Farm Size, Climate Adaptation, and Unequal Climate Damages across Countries *

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Abstract

We examine how climate damages vary across countries at different stages of development. Low-income countries rely more on small, subsistence-oriented farms, have a larger share of the population employed in agriculture, and face greater exposure to food insecurity. Using farm-level evidence from Italy, we find that smaller farms invest significantly less in adaptation technologies and, as a result, suffer larger productivity losses under climate change. We develop a structural transformation model with heterogeneous farm sizes, climate-induced declines in agricultural productivity, and endogenous adaptation investment. We calibrate the model to Italian farm-level and aggregate data. Holding the climate shock fixed, the model implies that poorer economies invest less in adaptation, experience larger declines in agricultural output, and face greater food insecurity. Using country-specific projected climate damages, the model predicts widening cross-country income gaps.

Keywords: Climate change, productivity, agriculture, farm size, adaptation technology, structural transformation.
JEL classification: O11, O14, O4.

*Preliminary draft. Please do not circulate. We are grateful for useful comments to participants at Toronto MacDev Reading Group. All remaining errors are our own. Contact: aadamo@yorku.ca, henry.kim@oecd.org, dnguyen@amherst.edu, matteo.rapagna@unich.it, and diego.restuccia@utoronto.ca.

1 Introduction

Climate change is projected to reduce agricultural productivity in many places of the world. As agriculture is the main source of income and production for a large share of population in low-income countries, these productivity losses can have substantial aggregate consequences. Lower agricultural productivity raises food insecurity and slows the reallocation of labor out of agriculture, depressing economy-wide income and potentially widening cross-country differences in living standards (Gollin et al., 2002; Restuccia et al., 2008; Herrendorf et al., 2014). In contrast, in rich economies where the agriculture sector is small and farmers can mitigate the impact of climate change, similar climate damages have limited aggregate effects.

A key reason why the same climate shock can have very different consequences across countries is the response through climate adaptation. Farms can mitigate climate change damages by changing inputs and practices—for example through irrigation, improved varieties, and management—but adaptation is costly and uneven (Deschênes and Greenstone, 2007; Burke and Emerick, 2016). We examine how adaptation, shaped by the structure of agricultural production, mediates the aggregate impact of climate change across countries at different levels of development. We focus on farm size as a structural determinant of adaptation capacity. Agriculture in lower income countries is dominated predominantly by small farms (Adamopoulos and Restuccia, 2014); if small farms adapt less and suffer larger realized losses from climate change, then developing countries would face larger loses on agricultural productivity and more food insecurity, with substantial general-equilibrium effects. This mechanism complements recent work emphasizing limits to adaptation through sectoral reallocation in the presence of subsistence needs (Gollin et al., 2007; Nath, 2025) and general-equilibrium channels operating through trade and comparative advantage (Costinot et al., 2016).

We first document empirical facts consistent with this mechanism. Across countries, low-income economies rely more on small, subsistence-oriented farms, employ much larger shares of workers in agriculture, and have a larger share of the population under food insecurity. We then use micro data from Italy to show that smaller farms use adaptation technologies at much lower rates and experience larger productivity losses from the same temperature shock. These patterns suggest that the farm-size distribution is a key determinant of the realized productivity impact of climate change.

Motivated by these facts, we develop a model of structural transformation with heterogeneous farm sizes, climate damages, and endogenous investment in adaptation technology. The model builds on Gollin et al. (2002) and Restuccia et al. (2008) and incorporates farm-size heterogeneity as in Adamopoulos and Restuccia (2014). Climate change reduces farm productivity, and farms choose adaptation to mitigate damages subject to a convex cost of technology investment. The model parameters are disciplined by micro estimates and calibrated to match data moments of the Italian economy.

We use the calibrated model to quantify the aggregate consequences of climate damages across economies at different levels of development. The experiments deliver three main results. First, for a common agricultural productivity shock, poorer economies adapt substantially less, leading to larger realized agricultural productivity losses, larger reallocations of labor into agriculture, larger declines in aggregate labor productivity, and large increases in the population under food insecurity. Second, limited adaptation by small farms is a key amplification mechanism and accounts for a sizable share of the rich–poor gap in food-security impacts. Third, when we incorporate projected damages that are larger in many low-income countries, the model implies very large welfare and food-security losses concentrated in the poorest economies and predicts that cross-country income differences widen under future climate scenarios.

