Offsetting the Impact of Climate Change on Food Production through Technological Adaptation

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Abstract

This study examines the impact of climate change on aggregate food production across countries with different levels of agricultural technology. Using a dynamic panel model, we find that a 1°C increase in global (local) temperature anomalies leads to an immediate decline in food production growth of about 3% (1%, respectively). These effects are persistent –lasting about seven years in the case of global anomalies and two years for local ones– and lead to cumulative food production losses of approximately 21.7% and 1.8%, respectively. These effects are not uniform across countries: high-tech countries appear more resilient, whereas low-tech countries experience significantly larger losses. These findings underscore the crucial role of technological adaptation in smoothing the adverse effects of rising temperatures on food production.
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1. Introduction

The challenge of feeding a growing global population is becoming increasingly complex as climate change intensifies. Rising temperatures, shifting precipitation patterns, and more frequent extreme weather events pose significant threats to food production [Lesk et al., 2016]. Future projections are not encouraging either. Total food demand is expected to increase by 35% to 56% between 2010 and 2050 [Van Dijk et al., 2021].

While many studies have documented the adverse effects of climate change on food production, yields and agricultural productivity growth [Lesk et al., 2016, Lobell et al., 2011, Mirón et al., 2023, Ortiz-Bobea et al., 2021, Schlenker and Roberts, 2009, among others], the potential adaptation through technological innovation remains less explored from a global perspective. Moore and Lobell [2014] use time-series and cross-sectional variation in subnational European agricultural data to find high potential effectiveness of private farmer adaptation for maize to future warming but large negative effects and only limited adaptation potential for other crops such as wheat and barley. While such micro-level evidence points to heterogeneous adaptive responses across crops and contexts, broader assessments emphasize that the impacts of climate change will be unevenly distributed. Climate change will fall heavily on the poorest, the most vulnerable, and those least able to adopt new technology [Parry and Swaminathan, 2010]. Recent evidence of irrigation alleviating the negative implications from temperature increases on global crop yields is found in Agnolucci et al. [2020]. Moreover, a recent global empirical assessment by Hultgren et al. [2025] finds that, under a moderate emissions scenario, adaptation

and income growth would offset roughly 6% of global crop losses by 2050 and 12% by 2100. Nonetheless, substantial residual damages remain—especially for maize, wheat and soybeans—while only rice avoids net losses. These impacts are concentrated in modern "breadbasket" regions, although low-income countries also suffer significantly [Hultgren et al., 2025].

Our study contributes to this literature in at least four ways. Firstly, we estimate the impact of climate change on aggregate food production using a comprehensive country-level panel dataset. Secondly, while most empirical studies –with the exception of Bilal and Känzig [2024]– exploit within-country variation in climate to identify the impact of temperature, we incorporate both country-level (local) and global temperature anomalies in our empirical framework to separately capture their distinct roles. By explicitly modeling both local and global anomalies, we are able to exploit aggregate time-series variation in global temperature, rather than relying solely on within-country variation that, by construction, filters out global climate signals. This distinction is critical: global temperature is a fundamental driver of systemic risk and long-run shifts in agricultural productivity, while local temperature captures spatial heterogeneity. Thirdly, we estimate a panel error correction model and trace the dynamic impacts and persistence of global and local temperature anomalies through local projection methods. This approach allows us to quantify both the immediate and cumulative effects of climate shocks, providing a richer understanding of their temporal structure. Finally, we assess heterogeneity in the effects of temperature anomalies across countries with different levels of agricultural technology using a heterogeneous panel framework.

We use a dynamic panel modeling approach to estimate the effect of global and local temperature anomalies on aggregate food production. Our estimates suggest that a 1°C increase in global (local) temperature anomalies leads to an immediate decline in food production growth of approximately 3% (1%). We found that these effects are not transitory: global anomalies are associated with a persistent negative response lasting about seven years, while the effects of local anomalies extend up to two years. Over this horizon, the cumulative decline in food production reaches roughly 21.7% in response to global anomalies and 1.8% to local anomalies.

Furthermore, we find that agricultural technologies—such as expanded use of fertilizers, advanced irrigation systems, and higher capital investment—play a significant role in offsetting the negative impacts of climate change. While earlier studies have emphasized the uneven effects of temperature shocks across income groups (e.g., rich vs. poor countries) as in Burke et al. [2015], Dell et al. [2012], Kahn et al. [2021], or across different climatic zones [Kahn et al., 2021], our contribution highlights the importance of technological capacity in shaping countries' vulnerability and adaptive potential.

Overall, our findings suggest that while climate change continues to pose significant risks to global food security, countries with higher technological capacities are better equipped to reduce these risks, offering hope for a more resilient global food system.

The paper is structured as follows. Section 2. presents the theoretical framework and the econometric strategy to identify the effect of climate change on food production. Section 3. describes the data. Section 4. discusses the main findings and tests the robustness of the results. Finally, Section 5. presents the discussions.

2. Theoretical framework

We model food production using a Cobb-Douglas production function, where food production depends on standard productive inputs as well as on technological and climatic conditions. The baseline specification is given by:

$$Y_{it} = A_{it} K_{it}^{\alpha} L_{it}^{\beta} N_{it}^{\gamma}, \tag{1}$$

where Y_{it} denotes total food production in country i and year t, K_{it}, L_{it}, and N_{it} represent the amounts of capital, labor, and land or natural resources used in food production, respectively. The term A_{it} captures total factor productivity (TFP), encompassing all other factors that influence output, that is, not only technological advances but also climatic conditions.

More specifically, we model TFP as a function of country and time fixed effects, climate conditions, and technological inputs such as fertilizer use and irrigation:

$$\ln(A_{it}) = \mu_i + \mu_t + W_{it} + f_{it} + i_{it}, \tag{2}$$

where μ_i and μ_t denote country and year fixed effects, respectively, accounting for unobserved heterogeneity across space and time. The term W_{it} captures local climate conditions, including temperature and precipitation anomalies, as well as the occurrence of extreme weather events. Following Kahn et al. [2021], we allow for asymmetric effects of temperature deviations from historical climate norms by defining positive and negative anomalies over a 30-year moving average window ($m = 30$) as:

$\left(\widetilde{T}_{it}(m)^{+} = \left[T_{it} - \frac{1}{m}\sum_{s=1}^{m} T_{it-s}\right] \cdot \mathbb{I}\left(\widetilde{T}_{it}(m) > 0\right)\right)$ and
$\left(\widetilde{T}_{it}(m)^{-} = \left[T_{it} - \frac{1}{m}\sum_{s=1}^{m} T_{it-s}\right] \cdot \mathbb{I}\left(\widetilde{T}_{it}(m) < 0\right)\right)$, with analogous expressions for precipitation anomalies $\widetilde{P}_{it}(m)^{+}$ and $\widetilde{P}_{it}(m)^{-}$. We also include binary indicators for drought and flood events occurring in year t and country i. The remaining terms, f_{it} and i_{it}, refer to fertilizer use and irrigated land area in log terms, respectively —two key technological inputs that may partially mitigate the negative effects of climate anomalies. All local climate variables are weighted by cropland area to better reflect agricultural exposure.

Combining equations (1) and (2), and introducing dynamics through a distributed lag structure on the variables, we reparameterize the model as an autoregressive distributed lag (ADL) specification. This leads to the panel error correction model (ECM) shown in equation (3), which captures both short-run and long-run dynamics. The full algebraic derivation is provided in Appendix A.

$$\begin{aligned}\Delta y_{it} = \mu_i + \mu_t + \gamma_1 \Delta k_{it} + \gamma_2 \Delta l_{it} + \gamma_3 \Delta n_{it} + \gamma_4 \Delta W_{it} + \gamma_5 \Delta f_{it} + \gamma_6 \Delta i_{it} \\ + \alpha \left[y_{it-1} - \beta_1 k_{it-1} - \beta_2 l_{it-1} - \beta_3 n_{it-1} - \beta_4 W_{it-1} - \beta_5 f_{it-1} - \beta_6 i_{it-1}\right] + \varepsilon_{it} \quad (3)\end{aligned}$$

where lowercase variables denote natural logarithms. The γ coefficients capture short-run effects of changes in productive inputs and climatic anomalies. The β coefficients reflect the long-run equilibrium relationship between inputs, climate, and output. Finally, the parameter α governs the correction toward the long-run equilibrium path.

This framework provides a basis for empirically assessing both the immediate and persistent impacts of climate variability on food productivity, while controlling for

technological adaptation and structural differences across countries and time.

This dynamic modeling approach allows us to take into account short-run as well long-run effects, encompassing an error correction model formulation. Estimates of the long-run coefficients give us the possibility to calculate the potential long lasting damages in production due to different scenarios of the level reached by temperature and other variables as consequences of climate change.

