure. I empirically examine these features in Appendix Figures A2-A4.

designates the importance of good k as an intermediate input for the production of good j (where coefficients are allowed to vary across sector-region j, n, but I do not include that notation in Equation (13) for clarity of exposition). These coefficients ($\in [0, 1]$) represent the share of good k from region m in the total intermediate input use by sector j in region n, which can be equal to zero if it is not used. The larger $\omega_{k,m}^{j,n}$, the more important the intermediate good from the sector-region tuple (k, m) for production of good j in region n.

Before characterizing the consumption side, it is useful to map the parameters introduced in the model to the empirics. The matrix $\mathbf{\Omega} = [\omega_{k,m}^{j,n}]$ summarizes the inter-sectoral inter-country first degree input linkages. The matrix (whose rows sum up to one because of constant return-to-scale technologies, and whose columns are the shares of sector j's output within the total inputs used by the other sectors) accounts for first-order effects of propagation through first degree sectoral interlinkages.

Consumption. In addition to the production side, the economy is populated by a representative household in each country n, which supplies inelastically one unit of labor and sector-specific capital, and has Cobb-Douglas preferences over $J + 1$ distinct goods, that is

$$U(c_1, ..., c_J, c_{J+1}) = \prod_{j=1}^{J+1} (c_j)^{\beta_j} \tag{14}$$

where c_j is the consumption of good j and β_j represents the various goods' shares in the household's utility function, normalized such that $\sum_j^{J+1} \beta_j = 1$.

Equilibrium. The equilibrium in this model is defined in the traditional way, as a vector of prices and quantities such that the representative household maximizes their utility; all firms maximize their profits taking prices as given, and markets clear. The equilibrium, however, does not have a closed-form representation. Thus, I consider a first-order approximation where elasticity parameter ξ is close to one. This assumption, besides guaranteeing a closed-form representation, has two implications. First, when $\xi = 1$, the model boils down to a traditional economy with Cobb-Douglas preferences and technologies (Acemoglu et al., 2016; Carvalho and Tahbaz-Salehi, 2019). A consequence of this is that each sector-country expenditure on various inputs as a fraction of its sales is invariant to the realization of the shocks and is thus exogenous. While previous micro level firm studies have documented that firms adjust trade patterns in response to natural disasters (Balboni et al., 2024; Castro-Vincenzi et al., 2024), Fact 4 in Section 3 demonstrates that the expenditure shares from agriculture $\omega_{Ag,m}$ do not respond to heat shocks, suggesting that the Cobb-Douglas model serves as a good approximation at the sector level.

Second, in the more general case with a nested constant elasticity of substitution structure the propagation of shocks follows two separate channels. First, a negative productivity shock in sector k results in an increase in its price which affects all sectors downstream that rely on good k as intermediate input. Second, sectors may adjust resource allocation across regions m within the same sector k and across sectors k depending on the elasticities of substitution. In a Cobb-Douglas economy, this last channel is not captured. For this reason, supply-side shocks only propagate downstream, while demand-side shocks propagate upstream (Acemoglu et al., 2016).[24] While Facts 1 and 2 indicate that extreme heat in agriculture can be interpreted as a negative productivity supply-side shock that reduces production and increases input prices, whether the Cobb-Douglas representation of the economy is a good approximation such that the shocks only propagate downstream remains an empirical question that I test below.

I characterize the equilibrium price and quantities under the set of simplifications that I detailed above. The representative firm in sector j chooses demands for labor, capital, and intermediate inputs to maximize profits:

$$\pi_n^j = p_j Y_n^j - wH_n^j - rK_n^j - \sum_k \sum_{m \neq n} (p_k X_{k,m} + p_{Ag} Q_m) - \sum_k p_k X_{k,n} - p_{Ag} Q_n \tag{15}$$

while taking all prices p, wage w and rental rate r as given. Market clearing conditions for good j, n are given by $Y_n^j = c_j + \sum_k X_{jk}$ and I can derive the first-order conditions for all inputs, but report only those for agricultural goods in region n for firms in sector j in region n, which are given by

$$Q_n = \frac{\omega_{Ag,n} Y_n^j p_j}{p_{Ag}} \tag{16}$$

Downstream propagation of extreme heat. Equation (16) summarizes the mechanism of propagation at play. Without loss of generality, consider the example of agricultural commodities Q_n in region n used as one of the two intermediate inputs used for production of good j in region n, together with intermediate input $X_{k,m}$, produced in sector k in region m. The rise in price of agricultural good p_Ag attributable to extreme heat conditions (as per Fact 2) induces sector j to decreases its demand for good Q_n, consequently leading to a reduction in its production of the good Y_n^j. To see this, one can rewrite Equation (17) for sector j's output in region n in log form (lowercase letters indicating logs)

[24] With Cobb-Douglas production technologies, the price effect (a negative shock increasing output prices and thus demand for inputs) and the quantity effect (as production decreases, demands for inputs decreases, too) cancel out, leaving supply-side shocks only propagating downstream.

$$y_n^j = \log \overline{z}_n^j + f(T_{nt}^j, \beta_j) + \omega_n^j \lambda k_n^j + \omega_n^j (1-\lambda) h_n^j + \omega_n^{jn} \log\left(Q_n(EH_n)\right) + \omega_{km}^{jn} \log\left(X_{k,m}\right) \quad (17)$$

where $Q_n(EH_n)$ is the agricultural output produced in region n and ω_n^{jn} is the share of agricultural output in region n within the total intermediate inputs used by firms in sector j in region m. Equation (17) suggests that heat shocks EH_n that reduce agricultural output Q_n impact sector's j production in region n, which decreases with elasticity ω_n^{jn}. This is the downstream propagation of extreme heat through first degree linkages. Remarkably, this is not the end of the propagation effect (Acemoglu et al., 2012). Sector whose input bundle includes j in region n are now subject to a higher order effect of extreme heat $\omega_n^{j,n\,2}$. This effect continues propagating with higher order linkages which can be summarized by the Leontief inverse matrix (Leontief, 1970), $\boldsymbol{L} = (\boldsymbol{I} - \boldsymbol{\Omega})^{-1}$, whose (j,k) elements denote the importance of sector k as a direct and indirect supplier to sector j.[25] Hereinafter, I explain how I bring this model to the data and quantify the cost of local and network weather shocks on the economy.

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. The empirical approach builds on the conventional methodology adopted in quasi-experimental research designs that typically only estimate local direct effects, ignoring spatial linkages (e.g., Dell et al., 2012; Burke et al., 2015). This 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. Therefore, when there are upstream and downstream relationships across space as those modelled here, spatial considerations become of first-order relevance. These challenges may result in violations of common identifying assumptions, including the stable unit treatment value assumption (SUTVA) with first-order effects. The SUTVA rules out that heat shock exposure in agriculture of a country would differentially affect outcomes in other countries, which I test for below. To account for

[25]While a sector's Domar weight (i.e., the sales share of a sector with respect to the economy's output) is a sufficient statistic for how shocks in a sector affect aggregate output (this result is commonly known as Hulten's theorem (Hulten, 1978)), in open-economy models like the one represented here the sales shares are no longer universal sufficient statistics (Baqaee and Farhi, 2024).

this channel, I design an econometric specification that builds on 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 estimating equation is written as follows

$$\Delta \log(GVA)_{jnt} = \beta_j ExtremeHeat_{jnt} + \sum_{\ell \in \{D;F\}} \gamma_j^{\ell} NetworkShock_{jnt}^{Dn,\ell} + \mathbf{W}'_{jnt}\delta_j + \alpha_{jn} + \lambda_{jt} + \mu_{nt} + \eta_{jnt} \tag{18}$$

where I regress the growth rate of value added in sector j in country n in year t for all five sectors in the economy on sector-specific extreme heat shocks.[26] Most importantly, the specification includes $NetworkShock_{jnt}^{Dn,\ell}$, defined as extreme heat conditions in agriculture weighted by downstream interdependence of sector j with the agricultural sector in geographic location ℓ (where $\ell \in \{Domestic; Foreign\}$). The specification also accounts for a second order polynomial of total precipitation in $\mathbf{W}_{jnt}$, and for a full set of two-way fixed effects at the country-sector α_{jn}, sector-year λ_{jt}, and country-year μ_{jt} level. The two-way fixed effects mean that my estimates only exploit variation across sectors within country-years. As a result, they absorb country-specific or sector-specific trends, or any differences in baseline sector specialization across countries.

This approach relies on the differential exposure of country-sector pairs to plausibly exogenous variation in extreme heat over time both locally and in domestic and foreign agriculture to identify γ_j^{Dom} and γ_j^{Fgn}. This research design is in nature similar to a shift-share (or "Bartik") approach. They are constructed as a weighted sum of a set of shocks, extreme heat in agriculture, with 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, while exposure shares can be endogenous (Borusyak et al., 2022). Identification and consistency of 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.[27]

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

[27]Appendix Figure A2 displays the residual variation in extreme heat in agriculture over time for each country, highlight China, India, and the United States.

Although exposure shares do not respond to extreme heat, the research design does not require them to be exogenous. Another challenge is that the sum of exposure shares is not constant, i.e., $\Omega^{Dom}_{jn\tau} = \omega^{j,Ag}_{n,\tau}$ and $\Omega^{Fgn}_{jn\tau} = \sum_{m \neq n} \omega^{j,Ag}_{n,m,\tau}$ vary across sector-country jn over time. In this case, even if shocks are uncorrelated and quasi-randomly assigned, the estimator will also leverage non-experimental variation in $\Omega^{Dom}_{jn\tau}$ and $\Omega^{Fgn}_{jn\tau}$ in addition to quasi-experimental variation in heat shocks. Even when heat shocks are random, sector-countries with higher agricultural shares $\Omega^{Dom}_{jn\tau}$ and $\Omega^{Fgn}_{jn\tau}$ will have systematically different values of shocks, leading to bias if they also have different unobservables. To address this challenge, the vector of controls $\mathbf{W}_{jnt}$ includes the sum of exposure shares (Borusyak et al., 2022). This approach ensures that quasi-experimental variation in heat shocks in agriculture is isolated conditional on a sector-country's 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 on sectoral production of trade-induced exposure to harmful extreme heat conditions in agriculture. As formulated in the theoretical framework and supported by the empirical evidence, extreme heat reduces agricultural productivity. By only considering the *direct* impact of local weather conditions on a given sector, one is omitting the amplification and transmission of these shocks due to the intersectoral reliance. A negligible or null effect of local weather conditions on a given sector may be amplified by extreme heat conditions hitting agricultural sectors around the world with strong commercial interlinkages with that sector. The effect would ripple down to downstream customer sectors that then use agricultural inputs less intensively in response to increases in agricultural prices and thus reduce their own production.

There are a number of advantages of using Equation (18) for empirical analyses of the aggregate and differential effects of heat shocks. 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. 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.

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 faced by country n

$$SpatialHeat_n^t \equiv \sum_{m \neq n} \frac{D_{mn}^{-\delta}}{\sum_{o \neq n} D_{on}^{-\delta}} ExtremeHeat_n^t, \tag{19}$$

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

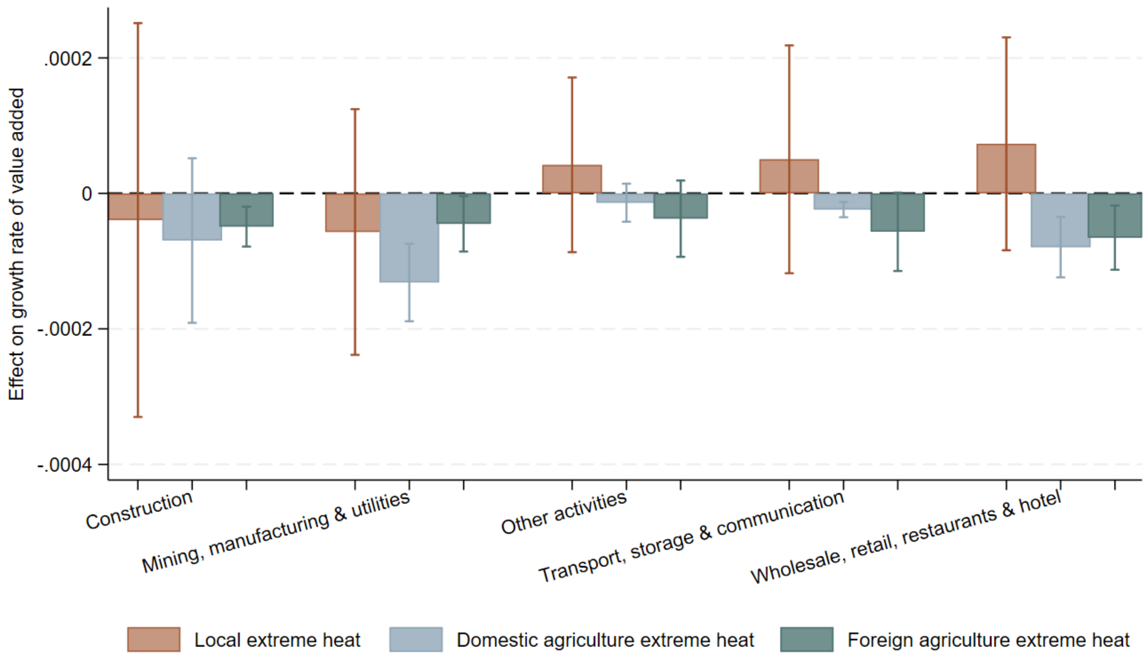
In this section, I report the results from the estimation of Equation (18) that quantifies the propagation of extreme heat on agriculture across the economy through the production network. Figure 6 displays the coefficients associated with local extreme heat conditions and downstream agricultural *network* heat decomposed into domestic and foreign.