Our paper relates to several strands of literature. First, it connects to empirical work on climate and agriculture that estimates how temperature shocks affect yields, revenues, and farm performance (Deschênes and Greenstone, 2007; Burke and Emerick, 2016). We contribute by documenting systematic heterogeneity across farms—smaller farms adapt less and suffer larger productivity losses—and by quantifying how these micro differences translate into aggregate outcomes in general equilibrium. Second, our paper builds on the macro-development literature on cross-country income differences and structural transformation out of agriculture (Gollin et al., 2002; Restuccia et al., 2008; Herrendorf et al., 2014; Adamopoulos and Restuccia, 2014). We introduce climate damages and endogenous adaptation as forces that shape agricultural productivity, the process of structural change, and the distribution of food consumption. Third, our analysis complements recent general-equilibrium approaches to climate impacts that emphasize trade, geography, and reallocation (Costinot et al., 2016; Nath, 2025). Our paper focuses on a different adaptation angle: how the farm-size distribution shapes investment in adaptation technologies and, in turn, realized agricultural damages and food insecurity across levels of development.

The remainder of the paper is organized as follows. Section 2 describes the data and summarizes key empirical patterns on farm size, adaptation, and climate sensitivity. Section 3 presents reduced-form evidence from the Italian farm microdata. Section 4 develops the model. Section 5 describes the calibration to the Italian economy and reports the quantitative results from the set of experiments. Section 6 concludes.

2 Data

This section describes the datasets used in the empirical analysis. We combine (i) farm-level microdata for Italy with (ii) gridded climate data to study adaptation and productivity responses at the farm level, and (iii) global datasets on potential yields and development outcomes to document cross-country patterns in farm structure and climate exposure.

Italian farm microdata (RICA/FADN). Our main micro dataset is the Italian Farm Accountancy Data Network (RICA), the Italian component of the EU farm accountancy system (FSDN/FADN), administered by CREA. RICA is an annual stratified survey covering roughly 11,000 farms per year and includes detailed information on farm production and accounts. We use the 2008–2022 waves. Key variables include output and input expenditures, land operated (hectares), labor use, and balance-sheet items. We construct a revenue-based measure of farm productivity (TFP) following standard approaches in the farm productivity literature (Chen et al. (2023)). We also build measures of adaptation using technology proxies observed in the data (e.g., area under drip irrigation). RICA identifies farms at the province level (NUTS-3), which allows us to merge farms to local climate conditions. After cleaning and applying standard sample restrictions, the main estimation sample contains approximately 99,000 farm-year observations.

Climate data (E-OBS). We measure local climate using the E-OBS gridded observational dataset from Copernicus, available daily at 0.1° resolution (about 11km) for Europe. We use daily maximum temperature and precipitation. Following the climate-economics literature, we summarize temperature exposure using annual measures such as the number of hot days (30–35°C) and very hot days (> 35°C), as well as annual average temperature. Precipitation is included as a control. For the farm-level analysis, we assign each province to the nearest E-OBS grid cell (or area-weighted average across cells within a province) and aggregate daily variables to the farm-year level.

Potential yields (GAEZ). For global and cross-sectional analyses, we use potential yield estimates from the Global Agro-Ecological Zones (GAEZ) database produced by FAO and IIASA. GAEZ provides high-resolution predictions of potential yields (tons per hectare) under given agro-climatic conditions, based on agronomic models that incorporate soil, elevation, and climate. We focus on baseline potential yields around the year 2000 (e.g., for wheat as a benchmark crop) and aggregate grid-cell outcomes to provinces or countries when needed. These measures provide a proxy for underlying agricultural productivity and a disciplined way to quantify climate-induced changes in potential yields.

Cross-country development and farm structure. To relate farm structure to development, we combine national measures of income from the Penn World Tables (GDP per capita in PPP terms) with historical series from the Maddison Project Database. We use country-level measures of average farm size (hectares), constructed from agricultural census and survey sources (e.g., FAO/WCA), and merge these with the development indicators. These data are used to document stylized facts on how farm size, agricultural employment, and exposure to climate damages vary across the income distribution.

Merging and construction. For Italy, we merge RICA to E-OBS at the province-year level and then estimate farm-level relationships between productivity/adaptation outcomes and temperature exposure. For the global component, we align GAEZ potential yields and climate measures to a common grid and then aggregate to the country level before merging with income and farm-size indicators. Throughout, we ensure consistent spatial and temporal alignment across sources and verify that results are robust to alternative assignment rules (nearest-neighbor vs. within-area averaging) and alternative climate summaries.

3 Empirical Findings

We document a set of empirical findings that motivate the mechanism in the model. We begin with the global climate environment: warming is projected to intensify, and increases in heat exposure are uneven across space. This implies large and heterogeneous losses in potential yields, with large losses concentrated in already warm regions.

We then show that the exposure to these climate risks is systematically greater in poorer countries. Agriculture accounts for a much larger share of employment and production in these economies, so a given decline in agricultural productivity has a larger aggregate impact. In addition, larger share of population live close to subsistence agroculture comsumption level, so adverse productivity shocks translate more directly into food insecrity and imply larger welfare loss.