Our approach is useful for both integrated and stationary –but persistent– time series. For instance, we can jointly model variables like production and inputs, for which panel unit root tests do not reject the null, with global and local temperature deviations, for which the same test reject the null allowing a deterministic linear trend. Table B.2 reports these tests.[1]

To assess the global component of warming explicitly, we re-estimate equation 3, replacing time fixed effects (μ_t) with global temperature anomalies – analogously defined as $\widetilde{T}_t(m) = T_t - \frac{1}{m}\sum_{j=1}^{m} T_{t-j}$ – while also including a linear time trend (τ). This yields the alternative specification:

$$\begin{aligned}\Delta y_{it} = \mu_i + \tau + \delta\widetilde{T}_{t-1}(m) + \gamma_1\Delta k_{it} + \gamma_2\Delta l_{it} + \gamma_3\Delta n_{it} + \gamma_4\Delta W_{it} + \gamma_5\Delta f_{it} + \gamma_7\Delta i_{it} \\ + \alpha\left[y_{it-1} - \beta_1 k_{it-1} - \beta_2 l_{it-1} - \beta_3 n_{it-1} - \beta_4 W_{it-1} - \beta_5 f_{it-1} - \beta_6 i_{it-1}\right] + \varepsilon_{it} \quad (4)\end{aligned}$$

Estimation results are presented in Section 4., where we also address robustness, sensitivity, and endogeneity concerns.

We focus on evaluating differences in the estimated effects for countries with distinct levels of agricultural technology and by grouping countries according to income level.

[1] We also test panel cointegration for the integrated variables in the equation 3, results are reported in Table B.6.

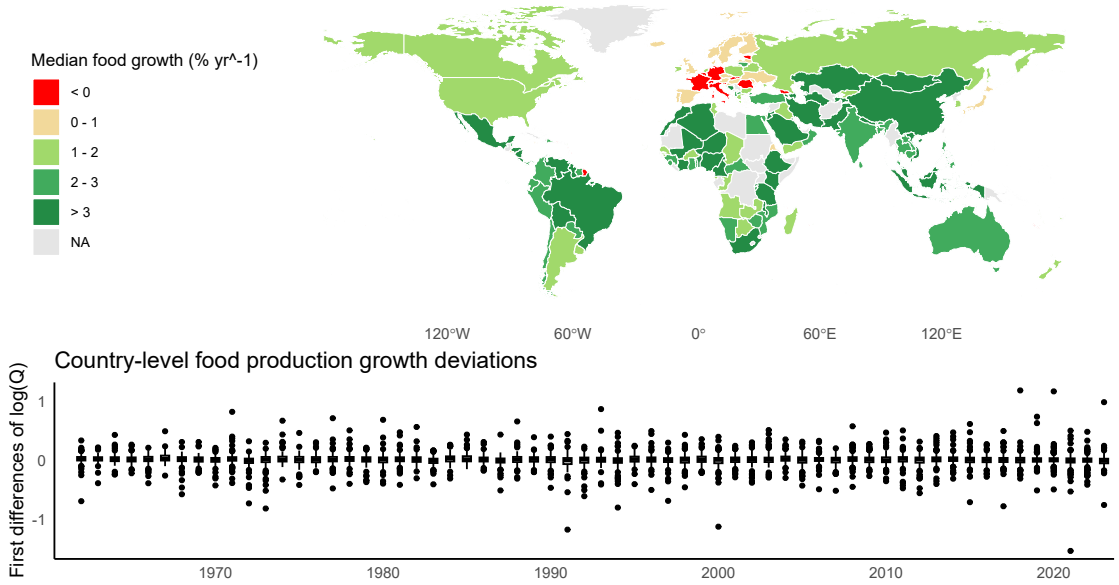
These heterogeneous responses are formally captured in the econometric model in equations 3 and 4 through interaction terms between the temperature anomaly variables and indicators for technology or income groups, allowing the marginal impact of climate shocks to vary across country types.

3. Data

We focus our analysis on the impact that climate change has had on the food production over 1961-2022 (T=62) at the country level. For this purpose, we consider an unbalanced panel dataset that includes data from 140 countries for which the FAO (Food and Agriculture Organization of the United Nations) provides at least thirty years of food production data, and for which information on key agricultural inputs—such as capital, labor, land use, and fertilizer use—is also available. Table B.1 show the list of countries considered in both datasets.

We use FAOSTAT data on gross agricultural production in constant prices, which includes primary crop and livestock outputs as well as minimally processed products recorded at the farm-gate level, but excludes processed agricultural goods.

Figure 1: Median annual growth rate in food production (1961-2022)



Gridded climate data at the country level are obtained from the Weighted Climate Dataset [Gortan et al., 2024], while global temperature data are sourced from NASA-GISTEMP v4.[2]

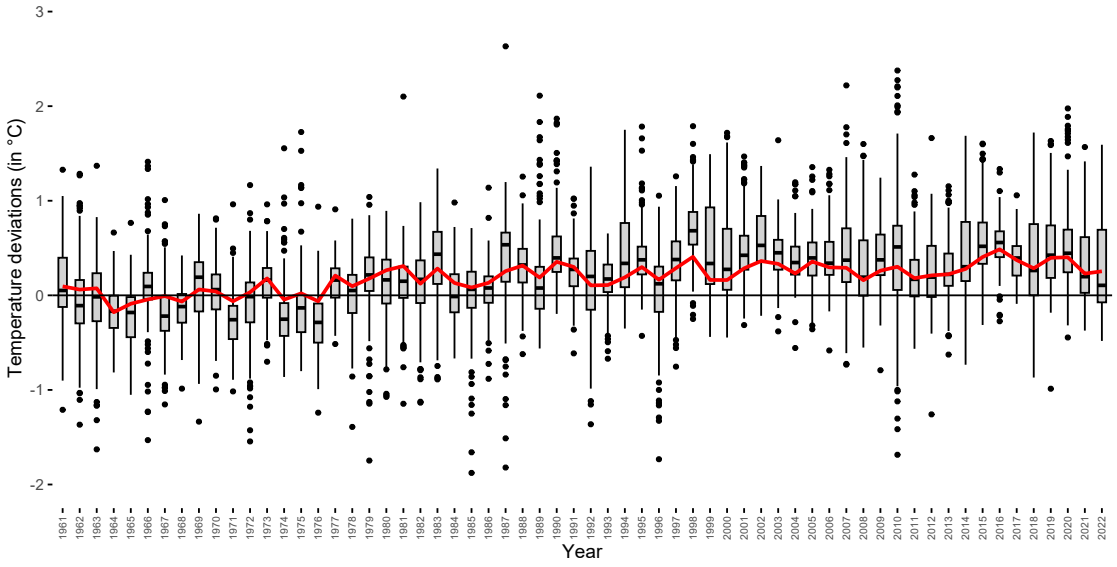
We measure global and local warming using temperature deviations from their historical norms per annum as in Kahn et al. [2021]. These deviations are calculated as the difference between the temperature in country i in year t and the time-varying historical norms of temperature over the preceding m years (here, $m = 30$). A positive deviation indicates that the observed temperature is warmer than the historical

[2]We use the Combined Land-Surface Air and Sea-Surface Water Temperature Anomalies (Land-Ocean Temperature Index, L-OTI), which report deviations from the 1951-1980 baseline average. To recover absolute global mean temperatures, we add $14°C$ - an estimate of the global mean surface air temperature for the 1951-1980 period provided by Hansen et al. [2010].

norms, while a negative anomaly signifies cooler conditions.[3]

Figure 2 shows the time series evolution of global (in red) and country (in gray) temperature deviations (in °C).

Figure 2: Global and country-specific temperature deviations



Note: Temperature anomalies are expressed in °C relative to a 30-year historical norm. Global anomalies (red) are based on NASA-GISTEMP; country-level anomalies (gray) are cropland-weighted averages.

We construct analogous measures for precipitation anomalies; however, their estimated effects were not statistically significant in our empirical models and are therefore omitted from the main analysis.

We also consider the effect of excessive or low precipitation on food production. We considered monthly records for the Standardized Precipitation-Evapotranspiration

[3]Unlike Kahn et al. [2021], we do not rescale the anomalies by the factor $2/(m+1)$.

Index (SPEI)[4], which can be used to compare across regions with markedly different climates. We considered the number of times within a year in a certain country that the SPEI exceeded 2.5 (extremely wet) or was less than -2.5 (extremely dry) to identify flood and drought events, respectively.

Gridded temperature and SPEI data were aggregated to the country level using weights on cropland area, ensuring that regions with greater agricultural relevance contribute more to the national average.[5] We argue that weighting climate variables by cropland area is a meaningful approach, as it better captures the impact of climate change in regions where crops are grown.

Table 1 shows the definitions of the variables included in our models. These variables are standard in the empirical literature on agricultural production functions [Griliches, 1964, Mundlak and Hellinghausen, 1982, Mundlak et al., 2012].