Starting from the coefficients on local extreme heat, the estimated effect on all sectors is not statistically distinguishable from zero. As previously concluded from a traditional regression estimating the effect of local direct extreme heat on sectoral value added, for all sectoral outcomes, the coefficients are not statistically different from zero. I then turn to the coefficients associated with domestic and foreign extreme heat conditions in agriculture. The coefficients measure the differential impact of exposure to extreme heat in agriculture on the growth rate of downstream sectoral value added per capita. The figure shows that the negative impact of local extreme heat in agriculture propagates to downstream sectors more exposed in terms of use of intermediate input goods from agriculture. For downstream sectors that heavily rely on agricultural goods as intermediate input, such as manufacturing, wholesale, retail, restaurants and hotels, the effect is more pronounced and statistically significant both for domestic and international agricultural shocks, suggesting that extreme heat propagates both across sectors and space. At the mean, the effect of one degree day exposure in domestic (foreign) agriculture reduces growth rate of manufacturing value added by 0.48% (0.19%). Similarly, domestic (foreign) agriculture reduces growth rate of wholesale, retail, restaurants and hotels value added by 0.26% (0.23%).

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 shocks may be biased since the treatment status of other units in the sample alters the potential expected outcome through shocks propagating from the agriculture sector. The statistical and economic significance of foreign network shocks suggests that also geographically distant weather fluctuations matter through input interlinkages. Second, from an economic perspective, agriculture-specific extreme heat conditions are amplified through input interlinkages, affecting other sectors beyond agriculture and also travelling beyond national borders. As a result, recent estimates on the economic damage of temperature increases may have been largely underestimated due to the omission of this propagation channel. On average, across the five downstream sectors, a one-degree day increase in exposure to domestic (foreign) agriculture extreme heat reduces the sectoral growth rate by 0.21% (0.18%). 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 per capita, the average effect across sector is 0.03%.

Beyond first degree sectoral interlinkages. The analysis has so far relied on first degree sectoral interlinkages in the production network. To account for the full transmission of shocks

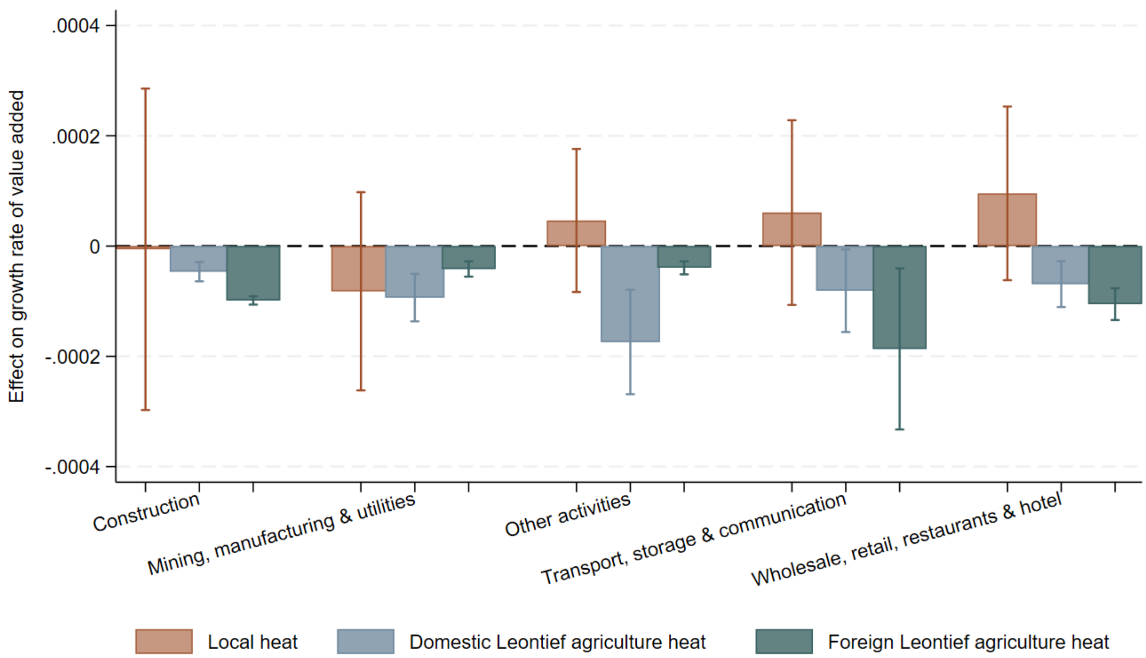
Figure 6. Local and downstream agriculture extreme heat on sectoral value added



Notes: Bars represent the sector-specific coefficients associated with local shocks and domestic and foreign downstream shocks, 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). The specification jointly estimates all sector-specific coefficients in a stacked 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. Bins represent the 95% confidence intervals with standard errors clustered at the country level.

over the network, I construct the Leontief inverse matrix, which summarizes the sector-specific technical coefficients of the shock propagation through a power series representation of the Leontief inverse (Leontief, 1970). By taking the inner product of agricultural heat shocks and the Leontief inverse matrix, I obtain a sector-specific shock that takes full inter-sectoral relations into account. I estimate a specification with agricultural heat shocks weighted by the Leontief-derived downstream coefficients and report the coefficients in Figure 7. By taking into account the full direct and indirect linkages of downstream sectors with agriculture, all sectors are negatively affected by both domestic and foreign heat shocks. The effect of extreme heat in agriculture percolates downstream to final goods and service sectors such as 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 exposure in domestic (foreign) agriculture reduces growth rate of manufacturing value added by 0.34% (0.15%). Similarly, domestic (foreign) agriculture reduces growth rate of wholesale, retail, restaurants and hotels value added by 0.22% (0.35%). On average, across the five downstream sectors, a one-degree day increase in exposure to domestic (foreign) agriculture extreme heat reduces the sectoral growth rate by 0.28% (0.27%).

Figure 7. Sector-specific response to agriculture extreme heat in a Leontief matrix



Notes: Bars represent the sector-specific coefficients associated with local extreme heat shocks and domestic and foreign downstream shocks 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 stacked 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. Bins represent the 95% confidence intervals with standard errors clustered at the country level.

Propagation over time. So far, the estimates indicate that extreme heat in agriculture propagates across sectors and countries with a contemporaneous short-run negative effect on downstream sectors. It might be, however, that the effects of extreme heat on agricultural production may take up one year to manifest in downstream sectors, particularly in those furthest away in the supply chain from direct agricultural inputs. This delayed impact is attributable to the time required for agricultural production to respond to extreme heat, as well as the staggered nature of the production processes within supply chains. In further 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. Additionally, 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 full 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. 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. To empirically test which of these two mechanisms dominate, I estimate the baseline regression including a one-year lagged measure of local, domestic, and foreign shocks. Appendix Figure B9 displays the six coefficients on contemporaneous and lagged direct and indirect heat impacts for each of the five downstream sectors. Local extreme heat is never statistically significant, however, an interesting pattern emerges for indirect extreme heat. Both domestic and foreign extreme heat in agriculture have a negative and statistically significant impact on for most sectors, with the effect larger in magnitude on lagged shocks, in particular for sectors further downstream.

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. But using a balanced sector-country sample, excluding certain large countries (China, India, Russia, United States), the 10% coldest or hottest countries does not substantially alter my baseline findings (Appendix Figures B10 and B11).

Upstream propagation. As a test for the validity of the Cobb-Douglas production function assumed in Section 4, I construct a measure of upstream exposure to heat shocks. Since extreme heat is a supply-side shock that reduces agricultural productivity, its output and increases its prices and thus percolates to downstream sector as a input shock, the theory 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 agriculture extreme heat does not propagate upstream, as demand-side shocks would, but only downstream, confirming that extreme heat in agriculture behaves as a supply-side productivity shock. The 12 coefficients on the effect of downstream agriculture propagating upstream are very close to zero in magnitude and not statistically significant.

Distance-weighted shocks. In an additional robustness check, I introduce the distance-weighted measure of $SpatialHeat$ constructed in Equation (19) 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. I empirically test for this hypothesis in my setting and find that the distance-weighted measure $SpatialHeat$ is not statistically significant and any conventional level and does not substantially alter the magnitude of the input-weighted network shocks, suggesting that distance-weighted exposure to extreme heat does not capture the effect identified by my network shocks (Appendix Figure B14).

7 Counterfactuals: Economic cost of warming

This section uses the estimated semi-elasticities to demonstrate how to incorporate spatial and sectoral linkages via intermediate inputs into quantification exercises of the impact of global warming. In particular, I quantify the role of input linkages across sectors and space in amplifying the welfare effects of global warming through two counterfactual exercises. Since the panel estimates obtained from the estimation refer to short-run elasticities in response to deviations from extreme heat, 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). These exercises are therefore based on the empirical observation of input linkages across sectors and countries and on the panel estimates of my analysis. The final objective is to show how the economic consequences of spatial and sectoral input linkages, estimated using quasi-experimental variation, can be incorporated into short-run elasticities to weather to help bridge the gap between quasi-experimental approaches and structural models of climate impacts (Costinot et al., 2016; Cruz and Rossi-Hansberg, 2021).

Because these exercises have the sole purpose of capturing sectoral and spatial linkages through intermediate inputs, I emphasize that it omits other potential general-equilibrium effects of climate change. First, I fix the spatial patterns of comparative advantage within plant species at recent historical values. This implies that I do not take into account other trends such as technological change (to the extent that this is not embedded in the unobserved heterogeneity captured by my set of fixed effects or quadratic country-sector specific time trends). Second, I do not consider other potential adjustments such across crops within the agricultural sector (Rising and Devineni, 2020), although Appendix Section E shows that I cannot reject the null hypothesis that agricultural production has not been adapting significantly in such a way that extreme heat exposure to agricultural crops has changed over time. My estimates, however, account for sectoral reallocation to the extent that sectoral value added losses are aggregated to compute domestic value added weighted by their respective shares.

7.1 Economic losses due to recent warming

In the first counterfactual, I use the estimated semi-elasticities and the data to estimate the impact of recent historical warming on the level and distribution of value added across countries. Using the panel estimates of the effect of local extreme heat in agriculture documented in Section 3 and the panel estimates of the effect that domestic and foreign agriculture extreme heat on downstream sectors in Section 6, I simulate how much slower or faster each sector in each country would have growing in each year over the 2001-2020 period, had the extreme heat exposure in agriculture stayed at its 1975-2000 average, and cumulate these effects over the period to compute the increase or decrease in value added (see Appendix Section I for additional details). This analysis provides estimates that are agnostic to the cause of recent warming and does not necessarily represent the impact of recent anthropogenic warming.

I begin by computing the effect of recent warming on agriculture value added. Compared to a counterfactual where local extreme heat had stayed constant to its average in the twentieth century, recent warming has a negative impact on agriculture value added around the world (the only countries that marginally benefit from changes in temperature with respect to 1975-2000 are Canada and Ireland). In particular, larger losses are concentrated in Northern Africa, Middle East and South-East Asia. Figure 8 shows the distribution of damages across countries (top map). On average, recent warming in agriculture is responsible for a 0.035% loss in total value added across countries.

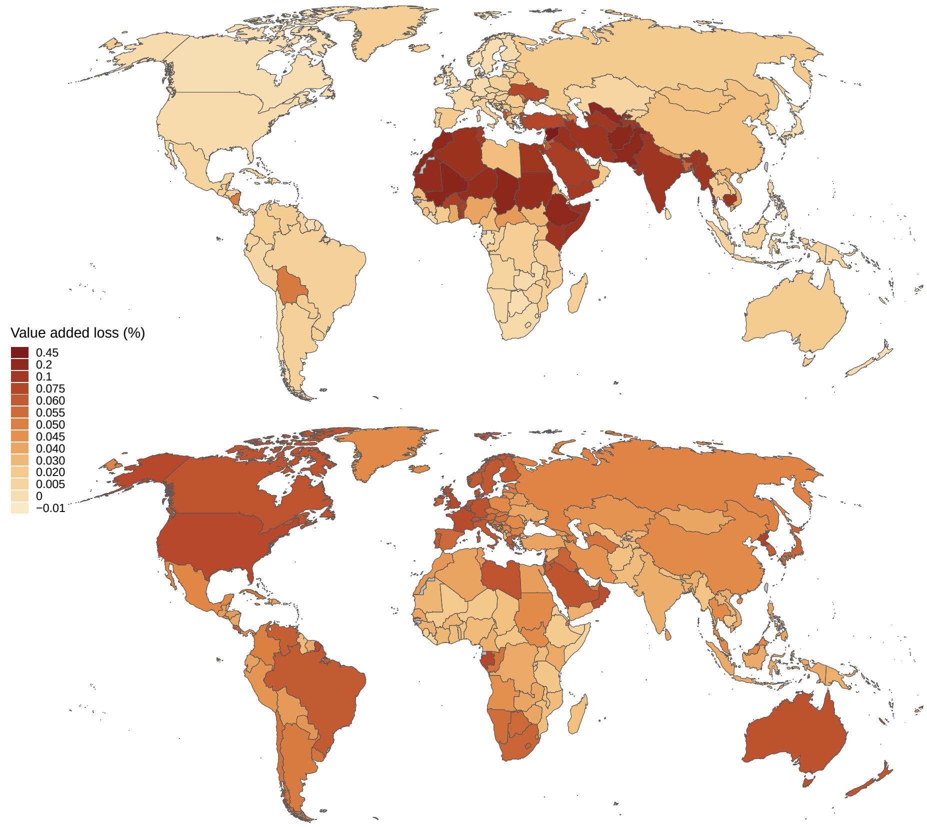
I then turn to the question of whether other sectors and countries that use intermediate inputs from agriculture have suffered from the increase in extreme heat exposure that agricultural commodities have experienced recently. To do so, I use the estimated semi-elasticities from Equation (18) that account for all the Leontief linkages between agriculture and downstream sectors and repeat the same exercise. I simulate how much slower or faster each sectors in each country would have grown in each year over the 2000-2020 period had domestic *and* foreign extreme heat exposure in agriculture stayed at its 1975-2000 average. Note that the semi-elasticities account for endogenous adjustments in trade patterns as observed in the data since the input linkages in Equations 3 are averaged over five years. To the extent that countries have been able to reduce their exposure to extreme heat from agriculture upstream sectors, this would be reflected in the data and in the counterfactuals that I run. Similarly, the estimates also account for observed sectoral reallocation. By weighing sector-specific value added losses by the country-specific share of each sector in total value added, if larger damages are experienced in sectors that only have a small or negligible share in total domestic production, this would be reflected in total national losses.

