



**HAL**  
open science

# **Agricultural Dynamics and Structural Transformation: Can they Withstand Weather Extremes?**

Kristin Muthui, Natalia Zugravu-Soilita

► **To cite this version:**

Kristin Muthui, Natalia Zugravu-Soilita. Agricultural Dynamics and Structural Transformation: Can they Withstand Weather Extremes?. *Environmental and Resource Economics*, 2026, 89 (1), <10.1007/s10640-025-01065-y>. <hal-05503047>

**HAL Id: hal-05503047**

**<https://hal.science/hal-05503047v1>**

Submitted on 13 Mar 2026

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire HAL, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons CC BY 4.0 - Attribution - International License



# Agricultural Dynamics and Structural Transformation: Can they Withstand Weather Extremes?

Kristin Muthui<sup>1</sup> · Natalia Zugravu-Soilita<sup>1</sup> 

Received: 6 February 2025 / Revised: 15 October 2025 / Accepted: 21 October 2025 /

Published online: 8 January 2026

© The Author(s) 2026

## Abstract

Extreme weather increasingly influences the economies of low- and middle-income countries, where agriculture remains a major employer. Yet its role in structural transformation is poorly understood. Using within-country anomalies for droughts, heatwaves and excess rainfall, we estimate a simultaneous-equations system for agricultural labour productivity and employment on a 35-country balanced panel (1996–2017). Static models suggest that extreme heat consistently depresses both labour productivity and agricultural employment, while moderate droughts appear benign in isolation but become highly damaging when combined with heat. Irrigation buffers isolated droughts and moderates heat-induced labour exits, yet offers little protection against compound shocks. Nevertheless, these static estimates overstate immediate impacts and underestimate longer-run effects. Once we incorporate persistence and compute long-run effects, isolated heatwaves lose significance, whereas compound “hot droughts” emerge as the main source of agricultural labour productivity decline, with cross-equation feedbacks further amplifying these losses. Excess rainfall consistently raises labour productivity but, by increasing short-term labour demand, slows reallocation and shifts the economy toward a more labour-intensive transformation trajectory. These results challenge the conventional view that labour productivity gains automatically draws workers out of agriculture: under certain climate conditions, higher output per worker can coincide with sustained labour intensity. Policy must therefore pair rapid-response safety nets for heat stress with longer-term investments tailored to the specific profiles of climatic risk.

**Keywords** Adaptation · Agricultural employment · Agricultural labour productivity · Labour reallocation · Structural transformation · Resilience · Weather extremes

**JEL Classification** C33 · O44 · Q15 · Q54 · Q56

---

✉ Natalia Zugravu-Soilita  
natalia.zugravu@uvsq.fr

<sup>1</sup> UMI SOURCE, Université Paris-Saclay, UVSQ, IRD, Guyancourt 78280, France

## 1 Introduction

*Structural transformation* refers to the reallocation of economic activity from low productivity sectors—typically agriculture—toward higher-productivity sectors, leading to sustained gains in income and living standards<sup>1</sup>. While this process fuelled rapid and inclusive growth in East Asia, recent episodes of growth in Latin America, Africa, and South Asia have largely unfolded without industrialization-led transformation (Rodrik et al. 2019). In sub-Saharan Africa in particular, *structural change*—the mere shift of labour across sectors—has often occurred at the expense of productivity growth, with workers moving into low-productivity services rather than into dynamic manufacturing industries. One key factor behind this divergence is the persistent stagnation in agricultural productivity, partly linked to the limited diffusion of Green Revolution technologies (Gollin et al. 2021). As a result, agriculture remains the main source of employment in many economies, casting doubt on their long-term development trajectories.

A number of factors have been identified to explain limited progress towards structural transformation, including liberalization and deregulation, weak institutions hindering innovation, an over-reliance on natural resource exports, urbanization accompanied by the growth of non-tradable sector, and challenges in land allocation contributing to rural-urban migration (Dabla-Norris et al. 2013; Dorin et al. 2013; Gollin et al. 2016; Rodrik et al. 2019; Kruse et al. 2022). Standard growth models attribute productivity growth to constraints in capital, labour, land (in agriculture), technological progress, and frictions in factor reallocation, and addressing these constraints is assumed to unlock productivity gains and structural transformation. However, these models often overlook the role of the natural environment, despite evidence that climatic and environmental conditions influence stocks, returns, and the pace of technological change, particularly in the agriculture sector (Barrett et al. 2023).

Recent research by Ortiz-Bobea et al. (2021) shows that anthropogenic climate change has reduced global agricultural total factor productivity (TFP) by about 21% since 1961, with even greater losses in Africa, Latin America, and the Caribbean, ranging from 26% to 34%. As extreme weather events intensify, it is therefore essential to examine not only their impact on agricultural TFP, but also their broader effects on the process of structural transformation (labour productivity and mobility), especially in low-income and emerging countries. Understanding these dynamics is critical to identifying development pathways that account for climate-related constraints while fostering economic growth.

This study extends the literature by providing the first cross-country test of how distinct weather anomalies—droughts, heatwaves, and excessive rainfall—jointly influence the two macro-level drivers of structural transformation: agricultural labour productivity and the sector's employment share. Using high-resolution ERA5 and CRU-TS data, we convert every extreme weather indicator into within-country z-scores, isolating episodic shocks from underlying climatic regimes and avoiding confounds linked to cross-country climate-zone differences. We formulate and estimate a theory-consistent system of simultaneous equations, which (i) treats labour productivity and employment as jointly endogenous, (ii) separates direct from indirect effects, (iii) traces short-run impacts and their long-run amplification through lagged adjustment and feedback loops, and (iv) explicitly models compound interactions such as “hot droughts”. This unified, comparative framework therefore disen-

---

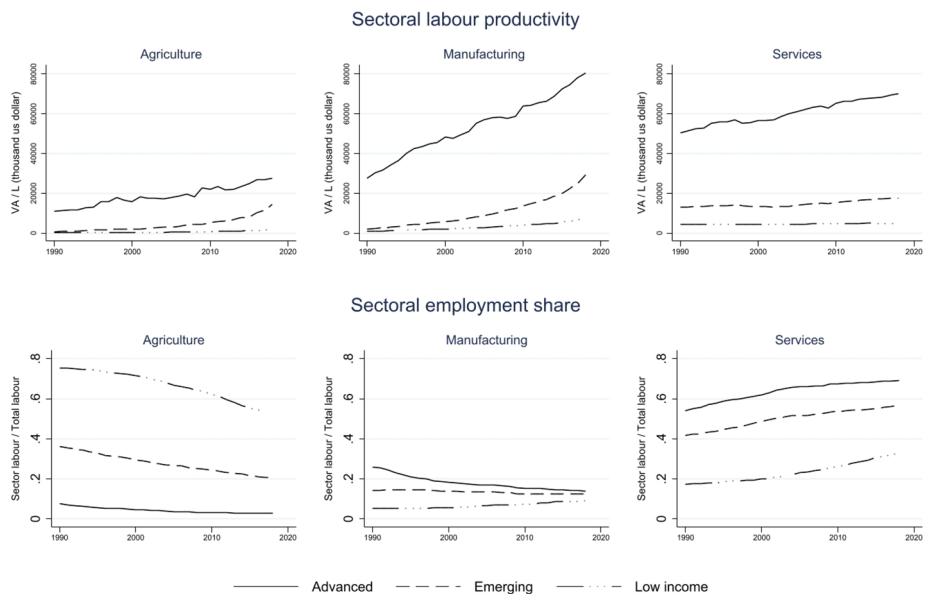
<sup>1</sup> See Sect. 3 on the theoretical foundations of structural transformation, which distinguishes it from mere structural change.

tangles the multiple channels—physiological, agronomic and allocative—through which extreme weather can accelerate, delay, or even reverse structural transformation across 35 climate-vulnerable low- and middle-income economies<sup>2</sup>.

After this brief introduction, Sect. 2 synthesises the main stylised facts on structural transformation under climate stress and reviews the relevant literature. Section 3 presents the conceptual framework that links extreme weather to agricultural labour dynamics. Section 4 details the empirical strategy and data. Estimation results are discussed in Sects. 5 and 6, while Sect. 7 summarises the principal findings and policy implications.

## 2 Framing the Debate: Literature and Stylized Evidence

Structural transformation typically follows three stylized patterns: a decline in agricultural employment driven by rising agricultural labour productivity, a hump-shaped evolution of industrial employment, and a sustained increase in service sector employment. Figure 1 illustrates these trends across sectors, based on data from the GGDC/UNU-WIDER Economic Transformation Database (ETD), which spans 1990–2018 and covers 51 countries across sub-Saharan Africa, Asia, the Middle East and North Africa, and Latin America.<sup>3</sup>



**Fig. 1** Sectoral labour productivity and employment shares in the GGDC/UNU-WETD sample of countries (1990–2018). Source: Economic Transformation Database, calculations, authors’ own

<sup>2</sup>The 35 countries retained in our regressions represent the subset of the 51 originally listed in the GGDC/UNU-WIDER database for which all necessary variables were available; the reduction is solely due to the automatic exclusion of countries with missing data, with no selection criteria applied. The country sample is detailed in Appendix A.2.

<sup>3</sup>Industry & Manufacturing LP includes ISIC Rev. 4 categories: Mining, Manufacturing, Utilities, Construction. Services LP includes Trade, Transport, Business, Financial, Real Estate, Government, and Other

Productivity has increased in all sectors but at varying rates. Manufacturing leads, driven by technological change, capital deepening, and higher value-added output. Services follow, buoyed by urbanization and middle-class demand though growth has recently slowed. Agriculture lags, especially in low-income countries. The figure also shows a continued decline in agricultural employment shares alongside rising services employment. However, many low-income economies experience labour shifts directly from agriculture to services without significant industrialization, consistent with Sen (2019). Despite declines, agricultural employment remains two to four times higher than in other groups. In emerging economies, services now account for the largest employment shares, followed by agriculture, indicating an incomplete structural transformation lacking a strong manufacturing base.

A substantial body of research has examined the drivers behind the atypical patterns of structural change observed in many low-income and emerging economies. The modest growth of manufacturing in many low-income countries largely stems from the expansion of small-scale domestic production, which has delivered limited productivity gains, especially when compared to the large-scale industrialization seen in East Asia (Kruse et al. 2022). Structural reforms under the Washington Consensus shifted demand toward non-tradable sectors, favouring services over manufacturing (Dabla-Norris et al. 2013). In parallel, commodity booms spurred urbanization without industrialization, resulting in “consumption cities” dominated by low-productivity services (Gollin et al. 2016). In Latin America, commodity dependence, overvalued exchange rates, and liberalization contributed to premature deindustrialization and stagnant productivity (McMillan et al. 2014). In sub-Saharan Africa, structural change has generated only modest productivity gains, constrained by limited labour reallocation (Rodrik et al. 2019).

Yet, one important gap in this literature concerns the role of climate change—particularly extreme weather events—in shaping structural transformation. This is especially relevant for low-income countries, where agriculture remains a dominant employer and is highly vulnerable to climate variability.

Temperature increases are closely associated with more erratic rainfall and higher risks of floods, droughts, and heatwaves (IPCC 2007). Recent assessments highlight intensifying droughts in regions like the Mediterranean, West Africa, and Central America, and growing flood risks in high-latitude areas (Meehl et al. 2005; IPCC 2021). The evidence clearly points to rising exposure to extreme events, with increasingly hot days in Africa, more frequent heavy rainfall in Asia and the Americas, and worsening drought conditions, especially in Africa as indicated by SPI-12 and SPEI-12 indices (see detailed climate anomaly data in the Appendix A, Fig. A.1).<sup>4</sup>

Agricultural systems in low-income countries are especially exposed due to limited adoption of Green Revolution technologies, weak infrastructure, and low investment in adaptive capacity. Climate shocks affect agriculture through multiple, compounding pathways. They reduce crop yields, and projected losses may reach 24% by 2030 (Jägermeyr et al. 2021), with long-run effects on productivity and growth despite possible short-term trade responses (Gollin et al. 2016). Extreme heat diminishes labour productivity and negatively affects health, education, and cognitive performance (Deschenes et al. 2009; Shayegh et al. 2021), accelerating rural outmigration (Barrios et al. 2006) and potentially suppress-

---

Services. Data are in gross value added at constant 2015 USD.

<sup>4</sup>SPI reflects rainfall anomalies; SPEI also includes temperature and evapotranspiration.

ing demand for non-agricultural goods (Schultz 1953; Johnston and Mellor 1961; Timmer 1988; Emerick 2018; Liu et al. 2023). Weather shocks also disrupt financial markets and investment decisions (Bansal et al. 2016; Addoum et al. 2020; Krueger et al. 2020), further limiting structural change. Finally, damage to infrastructure and supply chains compound these constraints (Adams et al. 2021).

While early research focused on the direct impact of temperature and precipitation shocks on GDP and sectoral output (Dell et al. 2012; Deryunga and Hsiang 2014; Burke et al. 2015), more recent studies explore how climate variability shapes broader structural change. For instance, Liu et al. (2023) examine the effects of rising temperatures on labour reallocation and urbanization in India, while Emerick (2018) shows how exogenous rainfall increases in India boost agricultural productivity in relation to transitions to non-agricultural employment.