We gathered annual data on labor, capital, land, and technology variables such as irrigation and the use of fertilizers at the country level from the ERS-USDA.[6]

[4]Raw gridded data is leveraged from the Consejo Superior de Investigaciones Científicas (CSIC v2.7, 1901-2020). See Vicente-Serrano et al. [2010]

[5]Cropland are sourced from the History Database of the Global Environment (HYDE), version 3.2., which provides the area of arable land and permanent crops within each grid cell, measured in square kilometers.

[6]https://www.ers.usda.gov/data-products/international-agricultural-productivity/

Table 1: Description of the variables used in the study.

Variable	Description	Units
Food production (Y_{it})	Gross agricultural production value	1000 USD (constant 2014–16)
Local temperature (T_{it})	Annual average temperature weighted by cropland area	°C
Global temperature (T_t)	Global annual mean temperature (land and ocean combined)	°C
Local precipitation (P_{it})	Annual cumulative precipitation weighted by cropland area	Millimeters (mm)
Droughts ($Droughts_{it}$)	Number of months in a year with SPEI below –2.5	Months per year
Floods ($Floods_{it}$)	Number of months in a year with SPEI above 2.5	Months per year
Labor (L_{it})	Number of economically active adults (male & female) primarily employed in agriculture	1000 persons
Capital (K_{it})	Value of net capital stock	\$1000 at constant 2015 prices
Land use (N_{it})	Quality-adjusted agricultural area	1000 has of "rainfed-equivalent cropland"
Irrigation (I_{it})	Ratio of area equipped for irrigation to total agricultural area	share (0-1)
Fertilizer (F_{it})	Total N, P_2O_5, K_2O nutrients from inorganic and organic fertilizers application per unit of agricultural area	metric tons per ha

Adaptation, through the incorporation of capital-intensive agricultural technologies, can help offset the negative impact of climate change on food production. Therefore, we use clustering techniques to analyze how groups of food-producing countries with

shared technological characteristics respond differently to global and local warming. Nations with greater financial and technological resources are often better equipped to adapt to climate change by incorporating advanced irrigation systems, using fertilizers, or net capital investments, among others. In contrast, resource-constrained countries may face heightened vulnerabilities, resulting in more severe impacts on agricultural yields and food security.

In this study, we group countries into clusters based on three technological variables: the amount of fertilizer applied per unit of agricultural land (F_{it}), the proportion of agricultural land that is irrigated (I_{it}), and the value of net capital stock at constant prices (K_{it}), to understand these disparities better.

To make these metrics comparable across countries, we calculate, for each country and year, the ratio of each indicator to its global annual mean ($F_{it}/\overline{F_t}$, $I_{it}/\overline{I_t}$, and $K_{it}/\overline{K_t}$). This provides a relative measure of technological intensity for each year. Then, for each country, we aggregate these relative indicators over time by computing the median for the entire period from 1960 to 2022 ($\widetilde{F_i} = median_t(F_{it}/\overline{F_t})$, $\widetilde{I_i} = median_t(I_{it}/\overline{I_t})$, and $\widetilde{K_i} = median_t(K_{it}/\overline{K_t})$). Finally, we apply K-means clustering using the three standardized technological variables. As a robustness check, we also implement hierarchical clustering (see Table B.8).

Table 2 presents the country-level averages of the three main variables used for the classification considering the K-means clustering allocation. The clustering algorithm groups countries into three categories: high-tech (19 countries), medium-tech (42 countries), and low-tech (77 countries).

Table 2: K-means clustering results based on country-level means

	High-Tech N=19	Med-Tech N=42	Low-Tech N=77
$\widetilde{F_i}$	2.912	0.741	0.512
$\widetilde{I_i}$	1.368	2.042	0.316
$\widetilde{K_i}$	3.661	0.344	0.381

A value above 1 for any of the relative indicators indicates that, on average, the country applied more fertilizer per hectare, irrigated a larger share of its cropland, or invested more capital in agriculture than the global average during the sample period. Conversely, values below 1 reflect below-average input intensity relative to the global distribution.

The results show that high-tech countries exhibit the highest levels of all three inputs, particularly in capital investment ($\widetilde{K_i} = 3.661$) and fertilizer use ($\widetilde{F_i} = 2.912$), while also maintaining a relatively high share of irrigated land ($\widetilde{I_i} = 1.368$). In contrast, medium-tech countries are characterized by relatively higher irrigation coverage ($\widetilde{I_i} = 2.042$) but lower fertilizer and capital use. Low-tech countries consistently fall below the global average across all three indicators, with especially low levels of irrigation ($\widetilde{I_i} = 0.316$) and fertilizer intensity ($\widetilde{F_i} = 0.512$). These patterns reflect structural constraints in agricultural input use and technology adoption. The resulting country classifications are visualized in Figure B.1.

4. Results

4.1. Baseline estimates

Table 3 reports the estimated panel error correction based model in which we distinguish the long-run effects from the short-run dynamics. The unrestricted version of our model is reported in table B.3.

Table 3: Panel error correction model estimations

Dependent Variable:	$\Delta \ln Y_{it}$ **(Food production growth)**	
Model:	(1)	(2)
Adjustment coefficient α	-0.077***	-0.078***
	(0.011)	(0.011)
Long-run effects		
$\ln L_{it-1}$	0.237***	0.236***
	(0.081)	(0.080)
$\ln K_{it-1}$	0.141***	0.141***
	(0.063)	(0.063)
$\ln N_{it-1}$	0.626***	0.625***
	(0.235)	(0.234)
Short-run dynamics		
$\Delta \ln Y_{it-1}$	-0.177***	-0.176***
	(0.031)	(0.031)
$\Delta \ln F_{it}$	0.020***	0.020***
	(0.005)	(0.005)
$\Delta \ln K_{it}$	0.245***	0.245***
	(0.067)	(0.067)
$\Delta \ln L_{it}$	0.039*	0.038*
	(0.022)	(0.022)
$\Delta \ln N_{it}$	0.573***	0.574***
	(0.036)	(0.035)
$Droughts_{it}$	-0.005***	-0.005***
	(0.001)	(0.001)
$\Delta \widetilde{T}_{it}(m)^{+}$	-0.009**	-0.010***
	(0.004)	(0.004)
$\Delta \widetilde{T}_{it}(m)^{-}$	0.0004	-0.002
	(0.007)	(0.008)
$\widetilde{T}_{t}(m)$		-0.031***
		(0.012)
τ		0.001***
		(0.0002)
Country FE	Yes	Yes
Year FE	Yes	No
$N \times T$	7,408	7,408
N	140	140
avg T	52.9	52.9
R^2	0.226	0.218

Notes: Driscoll-Kraay (L=2) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. Local temperature deviations and drought are weighted by cropland area. The long-run effects are calculated as the ratio of the unrestricted coefficient in B.3 and $-\alpha$, while the standard errors are calculated after taking derivatives in Equation 3 or 4 as in Banerjee et al. [1993].

Our results based on a dynamic agricultural production function align with the theoretical framework of a traditional agricultural production function, in which food production is determined by capital, labor, and land use.

We also verify that the estimated effects are not sensitive to the choice of m, the window length used to construct moving averages of temperature anomalies. Results for alternative values ($m = 20$ and $m = 40$) are remarkably stable across specifications (see Table B.7), reinforcing the robustness of our baseline findings.

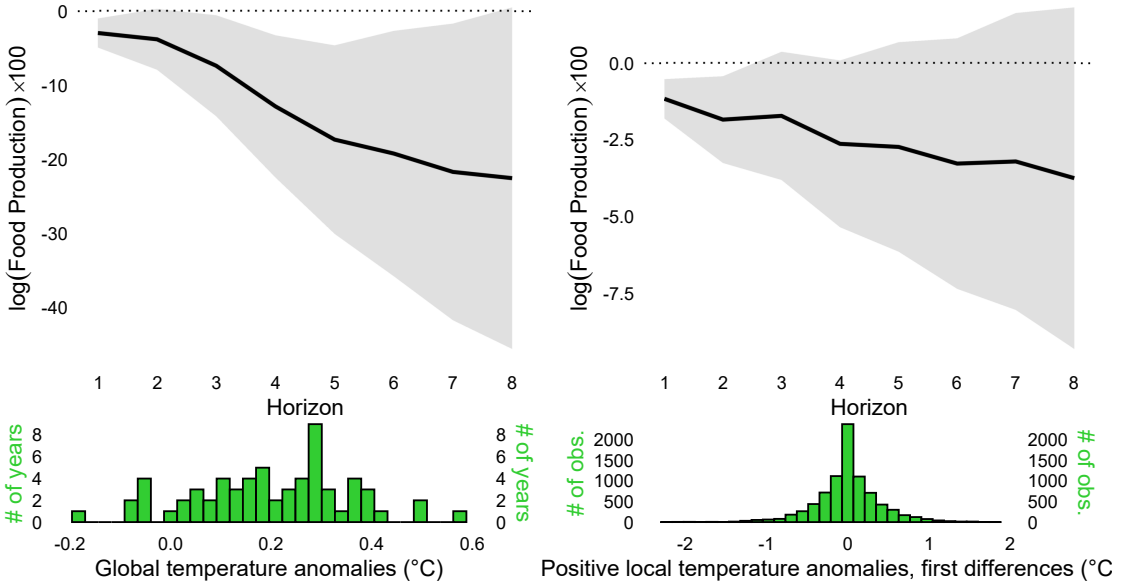
The different estimations of our food production function show that climate change —measured through global and local temperature deviations from historical norms— and drought episodes have a negative effect on food production. At the global level, a 1°C increase in temperature anomalies is associated with an immediate decline of approximately 3% in food production growth, cumulating to a 21.7% reduction over a seven-year horizon. Locally, a 1°C rise in positive temperature anomalies leads to a short-run decline of around 1%, with cumulative losses reaching 1.8% over two years. These cumulative responses are obtained using local projection methods, which allow us to trace the dynamic adjustment path of food production to climate shocks over time (see Figure 3).