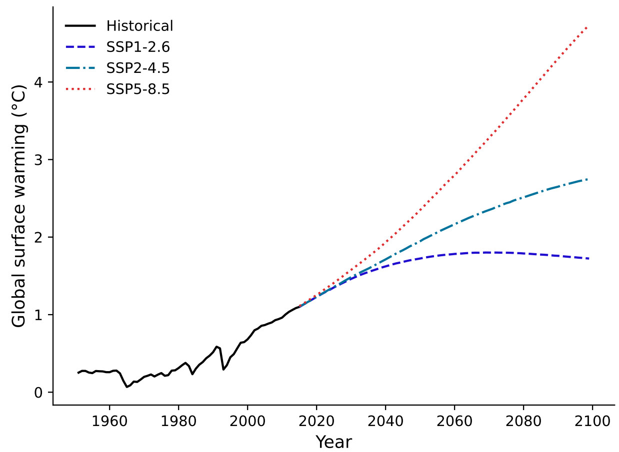
Finally, we present evidence on a mechanism that amplifies heat damages within agriculture. Adaptation is size-dependent: smaller farms adopt fewer mitigation technologies and therefore experience larger productivity losses from heat shocks. Farm-level panel evidence supports both parts of this channel—heat-related productivity losses are steeper at smaller size, and adoption attenuates the heat–productivity relationship. Complementary cross-country patterns point in the same direction: countries with smaller farms tend to exhibit lower proxies for adaptive capacity, consistent with the micro evidence.

3.1 Fact 1: Global warming and declining potential yields

Global temperatures have risen substantially since the pre-industrial period and are projected to increase further over the twenty-first century. Because crop growth is highly sensitive to temperature and water stress, continued warming implies sizable reductions in potential agricultural productivity. We highlight three patterns. First, global mean temperature has increased and continues to rise under alternative emissions trajectories (Figure 1). Second, warming is uneven across space, so the increase in heat exposure differs sharply across regions (Figure 2). Third, these temperature changes translate into large and spatially heterogeneous declines in potential yields of major staple crops, with the largest losses concentrated in already warm regions (Figure 3).

Global temperature projections. Figure 1 plots observed global temperature anomalies together with projections from the CMIP6 multi-model ensemble. Relative to the 1850–1900 baseline, global mean temperature has already increased by about 1.1°C. Under a low-emissions pathway (SSP1–2.6), warming stabilizes around 2°C by 2100; under a middle pathway (SSP2–4.5), it reaches roughly 3°C; and under a high-emissions pathway (SSP5–8.5), it exceeds 5°C. The key point is that further warming is projected across scenarios, with large differences in magnitude depending on emissions.

Figure 1: Global average temperature projections (CMIP6)



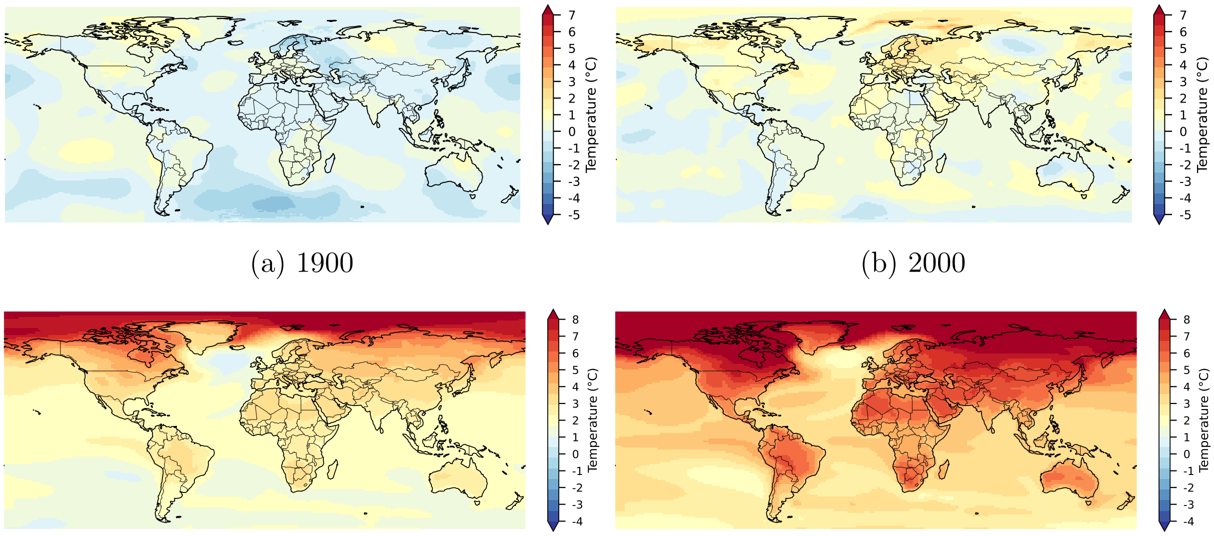
Notes: Temperature anomalies are relative to the 1850–1900 average. Data are from Fyfe et al. (2022). The solid black line shows historical observations. The dashed blue, dash-dotted navy, and dotted red lines show projections under SSP1–2.6, SSP2–4.5, and SSP5–8.5, respectively.