Our study builds on this growing literature by offering a broader, comparative perspective. We analyse a wide sample of low-income and emerging economies and examine multiple types of weather shocks—droughts, heatwaves, and heavy precipitation. Importantly, we capture both direct and indirect effects on agricultural employment and labour productivity, explore potential non-linearities and adaptation dynamics. While existing studies have primarily focused on single-country cases, our approach is, to our knowledge, the first to assess these static and dynamic relationships across a large international sample.

### 3 Theoretical Foundations and System Specification

We build on the decomposition framework proposed by McMillan et al. (2014) and further developed by Rodrik et al. (2019), which combines insights from dual economy models and neoclassical growth theory. In this view, structural transformation is a dual process: aggregate labour productivity grows through both within-sector improvements (as in Solow 1965) and the reallocation of labour from low- to high-productivity sectors, most notably out of agriculture. This twofold mechanism is particularly relevant in low-income and emerging economies, where agriculture still dominates employment and displays significant productivity gaps with the rest of the economy. A country's aggregate labour productivity at time  $t$  may thus be defined as a weighted average of sectoral productivities:

$$y_t = \theta_{a,t} * y_{a,t} + \theta_{na,t} * y_{na,t} \quad (1)$$

where  $y_{i,t}$  and  $\theta_{i,t}$  represent the labour productivity and employment share of sector  $i = \{a, na\}$  (agriculture and non-agriculture, respectively) at time  $t$ . The change in aggregate labour productivity between two periods,  $t - 1$  and  $t$ , can be decomposed into:

$$\Delta y_{t/t-1} = \underbrace{(y_{a,t} - y_{na,t}) * \Delta \theta_{a,t/t-1}}_{\text{Structural change}} + \underbrace{\theta_{a,t-1} * \Delta y_{a,t/t-1} + (1 - \theta_{a,t-1}) * \Delta y_{na,t/t-1}}_{\text{Within-sector change}} \quad (2)$$

This identity highlights two simultaneous forces: (i) *structural change* through labour reallocation across sectors, and (ii) *within-sector productivity growth*. In the early stages of development, agriculture plays a central role in triggering transformation: productivity gains release labour, while sustained growth in agriculture supports demand for non-agricul-

tural goods (Johnston and Mellor 1961; Timmer 1988). However, this dynamic is increasingly disrupted by climate shocks. To capture both channels, essential for *growth-leading structural transformation*—labour mobility and labour productivity growth—and their joint exposure to weather extremes, we estimate a system of simultaneous equations, modelling the agricultural employment share and the agricultural labour productivity, respectively.<sup>5</sup>

### 3.1 Agricultural Employment Share

The dual-economy literature (Lewis 1954; Johnston and Mellor 1961; Timmer 1988) predicts that labour leaves agriculture once productivity rises and opportunities emerge elsewhere. Guided by this logic and by recent micro-evidence on weather shocks and labour mobility (Emerick 2018; Liu et al. 2023), we explain the agricultural employment share,  $\theta_a = L_a/L$ , with the following parsimonious specification:

$$\theta_a = \alpha_0 + \alpha_1 y_a + \alpha_2 IPR + \alpha_3 K_a + \alpha_4 H_a + \alpha_5 WE + \alpha_6 PopTot + \alpha_7 ADR + \alpha_8 Open + \varepsilon_{\theta_a} \quad (3)$$

In this setting, the share of agricultural employment responds to (i) the productivity gap between sectors, (ii) factor endowments and weather shocks, and (iii) macro-demographic and trade conditions that mediate labour mobility.

*Explanation of covariates:* Productivity terms ( $y_a$  and  $IPR = \log(y_a/y_{na})$ )—capture the push-pull incentives that underpin labour reallocation in dual-economy models.<sup>6</sup> Physical ( $K$ ) and human ( $H$ ) capitals proxy for the mechanisation and skills that release labour from agriculture. Weather extremes ( $WE$ ) directly affect time use, migration, and local demand, transmitting weather shocks to employment shares (Emerick 2018; Liu et al. 2023). Population size ( $PopTot$ ) and the age dependency ratio ( $ADR$ ) shape effective labour supply<sup>7</sup>. Finally, trade and financial openness ( $Open$ ) alters relative prices and sectoral demand, thereby guiding labour flows (Matsuyama 1992, 2019).

<sup>5</sup>We limit the empirical system to changes in the agricultural employment share ( $\Delta\theta_a$ ) and in the agricultural labour productivity ( $\Delta y_a$ ) for two reasons. First, extreme weather shocks overwhelmingly strike agriculture—the pivotal sector in the early stages of development—so isolating its response captures the main channel through which climate affects structural transformation. Second, this parsimony clarifies the mechanisms: a weather-induced productivity shock can either impede or hasten labour reallocation out of farming, depending on how the rest of the economy adjusts, whereas direct effects on non-agricultural productivity are likely second-order in our sample.

<sup>6</sup>We include agricultural productivity in levels,  $y_a$ , and the log of inter-sectoral productivity ratio (IPR)—rather than  $y_a$  and  $y_{na}$  separately—for two reasons. First, the two variables embody *distinct* mechanisms that both reduce the agricultural employment share. A higher  $y_a$  reflects labour-saving technical change within farming (a “push” factor). By contrast, an increase in IPR signals that agriculture is catching up with non-agriculture; this modernisation raises farm incomes, boosts demand for industrial inputs and services, and thus pulls labour into those sectors, while simultaneously making agriculture less labour-intensive. Second, replacing  $y_{na}$  with the ratio mitigates multicollinearity:  $y_a$  and  $y_{na}$  in level form would enter with opposite signs but are highly correlated, whereas  $y_a$  plus IPR preserve informational content while maintaining independent regressors.

<sup>7</sup>ADR is the ratio of dependents (people younger than 15 or older than 64) to the working-age population (those aged 15–64). A high ADR signals a larger non-working population, influencing the pool of potential agricultural workers without directly affecting their productivity.

### 3.2 Agricultural labour productivity

The pillar of structural transformation is productivity growth within agriculture, measured as value added per worker in the agricultural sector, denoted  $y_a$ , which can be expressed as follows:

$$y_a = \frac{Y_a}{L_a} = \frac{A_a L_a^\delta K_a^\gamma H_a^\kappa T_a^{(1-\delta-\gamma-\kappa)}}{L_a} = A_a L_a^{(\delta-1)} K_a^\gamma H_a^\kappa T_a^{(1-\delta-\gamma-\kappa)} \tag{4}$$

where  $A_a$  represents the total factor productivity (TFP) in the agricultural sector; the term  $L_a^\delta K_a^\gamma H_a^\kappa T_a^{(1-\delta-\gamma-\kappa)}$  represents the Cobb-Douglas production function with constant returns to scale, where  $\delta$ ,  $\gamma$ , and  $\kappa$  denote the elasticities of labor  $L_a$ , physical capital  $K_a$ , and human capital  $H_a$ , respectively, utilised in the agricultural sector;  $T_a$  represents land available for agriculture. Taking the logarithm of both sides to linearize, we have:

$$\log(y_a) = \log(A_a) + (\delta - 1) \log(L_a) + \gamma \log(K_a) + \kappa \log(H_a) + (1 - \delta - \gamma - \kappa) \log(T_a) \tag{5}$$

TFP in agriculture reflects the efficiency with which inputs are converted into output and is highly sensitive to climatic conditions. Weather extremes, such as droughts, floods, and heatwaves, reduce TFP through crop damage, labour disruptions, land degradation, and reduced input efficiency (Costinot et al. 2016; Ortiz-Bobea et al. 2021; Chen et al. 2022). These shocks can persistently slow down productivity growth, particularly in low-income countries where adaptive capacity is limited (Gollin and Rogerson 2014; Iizumi and Ramanakutty 2015; Takakura et al. 2019). In addition to weather conditions, we model TFP as a function of institutional quality, foreign direct investment (FDI), population growth, and trade openness. FDI is crucial in low-income countries, where it can provide market access and technology, boosting agricultural productivity (Edeh et al. 2020). Population growth affects economic output by increasing demand for goods and services, spurring technological innovation, and enhancing productivity through land use intensification and adoption of new technologies (Rostow 1982; Romer 1990). Economies of scale arise from larger markets, attracting investment in R&D and driving agricultural advancements. Trade openness promotes efficient resource allocation via comparative advantage, facilitates technology diffusion, and fosters innovation and growth.

The labour productivity equation can therefore be expressed as follows:

$$\log(y_a) = \beta_0 + \beta_1 WE + \beta_2 FDI + \beta_3 PopGr + \beta_4 Open + \beta_5 INS + \beta_6 \log(L_a) + \beta_7 \log(K_a) + \beta_8 \log(H_a) + \beta_9 \log(T_a) + \varepsilon_{y_a} \tag{6}$$

with  $WE$  for weather extremes,  $FDI$  representing foreign direct investment,  $PopGr$  for population growth,  $OPEN$  standing for trade openness,  $INS$  for institutional quality,  $L_a$  for agricultural labour, and  $K_a$  and  $H_a$  representing physical and human capital in agriculture, respectively, and  $T_a$  denoting agricultural land<sup>8</sup>.

<sup>8</sup>We also include the proportion of irrigated land in a later specification to test the robustness of our model and to examine irrigation as a potential adaptation strategy to climate shocks.

### 3.3 Interlinked Dynamics - A Simultaneous Equations Approach

The relationship between agricultural dynamics required for structural transformation and extreme weather events, which is the focus of this paper, can therefore be described in a simultaneous equation model. By merging Eqs. 3 and 6—with additional functional transformations<sup>9</sup>, yields the following system of jointly determined equations:<sup>10</sup>

$$\begin{cases} \theta_a = \alpha_0 + \alpha_1 \log(y_a) + \alpha_2 WE + \alpha_3 IPR + \alpha_4 K_a + \alpha_5 H_a + \\ \alpha_6 PopTot + \alpha_7 ADR + \alpha_8 Open + \varepsilon_{\theta_a} \\ \log(y_a) = \beta_0 + \beta_1 \theta_a + \beta_2 WE + \beta_3 FDI + \beta_4 PopGr + \beta_5 Open + \\ \beta_6 INS + \beta_7 \log(K_a) + \beta_8 \log(H_a) + \beta_9 \log(T_a) + \varepsilon_{y_a} \end{cases} \quad (7)$$

where  $\varepsilon_{\theta_a}$  and  $\varepsilon_{y_a}$  represent error terms capturing unobserved factors and interact with each other (in a non-recursive model, these errors are correlated).

This system has three key advantages. First, it is rooted in structural economic theory, providing causal interpretability to the estimated coefficients. Second, it allows for simultaneous interactions between labour productivity and employment allocation—particularly important when assessing how weather shocks propagate through an economy with segmented labour markets. Third, it enables both static (contemporaneous) and dynamic (lag-augmented) versions of the model to be estimated, which is useful to assess both immediate and delayed responses to weather shocks.

## 4 Empirical Strategy

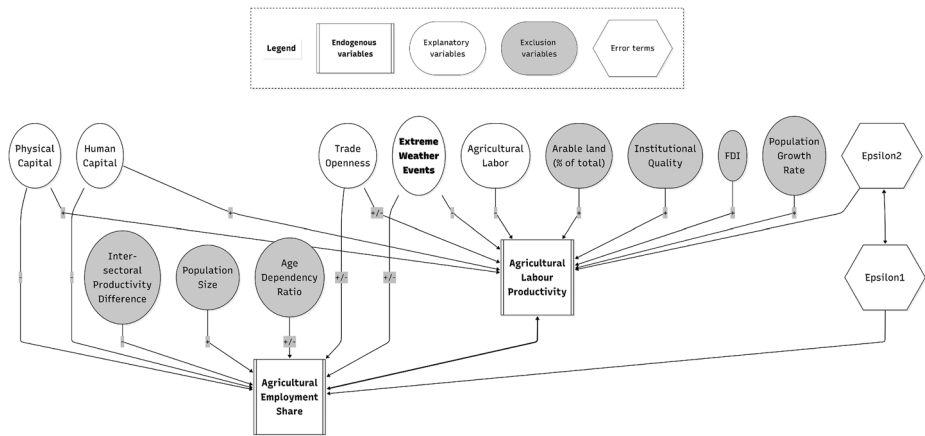
### 4.1 Empirical Framework and Identification Strategy

Our estimation approach relies on a structural system framework that links weather extremes to the dual dynamics of agricultural transformation. As depicted in Fig. 2, we estimate a non-recursive system of simultaneous equations, in which agricultural labour productivity ( $y_a$ ) and employment share ( $\theta_a$ ) are jointly determined and both influenced by extreme weather events ( $WE$ ), among other factors.