Figure 3 also helps interpret these dynamics by showing the empirical distribution of each anomaly variable used in the regressions. The magnitude and persistence of the estimated responses should be read in light of the domain over which these climate anomalies occur. The global temperature anomaly varies at the annual level and exhibits moderate dispersion across years. In contrast, local positive anomalies—defined in first differences— vary across countries and years and display a wider empirical range. These differences in the distribution of shocks, shown in the lower panels of the figure, contextualize the estimated impulse responses in the top panels and highlight that the dynamic effect of temperature shocks is intrinsically tied to

their observed magnitude and frequency in the data.

It is important to note that our measure of global temperature anomalies is derived from a composite index combining land-surface air and sea-surface temperature deviations, rather than being constructed as an average across countries. In addition, our results show that drought conditions also play a critical role: each additional month of drought within a year is associated with a 0.5% decrease in food production, holding other factors constant.

Figure 3: Dynamic responses of food production to global and local temperature anomalies



Note: The upper panels display local projection estimates of the cumulative effects of global (left) and local (right) temperature anomalies on log food production (scaled by 100). Shaded areas represent 90% confidence intervals. The bottom panels show the distribution of the temperature anomaly variables used in each regression model. The left histogram corresponds to global annual temperature anomalies (in °) and is based on the number of years in the sample. The right histogram depicts the distribution of positive local temperature anomalies in first differences and is based on the number of country-year observations. These temperature indicators are the short-run forcing variables in the panel error correction models.

Table B.4 shows that our results are robust to alternative specifications. Specifically, the findings in column (2) from Table 3 (which includes both global and local temperature deviations and drought episodes) hold when: (a) using unweighted local temperature anomalies and drought measures, and (b) omitting observations with residuals exceeding three standard deviations from the mean.

4.2. Addressing potential endogeneity

Due to the omitted variable bias problem in a cross-sectional approach, there is a long tradition to use a panel approach in agricultural economics. Deschênes and Greenstone [2007] is probably the first study to assess the impact of climate change on the agricultural sector using an econometric panel approach. However, the omitted variables are not the only source of bias, food production (and consumption) is also known to be a major source of greenhouse gas (GHG) emissions. The presence of feedback effects [Nordhaus, 1992] may lead to biased estimations. Recent evidence suggests that global food consumption alone could add nearly 1°C to warming by 2100 [Ivanovich et al., 2023].

As food production declines in response to increases in local and global temperature anomalies, greenhouse gas emissions may fall, which can, in turn, reduce temperature anomalies and subsequently, lead to an increase in food production. This (potential) feedback mechanism suggests the presence of reverse causality: while temperature anomalies affect food production, food production also influences temperature through emissions.

Any potential reverse causality could lead us to underestimate the impact of temper-

ature anomalies on food production. In this sense, we are likely identifying a lower bound of the actual effect. Therefore, the true decline in food production due to rising temperatures may be larger than our estimates suggest.

We additionally perform the following analysis to verify that our results are not affected by the exogeneity assumption about temperature anomalies. First, we exclude United States, China, India, and Russia from our dataset is a strategic way to alleviate potential feedback effects. These four countries play a central role in global food production, accounting for 42% of the world's total output during our sample period. They are among the largest CO_2 emitters, contributing to 48% of global CO_2 emissions over the same period. When emissions from land-use change are excluded, their share drops to about 8%. This implies that the remaining 40% of global emissions are primarily linked to land-use changes probably derived from agricultural practices. Therefore, by removing these countries from our dataset, we reduce the risk of capturing feedback effects and improve the identification of climate change impacts on food production.

Second, we also follow an instrumental variable approach to address potential endogeneity in the global and local temperature anomalies in our econometric specification. Specifically, we treat the following variables as potentially endogenous: global temperature anomalies $\widetilde{T}_t(m)$, and the annual changes in positive and negative local temperature anomalies, denoted by $\Delta\widetilde{T}_{it}(m)^+$ and $\Delta\widetilde{T}_{it}(m)^-$, respectively. These variables may be jointly determined with food production due to feedback effects. To overcome this challenge, we use a set of instruments that are plausibly correlated with temperature anomalies but exogenous to contemporaneous shocks in food

production. First, we include lagged radiative forcing anomalies from greenhouse gases, $\widetilde{RF}^{GHG}_{t-1}(m)$, and aerosols, $\widetilde{RF}^{aero}_{t-1}(m)$, both measured in watts per square meter (W/m^2) and expressed as deviations from their historical 30-year norm. Radiative forcing captures the net energy imbalance at the top of the atmosphere and is a well-established physical driver of global temperature trends, but its first lag is unlikely to be directly influenced by short-run changes in national food output. We also exploit spatial variation in climate anomalies by constructing average annual changes in temperature anomalies among neighboring countries. Specifically, we use $\Delta\widetilde{T}^{neighbors}_{it}(m)^{+}$ and $\Delta\widetilde{T}^{neighbors}_{it}(m)^{-}$, defined as the average positive and negative temperature deviations in at least five geographically proximate countries, excluding country i. The rationale is that neighboring climate anomalies are influenced by broader regional atmospheric dynamics and can serve as strong predictors of domestic climate variation while remaining exogenous to domestic agricultural output shocks.

All instruments are calculated as deviations from their respective historical climate norms, using a moving average window of $m = 30$ years. This IV strategy enables us to isolate the exogenous component of climate variation and obtain consistent estimates of its causal impact on food production.

Results of the exclusion of major CO_2 emitters and the IV approach are shown in Table 4.

Table 4: Panel error correction model estimations: addressing feedback effects

Dependent Variable:	$\Delta \ln Y_{it}$ **(Food production growth)**			
Specification:	Excluding CHN, IND, RUS, USA		IV-FE	
Model:	(1)	(2)	(3)	(4)
Adjustment coefficient α	-0.078***	-0.079***	-0.076***	-0.077***
	(0.009)	(0.009)	(0.009)	(0.009)
Long-run effects				
$\ln L_{it-1}$	0.235***	0.239***	0.018***	0.238***
	(0.079)	(0.079)	(0.071)	(0.068)
$\ln K_{it-1}$	0.132***	0.132***	0.139**	0.141**
	(0.064)	(0.064)	(0.060)	(0.058)
$\ln N_{it-1}$	0.634***	0.634***	0.622***	0.620***
	(0.182)	(0.182)	(0.131)	(0.125)
Short-run dynamics				
$\Delta \ln Y_{it-1}$	-0.176***	-0.175***	-0.177***	-0.177***
	(0.035)	(0.035)	(0.035)	(0.035)
$\Delta \ln F_{it}$	0.020***	0.020***	0.020***	0.020***
	(0.007)	(0.007)	(0.007)	(0.007)
$\Delta \ln K_{it}$	0.243***	0.243***	0.249***	0.244***
	(0.072)	(0.072)	(0.074)	(0.075)
$\Delta \ln L_{it}$	0.040*	0.039*	0.039*	0.040*
	(0.023)	(0.023)	(0.023)	(0.023)
$\Delta \ln N_{it}$	0.553***	0.555***	0.572***	0.573***
	(0.075)	(0.076)	(0.077)	(0.078)
$Droughts_{it}$	-0.005***	-0.005***	-0.005***	-0.079**
	(0.001)	(0.002)	(0.001)	(0.033)
$\Delta \widetilde{T}_{it}(m)^{+}$	-0.009**	-0.011***	-0.008**	-0.008**
	(0.004)	(0.003)	(0.004)	(0.004)
$\Delta \widetilde{T}_{it}(m)^{-}$	0.0008	-0.001	0.0009	-0.0005
	(0.005)	(0.006)	(0.007)	(0.007)
$\widetilde{T}_{t}(m)$		-0.032***		-0.079**
		(0.011)		(0.033)
τ		0.001***		0.002***
		(0.0002)		(0.0003)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
$N \times T$	7,207	7,207	7,350	7,350
N	136	136	139	139
avg T	53.0	53.0	52.9	52.9
R^2	0.226	0.218	0.226	0.216
F-test (1st stage) $\widetilde{T}_{t}(m)$	–	–	–	201.9 [0.000]
F-test (1st stage) $\Delta \widetilde{T}_{it}(m)^{+}$	–	–	9603.7 [0.000]	5602.0 [0.000]
F-test (1st stage) $\Delta \widetilde{T}_{it}(m)^{-}$	–	–	8578.2 [0.000]	5003.6 [0.000]
Wu-Hausman	–	–	0.207 [0.813]	0.557 [0.643]
Sargan	–	–	–	0.0004 [0.984]

Notes: Driscoll-Kraay (L=2) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. Local temperature deviations and drought are weighted by cropland area. The long-run effects are calculated as the ratio of the unrestricted coefficient in B.3 and $-\alpha$, while the standard errors are calculated after taking derivatives in Equation 3 or 4 as in Banerjee et al. [1993].