Uneven warming across space. Figure 2 shows that the rise in temperature is not uniform. Some regions experience substantially larger increases in heat exposure than others, reflecting both geography and baseline climate conditions. These spatial differences matter for agriculture because yield responses are highly nonlinear: damages rise sharply when temperatures move beyond crop-specific thresholds. The unequal pattern of warming therefore implies unequal pressure on attainable productivity across regions.

Projected changes in potential yields. Figure 3 summarizes projected changes in potential yields between 1981–2010 and 2071–2100 under a high-emissions scenario. The two panels report projections from two global climate models: the NOAA *Geophysical Fluid Dynamics Laboratory* model (GFDL) and the IPSL *Institut Pierre-Simon Laplace* model. For each country, we construct a crop-share-weighted average potential yield across major staples, and plot the ratio of future to current potential yields. Values below one indicate projected declines in attainable yields under otherwise favorable production conditions.

The projections imply large and uneven losses. Yield declines are concentrated in low-latitude, already warm regions, while some high-latitude regions exhibit modest gains. In

Figure 2: Temperature anomaly (°C)



(a) 1900

(b) 2000

(c) 2100: medium-emissions scenario

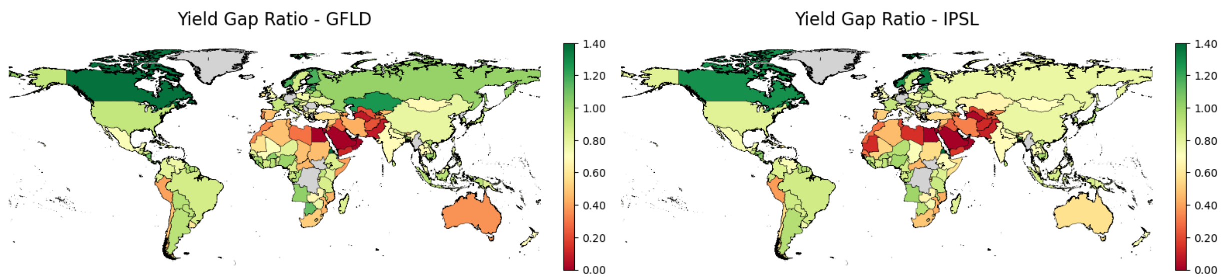
(d) 2100: high-emissions scenario

Notes: Temperature anomalies are relative to the 1850–1900 average. Data are from Rohde and Hausfather (2020). Panels show historical anomalies (1900, 2000) and projected anomalies for 2100 under medium- and high-emissions scenarios.

the cross-country distribution, the most adversely affected countries (bottom decile) experience losses on the order of xx% relative to current potential yields, while the least affected countries (top decile) see changes around xx% (including modest gains in some cases). These patterns also line up with income differences: countries in the bottom income decile lose about xx% on average, whereas countries in the top income decile lose about xx% (or experience small gains), reflecting both baseline climate conditions and the geography of warming.

Evidence on temperature and crop yields. A large empirical and simulation-based literature finds sizeable negative effects of higher temperatures on crop yields. Across meta-analyses and crop-model ensembles, a 1°C increase in growing-season temperature reduces yields of major cereals by roughly 3–7% on average. For example, Zhao et al. (2017) estimate yield elasticities of −7.4% for maize, −6.0% for wheat, −3.2% for rice, and −3.1% for soybean per 1°C. These magnitudes are consistent with the projected yield losses in Figure 3, and with

Figure 3: Projected change in crop-share-weighted potential yields under a high-emissions scenario



(a) NOAA GFDL model (b) IPSL model

Notes: Data are from the Global Agro-Ecological Zones (GAEZ) v4 database. The figure reports the ratio of projected to current potential yields for each country, where potential yields are computed under high-input and high-water-availability assumptions. Projections compare 2071–2100 to 1981–2010 under a high-emissions scenario. Country-level outcomes are constructed as crop-share-weighted averages across major staple crops, using baseline crop shares. The two panels use climate projections from the NOAA *Geophysical Fluid Dynamics Laboratory* (GFDL) model and the *Institut Pierre-Simon Laplace* (IPSL) model. Values below one indicate yield losses relative to current potential yields.

the broader conclusion that warming generates substantial risks for agricultural productivity, especially in warm regions.