The bottom map in Figure 8 shows the global distribution of losses (in % of total value added) on downstream sectors accounting for domestic and foreign exposure to extreme heat in agriculture. On average across countries, recent warming in agriculture is responsible for a 0.046% loss in total value added. This result indicates that accounting for input linkages, the cost of recent warming in agriculture in downstream sectors is larger by approximately 31%. Interestingly, the spatial distribution of damages across countries is much more homogeneous, and Europe, North America and Latin America incur larger losses. Overall, this result indicates that on average only 29% of the loss can be explained by the direct impact of extreme heat in agriculture on this sector. The remaining 71% of the total value added losses depends on the propagation of extreme heat impact effects to downstream sectors by way of the production network. Remarkably, the economic importance of the production network in amplifying extreme heat impacts is very close in magnitude to the 73% share of the indirect losses that contribute to the total economic cost of conflicts in India (Couttenier et al., 2022).

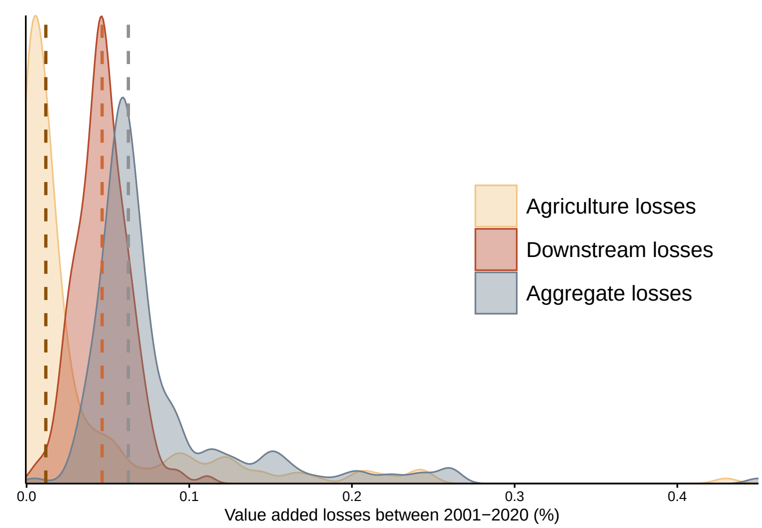
This result indicates that trade as an adaptation strategy to climate change can come at a cost. Without accounting for linkages across sectors and countries, the effects of extreme heat on agricultural production are concentrated locally in those countries whose share of agriculture in domestic value added is large. Vice versa, accounting for input linkages makes the world more interdependent and hence amplifies the effects of local agricultural productivity shocks across sectors and countries. Downstream sector use of agricultural inputs both domestically and internationally amplifies the propagation of local productivity shocks in agriculture induced by extreme heat.

Figure 8. Effect of recent warming on agriculture and aggregate value added losses (%)

(a) Global distribution in agriculture and on aggregate value added



(b) Density distribution of value added losses



Notes: The figure shows the total losses in value added (%) between 2001 and 2020, compared to a counterfactual where extreme heat in agriculture had remained at 1975-2000 baseline averages, instead of observed values. The world map above displays the total value added losses due to extreme heat in each country accounting only for losses in agriculture (weighted by the average share of agriculture in total value added). The world map below displays losses due to extreme heat in each country accounting for losses in all five downstream sectors induced by domestic and foreign extreme heat (and weighted by the average share of each sector's in total value added). The density plot displays the cross-country distribution of losses in agriculture, in downstream sectors, and the total aggregate losses accounting for both the effect of local extreme heat in agriculture and its downstream propagation across countries (dashed lines displays the mean). The sector-specific semi-elasticities are obtained from bootstrapping 1000 times the underlying panel estimates of Equation (18) with replacement.

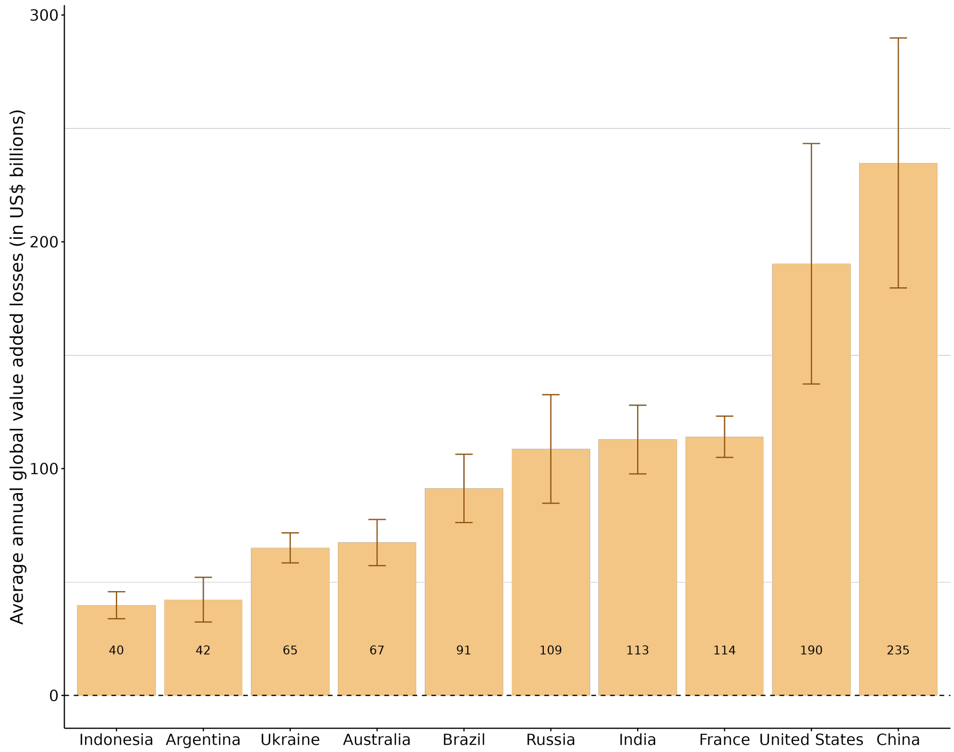
7.2 Propagation of extreme heat through the production network

In a second exercise, I quantify the macroeconomic aggregate impact of a shock in extreme heat conditions in a country and the differential global consequences of a country experiencing a shock. In essence, this counterfactual embeds 183 counterfactuals in which each country at a time experiences a shock in extreme heat conditions in agriculture of one standard deviation of the observed global extreme heat conditions in each year. This approach allows me to account for differential temporal variations in climatic conditions induced by global phemonena (e.g., El Niño) and for different country areas. I then use the estimated semi-elasticities in Equation 18 to obtain counterfactual growth rates and economic losses for each sector in each country, which I aggregate to obtain annual counterfactual losses/benefits in value added under each of the 183 counterfactuals.

I start by computing average annual global losses adding up all 183 counterfactuals. On average, if all countries experienced a one standard deviation shock in extreme heat exposure in agriculture, annual global losses would be around 1.62 trillion 2015US$ (95% CI: 1.57; 1.68). To give an idea of the estimated losses, global value added in my sample was on average 45 trillion 2015 US$ (where the maximum was recorded in 2019 and was more than 79 trillion US$). Therefore, on average, global value added losses due to a simultaneous increase by one standard deviation in extreme heat conditions in agriculture globally are around 3.5% of value added.

I then analyze the different 183 counterfactuals separately to infer where shocks in agriculture are more influential in the propagation across sectors and space. Figure 9 reports the ten largest annual global value added losses. Global losses are larger if China or the United States experience a shock, respectively, 235 and 190 billion US$. Counterfactuals show that there are large losses also if France, India, and Brazil experience an increase in extreme heat in agriculture. In particular, these five countries together make up more than 45% of world crop output. China is the leading producer of rice, wheat, tobacco, cotton, and ramie. While Costinot et al. (2016) only account for the local impact of climate change on crop output, these results indicate that shocks in these countries can also propagate to other sectors and countries. Overall, these findings indicate a strong positive relationship between the integration of the country's agricultural sector in the supply chain and the value added losses induced across sectors and space.

Figure 9. Annual global value added losses accounting for input linkages for a standard deviation increase in extreme heat in agriculture



Notes: The figure shows the average annual global value added losses in 2015$ billions for a one standard deviation increase in extreme heat in agriculture in a country in the x-axis, using sector-specific semi-elasticities from Equation (18) and aggregating across sectors and countries to obtain average global losses in a year. Brown bins indicate the 95% confidence intervals obtained from a 1000 bootstrap replications with replacement.

8 Conclusion

Recent studies have pushed forward the frontier for an accurate estimation of aggreggate economic losses induces by climate for an adequate quantification of the total economic impact of climate change (Bilal and Känzig, 2024; 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 weather shocks 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 (Acemoglu et al., 2012) to quantify the economic cost of global warming. The methodology is applied to global production networks constructed from input-output sectoral interlinkages and sectoral value added data combined with high-resolution daily temperatures between 1975 and 2020.

The analysis reveals that the input linkages work as an amplification mechanism of extreme heat conditions in agriculture across countries, generating substantial fluctuations in sectoral value added. Downstream sectors, including manufacturing, wholesale, retail, construction, that are unresponsive to local heat conditions, are shown to suffer 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 over the economy's production network can impact them, thus resulting in movements in macroeconomic aggregates. Using the reduced form estimates of my analysis to inform counterfactual simulations, I show that input linkages amplify value added losses in downstream sectors by around 31%. Global losses are sizable even for just a single country experiencing extreme heat in agriculture if the country is strongly interconnected in the global production network. This is the case for China, the US, France, India, Russia, and Brazil. A one standard deviation increase in extreme heat in each of these countries would lead to a total average annual global loss in value added equal to 852 billion US$.

For this reason, several important issues remain open to future research. First, the analysis provides modest but suggestive evidence on the role of adaptation of countries, in particular, that the effect of local extreme heat condition depends on climate and income. My analysis, however, cannot reject the hypothesis of little to modest evidence of countries' ability to reduce their exposure to upstream extreme heat in agriculture by adjusting input linkages in response to extreme heat. The analysis does not explicitly model adaptive investments, technological change, or other agriculture-specific adaptive responses (e.g. irrigation) that may heterogeneously affect the response functions and reduce climate damage. 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 (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 underlying weather risk from weather shock realizations and adaptive responses.

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

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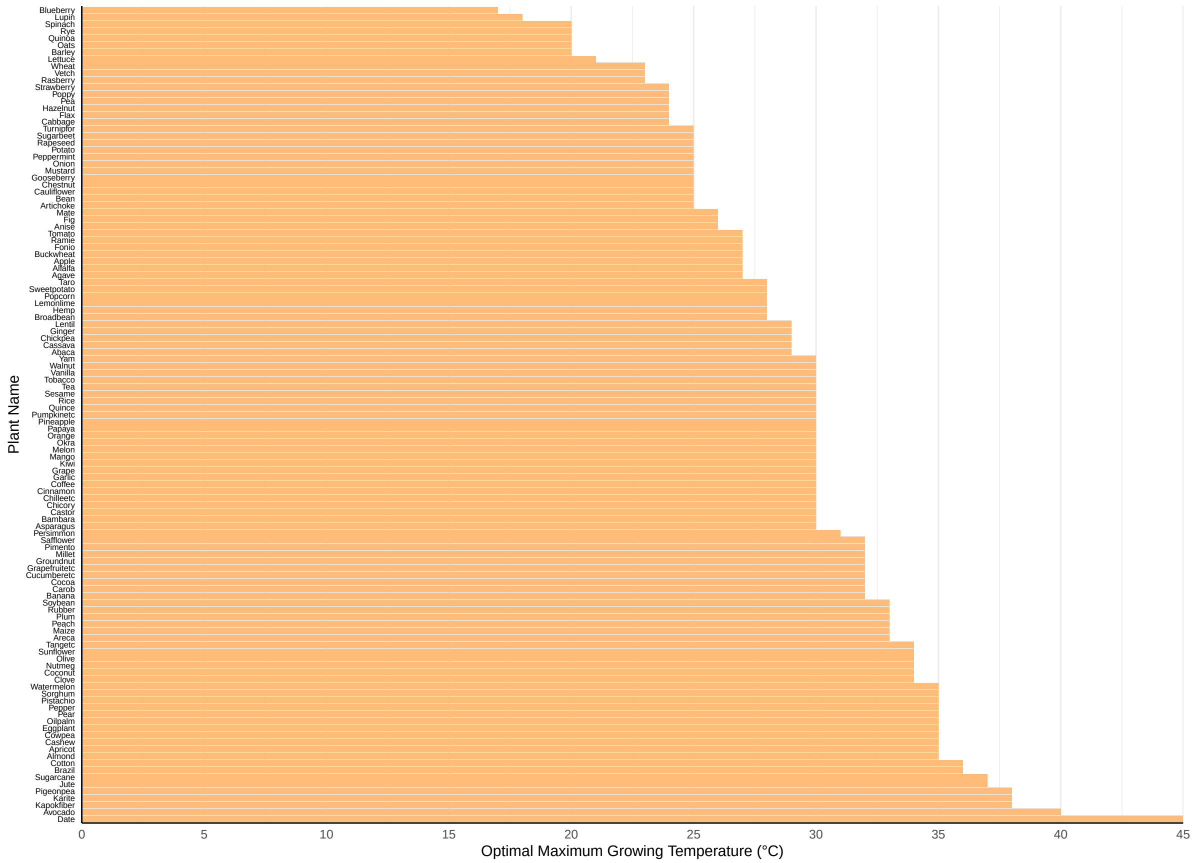
Appendix