Weather extremes can affect agricultural employment through direct and indirect channels. Directly, events such as droughts, floods, or heatwaves may constrain labour supply or disrupt seasonal work patterns. Indirectly, reduced on-farm productivity may alter incentives to remain in or exit agriculture. Employment levels, in turn, affect labour intensity and productivity, creating a feedback loop between the two. This interdependence implies that

<sup>9</sup>Two transformations improve both interpretation and identification: (i) we replace  $y_a$  with  $\log(y_a)$  in the employment share equation so that all productivity variables enter in logarithms. The log form yields elasticities that are scale-invariant, alleviates heteroskedasticity, and keeps the specification consistent with the log-linear production function in the second equation; (ii) in the productivity equation we substitute the level of agricultural labour  $L_a$  with its employment share  $\theta_a = L_a/L$ . Following the structural-dualism tradition, the share captures the relative availability of farm labour—rather than country size—and avoids the perfect collinearity that would arise from including both  $L_a$  and  $\theta_a$  in a simultaneous system.

<sup>10</sup>To ensure robustness, we limit the model to variables supported by clear theoretical and empirical justification. Potentially endogenous controls such as development aid are excluded, given their likely correlation with both weather shocks and productivity or employment outcomes, which would risk biasing identification.



**Fig. 2** Path model

both agricultural employment and labour productivity are endogenous, with potentially correlated error terms. To address these simultaneity and endogeneity concerns, we estimate the model using a two-step Generalized Method of Moments (GMM) estimator, suited for panel data.<sup>11</sup>

In addition to internal instruments generated through the panel GMM procedure (i.e., lagged values of endogenous regressors), our model identification strategy relies on a set of theory-based exclusion restrictions. Among the twelve explanatory variables included in the system, seven are used as external instruments, i.e. excluded from one of the two equations based on theoretical grounds, while retained in the other to ensure over-identification. Specifically, to identify the labour productivity equation, we exclude three variables: the intersectoral productivity ratio (IPR), total population size (*PopTot*), and the age dependency ratio (*ADR*). These are strong predictors of agricultural labour allocation but are unlikely to directly affect labour productivity. They capture demographic pressure and relative sectoral returns, shaping labour supply and mobility constraints, and therefore influence the employment share. Their impact on labour productivity is assumed to be indirect, operating through long-term compositional changes in the workforce. For example, *ADR* reflects the demographic burden on the working-age population and is commonly used to approximate rural labour availability, without a direct contemporaneous effect on output per worker.

Conversely, four variables, namely arable land (*Land*), foreign direct investment (*FDI*), population growth (*PopGr*), and institutional quality (*INS*), are included in the labour productivity equation but excluded from the employment share equation. These variables affect output per worker through input endowments, access to external capital and technologies, and the institutional environment that supports agricultural performance. Their influence on labour allocation is expected to be indirect and mediated through labour productivity. In rural economies with segmented labour markets and high mobility costs, employment shares tend to respond more directly to demographic pressures and relative sectoral returns

<sup>11</sup>GMM accounts for unobserved heterogeneity (fixed effects), allows for endogeneity of explanatory variables, and remains robust in the presence of heteroskedasticity and intra-cluster correlation (Nickell 1981; Wooldridge 2013). Compared to three-stage least squares, two-step GMM offers greater efficiency when over-identification is present.

than to structural productivity drivers (Emerick 2018). While our instruments are grounded in theory, their empirical validity is supported by the Hansen J test for over-identifying restrictions, reported in the detailed estimation results in Appendix B.

## 4.2 Data

For our dependent variables—*agricultural labour productivity* and *agricultural employment share*—we use the GGDC/UNU-WIDER Economic Transformation Database (ETD), which provides comprehensive, long-term, and internationally comparable sectoral data on employment and productivity in Africa, Asia, and Latin America from 1990 to 2018.<sup>12</sup> Agricultural labour productivity is calculated by dividing gross value added in agriculture by the number of persons engaged in this sector, and agricultural employment shares are calculated by dividing the number of persons engaged in agriculture by the total number of persons engaged in all sectors. We use the same data to compute inter-sectoral productivity ratio, defined as the log of agricultural labour productivity over non-agricultural labour productivity.<sup>13</sup>

To ensure robust causal identification of weather extremes' effects, we use meteorological indicators based on physical climate data rather than economic loss records, which can introduce bias due to their correlation with income levels (Felbermayr and Gröschl 2014; Hsiang and Jina 2014). Meteorological indicators provide exogenous variation less influenced by socioeconomic factors, improving reliability of estimates. They also capture non-linear effects of events like drought and extreme precipitation, which are otherwise hard to quantify (Berlemann and Wenzel 2018). We therefore use scientifically defined measures to ensure comparability across countries and over time. The following indicators are used:

- ***Drought\_spei***: The Standardized Precipitation-Evapotranspiration Index (SPEI-12), captures both precipitation and temperature-driven evapotranspiration, providing a robust measure of drought intensity and duration under climate change (Vicente-Serrano et al. 2010). Negative values indicate drier-than-average conditions. In our analysis, drought episodes are defined by negative SPEI-12 values.<sup>14</sup>
- ***ExtWetDays***: One of the 40 climate change indices developed by the ETCCDI, it measures precipitation during the 1% wettest days over the data period. Research by Zolina et al. (2010) and Fall et al. (2021) demonstrates that excessive precipitation significantly impacts the hydrologic cycle, including flooding.
- ***MaxHotDays***: This index measures the average number of days with temperatures exceeding 35 °C, a threshold selected by IPCC due to its critical impact on maize pol-

<sup>12</sup>The database covers 18 countries in sub-Saharan Africa, 20 in Asia, 4 in the Middle East and North Africa, and 9 in Latin America, using a harmonized sector classification (12 sectors) for consistency and comparability.

<sup>13</sup>Non-agricultural labour productivity is calculated by dividing the sum of gross value added of the remaining 11 non-agriculture sectors by the sum of their corresponding employment shares.

<sup>14</sup>SPEI-12 extends the SPI-12 by incorporating potential evapotranspiration (PET) derived from temperature data. It is calculated by fitting the climatic water balance (precipitation minus PET) to a probability distribution and standardizing the result, allowing for spatial and temporal comparability. SPEI values above -1 indicate normal to wet conditions; values between -2 and -1 indicate moderate to severe drought; and values less than or equal to -2 indicate extreme drought. We focus on drought conditions captured by SPEI values below -1. Values above -1 are set to zero. To account for non-linear effects and improve readability, we square the negative values.

ination and human health (Lobell and Gourджи 2012; Petitti et al. 2015). It is also an ETCCDI climate change detection index.

Given the heterogeneity of local climates and agricultural systems across and within countries over time, accounting for these differences is essential for accurate and meaningful analysis. We therefore apply intra-country z-score normalization to all of our weather shocks variables to enable standardized comparisons. Although the SPEI is already standardized based on a gamma distribution to allow for global comparability across countries, we apply an additional intra-country z-score normalization to enhance the granularity of our analysis. Although SPEI grid cells are already standardised to local climatology, spatial aggregation induces unequal variances across countries. We therefore re-scale the country-year mean by its own historical  $\sigma$  to obtain a truly comparable one- $\sigma$  drought shock. This approach allows us to identify, within a given country, periods during which moisture deficits (i.e., drought conditions) deviate significantly from that country's typical climatic variability.

Turning to the remaining explanatory variables, we use gross capital formation from the IMF capital stock database (log-transformed) to capture physical capital. Human capital is measured by average years of schooling from the Barro-Lee dataset. To capture economic globalization, we include the aggregate KOF Globalization Index, which reflects economic, social, and political integration, along with its Trade sub-index (*GlobalTrade*), and a separate measure of Foreign Direct Investment (*FDI*) from the World Bank. Additional variables sourced from the World Bank include: *Land* (arable land as a % of total land area), *IrrigLand* (% of total agricultural land), *ContrCorrup* (perceived corruption control index, as a proxy for the institutional quality), *ADR* (age dependency ratio), *PopTot* (total population, log-transformed), and *PopGR* (annual population growth rate). A time *Trend* variable captures effects of unmeasured time-evolving variables, such as adaptation to climate change.

Our study's variables, sources, and statistical summaries are detailed in Tables A.1 and A.3 in Appendix A. The regression analysis employs a balanced panel of 35 emerging and developing countries (Table A.2), covering the period from 1996 to 2017.

## 5 Empirical Results

Table 1 below reports the main estimation results on the relationship between extreme weather events and agricultural labor outcomes. The full set of estimated coefficients, including controls and extended specifications, is available in Table B.1 in Appendix B. The empirical strategy is structured around five core models, which progressively refine identification of the simultaneous effects of weather shocks on agricultural employment and labour productivity. These specifications sequentially account for structural climatic heterogeneity, incorporate non-linear interactions and adaptation responses, and allow for dynamic adjustment mechanisms.

The empirical models are grounded in the structural system of simultaneous equations introduced in Sect. 3 and formalized in Eq. 7, where agricultural labor productivity ( $\log(y_{at})$ ) and the share of agricultural employment ( $\theta_{at}$ ) are jointly determined as functions of extreme weather shocks (*WE*), productive factors, demographic variables, and broader structural conditions. Three complementary estimation strategies are implemented:

**Table 1** Direct and indirect effects of extreme weather events on structural transformation

	(1)	(2)	(3)	(4)	(5)
	static models				dynamic model
<b>Dep.var. - AgrEmplShare</b>					
<i>L.AgrEmplShare</i>					0.9260*** (0.0279)
<i>logAgrProd</i>	-0.0592*** (0.0134)	-0.0715*** (0.0164)	-0.0606*** (0.0156)	-0.0659*** (0.0188)	-0.0049** (0.0023)
ExtWetDays	0.0066 (0.0133)				
MaxHotDays	-0.0007*** (0.0002)				
Drought_spei	-0.0022* (0.0013)				
<i>z_ExtWetDays</i>		0.0029 (0.0026)	0.0016 (0.0030)	0.2972 (0.2202)	0.0012*** (0.0004)
<i>z_MaxHotDays</i>		-0.0082*** (0.0014)	-0.0078*** (0.0015)	0.0414 (0.0361)	0.0001 (0.0005)
<i>z_Drought_spei</i>		0.0002 (0.0017)	-0.0001 (0.0018)	0.1114 (0.0831)	0.0003 (0.0004)
IrrigLand				0.0020 (0.0014)	
<b>Dep.var. - logAgrProd</b>					
<i>L.logAgrProd</i>					0.9082*** (0.0385)
<i>AgrEmplShare</i>	-6.7793*** (0.4616)	-6.8035*** (0.6425)	-6.1127*** (0.7611)	-6.6294*** (0.7033)	-0.4496*** (0.1665)
ExtWetDays	-0.0039 (0.0839)				
MaxHotDays	-0.0054*** (0.0013)				
Drought_spei	-0.0231** (0.0099)				
<i>z_ExtWetDays</i>		0.0453*** (0.0151)	0.2862** (0.1344)	0.2814** (0.1296)	0.0504** (0.0251)
<i>z_MaxHotDays</i>		-0.0505*** (0.0134)	0.0619 (0.0928)	0.0474 (0.1023)	0.0088 (0.0203)
<i>z_Drought_spei</i>		0.0139 (0.0131)	2.0152** (0.9553)	1.9468** (0.9250)	0.4190** (0.1657)
<i>z_MaxHotDays * z_Drought_spei</i>			-2.2868** (1.0160)	-2.2492** (1.0005)	-0.4720*** (0.1722)
IrrigLand				-0.0184 (0.0159)	
<i>N</i>	814	770	770	770	770

Standard errors in parentheses; \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

- **Models 1 and 2** rely on a static specification estimated via system GMM for panel data. Weather shocks ( $WE$ ) enter linearly and additively, capturing average contemporaneous effects of droughts, heatwaves, and excess rainfall. The models differ in how they account for structural heterogeneity across countries in their exposure and responsiveness to the variability of weather extremes.
- **Models 3 and 4** extend the static framework by relaxing the linearity and separability assumptions. Interaction effects—particularly between heat and drought—are introduced to reflect compounding climate impacts. Model 4 further incorporates a proxy for adaptive capacity (irrigation coverage), allowing us to assess potential mitigation effects.
- **Model 5** introduces a dynamic specification by including lagged endogenous variables in both equations, resulting in a more temporally grounded version of Eq. 7.

Collectively, these models offer a robust framework for analysing the impacts of extreme weather on agricultural labour outcomes, incorporating non-linear effects, adaptive capacity, and dynamic adjustments. Detailed results are discussed further below.

## 5.1 Baseline Estimates and Control Variables

Overall, empirical findings remain broadly consistent with our theoretical expectations and continue to support the assumptions underlying our analytical framework. We thus begin with a brief examination of the effects of the control variables unrelated to extreme weather events, which display consistent and robust patterns across all model specifications (see Table B.1 in Appendix). This allows us to establish a baseline before focusing on the weather-related variables of primary interest.