The results in Table 4 confirm the robustness of our baseline estimates. Excluding the four largest CO_2 emitters —China, India, Russia, and the United States— does

not significantly alter the estimated short-run effects of temperature anomalies on food production. In particular, we continue to find that a 1°C increase in global (local) temperature anomalies is associated with a contemporaneous decline in food production growth of approximately 3% (1%). However, the instrumental variable (IV) specification reveals a larger estimated effect of global temperature anomalies, with a 1°C increase leading to a decline in food production growth of nearly 8%. This suggests that addressing potential endogeneity in climate variables may uncover stronger causal impacts of global warming on food production.

However, formal statistical tests indicate that the difference between the IV and fixed effects estimates is not statistically significant—the Wu-Hausman test does not reject the null hypothesis. Moreover, the Sargan test does not reject the overidentifying restrictions, providing no evidence that any of the excluded instruments are endogenous.

Finally, we also test whether temperature anomalies Granger cause changes in food production, or if the reverse is true. By testing for Granger causality in both directions, we can assess the directionality of the relationship and further ensure that reverse causality is not driving our results. Panel VAR-Granger causality tests indicate that temperature anomalies Granger cause changes in food production, and not vice versa (see Table B.5).

4.3. Evaluating adaptation through heterogeneous effects

Extensive empirical evidence indicates that temperature anomalies have heterogeneous effect on economic output across countries. Specifically, countries with hotter

climates and/or lower income levels tend to experience more severe adverse effects on economic output [Burke et al., 2015, Dell et al., 2012, Kahn et al., 2021]. However, evidence of heterogeneous climate change effects on agricultural output across countries remains scarce. As an exception, Moore and Lobell [2014] find that crop yields have experienced heterogeneous effects of long-term temperature and precipitation trends in Europe, with regions around the Mediterranean experiencing significant adverse impacts on most crops.

Building upon the observed heterogeneity of our sample, and informed by prior empirical research highlighting the uneven impact of temperature shocks on output, we explore whether the observed local temperature deviations from historical norms are predominantly driven by vulnerable groups (i.e. low income countries or low-tech countries). To investigate this, we enhance equations 3 and 4 by incorporating interaction terms between global or local positive temperature anomalies ($\widetilde{T}_t(m)$ or $\widetilde{T}_{it}(m)^+$) and indicators distinguishing between high-income and low-income countries ($\mathbb{I}$(country i is poor)), as well as between high-tech, med-tech and low-tech countries ($\mathbb{I}$(country i is low-tech)).

Following Burke et al. [2015], we define country i as poor (rich) based on whether the purchasing-power-parity-adjusted (PPP) GDP per capita was below (above) the global median in 1980. Alternatively, we classify countries as low-tech, med-tech or high-tech using the clustering approach detailed in section 3., which considers technological variables such as the share of agricultural land equipped for irrigation, fertilizer intensity and net capital investments over the entire sample period. Table 5 and Figure 4 report the results.

Table 5: Heterogeneity in temperature anomalies effects

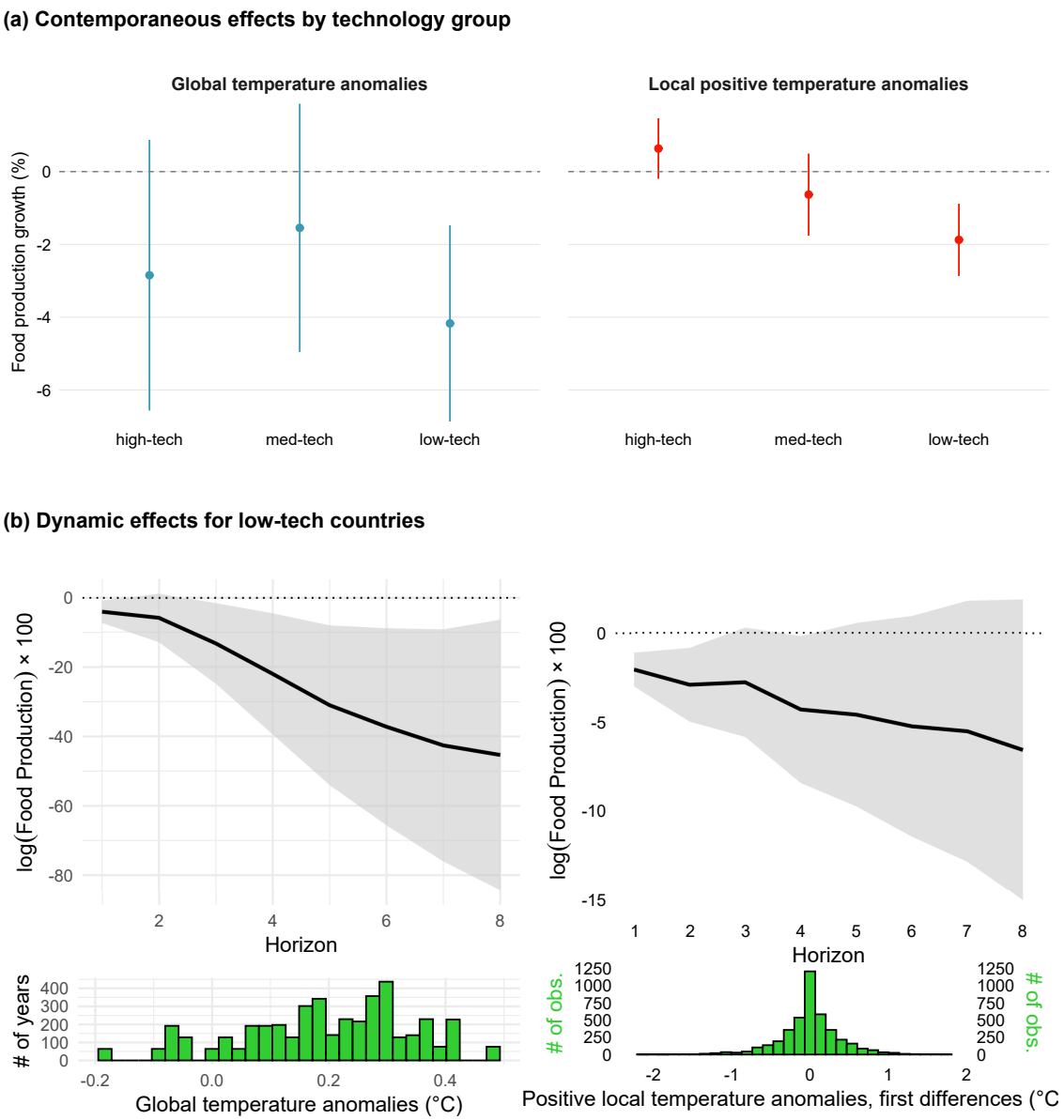
Dependent Variable:	$\Delta \ln Y_{it}$: Food production growth	
Model:	(1)	(2)
Adjustment coefficient α	-0.080***	-0.077***
	(0.011)	(0.012)
Long-run effects		
$\ln L_{it-1}$	0.249***	0.226***
	(0.76)	(0.084)
$\ln K_{it-1}$	0.143***	0.135***
	(0.061)	(0.065)
$\ln N_{it-1}$	0.619***	0.603***
	(0.225)	(0.182)
Short-run dynamics		
$\Delta \ln Y_{it-1}$	-0.173***	-0.173***
	(0.031)	(0.032)
$\Delta \ln F_{it}$	0.020***	0.017***
	(0.005)	(0.005)
$\Delta \ln K_{it}$	0.248***	0.272***
	(0.068)	(0.070)
$\Delta \ln L_{it}$	0.040*	0.038
	(0.022)	(0.027)
$\Delta \ln N_{it}$	0.574***	0.578***
	(0.035)	(0.037)
$Droughts_{it}$	-0.006***	-0.006***
	(0.001)	(0.001)
$\Delta \widetilde{T}_{it}(m)^{-}$	-0.002	-0.002
	(0.008)	(0.006)
$\Delta \widetilde{T}_{it}(m)^{+} \times \mathbb{I}$(country i is low-tech)	-0.019***	
	(0.005)	
$\Delta \widetilde{T}_{it}(m)^{+} \times \mathbb{I}$(country i is med-tech)	-0.006	
	(0.006)	
$\Delta \widetilde{T}_{it}(m)^{+} \times \mathbb{I}$(country i is high-tech)	0.006	
	(0.004)	
$\Delta \widetilde{T}_{it}(m)^{+} \times \mathbb{I}$(country i is poor)		-0.026***
		(0.008)
$\Delta \widetilde{T}_{it}(m)^{+} \times \mathbb{I}$(country i is rich)		-0.004
		(0.004)
$\widetilde{T}_{t}(m) \times \mathbb{I}$(country i is low-tech)	-0.042***	
	(0.014)	
$\widetilde{T}_{t}(m) \times \mathbb{I}$(country i is med-tech)	-0.015	
	(0.017)	
$\widetilde{T}_{t}(m) \times \mathbb{I}$(country i is high-tech)	-0.028	
	(0.019)	
$\widetilde{T}_{t}(m) \times \mathbb{I}$(country i is poor)		-0.023
		(0.015)
$\widetilde{T}_{t}(m) \times \mathbb{I}$(country i is rich)		-0.039**
		(0.019)
τ	0.001***	0.001***
	(0.0002)	(0.0002)
Country FE	Yes	Yes
Year FE	No	No
$N \times T$	7,292	6,648
N	138	117
max T	58	58
avg T	52.84	56.82
min T	25	25
R^2	0.223	0.227
Within R^2	0.204	0.211