Table of Contents

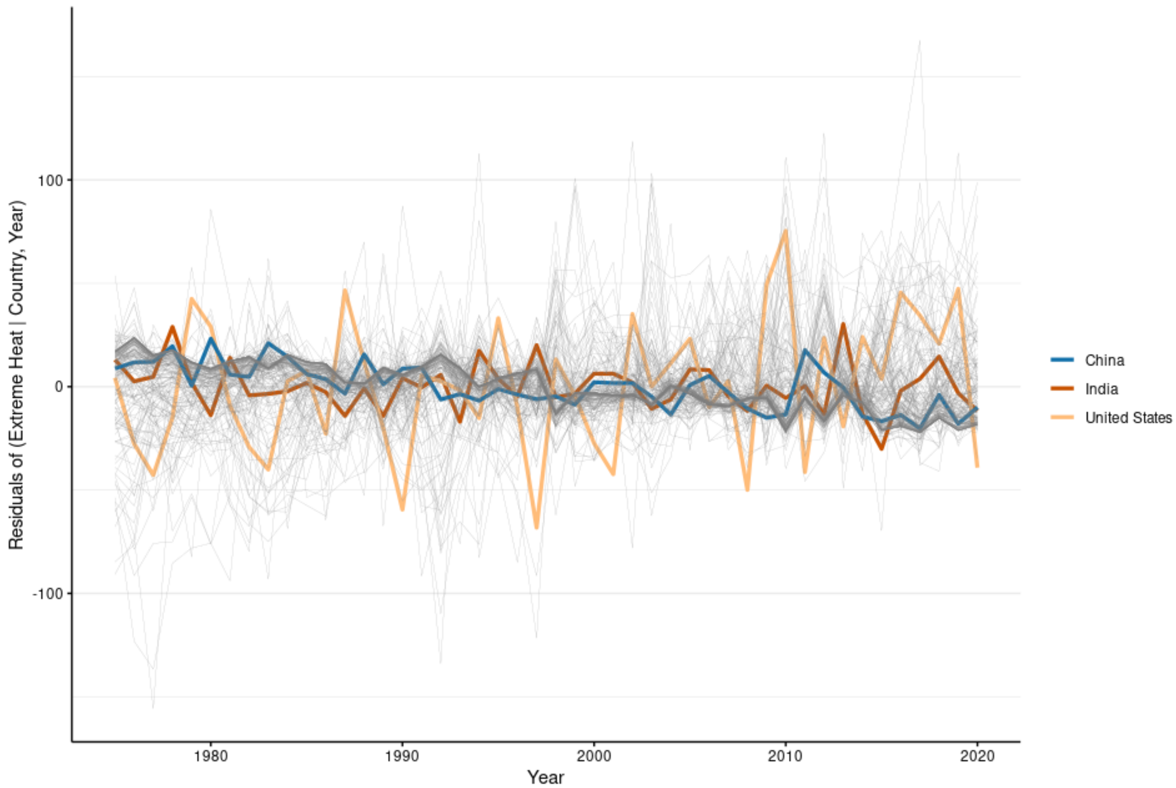
A Additional figures - Descriptive Statistics

Figure A1. Crops and optimal maximum growing temperature



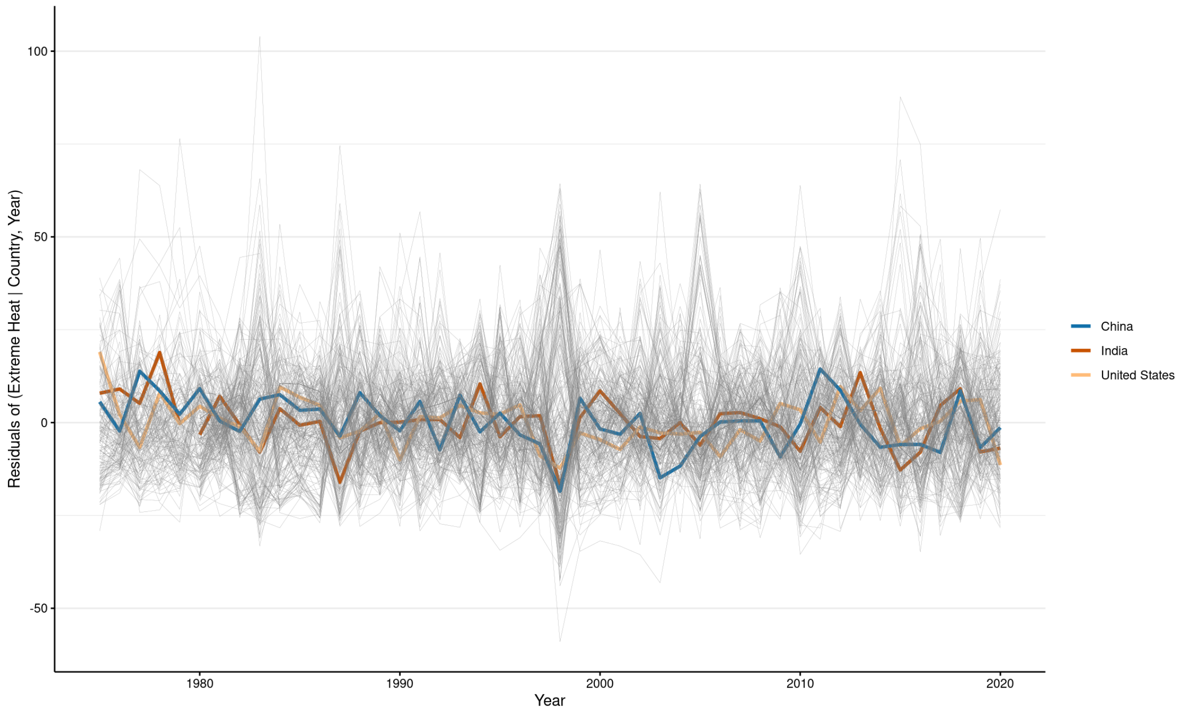
Notes: The figure shows the optimal maximum growing temperature for the 118 plant species in my final sample, as reported in the FAO EcoCrop (UN FAO, 2024).

Figure A2. Residuals in extreme heat exposure in agriculture



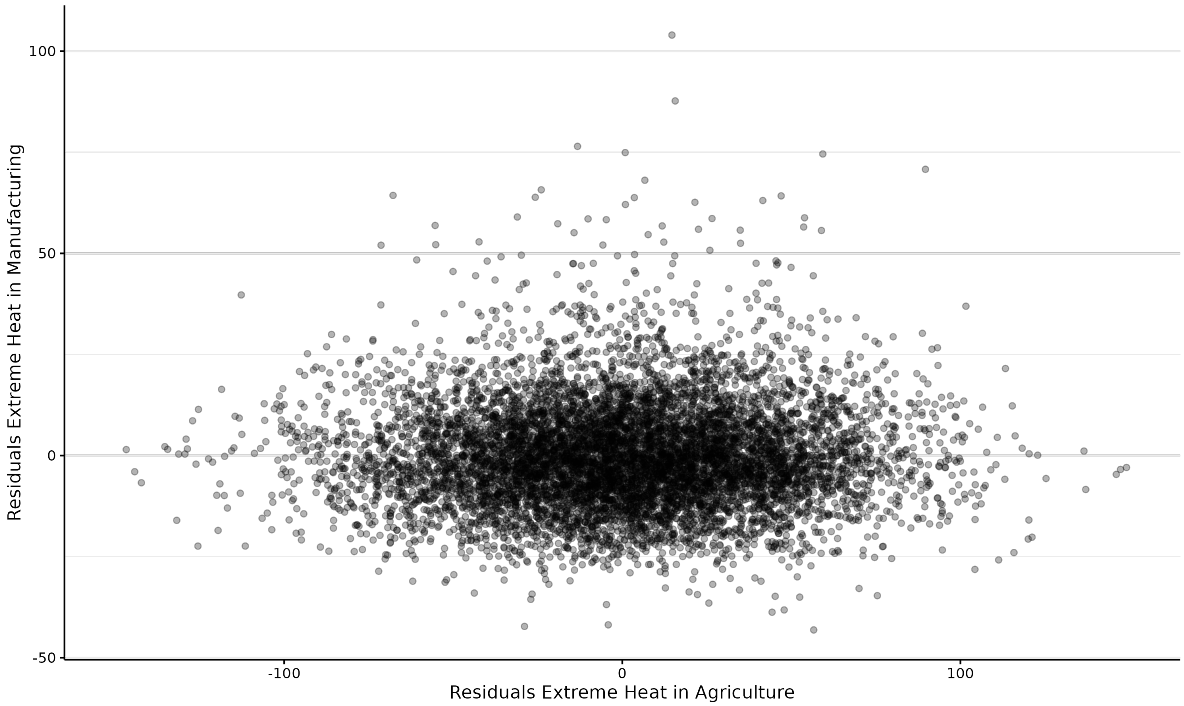
Notes: The figure shows the residuals in extreme heat exposure in agriculture obtained from a regression projecting extreme heat on country and year fixed effects.

Figure A3. Residuals in heat shocks in manufacturing



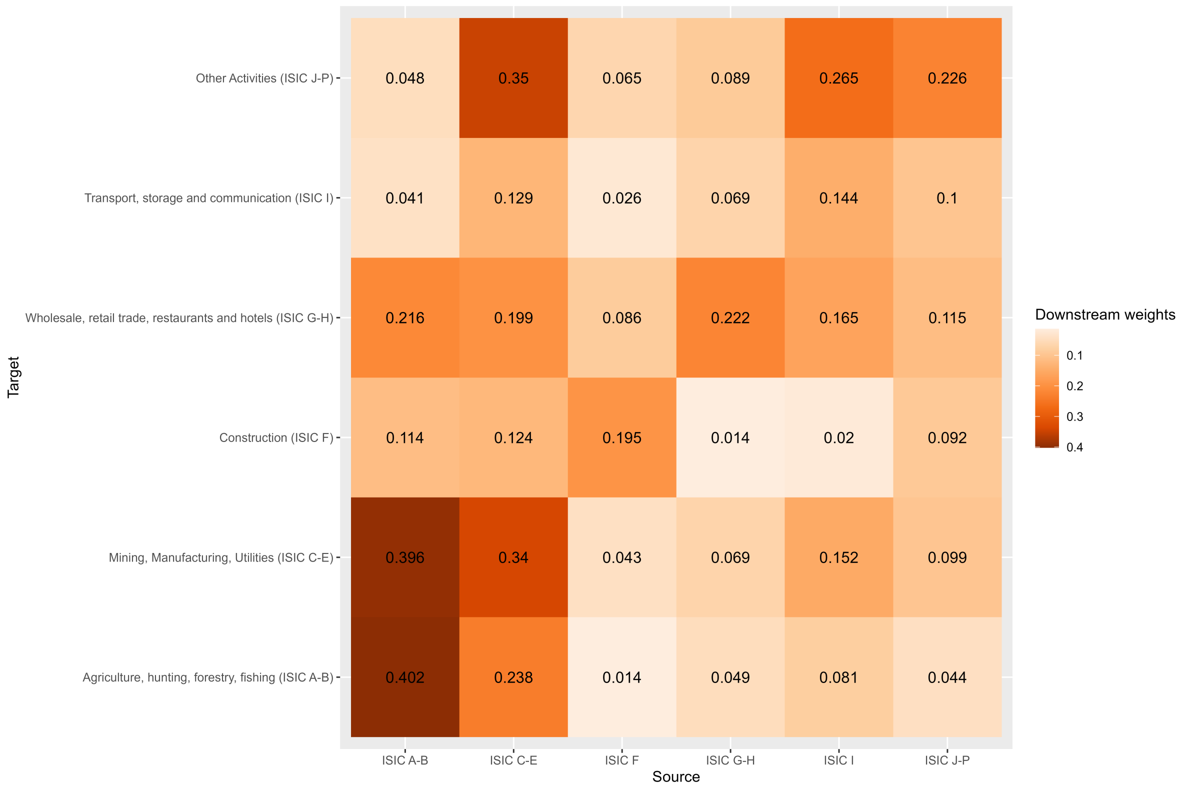
Notes: The figure shows the residuals in extreme heat exposure in manufacturing obtained from a regression projecting extreme heat on country and year fixed effects.