### 5.1.1 Direct Effects of Control Variables on Agricultural Employment Shares

Estimates show that both agricultural labour productivity ( $\log AgrProd$ ) and the intersectoral productivity ratio ( $IPR$ ) are negatively and significantly associated with the share of employment in agriculture, in line with the predictions of structural dualism and dual-sector models (Lewis 1954; Timmer 1988). Higher productivity within agriculture reduces the need for labour input—a classic “push” mechanism—while an increase in  $IPR$  (i.e., convergence of agricultural with non-agricultural productivity) reflects sectoral modernisation and broader economic transformation. The latter dynamic stimulates demand in non-agricultural sectors, reinforcing labour reallocation away from agriculture. The consistent negative sign on  $IPR$  confirms that employment decisions are shaped not only by gains within agriculture, but also by how those gains compare to productivity levels in other sectors.

Economy-wide accumulation of productive assets and skills is associated with a declining share of labour in agriculture. Higher levels of physical capital ( $\log KstockTot$ ) and average years of education ( $Educ$ ) are both negatively correlated with agricultural employment, consistent with the idea that capital deepening and human capital formation facilitate labour mobility toward more productive non-agricultural activities. Demographic variables, by contrast, tend to work in the opposite direction. Larger populations ( $\log PopTot$ ) and higher age dependency ratios ( $ADR$ ) are significantly associated with higher agricultural labour shares, suggesting that demographic pressure can slow the reallocation process—especially where job creation in modern sectors fails to keep pace with labour force growth. Finally,

the positive and often significant coefficient on the time *Trend* may reflect persistent structural rigidities or absorptive constraints outside agriculture, notably in lower-income contexts. Trade openness appears to have no systematic effect on agricultural labour shares, indicating limited direct influence of globalization on employment reallocation.

### 5.1.2 Direct Effects of Control Variables on Agricultural Labour Productivity

We observe that agricultural employment shares (*AgrEmplShare*) exert a strong negative effect on labour productivity, confirming the inverse relationship between labour abundance and productivity per worker in agriculture. Private capital (*logKstockPriv*) shows a positive but only occasionally significant effect. Public capital (*logKstockGov*) is consistently negative and significant (in the static model), possibly reflecting inefficiencies or misallocation, particularly when investments bypass productive agricultural uses. Educational attainment (*Educ*) is negatively associated with labour productivity across specifications, which may indicate skill mismatches, selective exit of educated workers from agriculture, or unobserved preferences for non-farm work.<sup>15</sup> Population growth (*PopGr*) is positively associated with productivity in static models, possibly reflecting land-use intensification or technology adoption. However, in dynamic models, the effect turns negative, suggesting that rapid demographic growth may strain agricultural systems once structural inertia and underemployment are considered. Arable land endowment (*Land*) shows a positive and significant association with labour productivity, suggesting potential returns to scale, scope for mechanisation or reduced land pressure. However, this may reflect extensive rather than intensive growth, as land quality and use intensity are not captured in our model. Globalisation, measured via the KOF Trade Index (*GlobalTrade*), is insignificant, while FDI openness (*logFDI*) is generally positive and significant, supporting the view that capital inflows enhance agricultural efficiency. Institutional quality (*ContrCorrup*) is insignificant in all models. The time trend (*Trend*) is initially positive and significant, indicating productivity gains over time. However, this effect vanishes once weather interactions (Model 3), irrigation (Model 4), and dynamic effects (Model 5) are included—suggesting that earlier trend gains may have captured unobserved weather shocks or adaptation dynamics.

## 5.2 From Raw Weather Extreme Indicators to Standardised Shocks

Turning to our core *weather extreme* variables, Table 1 focuses specifically on the results pertaining to extreme weather events.<sup>16</sup>

**Model 1** serves as the baseline specification and includes three raw indicators of weather extremes: an adjusted version of SPEI index (see Sect. 4.2) to capture drought conditions, the annual count of extreme hot days (*MaxHotDays*), and total precipitation on the top 1%

<sup>15</sup> It is important to note that our specifications capture the effects of education on agricultural labour productivity, rather than on total factor productivity (TFP). While education is often found to enhance TFP through innovation, managerial capacity, or adoption of modern techniques, its effect on output per worker may be negative in contexts where educated individuals leave agriculture for better opportunities elsewhere, or where their skills are underutilised within farming. This distinction is particularly relevant in low-income settings characterized by strong sectoral segmentation in labour markets, consistent with dual sector models in which agriculture often absorbs surplus labour that cannot be absorbed by other parts of the economy.

<sup>16</sup> For a detailed view of the outcomes for all variables involved in the study, please refer to the comprehensive tables provided in the Appendix B.

wettest days (*ExtWetDays*).<sup>17</sup> Both drought and extreme heat are significantly associated with lower agricultural labour productivity and a declining share of agricultural employment, indicating output losses and potential rural labour displacement. In contrast, extreme precipitation shows no significant effect at this stage. However, these indicators must be interpreted with caution, as they are not directly comparable across countries. Temperature and precipitation extremes are reported in absolute terms (e.g., event counts or cumulative values), which do not account for differing climate baselines. While the SPEI index is locally standardized to capture deviations from historical norms, this standardization is applied at the grid-cell level. Once values are aggregated to the national scale, the comparability is diminished due to spatial heterogeneity in baseline climate conditions and in the distribution of grid coverage across countries.<sup>18</sup>

To address this, **Model 2** applies intra-country  $z$ -score transformations to all three weather variables. For SPEI, we re-normalize the national annual average using each country's sample mean and standard deviation from 1995 to 2017. As detailed in Sect. 4.2, this improves comparability by aligning the reference baseline with the estimation window and mitigating heteroskedasticity from spatial aggregation. The resulting variable captures drought severity relative to each country's historical norm, allowing coefficients to be interpreted as the effect of a one-standard-deviation shock.<sup>19</sup> Estimation results from Model 2 reveal notable shifts. The effect of heat intensifies and becomes highly significant, particularly for agricultural employment share ( $-0.0082^{***}$ ), confirming that thermal stress consistently harms labour outcomes even after adjusting for local climate norms. In contrast, drought becomes insignificant in both equations, suggesting that its strong association in Model 1 (and Model 2bis in Table B.1) reflected structural aridity rather than within-country anomalies. When scaled to local climate history, average marginal impacts appear negligible. This may indicate offsetting mechanisms: drought could raise labour productivity by displacing less efficient workers faster than it reduces output, or mild deficits may aid yields by reducing disease or improving harvest conditions. Similarly, extreme wet events, previously insignificant, now show a weakly positive effect on productivity, possibly due to reduced water stress or labour-saving impacts. Overall, these results underscore the value of standardising climate variables to distinguish between structural differences and intensifying exposure to weather anomalies.

### 5.3 Compound Weather Effects and Adaptation

Building on the specification in Model 2, **Model 3** introduces an interaction term between *drought* and *extreme temperature anomalies* to capture potential non-linear climate effects. This adjustment is motivated by agronomic and physiological evidence showing that extreme heat and water deficits often co-occur and jointly exacerbate crop losses, labour stress, and

<sup>17</sup> It is important to note that *ExtWetDays* captures intense rainfall, not flooding. Since flood impacts depend on local factors such as hydrology, topography, and land use, they are difficult to measure consistently across countries. Consequently, our analysis may underestimate the effects of extreme rainfall in flood-prone areas.

<sup>18</sup> As discussed in the Data section, SPEI is derived by fitting a probability distribution (typically gamma or log-logistic) to the climatic water balance, and mapping it onto a standard normal distribution. Although this produces a mean-zero, unit-variance index at the grid-cell level, spatial aggregation introduces heteroskedasticity and scale inconsistencies across countries.

<sup>19</sup> As a robustness check, we also estimate a variant specification (Model 2bis) that retains the original SPEI values standardized at source. While theoretically comparable across space, this version may misalign with our national panel. Results, reported in Appendix B, Table B.1, support the main findings.

disruptions to farm activities (Lobell et al. 2011; Kjellstrom et al. 2016; Mora et al. 2017; Zhao et al. 2017; Ray et al. 2019). We therefore allow an explicit *heat\*drought* interaction in the labour productivity equation while retaining the three individual weather variables in both equations. The results in column 3 of Table 1 confirm the theoretical expectation.

The labour reallocation results remain consistent: extreme heat consistently exhibits a negative and highly significant effect on the agricultural employment share, whereas drought and excess rainfall do not show statistically significant associations. This suggests that employment shifts out of agriculture are primarily driven by heat stress rather than hydric anomalies. In the labour productivity equation, however, the introduction of the interaction term alters the interpretation of individual effects. The drought coefficient becomes large, positive, and significant, while the interaction term is strongly negative. This asymmetric result suggests that moderate droughts may coincide with productivity gains, possibly due to labour reallocation, selection effects, or crop substitution, but that these gains are more than offset when drought coincides with extreme heat. The heat coefficient becomes insignificant, indicating its productivity effects are contingent on concurrent moisture deficits. Extreme wet events retain a consistently positive and significant effect on labour productivity across models.

Quantitatively, a one-standard-deviation drought shock is associated with a significant labour productivity increase (+2.02 log points), but this gain is reversed when combined with extreme heat. The estimated interaction effect of  $z$ -SPEI and  $z$ -MaxHotDays is strongly negative and significant (-2.29), aligning with evidence that “hot droughts” heighten physiological stress and reduce farm efficiency beyond the sum of their individual effects. These findings underscore the importance of accounting for compound climatic stress rather than treating weather variables in isolation.<sup>20</sup>

The consistent labour productivity effects of compound stress raise questions about the role of structural adaptation. **Model 4** explores this by including the share of irrigated land as a proxy for resilience capacity. While irrigation is not statistically significant in either equation, its inclusion produces two shifts: (1) the positive drought effect on labour productivity attenuates slightly, suggesting a modest buffering role against isolated droughts; (2) the large negative effect of extreme heat on employment becomes insignificant, potentially reflecting irrigation’s role in sustaining farm activity during hot periods, limiting labour outflows rather than absorbing displaced workers. However, labour productivity remains highly vulnerable to compound climatic stress, as the interaction term between heat and drought remains large and significant, indicating that irrigation alone does not mitigate the destructive effect of simultaneous drought and heat on output per worker.<sup>21</sup>

<sup>20</sup> We further tested two broader climate formulations that are not displayed in Table 1, but whose full estimates are available on request. Two additional specifications augment with a *heat\*excess-rainfall* term, and nesting both the *heat\*drought* and *heat\*excess-rainfall* interactions. In both exercises the additional interactions are imprecisely estimated and do not change the substance of the results: their coefficients hover near zero, and overall fit is virtually unchanged. The reason is largely mechanical. Because all interaction terms are constructed from the same  $z$ -scored heat index, their simultaneous inclusion raises multicollinearity and inflates standard errors; in the extended specification including multiple interactions this variance inflation even pushes the previously significant *heat\*drought* coefficient just beyond conventional significance thresholds, although its point estimate remains virtually identical to that in Model 3. As these richer specifications add complexity without delivering new economic insight, we retain the leaner and more transparent Model 3 in Table 1 and simply acknowledge that the broader tests corroborate—rather than contradict—our central narrative.

<sup>21</sup> Additionally, interactions between irrigation and weather extreme variables (not reported here) were tested and found to be consistently non-significant, indicating that existing irrigation infrastructure is not yet suf-

The progression from Model 1 to Model 4 leads to three key conclusions. First, raw weather extreme indicators may conflate structural aridity with within-country episodic anomalies, leading to upward-biased estimates of drought effects. Second, temperature anomalies, particularly when interacting with drought, emerge as key drivers of agricultural labour productivity losses and delayed structural adjustment. Third, while irrigation is often cited as a buffer against climate risk, our results suggest it does not significantly moderate the productivity impact of compound drought-heat shocks.

## 5.4 Dynamic Modelling of Agricultural Labour Productivity and Employment Allocation

To explore the persistence of weather shocks over time, we adopt a dynamic specification (**Model 5** in Table 1). Model 3 provides the foundation for this extension, as it uses standardized weather variables, accounts for non-linear effects through the drought-heat interaction, and excludes statistically insignificant adaptation proxies like irrigation. Retaining this structure allows us to isolate both immediate and lagged effects of weather shocks on agricultural employment and labour productivity, and to assess how episodic disruptions may evolve into long-term constraints on structural transformation.

To capture the persistence of weather impacts, we include lagged dependent variables in both the employment and productivity equations, allowing for path dependency in structural transformation. Given the endogeneity of these lagged outcomes, we instrument them using their second lags and deeper, following the Arellano-Bond approach. This correction ensures valid identification while avoiding correlation between instruments and equation residuals, with the resulting model showing strong statistical performance (Hansen test:  $p=0.376$ ). We omit the linear time trend, as it is statistically insignificant and absorbs explanatory power from key structural variables (see Model 5bis in Table B.1, Appendix B). The dynamic specification already accounts for time-related variation through lagged outcomes and contemporaneous shocks, making the trend both redundant and a potential source of multicollinearity.

We do not include lagged weather variables, as their effects are implicitly captured by the autoregressive structure. Weather variables—particularly extreme drought, heat, and rainfall—exhibit temporal autocorrelation, making the inclusion of both current and lagged values problematic due to collinearity, inflated standard errors, and reduced significance. This is consistent with our empirical findings: once dynamic dependence is modelled, lagged weather shocks add little explanatory power and destabilize contemporaneous effects.<sup>22</sup> Including multiple lags also increases model dimensionality, risking overfitting in moderately sized panels. In line with parsimony, we therefore retain only contemporaneous weather extremes, interpreting their effects as both immediate and forward-propagating through the system's dynamics.