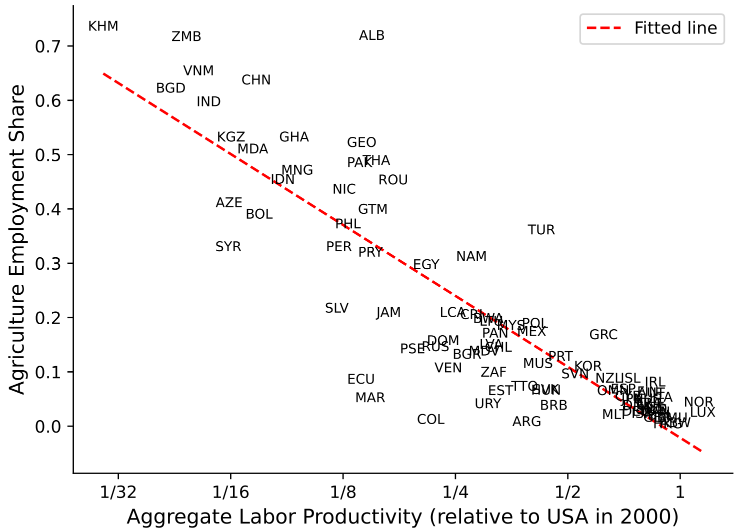
Table 1: Yield response to a 1°C temperature increase

Crop	**Yield change (%)**	**Source**
Maize	−7.4	Zhao et al. (2017)
Wheat	−6.0	Zhao et al. (2017)
Rice	−3.2	Zhao et al. (2017)
Soybean	−3.1	Zhao et al. (2017)
Wheat (multi-model mean)	−6.0 to −8.5	Liu et al. (2019)
Global cereals (range)	−3.0 to −7.0	Rosenzweig et al. (2014); IPCC (2021)

3.2 Fact 2: Poorer countries rely more on agriculture and operate at smaller scale

A second set of facts show how agricultural share varies with income. In poorer countries, a much larger share of the labor force works in agriculture, and the sector accounts for a larger fraction of aggregate production. As countries develop, labor reallocates out of agriculture

Figure 4: Agricultural employment share and GDP per capita (2000)



Notes: Country codes denote country observations. Agricultural employment shares are from FAOSTAT. GDP per capita is from the Penn World Table (Feenstra et al., 2015).

toward more productive sectors (Gollin et al., 2002; Restuccia et al., 2008; Gollin et al., 2014). Figure 4 illustrates this pattern: agricultural employment shares are high in low-income economies and decline sharply with GDP per capita. This matters for climate vulnerability because a given fall in agricultural productivity mechanically has a larger aggregate impact when agriculture employs a larger share of workers and production.

A closely related fact is that farming is much more small-scale in poorer countries. Average farm size is strongly increasing in income (Figure 5). Panel (a) plots average farm size against GDP per capita and shows a steep positive relationship. Panel (b) adjusts farm size for cross-country differences in agricultural land endowments; the relationship remains, indicating that land availability alone does not account for the pattern. Following Adamopoulos and Restuccia (2014), this points to frictions—including land-market distortions, tenure systems, and constraints on capital deepening—that limit consolidation and prevent scale from rising in poorer economies. This scale gap is central for our mechanism because many mitigation technologies involve fixed costs and complementary investments, so adoption incentives are likely to differ by scale.