Notes: Driscoll-Kraay standard errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. Local temperature and drought are weighted by cropland area. The long-run effects are calculated as the ratio of the unrestricted coefficient and $-\alpha$, while the standard errors are calculated after taking derivatives in the augmented Equation 4 as in Banerjee et al. [1993].

The results, shown in Table 5, reveal notable asymmetries across income groups. In the case of local temperature anomalies, the negative effects are concentrated in low-income countries, while the estimated impacts are statistically insignificant for higher-income countries. This result is consistent with findings by the literature [Burke et al., 2015, Kahn et al., 2021]. However, for global temperature anomalies, we find, counterintuitively, a similarly negative and statistically significant effect for high-income countries.

In contrast, the classification by technological development yields results consistent with theoretical expectations regarding adaptation possibilities. For local temperature anomalies, the negative effects are found in low-tech countries, while the estimated impacts are statistically insignificant for countries in the medium and high-tech groups. Moreover, for global temperature anomalies too, we find negative and statistically significant effects in low-tech countries, whereas no significant impact is observed for medium and high-tech countries. Importantly, these patterns remain robust when we use an alternative classification of countries based on hierarchical clustering: as shown in Table B.9, the negative and statistically significant impact of local and global temperature anomalies persists for low-tech, but not for high-tech countries under this alternative grouping.

Figure 4: Contemporaneous and dynamic effects of temperature anomalies on food production growth, by technology level



Note: Error bars represent 95% confidence intervals based on Driscoll-Kraay standard errors, with a maximum lag of two. Local temperature anomalies are weighted by cropland area. Estimates correspond to short-run coefficients from the panel error correction model.

Figure 4 presents both the contemporaneous and dynamic effects of global (left) and local positive (right) temperature anomalies on food production growth, disaggregated by agricultural technology level (high-tech, medium-tech, and low-tech countries). The top panel shows the short-run coefficients estimated from a panel error correction model with interaction terms, while the bottom panel depicts cumulative dynamic responses obtained from local projections, restricted to the subset of low-tech countries.

The top panel illustrates that global temperature anomalies are associated with negative effects across all technology groups, although these estimates are not statistically significant at traditional levels for high- and medium-tech countries. In contrast, the right panel highlights more distinct heterogeneity in the response to local positive temperature anomalies. While the estimated effects are close to zero and statistically insignificant for high- and medium-tech countries, the effect becomes notably more negative and statistically significant in low-tech countries. These results provide visual confirmation of the greater vulnerability of low-tech agricultural systems to local climatic shocks, reinforcing the idea that technological adaptation plays a crucial role in buffering the adverse effects of rising temperatures.

The dynamic responses shown in the lower panels further reinforce this vulnerability: food production in low-tech countries declines persistently in response to both global and local temperature shocks. These results underscore the critical role of technological capacity in moderating exposure to climatic variability and suggest that adaptation gaps may amplify the effects of rising temperatures in technologically constrained agricultural systems.

5. Conclusions

Feeding a growing global population as climate change intensifies poses a major challenge for food security and economic stability. Our study contributes to understanding this challenge by examining the dynamic effects of both global and local temperature anomalies on food production growth across countries with varying technological capacity. We emphasize the critical role of technological adaptation in smoothing the adverse impacts of rising temperatures.

Using a dynamic panel model, we find that a 1°C increase in global temperature anomalies leads to an immediate decline in food production growth of approximately 3%, while a 1°C rise in local temperature anomalies reduces food production growth by around 1% in the short run. These effects are not transitory: local projection estimates show that the impact of global temperature anomalies persists for about seven years, resulting in a cumulative decline of 21.7% in food production. In the case of local anomalies, the effect extends up to two years, with a cumulative decline of roughly 1.8%.

These effects are heterogeneous across countries. Medium- and high-technology countries exhibit resilience to local temperature shocks, with estimated effects close to zero and statistically insignificant. In contrast, low-tech countries experience significantly larger and persistent losses from both global and local temperature anomalies. This disparity shows the vulnerability of countries with less advanced technology, which may lack the capacity to adapt to changing climatic conditions. The findings highlight the importance of technological adaptation in buffering agricultural systems from the adverse effects of global warming.

The robustness of our findings is reinforced through various sensitivity checks, and the omission of outliers. The estimated impacts remain stable when excluding major agricultural and emission-intensive countries—China, India, Russia, and the United States. Moreover, our instrumental variable strategy, which addresses potential endogeneity of climate variables, reveals a stronger effect of global temperature anomalies. This reinforces the view that the baseline estimates may be conservative. Additionally, Granger causality tests support a unidirectional relationship from temperature anomalies to food production, further reducing concerns about reverse causality.

Our findings emphasize the urgent need for targeted investments in agricultural technologies and adaptive capacity, particularly in the most vulnerable regions. Policies promoting technological diffusion, improved irrigation infrastructure, and climate-resilient agricultural practices can play a pivotal role in reducing the disparity between high- and low-tech countries, fostering a more resilient and equitable global food system.

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A Derivation of the Error Correction Model

Consider an economy composed of heterogeneous agricultural producers indexed by $j = 1, \ldots, J_i$ within each country i. Each producer operates a Cobb-Douglas production technology:

$$Y_{ijt} = A_{ijt} K_{ijt}^{\alpha} L_{ijt}^{\beta} N_{ijt}^{\gamma}, \tag{A.1}$$

where Y_{ijt} denotes the output of farmer j in country i at time t; A_{ijt} is total factor productivity (TFP); and K_{ijt}, L_{ijt}, and N_{ijt} are capital, labor, and land inputs, respectively.

Taking logarithms:

$$y_{ijt} = \ln A_{ijt} + \alpha k_{ijt} + \beta l_{ijt} + \gamma n_{ijt}, \tag{A.2}$$

where lowercase variables denote log-transformed quantities (e.g., $y_{ijt} = \ln Y_{ijt}$, etc.). To derive a macro-level relationship, we assume that aggregate output at the country level Y_{it} is the sum of the outputs of individual farmers:

$$Y_{it} = \sum_{j=1}^{J_i} Y_{ijt}. \tag{A.3}$$

Under standard regularity conditions, this aggregation implies a relationship of the form:

$$y_{it} = \ln A_{it} + \alpha k_{it} + \beta l_{it} + \gamma n_{it}, \tag{A.4}$$

where y_{it}, k_{it}, l_{it}, and n_{it} now denote country-level aggregates, and $\ln A_{it}$ represents average total factor productivity.