---

ficiently targeted or scaled to alter the climate-labour-productivity nexus in a statistically detectable way. These findings suggest that the role of irrigation in adaptation, while conceptually promising, remains limited in practice—at least within the countries and time frame of this panel. More granular data on irrigation types, spatial coverage, and management systems would be needed to fully evaluate its adaptation potential under compound stress conditions.

<sup>22</sup> Results from these alternative specifications are not included here for brevity, but are available upon request.

The dynamic specification (Model 5 in Table 1) confirms the persistence of structural inertia in agricultural labour dynamics. The estimated coefficients on lagged agricultural employment (0.93) and lagged labour productivity (0.91) indicate a high degree of persistence in both dependent variables. This aligns with the well-established inertia of agricultural systems, especially in developing countries, where structural rigidities and limited non-farm absorption capacity slow down adjustment processes.

We also observe a shift in the role of WE variables in the dynamic Model 5 compared to the static Model 3. In the agricultural employment equation, extreme heat, which previously showed a strong negative association with agricultural labour shares, loses significance once dynamic adjustment is introduced. In contrast, extreme wet events become positively and significantly associated with agricultural employment. This asymmetry points to distinct adjustment dynamics. Heat shocks likely trigger immediate physiological constraints on outdoor work, causing abrupt, *distress-driven exits* from agriculture (Shayegh et al. 2021). These one-off shocks leave little room for adaptation in the short run. In contrast, wet extremes raise labour demand through organisational disruptions—such as drainage or pest control—thus *delaying*, rather than reversing, reallocation away from agriculture. These differentiated impacts suggest that policy responses must be shock-specific: rapid-response safety nets may be more effective for heat-induced displacement, while wet-related disruptions call for investments in infrastructure and risk management systems that support gradual adjustment.

In the labour productivity equation, the coefficient on drought remains positive and statistically significant, albeit smaller than in Model 3. This finding supports the idea that isolated droughts—when not accompanied by extreme heat—may coincide with efficiency gains via agronomic adjustments. However, this smaller magnitude should not be interpreted as a weaker overall effect. In the dynamic specification of Model 5, the coefficient captures only the immediate (short-run) response, whereas the total (long-run) effect depends on the persistence of labour productivity over time (see Sect. 6.1). In contrast, the static model (Model 3) conflates short- and long-term associations due to the absence of lagged outcomes. Finally, the *heat\*drought* interaction remains strongly negative and highly significant, indicating that compound weather shocks continue to undermine agricultural labour productivity even after accounting for both structural characteristics and temporal dynamics.

## 6 Extended Analysis: From Coefficients to Structural impacts

### 6.1 Immediate Versus Long-Term Effects and the Speed of Adjustment

The dynamic specification in Model 5 distinguishes between **short-run** (immediate) and **long-run** (persistent) effects of weather anomalies on agricultural labour outcomes. Coefficients on WE variables capture short-run impacts, while long-run effects are derived by dividing these by one minus the lagged dependent variable's coefficient, reflecting the model's autoregressive structure (see our methodological note C.1 in Appendix).

Before turning to the decomposition of direct and indirect effects in Sect. 6.2, we first examine how dynamic adjustment mechanisms amplify the initial impact of weather shocks over time, and assess the time horizon over which their effects materialize. Our focus is on the two weather shocks that remain consistently significant across equations: (i) extreme wet conditions, which notably affect the agricultural employment share (and also labour

productivity, though this effect is addressed later); and (ii) compound hot-drought events, which exert a strong influence on agricultural labour productivity.

### 6.1.1 Modest Delay in Labour Reallocation Under Precipitation Anomalies

For extreme wet conditions, the estimated short-run effect on agricultural employment share is modest—only +0.0012 percentage points (pp) for a one-standard-deviation anomaly. However, due to the high persistence of the outcome variable ( $\rho = 0.9260$ ), the total long-run effect accumulates to roughly 0.0162 pp:

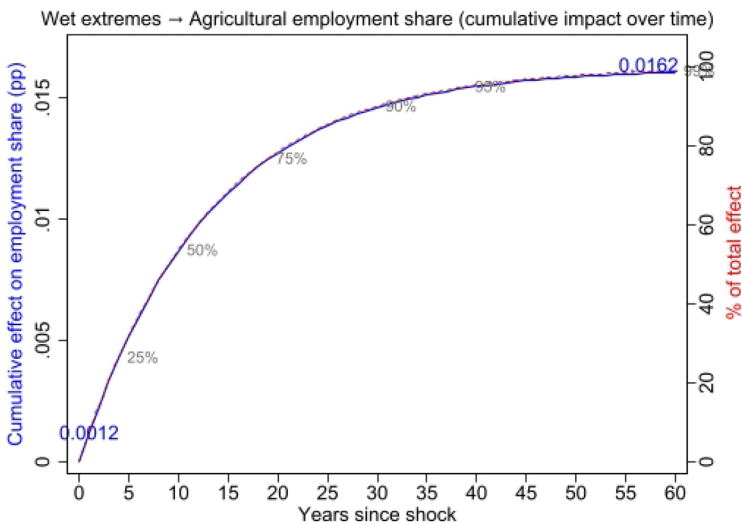
$$\text{Long-run effect} = \frac{0.0012}{1 - 0.9260} \approx 0.0162 \text{ pp}$$

This implies that the long-term effect is **13.5 times** larger than the initial impact.

However, due to strong inertia in employment dynamics, convergence is slow: half the total effect materialises after 8 years, and 99% is reached only after 59 years (Fig. 3; Table C.1). This gradual adjustment supports the interpretation of wet extremes as shocks that *delay*, rather than reverse, structural transformation—temporarily increasing labour demand for moisture-related tasks (e.g., drainage, disease control) in wetter years.

### 6.1.2 Persistent Collapse in Labour Productivity Under “Hot Droughts”

By contrast, compound “hot droughts” have a strong and persistent negative effect on agricultural labour productivity. While the estimated short-run coefficient on the interaction term ( $z\_MaxHotDays \times z\_Drought\_spei$ ) is  $-0.472$  log-points, it should not be interpreted in isolation. Given that the variable also includes a significant main effect of drought (+0.419), the net marginal impact of a one-standard-deviation increase in both heat and



**Fig. 3** Convergence of long-run effect of extreme wet conditions on agricultural employment share

drought is  $-0.053$  log-points, which implies an immediate productivity loss of approximately  $-5.2\%$ .<sup>23</sup> Due to strong persistence in agricultural productivity ( $\rho = 0.9082$ ), this short-run loss is greatly amplified over time. The corresponding long-run direct effect is:

$$\frac{-0.053}{1 - 0.9082} \approx -0.577 \text{ log-points}$$

which equates to a long-run productivity reduction of roughly  $-43.8\%$ .

The long-run impact is therefore over **8 times larger** than the immediate effect. Over half of the long-run loss is realised within 7 years, and 99% within 47 years (see Fig. 4 and Table C.2).

### 6.1.3 Static Versus Dynamic Sensitivities

As shown in Sect. 5, static models, by ignoring dynamic feedback mechanisms, overstate immediate impacts and miss cumulative damage. Dynamic models capture both the *pace* and *persistence* of weather shocks amid slow structural adjustment. To illustrate this point, Table 2 compares **hot drought** effects on agricultural labour productivity: the static Model 3 estimates a  $-0.2716$  ( $= +2.0152 - 2.2868$ ) log-point loss (about  $-24\%$ ), while the dynamic Model 5 shows a smaller immediate drop ( $-5.2\%$ ) but a much more severe long-run loss ( $-44\%$ ), if no structural transformation occurs. These findings underscore the importance of situating weather extremes and agricultural labour interactions within a dynamic framework to assess both vulnerability and adaptive capacity.

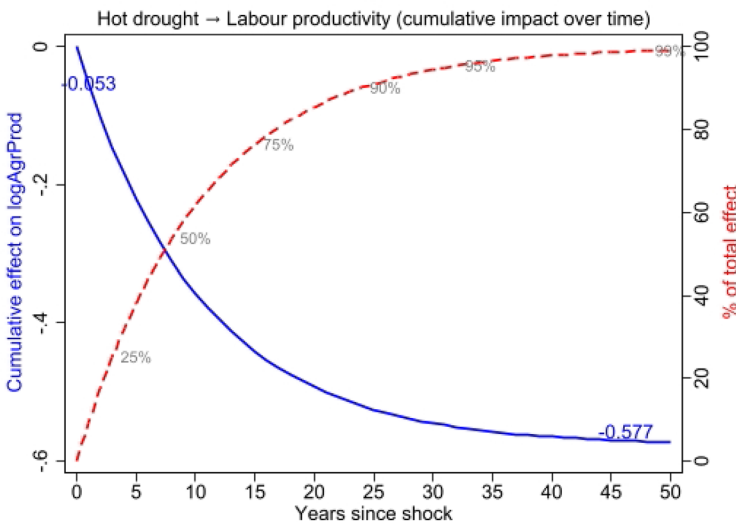


Fig. 4 Convergence of the long-run effect of “hot droughts” on agricultural labour productivity

<sup>23</sup> Computed as  $100 \times (\exp(-0.053) - 1) \approx -5.2\%$ . A technical discussion of interaction terms can be found in Appendix C.2.

**Table 2** Estimated impact of a one-standard-deviation increase in “hot droughts” on agricultural labour productivity

Model	Estimated effect (log-points)	Interpretation
Static (Model 3)	-0.2716	~ 24% decline; no dynamic adjustment
Dynamic (Model 5) - short run	-0.053	5.2% immediate drop
Dynamic (Model 5) - long run	-0.577	up to 44% loss, reached over ~47 years ( $\rho = 0.9082$ ) if no adjustment

## 6.2 Structural Feedback Loops and the Transmission of Weather Shocks

As discussed in Sect. 3, our framework incorporates mutual feedback between agricultural employment share and labour productivity—each entering as a regressor in the other’s equation—and thus allows us to capture bidirectional linkages: weather shocks influence each outcome both directly and indirectly via their effect on the other. These effects accumulate due to high persistence in both series (lag coefficients  $> 0.9$ ). We therefore compute the impact of statistically significant weather shocks along three distinct transmission channels: (i) the *short-run direct effect*; (ii) the *long-run direct effect*, which reflects the cumulative impact amplified by persistence in the outcome variable; and (iii) the *long-run indirect effect* transmitted through structural feedback between agricultural labour productivity and employment share. These components jointly inform the total long-run effect. The decomposition procedure is formally described in Appendix C.3.

### 6.2.1 Extreme Wet Events: Direct Labour Productivity Gains and Modest Reallocation Delays

As shown in Model 5, extreme wet anomalies ( $z_{ExtWetDays}$ ) exert distinct yet interconnected effects on agricultural employment and labour productivity. On the employment side, wet shocks lead to a statistically significant short-run increase of +0.0012 percentage points in the agricultural labour share. Given the high persistence of this variable ( $\rho = 0.926$ ), the long-run direct effect rises to +0.0162 percentage points, suggesting a temporary slowdown in labour reallocation due to increased seasonal demand for moisture-related tasks. At the same time, wet anomalies raise agricultural labour productivity: the short-run direct effect is +0.0504 log-points, and the long-run gain reaches +0.549 log-points ( $\approx +73\%$ ). This likely reflects agronomic benefits from improved moisture availability under non-flood conditions. The simultaneous equations structure allows us to trace indirect feedbacks: the rise in employment induced by rainfall slightly depresses productivity via the estimated elasticity ( $-0.4496$ ), resulting in a modest indirect long-run loss of  $-0.0059$  log-points. Conversely, productivity gains reduce agricultural labour shares through a negative cross-equation effect ( $-0.0049$ ), contributing a small indirect reduction of  $-0.0033$  percentage points in the long run. These feedback effects are computed based on a single iteration of the interaction mechanism. While in theory such loops could propagate further, we limit our analysis to first-order effects for tractability. Overall, extreme wet events yield a substantial long-run increase in agricultural labour productivity alongside a modest but persistent rise in employment share. This joint outcome deviates from the conventional narrative of struc-

tural transformation, where productivity gains typically enable labour exit from agriculture. Instead, it reveals an alternative pathway in which labour productivity improvements, driven by precipitation anomalies, may actually sustain or even necessitate continued labour intensity within the sector. Far from rendering agricultural labour obsolete, such dynamics underscore its enduring relevance, particularly in contexts where adaptation to climate variability requires human input in increasingly complex agro-ecological conditions.