(a) Average farm size (b) Endowment-adjusted average farm size

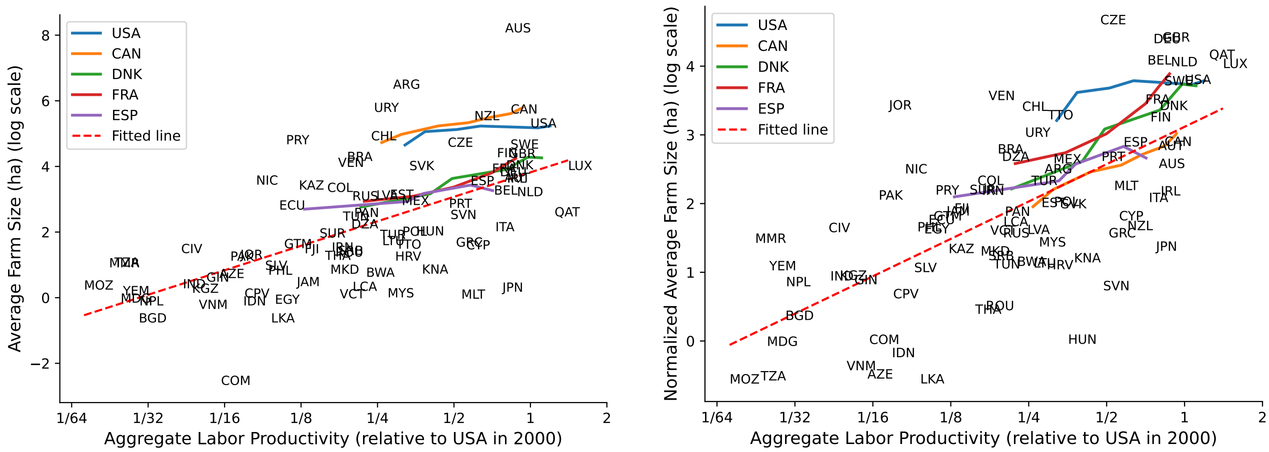


Figure 5: Average farm size and GDP per capita across countries (2000)

Notes: Country codes denote country observations. Farm size is measured in hectares (log scale). Panel (b) adjusts farm size for agricultural land endowments by scaling each country's land per capita to match the United States. Farm size data are from FAOSTAT. GDP per capita is from the Penn World Table (Feenstra et al., 2015).

Finally, food insecurity is far more prevalent in low-income economies (Figure 6). The fraction of the population facing moderate or severe food insecurity is close to zero in most high-income countries but remains large in many poorer countries. This pattern indicates that a larger share of households is close to subsistence levels of food consumption, so climate-driven productivity declines are more likely to generate meaningful welfare losses through heightened food insecurity.

Taken together, these cross-country facts imply that poorer countries are more exposed to climate risk: agriculture is larger, farms are smaller, and more households operate close to subsistence. The next section turns to micro evidence on whether small farm size is associated with lower adaptation and larger heat-related productivity losses, and whether adaptation can mitigate these losses.

Figure 6: Food insecurity and GDP per capita

Notes: Country codes denote country observations. Food insecurity is the share of the population facing moderate or severe food insecurity (percent), from FAOSTAT. GDP per capita is from the Penn World Table (Feenstra et al., 2015).

3.3 Fact 3: Smaller farms are more climate-vulnerable because they adopt less adaptation

We now turn to farm-level evidence on how Heat Shocks interact with farm size and technology adoption. Using microdata from the Italian farm panel (RICA), we document three patterns. First, Heat Shocks reduce productivity growth, and the losses are systematically larger for smaller farms. Second, adoption of mitigation technologies is increasing in farm size: smaller farms adapt less. Third, adaptation attenuates the productivity impact of Heat Shocks, with causal evidence from an instrumental-variable strategy.

Productivity response to Heat Shocks and baseline farm size. We begin by estimating how Heat Shocks affect farm productivity growth and whether the effect depends on baseline size:

$$\Delta \log(\mathrm{TFP}_{it}) = \beta_0 \log(\mathrm{FarmSize}_{i0}) + \beta_1\,\mathrm{HeatShock}_{it} + \beta_2 \big(\mathrm{HeatShock}_{it} \times \log(\mathrm{FarmSize}_{i0})\big) + \gamma_t + X_{it}'\theta + \varepsilon_{it}, \tag{1}$$

where $\Delta \log(\text{TFP}_{it})$ is farm-level TFP growth, and $\log(\text{FarmSize}_{i0})$ is baseline farm size measured at the start of the panel. We measure HeatShock_{it} as a deviation of local temperature from its long-run mean at the farm location (i.e., a temperature anomaly relative to the local climate normal), following the standard approach in the climate–agriculture literature, γ_t controls for common shocks. Identification comes from within-farm variation in local weather over time, with baseline size predetermined relative to contemporaneous shocks.

Table 2: Heat Shocks, farm size, and TFP

Dependent variable: $\Delta \log(\text{TFP}_{it})$ *Heat Shock measure:*	(1) Very hot days (> 35°C)	(2) Hot days (30–35°C)	(3) Temperature
$\log(\text{FarmSize}_{i0})$	0.079***	0.026	0.040
	(0.019)	(0.024)	(0.107)
Heat Shock	-0.041***	-0.009***	-0.034**
	(0.009)	(0.002)	(0.016)
$\log(\text{FarmSize}_{i0}) \times$ Heat Shock	0.012***	0.003***	0.004
	(0.003)	(0.001)	(0.006)
Constant	7.104***	7.287***	7.608***
	(0.064)	(0.080)	(0.278)
Observations	99,072	99,072	99,072
Year × sector FE	✓	✓	✓
Year × altitude FE	✓	✓	✓