We specify country-level TFP as:

$$\ln A_{it} = \mu_i + \mu_t + W_{it} + f_{it} + i_{it}, \tag{A.5}$$

where μ_i and μ_t are country and time fixed effects, W_{it} captures climatic factors such as temperature or precipitation anomalies, f_{it} represents climate extremes (e.g., floods or droughts), and i_{it} reflects adaptive capacity or irrigation infrastructure. Substituting A.5 into A.4 yields the country-level production function in reduced form:

$$y_{it} = \mu_i + \mu_t + W_{it} + f_{it} + i_{it} + \alpha k_{it} + \beta l_{it} + \gamma n_{it} + \varepsilon_{it}, \tag{A.6}$$

where ε_{it} is a stochastic disturbance term. When the underlying series exhibit persistence or stochastic trends, this relation is embedded in a dynamic autoregressive distributed lag (ADL) specification:

$$\begin{aligned} y_{it} = {} & \delta_0 + \delta_1 y_{it-1} + \theta_1 k_{it} + \theta_2 k_{it-1} + \theta_3 l_{it} + \theta_4 l_{it-1} + \theta_5 n_{it} + \theta_6 n_{it-1} \\ & + \theta_7 W_{it} + \theta_8 W_{it-1} + \theta_9 f_{it} + \theta_{10} f_{it-1} + \theta_{11} i_{it} + \theta_{12} i_{it-1} + u_{it}, \end{aligned} \tag{A.7}$$

Rewriting this ADL model in its *error correction form* facilitates the distinction between short-run adjustments and long-run equilibrium:

$$\begin{aligned} \Delta y_{it} = {} & \pi_0 + \alpha \left(y_{it-1} - \beta_1 k_{it-1} - \beta_2 l_{it-1} - \beta_3 n_{it-1} - \beta_4 W_{it-1} - \beta_5 f_{it-1} - \beta_6 i_{it-1} \right) \\ & + \gamma_1 \Delta k_{it} + \gamma_2 \Delta l_{it} + \gamma_3 \Delta n_{it} + \gamma_4 \Delta W_{it} + \gamma_5 \Delta f_{it} + \gamma_6 \Delta i_{it} + u_{it}, \end{aligned} \tag{A.8}$$

with $\alpha < 0$ governing the speed of convergence to the long-run path and γ_j reflecting short-run elasticities.

The final estimated model includes fixed effects explicitly:

$$\Delta y_{it} = \mu_i + \mu_t + \gamma_1 \Delta k_{it} + \gamma_2 \Delta l_{it} + \gamma_3 \Delta n_{it} + \gamma_4 \Delta W_{it} + \gamma_5 \Delta f_{it} + \gamma_6 \Delta i_{it} + \alpha \left[y_{it-1} - \beta_1 k_{it-1} - \beta_2 l_{it-1} - \beta_3 n_{it-1} - \beta_4 W_{it-1} - \beta_5 f_{it-1} - \beta_6 i_{it-1} \right] + \varepsilon_{it}. \tag{A.9}$$

This error correction representation allows us to assess both the persistence of climate shocks and the mechanisms through which national food production adjusts over time, grounded in micro-level production theory and consistent with macro-level panel econometric analysis.

B Tables and Figures

Table B.1: All 140 food producing countries by continent, 1961-2022

Continent	Countries
Africa (39)	Algeria, Angola, Benin, Botswana, Burkina Faso, Burundi, Cabo Verde, Cameroon, Central African Republic, Chad, Congo, Côte d'Ivoire, Egypt, Equatorial Guinea, Eritrea, Ethiopia, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Madagascar, Malawi, Mali, Mauritius, Morocco, Mozambique, Namibia, Niger, Nigeria, Rwanda, Senegal, Sierra Leone, South Africa, Togo, Tunisia, United Republic of Tanzania, Zambia, Zimbabwe
America (25)	Argentina, Belize, Bolivia (Plurinational State of), Brazil, Canada, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Guyana, Honduras, Jamaica, Mexico, Nicaragua, Panama, Paraguay, Peru, Puerto Rico, Suriname, Trinidad and Tobago, United States of America, Uruguay, Venezuela (Bolivarian Republic of)
Asia (37)	Azerbaijan, Bangladesh, Bhutan, Brunei Darussalam, Cambodia, China, mainland, Cyprus, Georgia, India, Indonesia, Iran (Islamic Republic of), Iraq, Israel, Japan, Jordan, Kazakhstan, Kuwait, Lao People's Democratic Republic, Lebanon, Malaysia, Mongolia, Nepal, Oman, Pakistan, Palestine, Philippines, Qatar, Republic of Korea, Saudi Arabia, Sri Lanka, Tajikistan, Thailand, Timor-Leste, Turkmenistan, Türkiye, Viet Nam, Yemen
Europe (34)	Albania, Austria, Belarus, Bulgaria, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Malta, Netherlands (Kingdom of the), North Macedonia, Norway, Poland, Portugal, Republic of Moldova, Romania, Russian Federation, Slovakia, Slovenia, Spain, Sweden, Switzerland, Ukraine, United Kingdom of Great Britain and Northern Ireland
Oceania (5)	Australia, Fiji, New Caledonia, New Zealand, Vanuatu

Table B.2: Panel unit root test (Im-Pesaran-Shin)

	IPS statistic (with trend)		IPS statistic (with drift)
y_{it}	5.309	Δy_{it}	-96.984***
k_{it}	8.817	Δk_{it}	-38.987***
l_{it}	6.559	Δl_{it}	-54.842***
n_{it}	0.998	Δn_{it}	-55.546***
f_{it}	-3.617***	Δf_{it}	-90.478***
$\widetilde{T}_{it}(m)$	-58.641***	$\Delta\widetilde{T}_{it}(m)$	-100.00***

Notes: Lag length selected by SIC. *** p<0.01, **p<0.05, *p<0.10.

Table B.3: Unrestricted panel error correction model estimations

Dependent Variable:	$\Delta \ln Y_{it}$: Food production growth	
Model:	(1)	(2)
$\ln Y_{it-1}$	-0.077***	-0.078***
	(0.011)	(0.009)
$\ln L_{it-1}$	0.018***	0.018***
	(0.005)	(0.005)
$\ln K_{it-1}$	0.011***	0.011**
	(0.004)	(0.004)
$\ln N_{it-1}$	0.048***	0.048***
	(0.012)	(0.009)
$\Delta \ln Y_{it-1}$	-0.177***	-0.176***
	(0.031)	(0.035)
$\Delta \ln F_{it}$	0.020***	0.020***
	(0.005)	(0.007)
$\Delta \ln K_{it}$	0.245***	0.245***
	(0.067)	(0.071)
$\Delta \ln L_{it}$	0.039*	0.038*
	(0.022)	(0.023)
$\Delta \ln N_{it}$	0.573***	0.574***
	(0.036)	(0.077)
$\Delta \widetilde{T}_{it}(m)^{+}$	-0.009**	-0.010***
	(0.004)	(0.003)
$\Delta \widetilde{T}_{it}(m)^{-}$	0.0004	-0.002
	(0.007)	(0.006)
D_{it}	-0.005***	-0.005***
	(0.001)	(0.002)
$\widetilde{T}_{t}(m)$		-0.031***
		(0.010)
τ		0.001***
		(0.0002)
Country FE	Yes	Yes
Year FE	Yes	No
$N \times T$	7,408	7,408
N	136	136
max T	58	58
avg T	52.91	52.91
min T	25	25
R^2	0.226	0.218
Within R^2	0.196	0.199

Notes: Driscoll-Kraay (L=2) standard-errors in parentheses for estimations. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. Local temperature anomalies and drought are weighted by cropland area.

Table B.4: Robustness checks

Dependent Variable:	$\Delta \ln Y_{it}$: Food production growth	
Specification	Unweighted local climate variables	Omitting residuals beyond +/- 3SD
Model:	(1)	(2)
$\ln Y_{it-1}$	-0.077***	-0.081***
	(0.011)	(0.012)
$\ln L_{it-1}$	0.018***	0.021***
	(0.005)	(0.006)
$\ln K_{it-1}$	0.011***	0.013***
	(0.004)	(0.004)
$\ln N_{it-1}$	0.048***	0.048***
	(0.013)	(0.014)
$\Delta \ln Y_{it-1}$	-0.177***	-0.174***
	(0.031)	(0.034)
$\Delta \ln F_{it}$	0.020***	0.020***
	(0.005)	(0.005)
$\Delta \ln K_{it}$	0.245***	0.278***
	(0.067)	(0.076)
$\Delta \ln L_{it}$	0.038*	0.038
	(0.022)	(0.026)
$\Delta \ln N_{it}$	0.555***	0.558***
	(0.034)	(0.035)
$\Delta \widetilde{T}_{it}(m)^{+}$	-0.010**	-0.010**
	(0.004)	(0.004)
$\Delta \widetilde{T}_{it}(m)^{-}$	-0.001	-0.003
	(0.007)	(0.008)
$Droughts_{it}$	-0.005***	-0.007***
	(0.001)	(0.002)
$\widetilde{T}_{t}(m)$	-0.032***	-0.035***
	(0.012)	(0.012)
τ	0.001***	0.001***
	(0.0002)	(0.0002)
Country FE	Yes	Yes
Year FE	No	No
$N \times T$	7,408	5,977
N	140	117
max T	58	58
avg T	52.91	51.09
min T	25	17
R^2	0.217	0.228
Within R^2	0.198	0.209

Notes: Driscoll-Kraay standard errors are reported in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table B.5: Panel VAR-Granger causality Wald test

Equation	Excluded	χ^2 stat	df	p-value
$\Delta \ln Y_{it}$	$\Delta \widetilde{T}_{it}(m)$	22.705	2	0.000
$\Delta \widetilde{T}_{it}(m)$	$\Delta \ln Y_{it}$	0.502	2	0.778

Notes: The null hypothesis is that the excluded variable does not-Granger cause the equation variable. The estimated PVAR included 2 lags and controls for fertilizer, irrigation, capital, labor and land use.