### 6.2.2 Hot Droughts: Compound Losses and Cumulative Resilience Breakdowns

The most damaging climate shock in our model is the compound interaction between extreme heat and drought ( $z_{MaxHotDays} \times z_{Drought\_spei}$ ). While extreme heat alone becomes insignificant in Model 5, drought maintains a positive coefficient (+0.4190), and the interaction term is strongly negative (−0.4720). Evaluated at one standard deviation for each component, the net short-run effect of a hot drought episode is −0.053 log-points ( $\approx -5.2\%$ ). With high productivity persistence ( $\rho = 0.9082$ ), this translates into a long-run direct loss of −0.577 log-points ( $\approx -44\%$ ). Indirect feedback compounds this impact: the induced labour productivity shock raises the employment share via its own elasticity (−0.0049), which in turn depresses labour productivity through the opposite cross-equation effect (−0.4496), generating an additional long-run loss of labour productivity −0.0171 log-points. Summing long-run direct and *first-order* feedback effects yields a total long-run productivity decline of −0.5941 log-points ( $\approx -45\%$ ). These effects underscore the severity of hot-drought interactions, which simultaneously disrupt physiological capacity, production conditions, and labour organisation. In contrast to isolated anomalies, compound events impose layered stresses, leaving little room for short-term adaptation and increasing the risk of cumulative sectoral decline.

## 7 Conclusion

This paper investigates how extreme weather events—specifically droughts, heatwaves, and excessive rainfall—affect agricultural labour outcomes and, by extension, the broader process of structural transformation in low- and middle-income countries. Grounded in a dual-sector theoretical framework that captures both within-sector productivity dynamics and intersectoral labour reallocation, we develop a system of simultaneous equations linking agricultural labour productivity and employment shares. The model is estimated on a 35-country (balanced) panel spanning 1996–2017 using both static and dynamic specifications, with particular attention to the role of weather anomalies measured as within-country standardised deviations (*z*-scores). This system-based approach captures direct and indirect effects, as well as feedback loops, offering new insights into the timing, persistence, and mechanisms of climate-induced structural change.

In static specifications, extreme heat consistently emerges as the most damaging climate stressor, exerting significant negative effects on both agricultural employment and labour productivity. These findings hold even after controlling for structural climate conditions, confirming that temperature anomalies—rather than chronic aridity—drive short-term labour displacement and productivity losses. By contrast, the effects of drought are more nuanced: while moderate droughts are sometimes associated with temporary productivity

gains, likely via labour reallocation or agronomic adjustments, these gains are entirely offset when droughts co-occur with extreme heat. The interaction of heat and drought—so-called “hot droughts”—produces the most severe losses, reflecting compound impacts on physiological capacity, crop viability, and farm organisation. Excess rainfall, on the other hand, is found to raise employment in agriculture and simultaneously improve labour productivity. Yet, this also delays reallocation away from agriculture, as increased moisture-related tasks (e.g., drainage, pest control) temporarily raise labour demand, sustaining employment in the sector.

Dynamic estimations reveal that the consequences of weather shocks unfold over time and are amplified through feedback mechanisms. In particular, compound “hot droughts” lead to persistent declines in agricultural labour productivity, with long-run effects reaching nearly  $-45\%$ . These shocks not only depress current output but also delay structural adjustment by inducing labour retention in low-productivity contexts. Wet extremes present an opposite dynamic: while they slow reallocation in the short term, they result in substantial long-run productivity gains. These outcomes illustrate how climate anomalies influence both the direction and pace of rural transformation and demonstrate that static models tend to understate long-term damage by ignoring slow adjustment processes.

Crucially, the estimated feedback loops between productivity and employment show that climate shocks affect one outcome in ways that propagate to the other. For example, a productivity loss reduces incentives to exit agriculture, thereby slowing transformation and reinforcing inefficiency—a vicious cycle that cannot be captured by single-equation models. Our use of a system-based approach thus enables a more complete understanding of how climate stress interacts with rural labour markets.

Several policy implications follow. First, adaptation strategies must be tailored to the nature of the shock. Heat-induced labour displacement calls for rapid-response mechanisms, such as temporary employment programmes or safety nets. In contrast, excess rainfall—while less immediately disruptive—requires investments in infrastructure and farm management systems that can absorb additional labour demand without locking workers into low-productivity sectors. Second, irrigation, often viewed as a silver bullet, shows only limited protective capacity: it buffers isolated droughts and may reduce heat-induced exits, but fails to mitigate the combined effects of heat and drought. Broader resilience strategies, including crop diversification, improved extension services, and the development of off-farm employment opportunities, are therefore essential.

Finally, our results call for a shift in the way structural transformation is conceptualised under climate stress. Rather than assuming that productivity gains will naturally drive labour out of agriculture, our findings show that in some cases—particularly under wet anomalies—labour remains in the sector to sustain those very gains. This challenges the conventional assumption that modernisation renders agricultural labour obsolete. On the contrary, climate variability may increase the need for labour-intensive responses, highlighting the continued relevance of rural employment in adaptation pathways.

Future research should examine how local institutions, land tenure regimes, and governance quality mediate these dynamics. Micro-level studies could provide further insight into household decision-making, migration, and adaptation trade-offs. As weather extremes become more frequent and intense, such knowledge will be critical to designing policies that not only build resilience but also enable inclusive and climate-compatible economic transformation.

## Appendices

### A. Data Description

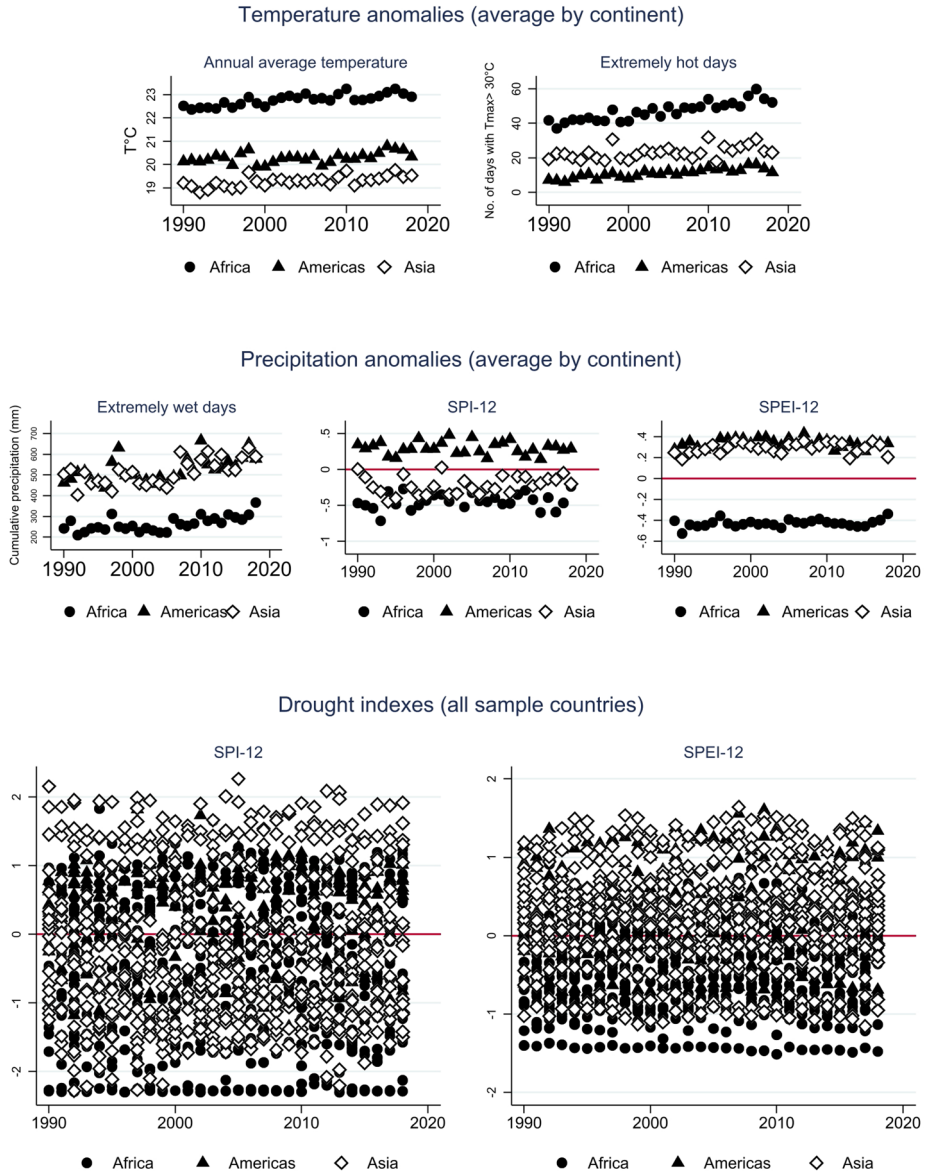
**Table A.1** Data definition and sources

Variable	Definition	Source
<b>AgrEmplShare</b>	Employment in agriculture (% of total employment)	GGDC/UNU-WIDER ETD
<b>AgrProd</b>	Agriculture VA / Agriculture employment (USD altern. conv. factor)	GGDC/UNU-WIDER ETD
<i>nonAgrProd</i>	VA (11 non-agriculture sectors) / employment (USD altern. conv. factor)	GGDC/UNU-WIDER ETD
<i>logAgrProd</i>	<i>log(AgrProd)</i>	Authors' calculation
<i>IPR</i>	<i>log(AgrProd/nonAgrProd)</i>	Authors' calculation
<b>Land</b>	Arable land (% of land area)	WB
<b>IrrigLand</b>	Agricultural irrigated land (% of total agricultural land)	WB
<b>Educ</b>	Years of education	Barro-Lee Education Attainment Dataset
<i>logEduc</i>	<i>log(Educ)</i>	Authors' calculation
<b>ADR</b>	Age dependency ratio, young (% of working-age population)	WB
<b>PopGr</b>	Population growth	WB
<b>PopTot</b>	Total population	WB
<i>logPopTot</i>	<i>log(PopTot)</i>	Authors' calculation
<b>KstockTot</b>	Total capital stock (gov+priv+ppp)	IMF
<i>logKstockTot</i>	<i>log(KstockTot)</i>	Authors' calculation
<b>KstockGov</b>	General government capital stock	IMF
<i>logKstockGov</i>	<i>log(KstockGov)</i>	Authors' calculation
<b>KstockPriv</b>	Private capital stock	IMF
<i>logKstockPriv</i>	<i>log(KstockPriv)</i>	Authors' calculation
<b>FDI</b>	Direct investment equity flows in the reporting economy	WB
<i>logFDI</i>	<i>log(FDI+abs(FDI<sub>min</sub>+1))</i>	Authors' calculation
<b>Globalisation</b>	KOF Index of Globalization	Dreher (2006)
<b>GlobalPol</b>	KOF Political Globalisation Index	KOF
<b>GlobalTrade</b>	KOF Trade Globalisation Index	KOF
<b>ContrCorrup</b>	Corruption control index	WB WGI
<b>MaxHotDays</b>	Count of days $\geq 35^\circ\text{C}$ (annual)	ETCCDI
<b>ExtWetDays</b>	Accumulated precipitation during 1% of wettest days (annual)	ETCCDI
<b>SPEI_12</b>	Standardized Precipitation-Evapotranspiration Index (12-month)	CRU
<i>Drought_spei</i>	$(SPEI_{12})^2$ if $SPEI_{12} \leq -1$	Authors' calculation

**Table A.2** List of countries

Africa	Americas	Asia
Botswana	Argentina	Bangladesh
Cameroon	Bolivia	Cambodia
Ghana	Brazil	China
Kenya	Colombia	India
Lesotho	Costa Rica	Indonesia
Malawi	Ecuador	Malaysia
Mozambique	Mexico	Myanmar
Namibia	Peru	Nepal
Senegal		Pakistan
South Africa		Philippines
Tanzania		Sri Lanka
Tunisia		Thailand
Uganda		Turkey
Zambia		
14	8	13

Note: 22 observations for each country (1996-2017)



**Fig. A.1** Extreme weather events in GGDC/UNU-WETD sample of countries (1990–2018). Source: Climatic Research Unit, calculations, authors' own

**Table A.3** Summary statistics

	count	mean	sd	min	max
year	770			1996	2017
AgrEmplShare	770	0.4133778	0.2120455	0.0518967	0.8460292
AgrProd	770	3564.552	7093.055	177.5639	61523.43
logAgrProd	770	7.370202	1.171912	5.17933	11.02717
IPR	770	1.86787	2.726653	-3.967822	8.12391
MaxHotDays	770	30.24781	38.52377	0	212.69
z_MaxHotDays	770	0.1185198	0.9709254	-2.236687	4.079968
SPEI_12	770	-0.1766465	1.042721	-3.072733	2.717108
Draught_spei	770	0.5791041	1.244389	0	9.441688
z_Draught_spei	770	-0.0495245	0.9239418	-1.027185	4.536034
ExtWetDays	770	5.928262	0.5326305	3.991389	7.536225
z_ExtWetDays	770	0.0542616	0.9677367	-3.006502	2.679278
Educ	770	6.653649	2.133215	0.9591233	11.59177
PopGr	770	1.719647	0.7802262	-0.6163564	3.755687
PopTot	770	1.17e+08	2.83e+08	1504724	1.39e+09
logPopTot	770	17.27956	1.499361	14.22412	21.04997
ADR	770	59.70532	19.78535	23.66923	106.8938
Land	770	16.07608	14.15563	0.3211406	64.94584
IrrigLand	770	11.93147	10.3355	0.1288378	41.65767
KstockTot	770	1773.852	4837.696	7	54542
logKstockTot	770	5.629448	2.001702	1.94591	10.90673
KstockPriv	770	1050.2	2431.996	4	27994
logKstockPriv	770	5.208243	2.032886	1.386294	10.23975
KstockGov	770	698.9935	2586.079	3	26396
logKstockGov	770	4.382924	1.949809	1.098612	10.18097
Globalisation	770	54.68041	10.33464	23.56341	81.39252
GlobalTrade	770	45.48257	12.85626	17.30428	82.50341
FDI	770	8.70e+09	2.89e+10	-4.55e+09	2.91e+11
logFDI	770	22.7465	1.124896	0	26.41186
ContrCorrup	770	-0.4023027	0.516745	-1.67334	1.216737