Notes: The unit of analysis is a farm–year. The dependent variable is farm-level TFP growth, $\Delta \log(\text{TFP}_{it})$. Columns (1)–(3) estimate equation (1) using alternative measures of Heat Shocks, constructed as deviations from the location-specific long-run mean (local climate normal): the number of very hot days (> 35°C), the number of hot days (30–35°C), and the anomaly in growing-season mean temperature. All specifications include year-by-sector and year-by-altitude fixed effects. Standard errors are clustered at the provincial level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The estimates imply $\beta_1 < 0$ and $\beta_2 > 0$: Heat Shocks reduce productivity growth on average, but the losses are smaller for larger farms. Appendix Table A.5 reports average marginal effects by baseline size quintile and shows that damages are concentrated among smaller farms, becoming much weaker for the largest farms. Appendix Figure A.1 provides complementary evidence from quantile regressions, which show that the attenuation by size is particularly pronounced at higher percentiles of the productivity distribution.

Farm size and adaptation. We next test whether adaptation is size-dependent:

$$
\begin{aligned}
\log(\mathrm{Drip}_{it}+1) = \gamma_1 \log(\mathrm{FarmSize}_{i0}) &+ \gamma_2 \mathrm{TempShock}_{it} \\
&+ \gamma_3 \log(\mathrm{FarmSize}_{i0}) \cdot \mathrm{TempShock}_{it} \\
&+ \alpha_i + \gamma_t + X_{it}'\theta + u_{it}.
\end{aligned}
\tag{2}
$$

where $\log(\mathrm{Drip}_{it}+1)$ measures drip (or micro-) irrigation adoption intensity, and $\mathrm{HeatShock}_{it}$ is the temperature anomaly defined above. Column (2) of Table 3 shows that Heat Shocks reduce adoption on average, while the positive interaction term implies that adoption responses are weaker for larger farms and more pronounced among small farms. The same qualitative pattern holds when we condition on baseline productivity rather than baseline size (Table A.4) and when we examine marginal effects across the baseline size distribution (Appendix Figure A.2).

Adaptation mitigates productivity losses: OLS and IV evidence. Finally, we estimate whether adaptation flattens the temperature–productivity relationship:

$$
\Delta \log(\mathrm{TFP}_{it}) = \beta_1 \log(\mathrm{Adapt}_{it}) + \delta_1 \mathrm{HeatShock}_{it} + \delta_2 \big(\mathrm{HeatShock}_{it} \times \log(\mathrm{Adapt}_{it})\big) + X_{it}'\theta + \gamma_t + \eta_{it},
\tag{3}
$$

where $\log(\mathrm{Adapt}_{it})$ measures adaptation intensity (e.g., irrigated area equipped with water-saving technologies) and $\mathrm{HeatShock}_{it}$ is the temperature anomaly defined above. The coefficient of interest is δ_2: a positive value implies that farms with greater adaptation intensity experience smaller productivity losses when Heat Shocks increase.

Because adaptation can be endogenous, we instrument $\log(\mathrm{Adapt}_{it})$ and $\mathrm{HeatShock}_{it} \times \log(\mathrm{Adapt}_{it})$ using farm-level access to EU environmental and agro-climatic investment funds and the interaction of these funds with $\mathrm{HeatShock}_{it}$. The first stage is strong, and 2SLS esti-

Table 3: Farm size, Heat Shocks, and adaptation (drip irrigation)

Dependent variable: $\log(\text{Drip}_{it}+1)$ *Heat Shock measure:*	(1)	(2) Temperature anomaly
$\log(\text{FarmSize}_{i0})$	0.093***	0.086***
	(0.002)	(0.021)
Heat Shock		-0.054***
		(0.019)
$\log(\text{FarmSize}_{i0}) \times$ Heat Shock		0.011**
		(0.004)
Constant	0.057***	0.075
	(0.007)	(0.053)
Observations	85,514	61,069
Year FE	✓	✓
Sector FE	✓	✓

Notes: The unit of analysis is a farm–year. The dependent variable is $\log(\text{Drip}_{it}+1)$, where Drip_{it} measures drip (or micro-) irrigation adoption intensity. "Heat Shock" is the deviation of growing-season mean temperature from its location-specific long-run mean (local climate normal). All specifications include year and sector fixed effects. Standard errors are clustered at the provincial level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

mates imply that adaptation significantly mitigates the productivity impact of Heat Shocks among farms whose adoption responds to these funding opportunities.

The 2SLS coefficient on the interaction term is positive and statistically significant, indicating that adaptation mitigates the productivity impact of Heat Shocks. Interpreting the interaction in (3), a 1% increase in adaptation intensity reduces the marginal TFP loss from a 1°C increase in the temperature anomaly by roughly 0.10–0.13 percentage points in our baseline specifications.