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



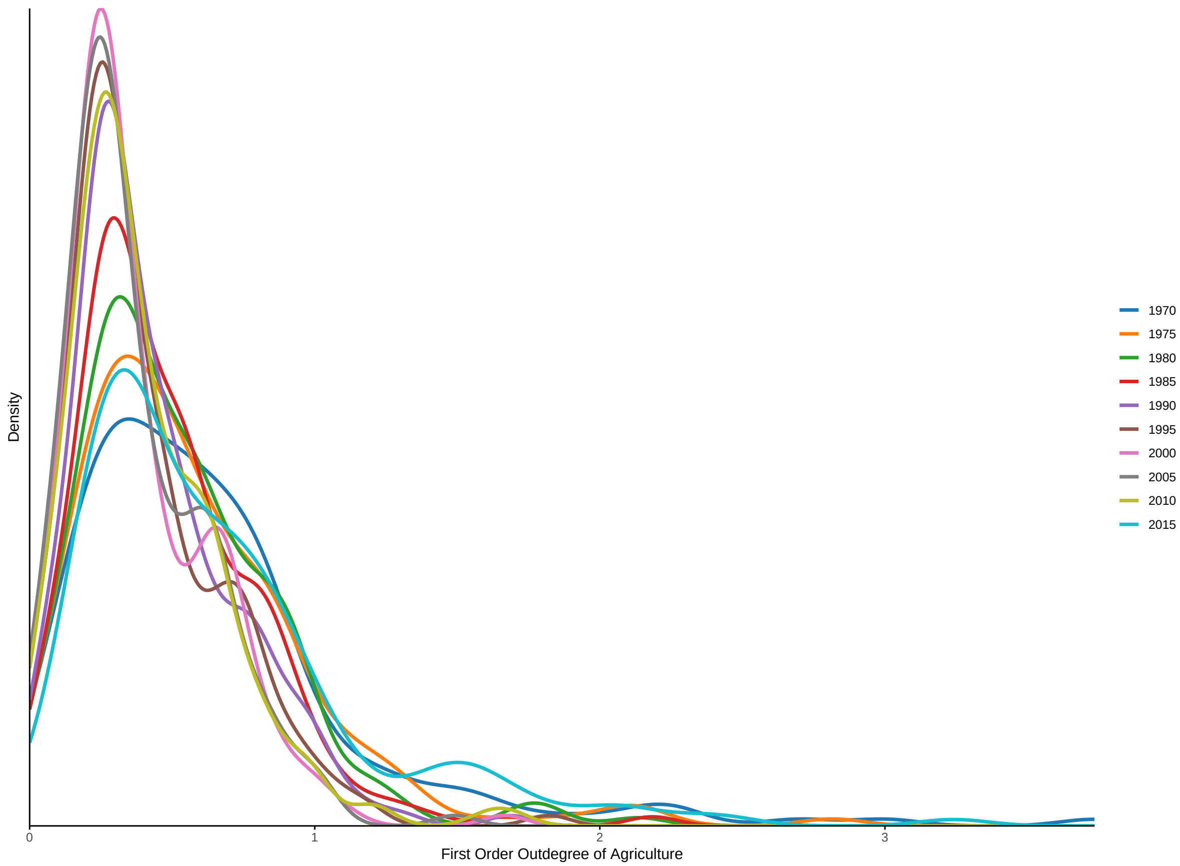
Notes: The figure shows the scatter plot of the residuals in extreme heat in agriculture and in manufacturing obtained after conditioning on country- and year- fixed effects. The relationship between the residuals in the final sample is not statistically different from zero (p-value equal to 0.61).

Figure A5. Average downstream linkages across countries



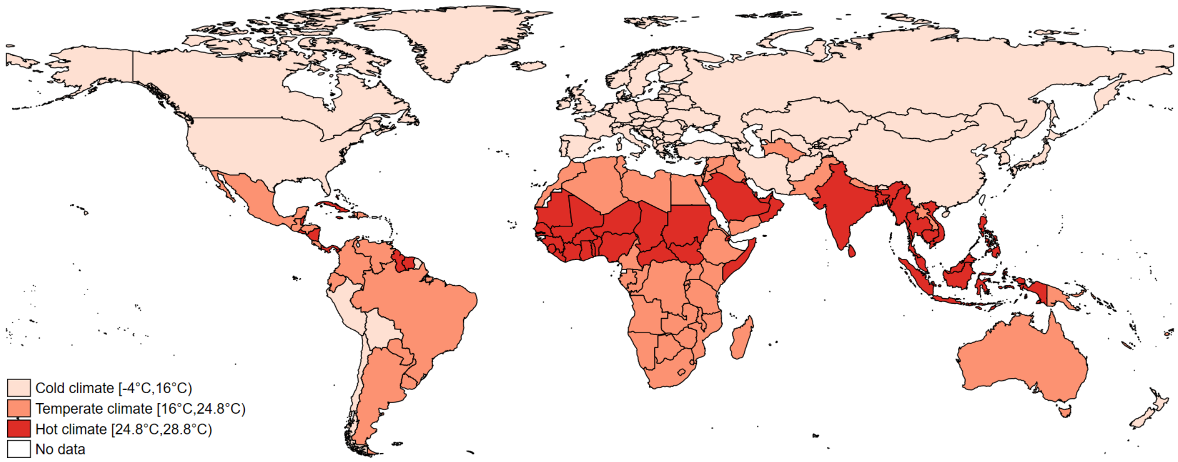
Notes: The figure shows the average downstream linkages across countries by sector, constructed from the perspective of Source sectors on the x-axis.

Figure A6. Density distribution of first order outdegree 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).

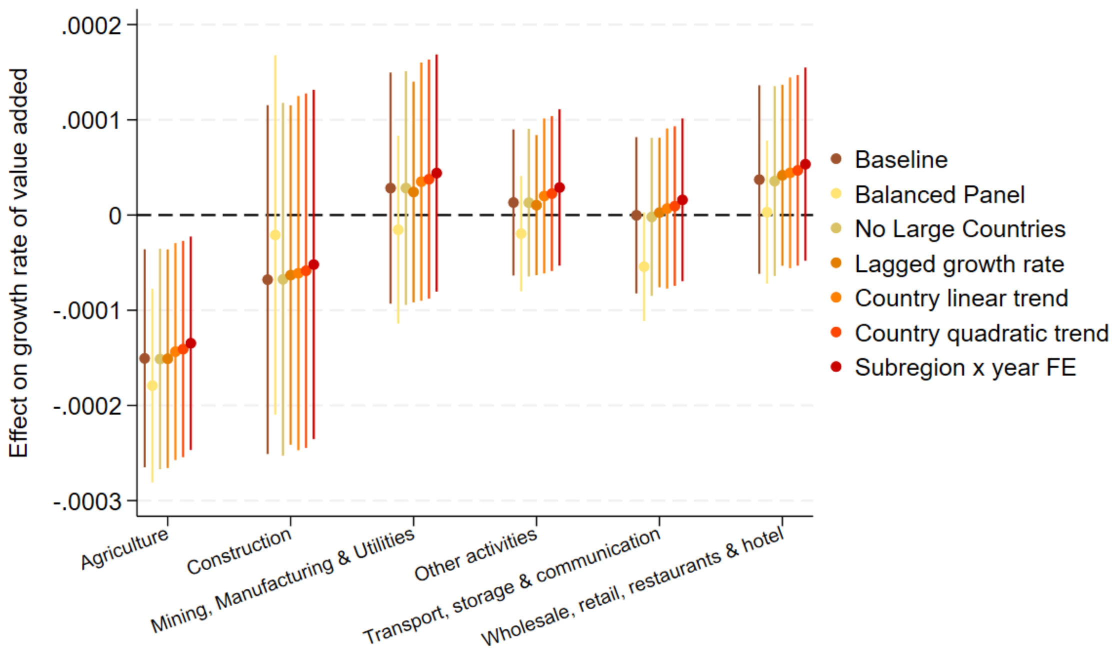
Figure A7. Countries in the sample by climatic zone



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 Figure H1.

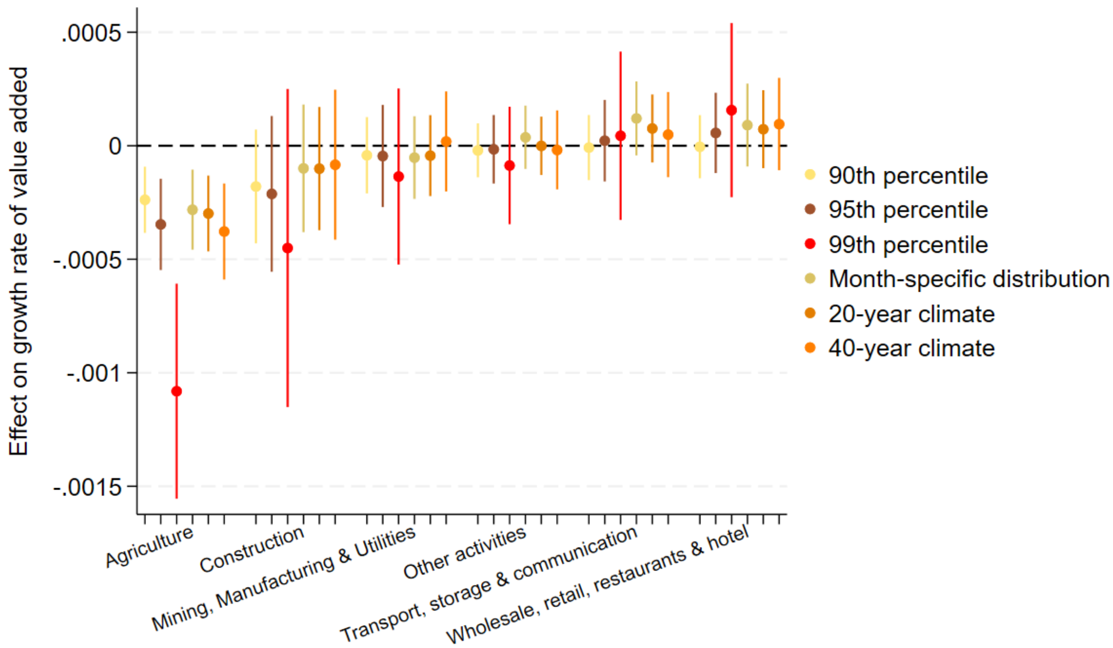
B Additional figures - Robustness and additional results

Figure B1. Robustness 1: Response to local extreme heat



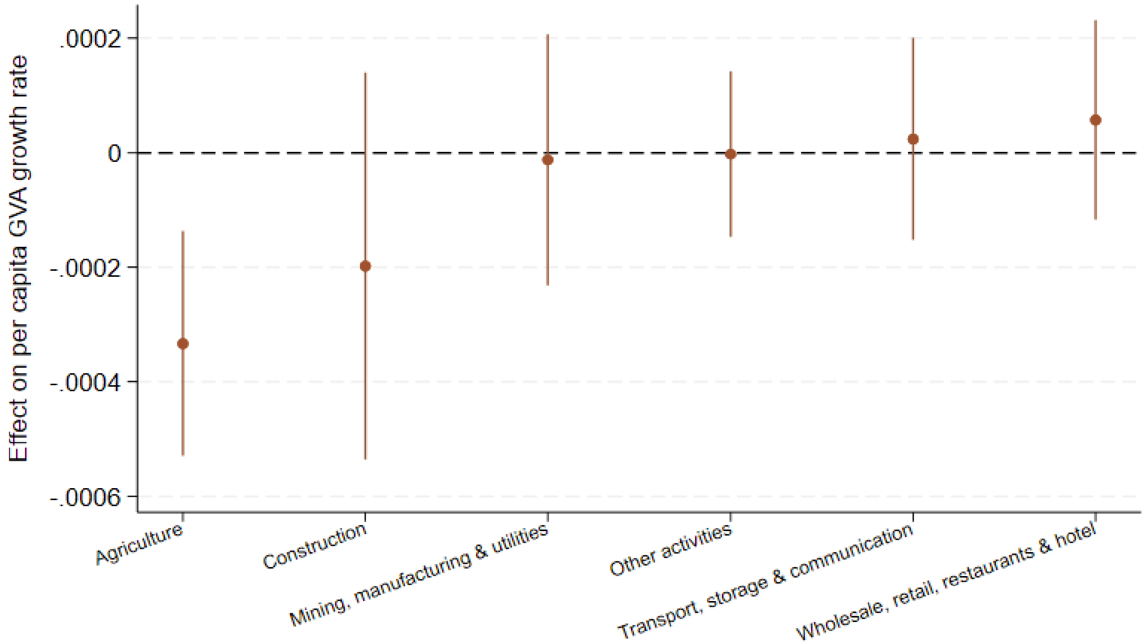
Notes: The figure shows the regression estimates for the country-average number of degree days of extreme heat using a sector-country balanced panel; excluding large countries (Brazil, China, India, Russia, US); including lagged growth rate; including country-specific linear trends; including linear and quadratic country-specific trends; including subregion-by-year fixed effects. All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects. Bins represent the 95% confidence intervals around point estimates. Subregions divide the world into 17 zones: Australia and New Zealand, Central Asia, Eastern Asia, Eastern Europe, Latin America and the Caribbean, Melanesia, Northern Africa, Northern America, Northern Europe, Polynesia, South-eastern Asia, Southern Asia, Southern Europe, Sub-Saharan Africa, Western Asia, Western Europe.