**B. Detailed Estimation Results**

**Table B.1** Effects of weather-extreme events on agriculture labour dynamics

	(1)	(2)	(2bis)	(3)	(4)	(5)	(5bis)
	static models				dynamic models		
<b>Dep.var.:</b>							
<b>AgrEmplShare</b>							
<i>L1.</i>						0.9260***	0.9594***
<i>AgrEmplShare</i>						(0.0279)	(0.0301)
<b>logAgrProd</b>	-0.0592***	-0.0715***	-0.0709***	-0.0606***	-0.0659***	-0.0049***	-0.0024
	(0.0134)	(0.0164)	(0.0163)	(0.0156)	(0.0188)	(0.0023)	(0.0025)
IPR	-0.0059***	-0.0049***	-0.0048***	-0.0072***	-0.0044	-0.0006***	-0.0004***
	(0.0020)	(0.0026)	(0.0026)	(0.0034)	(0.0037)	(0.0003)	(0.0002)
logKstockTot	-0.0474***	-0.0549***	-0.0545***	-0.0579***	-0.0805***	-0.0040***	-0.0016
	(0.0099)	(0.0119)	(0.0119)	(0.0119)	(0.0180)	(0.0019)	(0.0021)
Educ	-0.0173***	-0.0113***	-0.0115***	-0.0141***	-0.0118***	-0.0007	-0.0002
	(0.0052)	(0.0059)	(0.0058)	(0.0065)	(0.0066)	(0.0007)	(0.0007)
logPopTot	0.0641***	0.0676***	0.0675***	0.0693***	0.0855***	0.0047***	0.0020
	(0.0075)	(0.0076)	(0.0075)	(0.0074)	(0.0161)	(0.0021)	(0.0024)
ADR	0.0028***	0.0025***	0.0025***	0.0021***	0.0025***	0.0001***	0.0001***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0008)	(0.0001)	(0.0001)
Globalisation	-0.0021	-0.0009	-0.0009	-0.0017	0.0010	-0.0000	-0.0000
	(0.0016)	(0.0016)	(0.0016)	(0.0017)	(0.0027)	(0.0001)	(0.0001)
Trend	0.0035***	0.0034***	0.0035***	0.0035***	-0.0166		0.0000
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0148)		(0.0001)
MaxHotDays	-0.0007***						
	(0.0002)						
Drought_spei	-0.0022***		-0.0016				
	(0.0013)		(0.0013)				
ExtWetDays	0.0066						
	(0.0133)						
z_MaxHotDays		-0.0082***	-0.0076***	-0.0078***	0.0414	0.0001	-0.0000
		(0.0014)	(0.0018)	(0.0015)	(0.0361)	(0.0005)	(0.0006)
z_Drought_spei		0.0002		-0.0001	0.1114	0.0003	-0.0000
		(0.0017)		(0.0018)	(0.0831)	(0.0004)	(0.0005)
z_ExtWetDays		0.0029	0.0022	0.0016	0.2972	0.0012***	0.0010***
		(0.0026)	(0.0024)	(0.0030)	(0.2202)	(0.0004)	(0.0004)
IrrigLand					0.0020		
					(0.0014)		
Constant	8.0467***	9.1535***	9.1072***	9.9756***	10.7990***	1.0603***	0.8772***
	(0.8887)	(1.6956)	(1.7087)	(1.3947)	(1.7391)	(0.4200)	(0.3504)
<b>Dep.var.:</b>							
<b>logAgrProd</b>							
<i>L1.logAgrProd</i>						0.9082***	0.9106***
						(0.0385)	(0.0317)
<b>AgrEmplShare</b>	-6.7793***	-6.8035***	-6.8219***	-6.1127***	-6.6294***	-0.4496***	-0.4518***
	(0.4616)	(0.6425)	(0.6388)	(0.7611)	(0.7033)	(0.1665)	(0.1362)
logKstockPriv	0.1128**	0.0726	0.0746	0.1728	0.1470	0.0146	0.0182
	(0.0454)	(0.0837)	(0.0840)	(0.1080)	(0.0964)	(0.0182)	(0.0162)

**Table 6** (continued)

	(1)	(2)	(2bis)	(3)	(4)	(5)	(5bis)
	static models			dynamic models			
logKstockGov	-0.1292*** (0.0369)	-0.1136 (0.0716)	-0.1152 (0.0717)	-0.2180** (0.1047)	-0.1646* (0.0913)	-0.0105 (0.0176)	-0.0147 (0.0156)
Educ	-0.1908*** (0.0312)	-0.1451*** (0.0403)	-0.1468*** (0.0396)	-0.1349*** (0.0488)	-0.1367*** (0.0523)	-0.0121* (0.0067)	-0.0125** (0.0058)
PopGr	0.2997*** (0.0513)	0.2585*** (0.0440)	0.2579*** (0.0442)	0.0132 (0.1307)	-0.0604 (0.1744)	-0.0341** (0.0172)	-0.0187 (0.0151)
Land	0.0057** (0.0023)	0.0035 (0.0022)	0.0034 (0.0022)	0.0042 (0.0033)	0.0083** (0.0036)	-0.0002 (0.0005)	-0.0003 (0.0004)
GlobalTrade	0.0011 (0.0032)	0.0001 (0.0042)	0.0001 (0.0042)	-0.0005 (0.0049)	-0.0026 (0.0066)	-0.0005 (0.0008)	0.0000 (0.0007)
logFDI	0.0978*** (0.0283)	0.0430 (0.0622)	0.0457 (0.0624)	0.0664** (0.0303)	0.0539** (0.0274)	0.0067 (0.0048)	0.0091** (0.0040)
ContrCorrup	-0.0571 (0.0708)	-0.1001 (0.1000)	-0.1015 (0.0995)	-0.0185 (0.1209)	-0.1443 (0.1392)	-0.0004 (0.0234)	-0.0083 (0.0179)
Trend	0.0346*** (0.0043)	0.0338*** (0.0044)	0.0341*** (0.0043)	0.0056 (0.0159)	-0.0006 (0.0178)		0.0005 (0.0023)
MaxHotDays	-0.0054*** (0.0013)						
Drought_spei	-0.0231** (0.0099)		-0.0061 (0.0104)				
ExtWetDays	-0.0039 (0.0839)						
z_MaxHotDays		-0.0505*** (0.0134)	-0.0450*** (0.0145)	0.0619 (0.0928)	0.0474 (0.1023)	0.0088 (0.0203)	0.0034 (0.0180)
z_Drought_spei		0.0139 (0.0131)		2.0152** (0.9553)	1.9468** (0.9250)	0.4190** (0.1657)	0.2920* (0.1555)
z_ExtWetDays		0.0453*** (0.0151)	0.0383** (0.0159)	0.2862** (0.1344)	0.2814** (0.1296)	0.0504** (0.0251)	0.0429* (0.0239)
z_MaxHot-Days*z_Drought_spei				-2.2868** (1.0160)	-2.2492** (1.0005)	-0.4720*** (0.1722)	-0.3365** (0.1672)
IrrigLand					-0.0184 (0.0159)		
Number of obs	814	770	770	770	770	770	770
Hansen J statistic	13.5324	12.1148	12.211	10.2044	10.0502	9.6923	11.3375
Hansen J p-value	0.3316	0.2774	0.2712	0.3342	0.1857	0.3760	0.1246

Standard errors in parentheses; \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

**Notes to Table B.1.** Estimates are obtained using a two-step GMM estimator applied to a system of two simultaneous equations: (1) the share of employment in agriculture (*AgrEmplShare*) and (2) agricultural labour productivity (*logAgrProd*). Estimation is performed with Stata's `gmm` command using an unadjusted initial weighting matrix (`winitial(unadjusted, independent)`) to prevent singularity issues, and a clustered second-stage weighting matrix (`wmatrix(cluster country)`) to allow for within-country heteroskedasticity. Standard errors are unadjusted GMM estimates (`vce(unadjusted)`), compatible with

the twostep estimator used for improved efficiency (by accounting for the actual variance structure in the data). In the dynamic specification, lagged dependent variables are instrumented using their second lags (L2.) to address potential endogeneity. In the static version, only externally sourced instruments are used. The Hansen *J*-statistic tests the joint validity of instruments under the null hypothesis of exogeneity. The dataset covers 35 countries over the 1996–2017 period (balanced panel). Reported coefficients are second-step estimates, with asymptotic standard errors in parentheses.

### C. Methodological Notes

#### C.1. Convergence Time to Long-Run Effect

To determine how long it takes for a shock to reach a given proportion of its total long-run effect, we compute the cumulative dynamic impact in a standard autoregressive model.

Let  $\beta$  denote the short-run effect of a shock, and  $\rho$  the coefficient on the lagged dependent variable in a dynamic equation of the form:

$$Y_{it} = \rho Y_{it-1} + \beta X_{it} + \varepsilon_{it}$$

The cumulative effect after  $t$  years is given by the partial sum of a geometric progression:

$$\text{Cumulative impact at year } t = \beta \cdot \sum_{j=0}^t \rho^j = \beta \cdot \frac{1 - \rho^{t+1}}{1 - \rho}$$

The total long-run effect is the limit of this sum as  $t \rightarrow \infty$ :

$$\text{Long-run effect} = \frac{\beta}{1 - \rho}$$

To compute the number of years required to reach a target percentage  $p\%$  of the total long-run effect, we solve for the smallest integer  $t$  such that:

$$\frac{\beta \cdot \frac{1 - \rho^{t+1}}{1 - \rho}}{\frac{\beta}{1 - \rho}} \geq \frac{p}{100} \Rightarrow 1 - \rho^{t+1} \geq \frac{p}{100} \Rightarrow \rho^{t+1} \leq 1 - \frac{p}{100}$$

**Table C.1** Convergence time to long-run effect of precipitation anomalies on agricultural employment share

% of Long-Run Effect	Years Required
25%	3
50%	8
75%	17
90%	29
95%	38
99%	59

**Table C.2** Convergence time to long-run effect of “hot drought” (combined drought and heat anomalies) on agricultural labour productivity

% of Long-Run Effect	Years Required
25%	2
50%	7
75%	14
90%	23
95%	31
99%	47

Taking logarithms:

$$t \geq \frac{\log\left(1 - \frac{p}{100}\right)}{\log(\rho)} - 1$$

We compute this for various threshold values of  $p \in \{25, 50, 75, 90, 95, 99\}$  to obtain the convergence timeline, reported in tables below (model specification 5 in Table B.1).

### C.2. Interpreting Interaction Terms

In specifications including interaction terms—such as the combined effect of drought and extreme heat—the full marginal impact of a joint shock must be computed by summing the relevant components. Specifically, if a model includes both a main effect (e.g., *Drought*) and an interaction term (e.g., *Heat* × *Drought*), then the marginal effect of a one-standard-deviation increase in both variables is:

$$\text{Marginal effect} = \beta_{\text{drought}} + \beta_{\text{heat}} + \beta_{\text{interaction}}$$

This stems from the functional form of the model. For instance, the estimated equation for agricultural labour productivity can be written as:

$$\log(y_{it}) = \rho \log(y_{it-1}) + \beta_1 \cdot \text{Drought}_{it} + \beta_2 \cdot \text{Heat}_{it} + \beta_3 \cdot (\text{Drought}_{it} \times \text{Heat}_{it}) + \varepsilon_{it}$$

Taking partial derivatives with respect to a simultaneous increase in both *Drought* and *Heat* (each by one standard deviation), we obtain:

$$\frac{\partial \log(y)}{\partial \text{Drought}} + \frac{\partial \log(y)}{\partial \text{Heat}} + \frac{\partial \log(y)}{\partial (\text{Drought} \times \text{Heat})} = \beta_1 + \beta_2 + \beta_3$$

In our application (Model 5), the short-run coefficient on *Drought* is  $\beta_1 = +0.419$ , on *Max-HotDays* is  $\beta_2 = +0.009$  (but not statistically significant from zero), and the coefficient on the interaction term is  $\beta_3 = -0.472$ . Therefore, the full marginal short-run (statistically significant) effect of a one-sigma hot drought shock is:

$$\beta_{\text{hot drought}} = +0.419 + (-0.472) = -0.053$$

This calculation reflects the combined impact of experiencing both anomalies simultaneously, compared to a baseline with neither. Ignoring the main effect and interpreting the interaction coefficient in isolation would overstate the marginal damage of the joint shock.