Table B.6: Panel cointegration tests

Pedroni	Westerlund
-12.029***	-8.317***

Notes: The null hypothesis is no cointegration for the variables entering the long-run equation and the alternative hypothesis is that all panels are cointegrated. Both tests include panel-specific autoregressive term and panel-specific time trends. Pedroni's statistic is a modified Phillips-Perron t statistic, while Westerlund's statistic is variance ratio. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table B.7: Panel error correction model estimations: sensitivity to m in temperature anomalies

Dependent Variable:	$\Delta \ln Y_{it}$ (Food production growth)			
	m =20		m =40	
	(1)	(2)	(3)	(4)
Adjustment coefficient α	-0.077***	-0.077***	-0.077***	-0.078***
	(0.011)	(0.009)	(0.011)	(0.011)
Long-run effects				
$\ln L_{it-1}$	0.237***	0.235***	0.237***	0.236***
	(0.081)	(0.081)	(0.081)	(0.081)
$\ln K_{it-1}$	0.141***	0.142***	0.141***	0.138***
	(0.063)	(0.070)	(0.063)	(0.063)
$\ln N_{it-1}$	0.626***	0.624***	0.626***	0.626***
	(0.235)	(0.172)	(0.234)	(0.234)
Short-run dynamics				
$\Delta \ln Y_{it-1}$	-0.177***	-0.175***	-0.177***	-0.175***
	(0.031)	(0.036)	(0.031)	(0.031)
$\Delta \ln F_{it}$	0.020***	0.020***	0.020***	0.020***
	(0.005)	(0.007)	(0.005)	(0.005)
$\Delta \ln K_{it}$	0.245***	0.246***	0.245***	0.246***
	(0.066)	(0.075)	(0.067)	(0.067)
$\Delta \ln L_{it}$	0.039*	0.038*	0.039*	0.038*
	(0.022)	(0.022)	(0.022)	(0.022)
$\Delta \ln N_{it}$	0.573***	0.574***	0.573***	0.574***
	(0.035)	(0.071)	(0.036)	(0.035)
$Droughts_{it}$	-0.005***	-0.005***	-0.005***	-0.005***
	(0.001)	(0.002)	(0.001)	(0.001)
$\Delta\widetilde{T}_{it}(m)^{+}$	-0.010**	-0.011***	-0.008**	-0.009**
	(0.004)	(0.003)	(0.004)	(0.004)
$\Delta\widetilde{T}_{it}(m)^{-}$	0.001	-0.001	-0.001	-0.003
	(0.007)	(0.005)	(0.007)	(0.008)
$\widetilde{T}_{t}(m)$		-0.030***		-0.031**
		(0.010)		(0.012)
τ		0.001***		0.001***
		(0.0002)		(0.0002)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
$N \times T$	7,408	7,408	7,408	7,408
N	140	140	140	140
avg T	52.9	52.9	52.9	52.9
R^2	0.226	0.218	0.226	0.218

Notes: Driscoll-Kraay (L=2) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. Local temperature deviations and drought are weighted by cropland area.

Figure B.1: Clustering of countries by technology level (1960-2022)

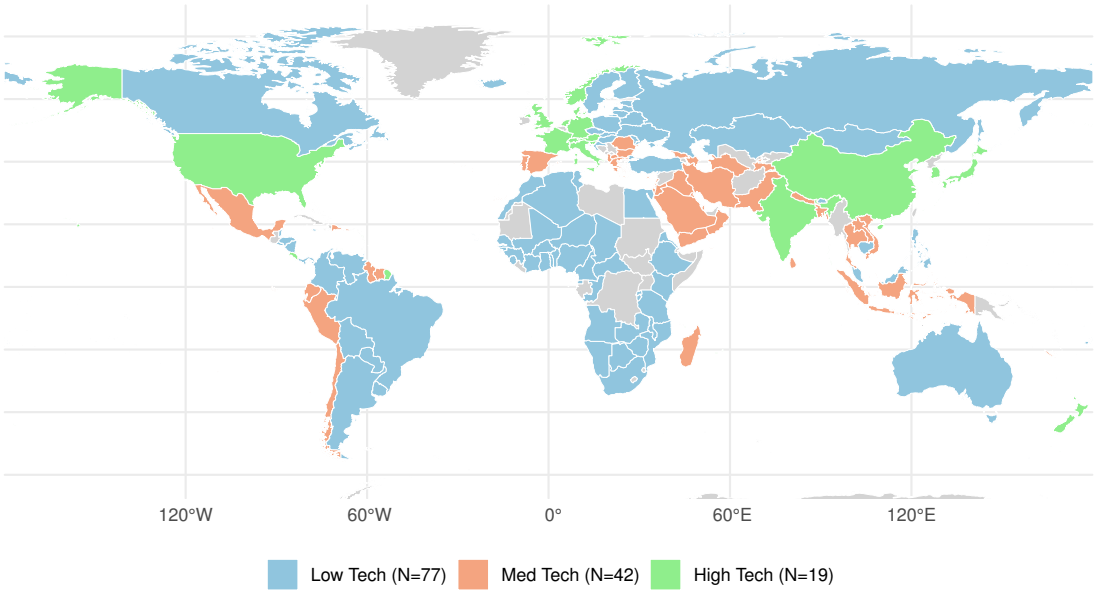

Table B.8: Hierarchical clustering results based on country-level means

	High-Tech N=7	Med-Tech N=73	Low-Tech N=58
$\widetilde{F_i}$	2.060	1.348	0.305
$\widetilde{I_i}$	1.692	1.502	0.251
$\widetilde{K_i}$	8.316	0.426	0.413

Table B.9: Heterogeneity in temperature anomalies effects using hierarchical clustering

Dependent Variable:	$\Delta \ln Y_{it}$: Food production growth	
Model:	(1)	(2)
Adjustment coefficient α	-0.079***	-0.077***
	(0.011)	(0.012)
Long-run effects		
$\ln L_{it-1}$	0.250***	0.226***
	(0.084)	(0.084)
$\ln K_{it-1}$	0.145***	0.135***
	(0.066)	(0.065)
$\ln N_{it-1}$	0.623***	0.603***
	(0.180)	(0.182)
Short-run dynamics		
$\Delta \ln Y_{it-1}$	-0.173***	-0.173***
	(0.031)	(0.032)
$\Delta \ln F_{it}$	0.020***	0.017***
	(0.005)	(0.005)
$\Delta \ln K_{it}$	0.246***	0.272***
	(0.068)	(0.070)
$\Delta \ln L_{it}$	0.040*	0.038
	(0.022)	(0.027)
$\Delta \ln N_{it}$	0.573***	0.578***
	(0.035)	(0.037)
$Droughts_{it}$	-0.006***	-0.006***
	(0.001)	(0.001)
$\Delta\widetilde{T}_{it}(m)^+ \times \mathbb{I}$(country i is low-tech)	-0.022***	
	(0.006)	
$\Delta\widetilde{T}_{it}(m)^+ \times \mathbb{I}$(country i is med-tech)	-0.005	
	(0.004)	
$\Delta\widetilde{T}_{it}(m)^+ \times \mathbb{I}$(country i is high-tech)	0.0008	
	(0.005)	
$\Delta\widetilde{T}_{it}(m)^+ \times \mathbb{I}$(country i is poor)		-0.026***
		(0.008)
$\Delta\widetilde{T}_{it}(m)^+ \times \mathbb{I}$(country i is rich)		-0.004
		(0.004)
$\Delta\widetilde{T}_{it}(m)^-$	-0.002	-0.002
	(0.008)	(0.006)
$\widetilde{T}_t(m) \times \mathbb{I}$(country i is low-tech)	-0.036**	
	(0.015)	
$\widetilde{T}_t(m) \times \mathbb{I}$(country i is med-tech)	-0.028**	
	(0.012)	
$\widetilde{T}_t(m) \times \mathbb{I}$(country i is high-tech)	-0.018	
	(0.018)	
$\widetilde{T}_t(m) \times \mathbb{I}$(country i is poor)		-0.023
		(0.015)
$\widetilde{T}_t(m) \times \mathbb{I}$(country i is rich)		-0.039**
		(0.019)
τ	0.001***	0.001***
	(0.0002)	(0.0002)
Country FE	Yes	Yes
Year FE	No	No
$N \times T$	7,292	6,648
N	138	117
max T	58	58
avg T	52.84	56.82
min T	25	25
R^2	0.222	0.227
Within R^2	0.204	0.211

Notes: Driscoll-Kraay standard errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. Local temperature and drought are weighted by cropland area. The long-run effects are calculated as the ratio of the unrestricted coefficient and $-\alpha$, while the standard errors are calculated after taking derivatives in the augmented Equation 4 as in Banerjee et al. [1993].