Figure B2. Robustness 2: Response to local extreme heat



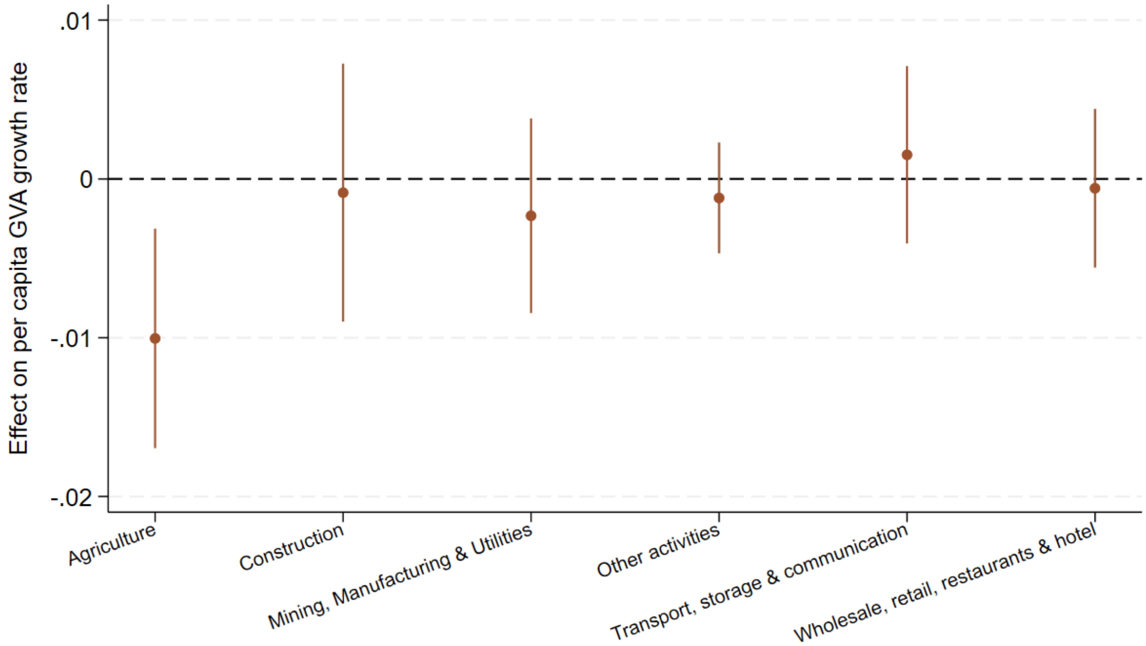
Notes: The figure shows the regression estimates constructing the extreme heat exposure differently: I use different percentiles of the grid-specific distribution (90, 95 - the baseline - and 99); I construct heat exposure relative to the 95th percentile of each grid-month specific distribution of temperature 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 per capita



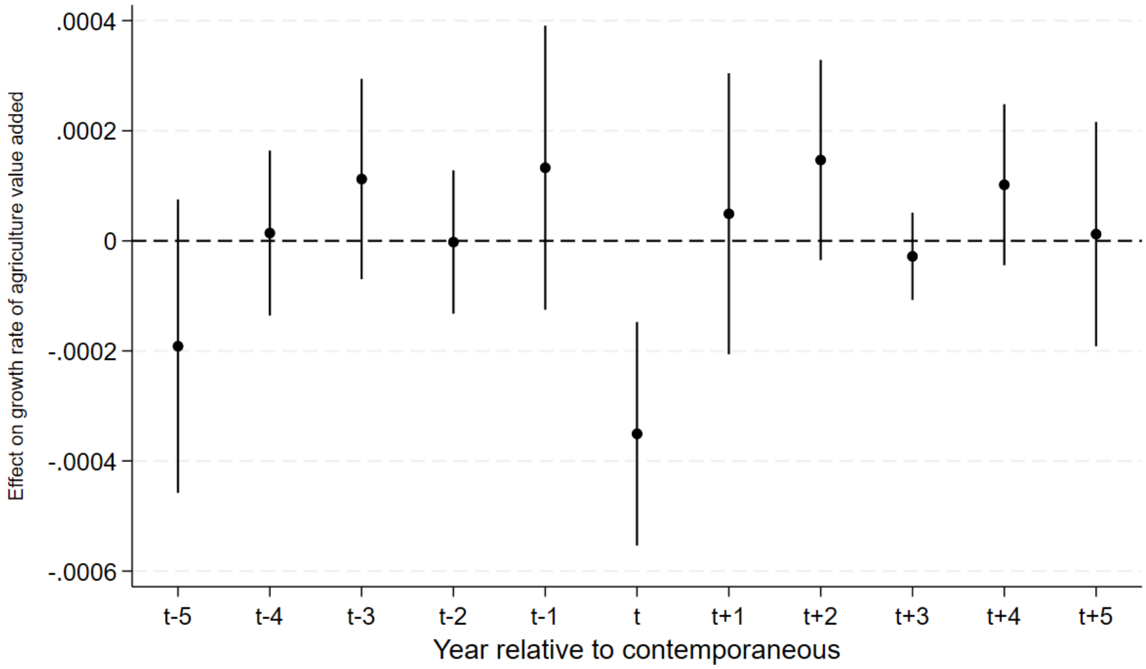
Notes: The figure shows the regression estimates for the country-average number of days above the 95$^{\text{th}}$ percentile of the daily distribution in temperature. All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year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

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



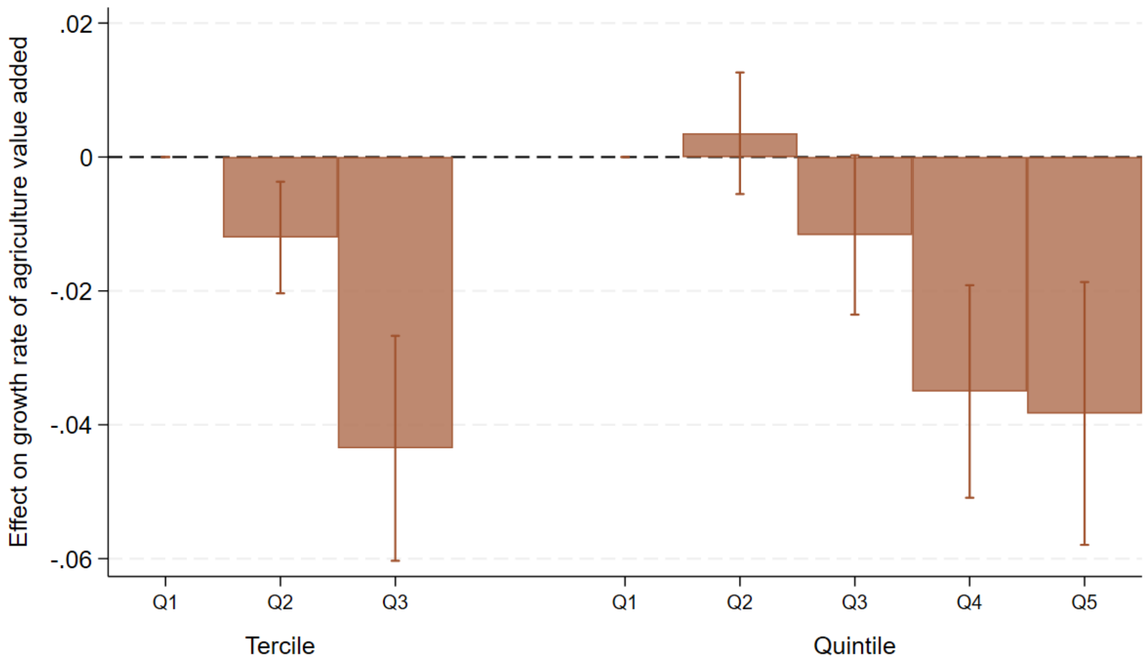
Notes: The figure shows the regression estimates of the temperature shocks constructed as in Equation (2). All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects and controlling for a sector-specific second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

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



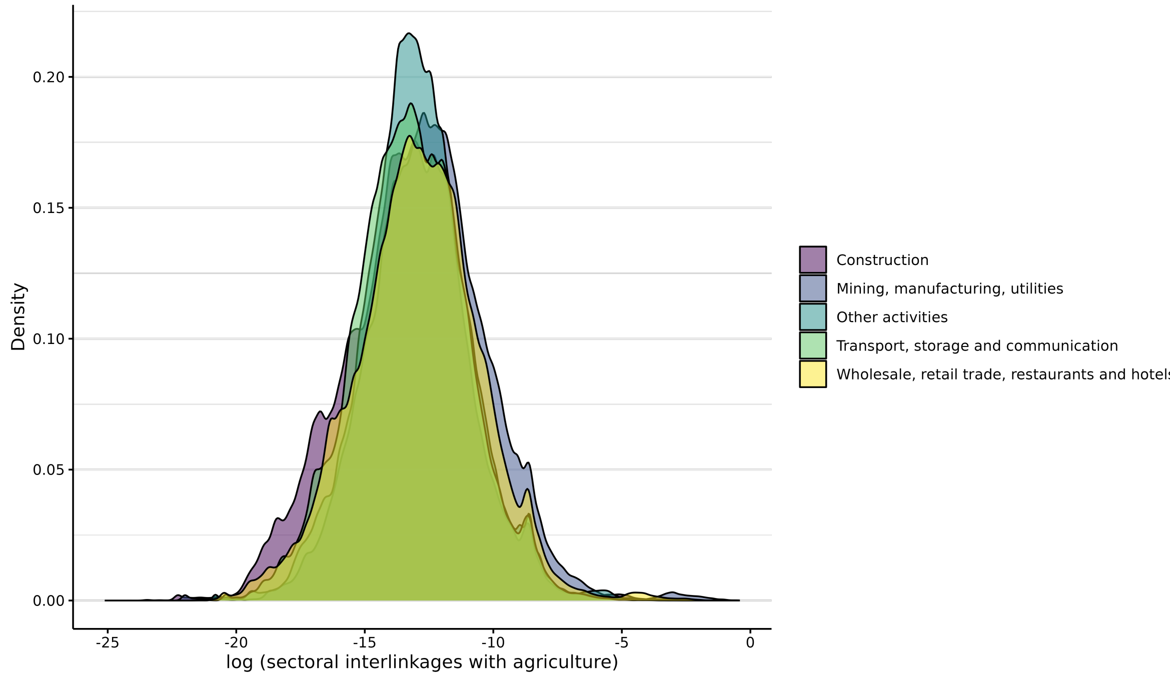
Notes: The figure shows the regression estimates of the temperature shocks constructed as in Equation (2). All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects and controlling for a sector-specific second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

Figure B6. Quantiles of Extreme Heat on Agriculture Value Added



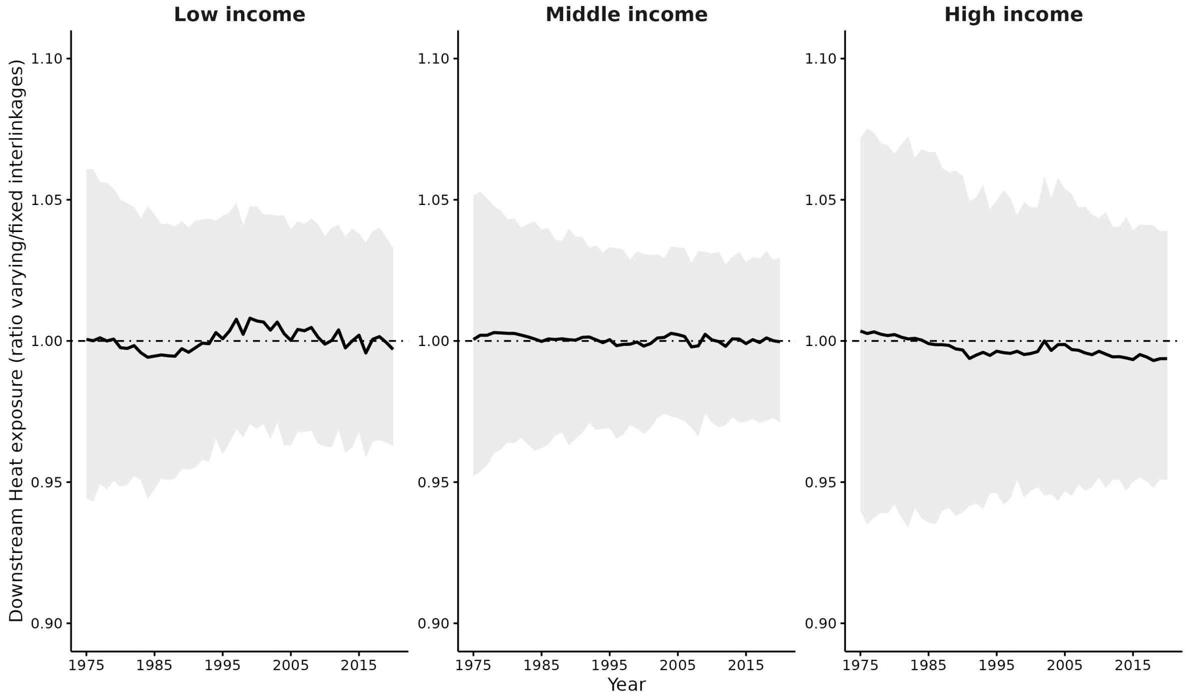
Notes: The figure shows the regression estimates for the measure of extreme heat (degree days) constructed as in Equation (1) on the growth rate of agricultural value added and categorized by terciles or quintiles. Each set of bars corresponds to the estimates from a single regression which accounts for linear and quadratic terms of precipitation, and country and year fixed effects. Bins 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



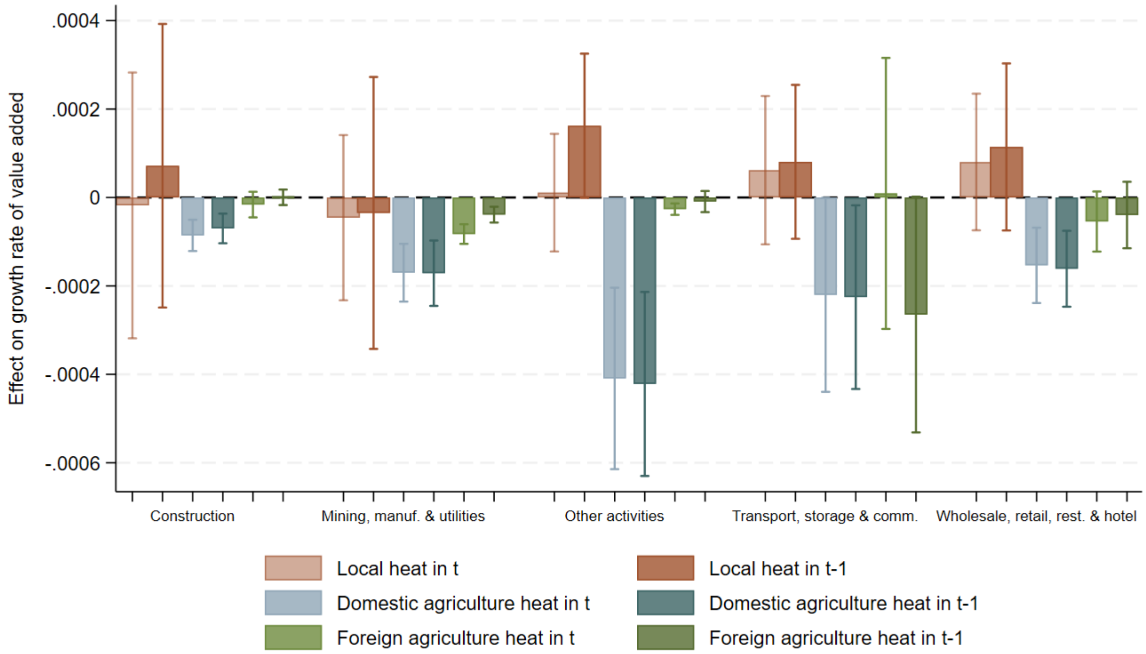
Notes: The figure plots the sector-specific density distribution of the (log) of interlinkages with agriculture used as outcome variable in Equation (9).