### C.3. Direct, Indirect, and Total Long-Run Effects

To compute the full impact of weather shocks in our dynamic specification (Model 5), we distinguish between:

- **Short-run (SR) or immediate direct effect:** The estimated coefficient from the model (e.g.,  $\beta_{\text{shock}}$ ).
- **Long-run (LR) direct effect:** Given the presence of lagged dependent variables, the cumulative (steady-state) effect of a shock is calculated as:

$$\text{Direct LR effect} = \frac{\beta_{\text{shock}}}{1 - \rho}$$

where  $\rho$  is the coefficient on the lagged dependent variable (see the note C.1).

- **Indirect effect via feedback loop:** When outcome variables are interdependent (e.g., agricultural labour productivity affects agricultural employment share and vice versa), a shock affecting one variable transmits indirectly to the other. For example, a shock  $S$  affecting labour productivity ( $y$ ), which in turn affects employment share ( $\theta$ ), generates:

$$\text{Indirect SR effect on } \theta = \alpha_1 \cdot \beta_S^{(y)}$$

$$\text{Indirect LR effect on } \theta = \frac{\alpha_1 \cdot \beta_S^{(y)}}{1 - \rho_\theta}$$

where  $\alpha_1$  is the coefficient of  $y$  in the employment share ( $\theta$ ) equation, and  $\rho_\theta$  is the lag coefficient in the  $\theta$  equation (see Eq. 7, Sect. 3).

- **Total long-run effect:** The sum of the direct and indirect effects.

\*\*\*

**Example -Hot drought effect** (combined drought and heat anomalies) **on agricultural labour productivity:**

- Direct, statistically significant, coefficients:
  - Drought:  $\beta_{\text{drought}} = +0.4190$
  - Interaction (heat  $\times$  drought):  $\beta_{\text{interaction}} = -0.4720$

- Marginal **short-run direct** effect for a one-sigma increase in both drought and heat:  $\Delta y = \beta_{\text{heat}} + \beta_{\text{drought}} + \beta_{\text{interaction}} = n.s. + 0.4190 - 0.4720 = -0.053$
- Lag coefficient on labour productivity:  $\rho_y = 0.9082$
- **Long-run direct effect:**  $\frac{-0.053}{1-0.9082} \approx \frac{-0.053}{0.0918} \approx -0.577$
- **Long-run indirect effect via employment feedback:**
  - Impact of labour productivity on employment share:  $\alpha_1 = -0.0049$
  - Cross-equation elasticity (impact of employment share on labour productivity):  $\beta_1 = -0.4496$
  - Lag coefficient on employment share:  $\rho_\theta = 0.926$
  - Short-run *indirect* effect on employment share:  $(-0.0049) \times (-0.053) = +0.00026$
  - Long-run *indirect* effect on employment share:  $\frac{+0.00026}{1-0.926} \approx +0.0035$
  - Feedback on labour productivity:  $\frac{-0.4496 \times 0.0035}{1-0.9082} \approx -0.0171$
- **Total long-run impact** of a hot drought shock on the agricultural labour productivity:  $(-0.577) + (-0.0171) = -0.5941 \text{ log - points } (\approx -45\%)^{24}$

These calculations reveal how short-term weather anomalies propagate through structural inertia and cross-variable dynamics, amplifying or dampening their initial effects over time.

**Funding** Open access funding provided by Université de Versailles Saint-Quentin-en-Yvelines.

**Data Availability** The data that support the findings of this study are available from the authors upon reasonable request.

## Declarations

**Competing Interests** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

**Generative AI and AI-assisted Technologies in the Writing Process** During the preparation of this work, the authors partially used ChatGPT for language translation and editing. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

**Open Access** This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

<sup>24</sup>Computed as  $100 \times (\exp(-0.5941) - 1) \approx -44.8\%$

## References

- Adams KM, Benzie M, Croft S, Sadowski S (2021) Climate change, trade, and global food security: a global assessment of transboundary climate risks in agricultural commodity flows. *Sei report*, Stockholm Environment Institute, Stockholm
- Addoum JM, Ng DT, Ortiz-Bobea A (2020) Temperature shocks and establishment sales. *Rev Financ Stud* 33(3):1331–1366
- Bansal R, Ochoa M, Kiku D (2016) Climate change and growth risks. NBER Working Paper 23009, National Bureau of Economic Research. Working paper, Cambridge, MA
- Barrett CB, Ortiz-Bobea A, Pham T (2023) Structural transformation, agriculture, climate, and the environment. *Rev Environ Econ Policy* 17(2):195–216
- Barrios S, Bertinelli L, Strobl E (2006) Climatic change and rural–urban migration: the case of sub-saharan africa. *J Urban Econ* 60(3):357–371
- Berlemann M, Wenzel D (2018) Precipitation and economic growth. CESifo Working Paper Series 7258, CESifo. Working paper
- Burke M, Hsiang S, Miguel E (2015) Global non-linear effect of temperature on economic production. *Nature* 527:235–239
- Chen Y, Gong B, Kim S (2022) Climate shocks and agricultural productivity: micro-evidence from China. *J Environ Econ Manag* 114:102706
- Costinot A, Donaldson D, Smith C (2016) Evolving comparative advantage and the impact of climate change in agricultural markets: evidence from 1.7 million fields around the world. *J Political Econ* 124(1):205–248
- Dabla-Norris E, Thomas AH, Garcia-Verdu R, Chen Y (2013) Benchmarking structural transformation across the world. Technical Report 2013/176, International Monetary Fund
- Dell M, Jones B, Olken B (2012) Growth: evidence from the last half century. *Am Econ J Macroecon* 4(3):66–95
- Deryunga T, Hsiang S (2014) Does the environment still matter? Daily temperature and income in the United States. NBER Working Papers, 20750
- Deschenes O, Greenstone M, Guryan J (2009) Climate change and birth weight. *Am Econ Rev* 99(2):211–217
- Dorin B, Hourcade JC, Benoit-Cattin M (2013) A world without farmers? The lewis path revisited. Technical Report hal-00866413, CIRED Working Papers. Working paper
- Dreher A (2006) Does globalization affect growth? Evidence from a new index of globalization. *Appl Econ* 38(10):1091–1110
- Edeh CE, Eze CG, Ugwuanyi SO (2020) Impact of foreign direct investment on the agricultural sector in Nigeria (1981–2017). *Afr Dev Rev* 32(4):551–564
- Emerick K (2018) Agricultural productivity and the sectoral reallocation of labor in rural India. *J Dev Econ* 135:488–503
- Fall CMN, Lavayssse C, Drame MS, Panthou G, Gaye AT (2021) Wet and dry spells in Senegal: comparison of detection based on satellite products, reanalysis, and in situ estimates. *Nat Hazards Earth Syst Sci* 21(3):1051–1051
- Felbermayr G, Gröschl J (2014) Naturally negative: the growth effects of natural disasters. *J Dev Econ* 111:92–106
- Gollin D, Hansen C, Wingender A (2021) Two blades of grass: the impact of the green revolution. *J Political Econ* 129(8)
- Gollin D, Jedwab R, Vollrath D (2016) Urbanization with and without industrialization. *J Econ Growth* 21:35–70
- Gollin D, Rogerson R (2014) Productivity, transport costs and subsistence agriculture. *J Dev Econ* 107:38–48
- Hsiang SM, Jina AS (2014) The causal effect of environmental catastrophe on long-run economic growth: evidence from 6,700 cyclones. NBER Working Paper 20352, National Bureau of Economic Research, Cambridge, MA. Working paper
- Iizumi T, Ramankutty N (2015) How do weather and climate influence cropping area and intensity? *Glob Environ Change* 33:1–10
- IPCC (2007) Climate change 2007: the physical science basis. Contribution of working group I to the fourth assessment report of the intergovernmental panel on climate change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA
- IPCC (2021) Climate change 2021: the physical science basis. Contribution of working group I to the sixth assessment report of the intergovernmental panel on climate change. Volume in press Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA
- Jägermeyr J, Müller C, Ruane AC et al (2021) Climate impacts on global agriculture emerge earlier in new generation of climate and crop models. *Nat Food* 2:873–885

- Johnston BF, Mellor JW (1961) The role of agriculture in economic development. *Am Econ Rev* 51(4):566–593
- Kjellstrom T, Briggs D, Freyberg C, Lemke B, Otto M, Hyatt O (2016) Heat, human performance, and occupational health: a key issue for the assessment of global climate change impacts. *Annu Rev Public Health* 37:97–112
- Krueger P, Sautner Z, Starks LT (2020) The importance of climate risks for institutional investors. *Rev Financ Stud* 33(3):1067–1111
- Kruse H, Mensah E, Sen K, De Vries G (2022) A manufacturing (re) naissance? industrialization in the developing world. *IMF Econ Rev* 71(2):439
- Lewis WA (1954) Economic development with unlimited supplies of labor. *Manch Sch Econ Soc Stud* 22(2):139–191
- Liu M, Shamdasani Y, Taraz V (2023) Climate change and labor reallocation: evidence from six decades of the Indian census. *Am Econ J Econ Policy* 15(2):395–423
- Lobell DB, Gourdji SM (2012) The influence of climate change on global crop productivity. *Plant Physiol* 160(4):1686–1697
- Lobell DB, Schlenker W, Costa-Roberts J (2011) Climate trends and global crop production since 1980. *Science* 333(6042):616–620
- Matsuyama K (1992) Agricultural productivity, comparative advantage, and economic growth. *J Econ Theory* 58(2):317–334
- Matsuyama K (2019) Engel's law in the global economy: demand-induced patterns of structural change, innovation, and trade. *Econometrica* 87(2):497–528
- McMillan M, Rodrik D, Verduzco-Gallo Í (2014) Globalization, structural change, and productivity growth, with an update on Africa. *World Dev* 63:11–32
- Meehl G, Arblaster J, Tebaldi C (2005) Understanding future patterns of increased precipitation intensity in climate model simulations. *Geophys Res Lett* 23:18
- Mora C, Dousset B, Caldwell I, Powell F, Geronimo R, Bielecki C, Counsell C, Dietrich B, Johnston E, Louis L et al (2017) Global risk of deadly heat. *Nat Clim Change* 7(7):501–506
- Nickell S (1981) Biases in dynamic models with fixed effects. *Econometrica* 49(6):1417–1426
- Ortiz-Bobea A, Ault TR, Carrillo CM, Chambers RG, Lobell DB (2021) Anthropogenic climate change has slowed global agricultural productivity growth. *Nat Clim Change* 11(4):306–312
- Petitti D, Hondula D, Yang S, Harlan S, Chowell G (2015) Multiple trigger points for quantifying heat-health impacts: new evidence from a hot climate. *Environ Health Perspect* 124
- Ray DK, West PC, Clark M, Gerber JS, Prishchepov AV, Chatterjee S (2019) Climate change has likely already affected global food production. *PLoS One* 14(5):e0217148
- Rodrik D, Diao X, McMillan M (2019) The recent growth boom in developing economies: a structural-change perspective. Palgrave Macmillan. August 2019.
- Romer PM (1990) Endogenous technological change. *J Political Econ* 98(5):S71–S102
- Rostow WW (1982) Population and technological change: a study of long-term trends. *J Econ Hist* 42(1):265–266
- Schultz T (1953) The economic organization of agriculture, vol 20. McGraw Hill Book Company, New York
- Sen K (2019) Structural transformation around the world: patterns and drivers. *Asian Dev Rev* 36(2):1–31
- Shayegh S, Manoussi V, Dasgupta S (2021) Climate change and development in South Africa: the impact of rising temperatures on economic productivity and labour availability. *Clim Dev* 13(8):725–735
- Solow RM (1965) Technology and unemployment. *Public Interest* 1:17
- Takakura J, Fujimori S, Hanasaki N, Hasegawa T, Takahashi K, Masui T (2019) Climate change impacts on crop yields and their monetary values in Japan. *Environ Res Lett* 14(1):014001
- Timmer CP (1988) The agricultural transformation. In: Chenery H, Srinivasan TN (eds) *Handbook of development economics*, vol I. Elsevier, Amsterdam, pp 275–331
- Vicente-Serrano S, Beguería S, López-Moreno J (2010) A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. *J Clim* 23:1696–1718
- Wooldridge JM (2013) *Introductory econometrics: a modern approach.*, 5th edn. South-Western, Mason, OH
- Zhao C, Liu B, Piao S, Wang X, Lobell DB, Huang Y, Huang M, Yao Y, Bassu S, Ciais P et al (2017) Temperature increase reduces global yields of major crops in four independent estimates. *Proc Natl Acad Sci USA* 114(35):9326–9331
- Zolina O, Simmer C, Gulev SK, Kollet S (2010) Changing structure of European precipitation: longer wet periods leading to more abundant rainfalls. *Geophys Res Lett* 37(6)