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.

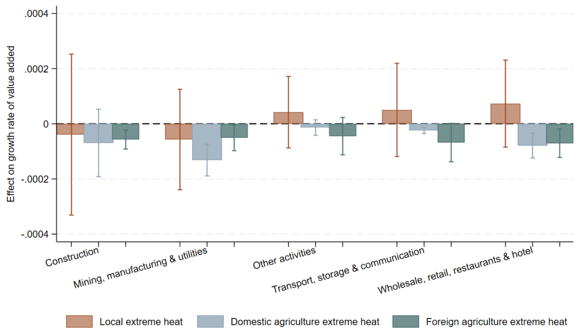
Figure B9. Contemporaneous and lagged response to agriculture extreme heat in a Leontief matrix



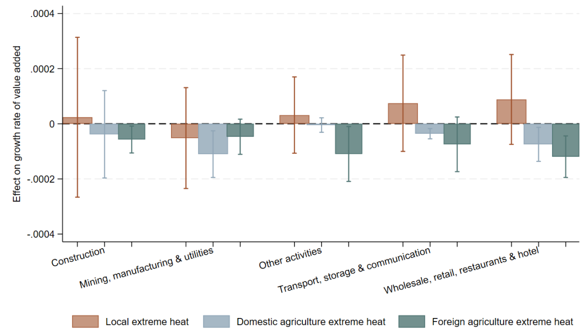
Notes: Bars represent the sector-specific coefficients associated with contemporaneous and one-year lagged local extreme heat shocks and domestic and foreign downstream shocks constructed using the extreme heat exposure measure constructed as in Equation (1). Domestic and foreign downstream shocks are 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 stacked 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. Bins represent the 95% confidence intervals with standard errors clustered at the country level.

Figure B10. Robustness: Alternative specifications for first degree linkages

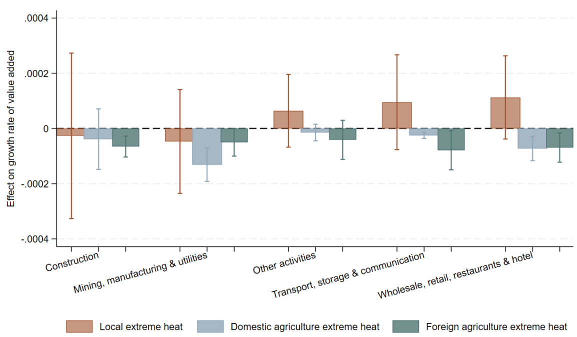
(a) Country quadratic time trends



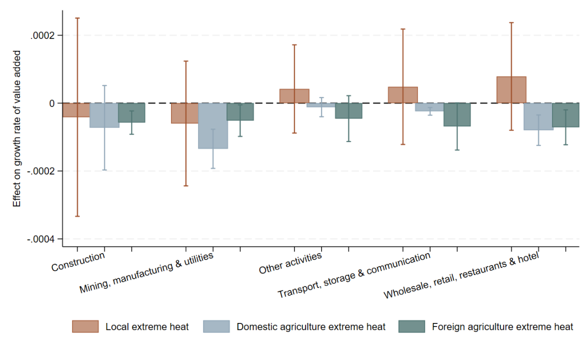
(b) Country-sector quadratic time trends



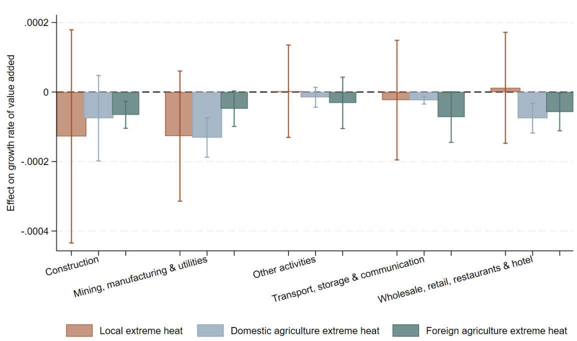
(c) Balanced panel



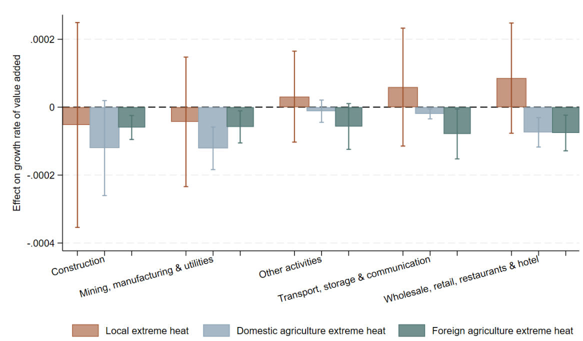
(d) Excluding "large" countries



(e) Exclude 10% coldest



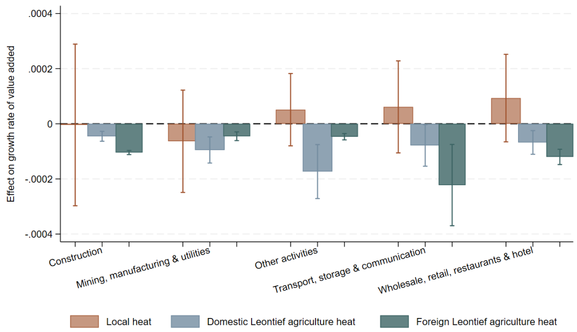
(f) Exclude 10% hottest



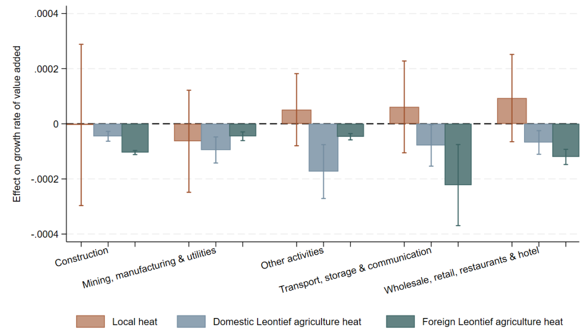
Notes: The figure shows the sector-specific coefficients associated with local extreme heat and domestic and foreign downstream agricultural heat shocks. Panel (a) shows the estimates accounting for country-specific quadratic time trends; Panel (b) accounts for country-sector specific quadratic time 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. Bins represent the 95% confidence intervals around point estimates with standard errors clustered at the country level.

Figure B11. Robustness: Alternative specifications for Leontief matrix

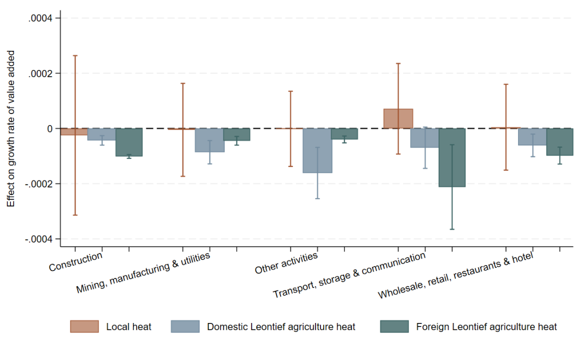
(a) Country quadratic time trends



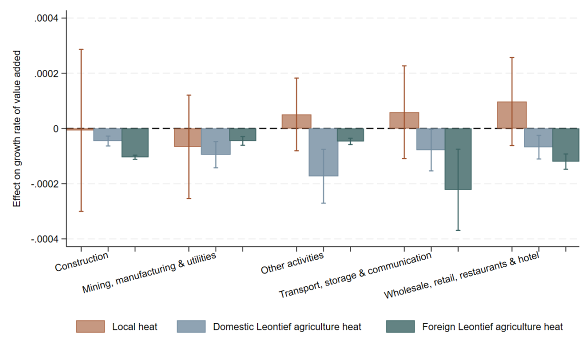
(b) Country-sector quadratic time trends



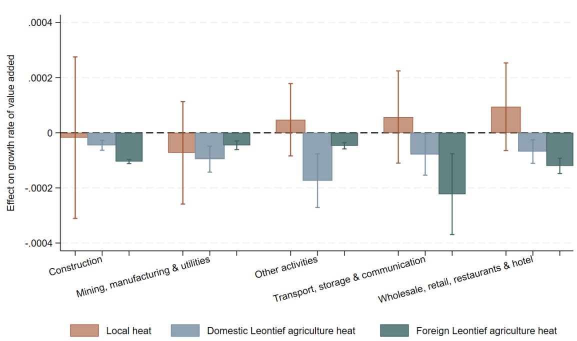
(c) Balanced panel



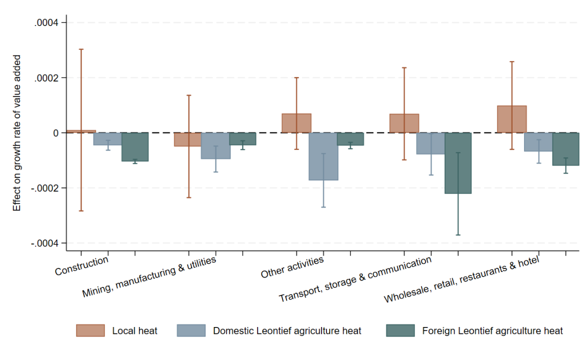
(d) Excluding "large" countries



(e) Exclude 10% coldest

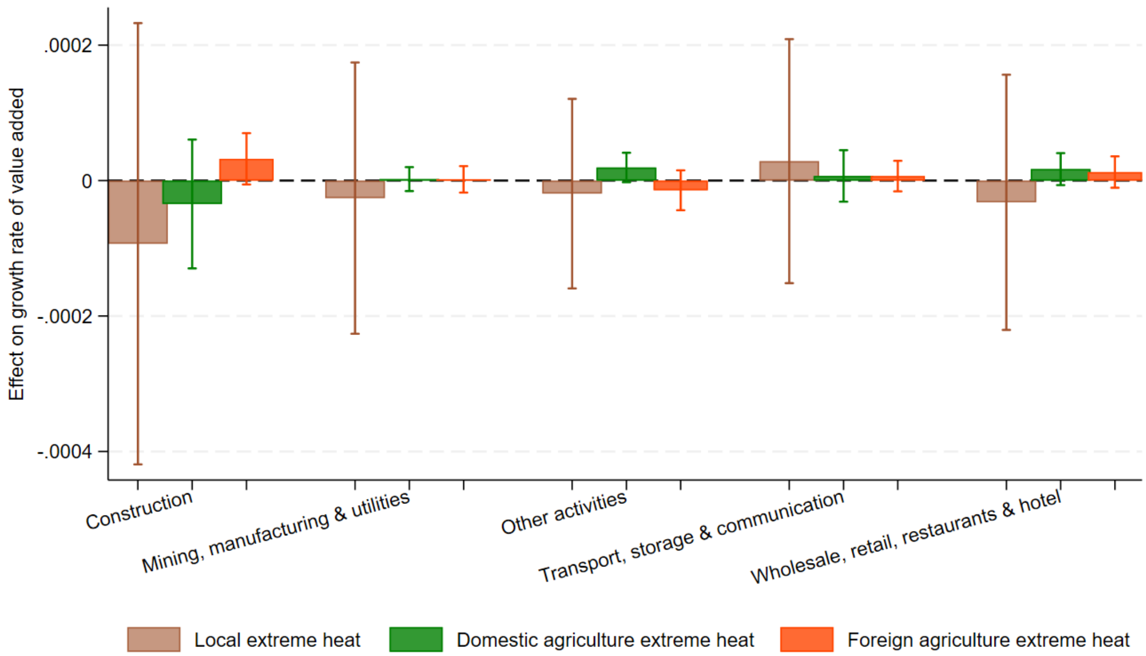


(f) Exclude 10% hottest



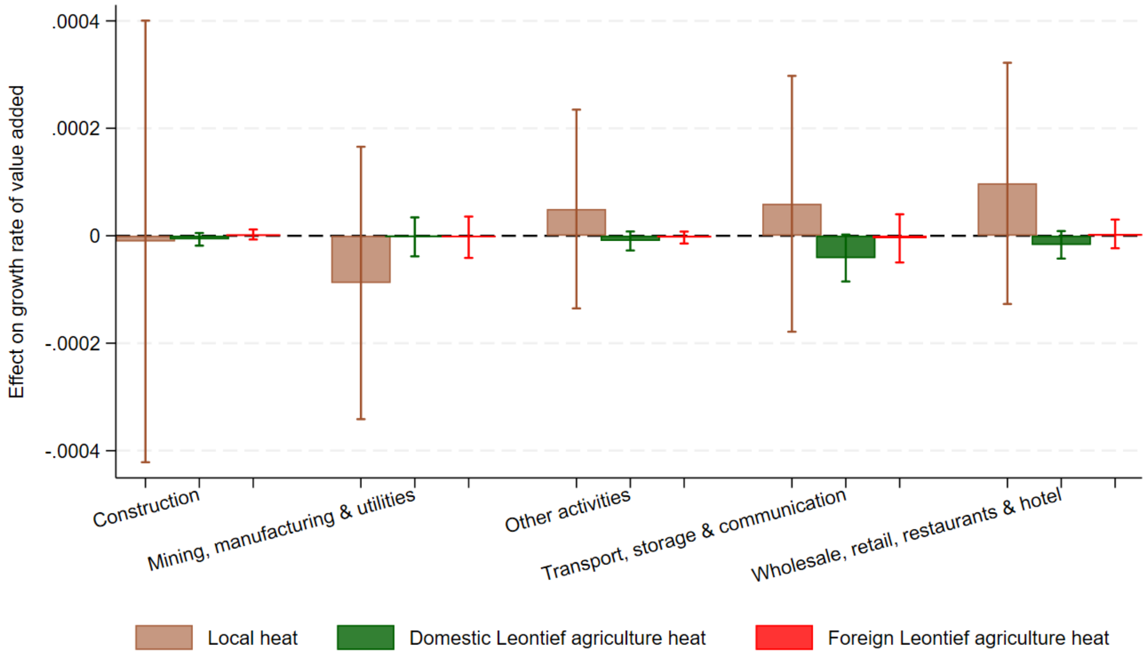
Notes: The figure shows the sector-specific coefficients associated with local extreme heat and domestic and foreign downstream agricultural heat shocks using the Leontief inverse matrix. Panel (a) shows the estimates accounting for country-specific quadratic time trends; Panel (b) accounts for country-sector 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. Bins 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



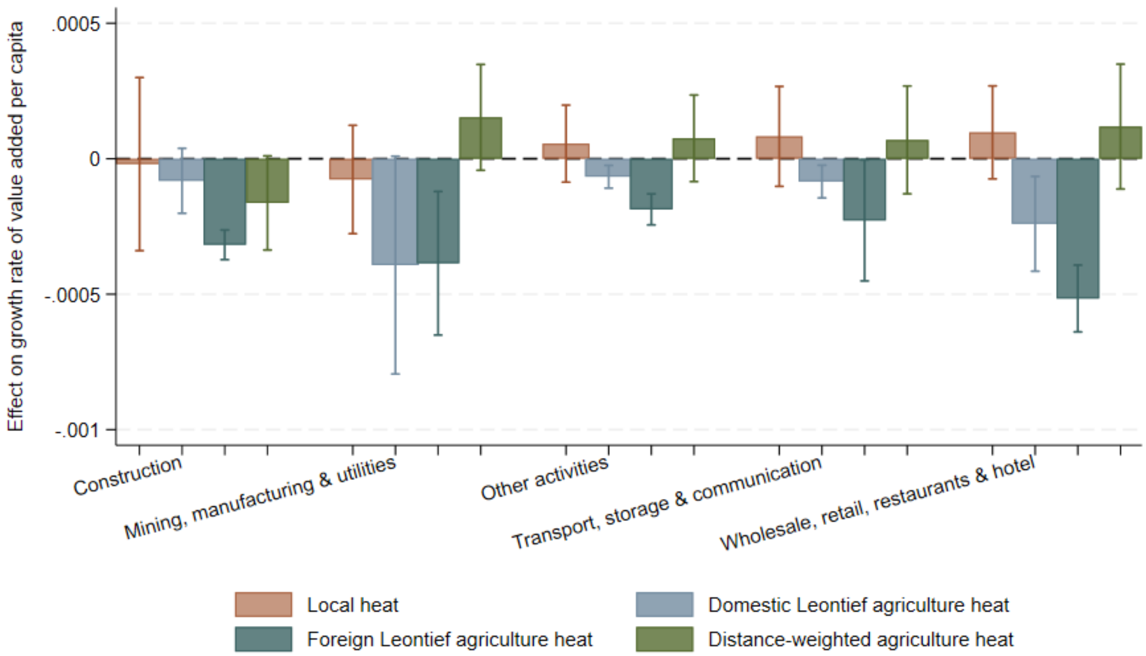
Notes: Bars represent the sector-specific coefficients associated with local shocks and domestic and foreign upstream shocks, using the extreme heat exposure measure constructed as in Equation (1). The specification jointly estimates all sector-specific coefficients in a stacked regression model that accounts for country-sector, sector-year, country-year fixed effects and sector-specific second-order polynomial of total precipitation and sum of exposure shares. Bins 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^{th} percentile of the daily temperature distribution. Domestic upstream shocks are constructed as the average weather shock in agriculture in the same country as the sector of interest weighted by the upstream interdependence with each sector. Symmetrically, foreign upstream shocks are constructed as the average weather shock in the agriculture sector abroad weighted by the upstream interdependence with each sector. The specification jointly estimates all sector-specific coefficients in a stacked regression model 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. Bins 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 stacked 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. Bins represent the 95% confidence intervals with standard errors clustered at the country 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.

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). Production possibilities for sector j in region n are described by a constant returns-to-scale Cobb-Douglas technology whose inputs are capital and labor:

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

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

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

Traditionally, the reduced form effect of temperature $\hat{\beta}$ on output per capita is estimated under the assumption that the residual variation in temperature is not correlated with the error term once absorbed unit- and time-specific unobserved heterogeneity (which also captures the unit-specific capital-to-output ratio).

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 (Akyapi et al., 2024; Newell et al., 2021; Letta and Tol, 2019). Nevertheless, this measure does not inform how atypical the weather realization is with respect to individual expectations since it neglects any information provided by the levels and assumes that individuals rationally update their beliefs annually, under an implicit instantaneous model of adaptation. 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 $\mathbb{E}(\nu^2_{T_{n;t}}) = \sigma^2_{T_n}$.

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).

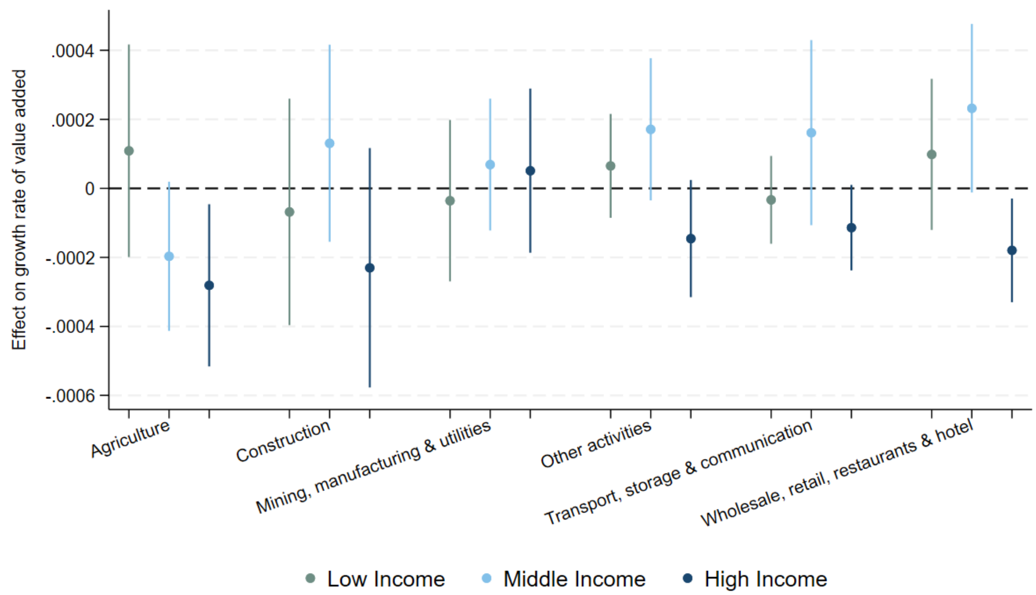
H Heterogeneous effects of local extreme heat across adaptation potential

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).

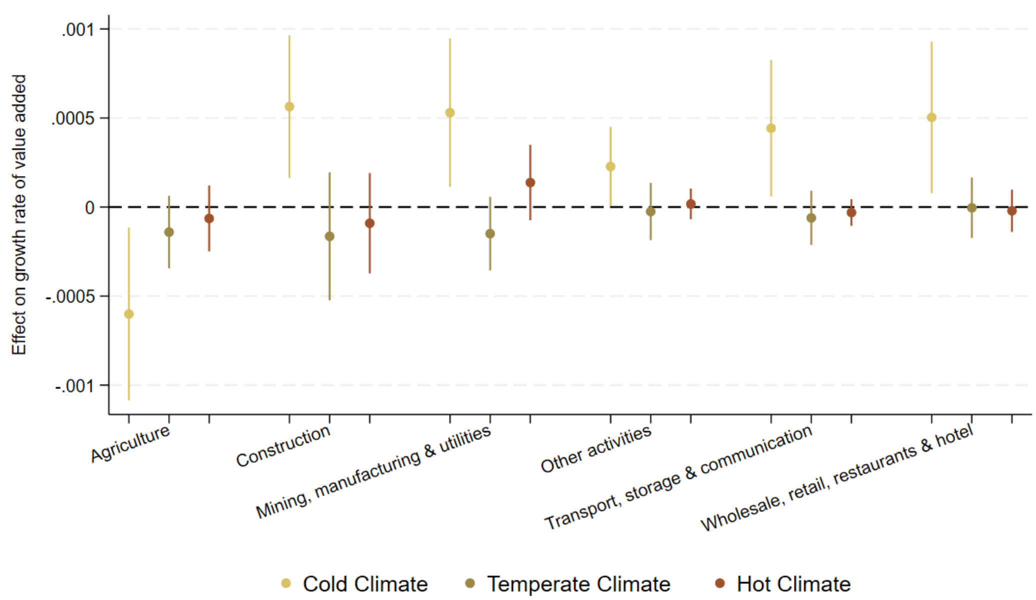
Appendix Figure H1 graphically presents the coefficient associated with heat shocks interacted with income and climate terciles. Starting from heterogeneity by income, agricultural value added becomes more sensitive to extreme heat as income rises. This result, perhaps surprising at first, could be explained by differences in improved technologies, infrastructure, or insurance that influence producer strategies (Hultgren et al., 2022). There is not substantial heterogeneity in the response of other sectors to extreme heat conditions by income, with the estimate 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 stacked regression model fully saturated with country-sector and sector-year fixed effects and controlling for a second order polynomial in precipitation. Bins represent the 95% confidence intervals with standard errors clustered at the country-level.

I Quantifying the cost of recent warming accounting for sectoral and spatial linkages

Here, I provide additional details on the construction of the counterfactuals in Section 7. To understand the differential and aggregate cost of recent warming, I use the estimates of the effect of local extreme heat and exposure to domestic and foreign agriculture extreme heat to simulate how much slower or faster each sector in each country would have grown annually over the 2001-2020 period, compared to a scenario under which extreme heat stayed at its 1974-2000 average, and cumulate these effects over the period to calculate the increase or decrease in total value added. This computation does not necessarily represent the differential impact of recent anthropogenic warming accounting for network shocks and is instead agnostic to the cause of recent warming.

First, I compute the cost of annual warming in 2001-2020 compared to a counterfactual where extreme heat exposure stayed constant at the period 1970-2000. Importantly, I do so both only using the semi-elasticities from local extreme heat and including the semi-elasticities to extreme heat exposure in agriculture (both domestic and abroad). I bootstrap 1000 times the underlying panel estimates from Equation (18) and use the $\widehat{\beta_j}$'s and $\widehat{\gamma_{j,\ell}}$'s obtained from this exercise, as the sector-specific estimates for the effect of local extreme heat, domestic and foreign downstream exposure to agricultural extreme heat to compute the counterfactual growth rate g:

$$g_{jnt}^{local} = \widehat{\beta}_j(ExtremeHeat_{nt} - \widetilde{ExtremeHeat}_{nt}) \tag{I.1}$$

$$\begin{aligned} g_{jnt}^{global} &= (\widehat{\beta}_j ExtremeHeat_{nt} + \sum_{\ell \in \{D;F\}} \widehat{\gamma}_{j,\ell} NetworkShock_{jnt}^{Dn,\ell}) \\ &- (\widehat{\beta}_j \widetilde{ExtremeHeat}_{nt} + \sum_{\ell \in \{D;F\}} \widehat{\gamma}_{j,\ell} \widetilde{NetworkShock}_{jnt}^{Dn,\ell}) \end{aligned} \tag{I.2}$$

where $ExtremeHeat_{nt}$ is the observed extreme heat measure constructed in Equation (1), $\widetilde{ExtremeHeat}_{nt}$ is the counterfactual extreme heat measure in the 1970-2000 period, and symmetrically for $NetworkShock$, which is constructed as detailed in Equations (5) and (6). I compute sector j's counterfactual value added levels in year t omitting and accounting for indirect shocks

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

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

$$\%\overline{\text{LOSS}}^p_{jn} = \sum_{t=2001}^{2020} \frac{e^{\hat{Y}^p_{jnt}} - e^{Y_{jnt}}}{e^{Y_{jnt}}} \tag{I.4}$$

to obtain a measure of the average cost of recent warming at the sector level omitting and accounting for input linkages with agriculture. The aggregate loss in value added across sectors for country n is

$$\%\overline{\text{LOSS}}^p_{n} = \sum_{j}^{J} \%\lambda_{jn} \overline{\text{LOSS}}^p_{jn} \tag{I.5}$$

where λ_{jn} is the average share of total value added of sector j in country n. Figure 8 reports the country-level losses computed only in the case of damages to agriculture (top map) and summing over all other five sectors in the economy (bottom map).