Table 4: Adaptation, Heat Shocks, and TFP growth: OLS and IV (2SLS) estimates

Dependent variable: $\Delta\log(\text{TFP}_{it})$	(1) OLS	(2) OLS	(3) 2SLS	(4) 2SLS
$\log(\text{Adapt}_{it})$	0.0121	0.0182**	0.045**	0.057**
	(0.00728)	(0.00780)	(0.019)	(0.025)
$\text{HeatShock}_{it} \times \log(\text{Adapt}_{it})$	0.0190	0.0236	0.126**	0.103**
	(0.02299)	(0.02065)	(0.062)	(0.045)
HeatShock_{it}	-0.0581	-0.0545	-0.184**	-0.147*
	(0.05377)	(0.05039)	(0.089)	(0.076)
Observations	3,079	3,270	3,079	3,270
Year FE	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓
Altitude FE	✓	✓	✓	✓
Kleibergen–Paap F			11.99	19.98

Notes: The unit of analysis is a farm–year. The dependent variable is farm-level TFP growth, $\Delta\log(\text{TFP}_{it})$. HeatShock_{it} is the temperature anomaly (deviation from the location-specific long-run mean). Endogenous regressors are $\log(\text{Adapt}_{it})$ and $\text{HeatShock}_{it} \times \log(\text{Adapt}_{it})$, instrumented with the log of EU environmental and agro-climatic funds received by the farm and its interaction with HeatShock_{it}. All specifications include year, sector, and altitude fixed effects; standard errors are clustered at the province level.

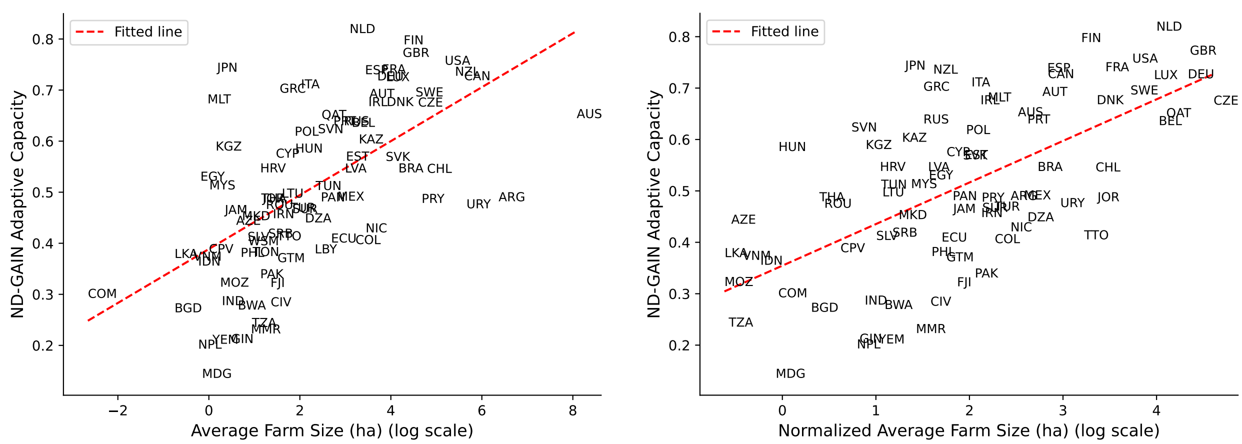
3.4 Fact 4: Countries with larger average farm size exhibit higher climate adaption capacity

The farm-level evidence from Italy suggests that farm size is a key determinant of adaptation: smaller farms adopt less and are more exposed to productivity losses from temperature shocks. We next ask whether the same scale pattern is visible in cross-country data. To do so, we combine measures of average farm size with a country-level index of adaptive capacity from the ND-GAIN dataset. The ND-GAIN adaptive capacity index summarizes a country's readiness and ability to cope with climate risks through economic, institutional, and infrastructural conditions. In the data, countries with larger farms exhibit systematically higher adaptive capacity.

Figure 7a plots the ND-GAIN adaptive capacity index against average farm size. The relationship is positive and strong: countries with small farms tend to score low on adaptive capacity, while countries with large farms tend to score high. This correlation is robust to adjusting farm size for differences in agricultural land endowment. Figure 7b repeats the exercise using "endowment-adjusted" farm size, constructed by scaling each country's average farm size to the counterfactual level it would have if the country had the same agricultural land per capita as the United States. The positive association remains, suggesting that the farm size gradient in adaptive capacity does not simply reflect land abundance.

The cross-country evidence provides further cross-country evidence suggesting that small farm tend to have weaker adaptive capacity, consistent with a lower propensity to adopt mitigation technologies and a higher vulnerability to climate shocks.

Figure 7: Adaptive capacity and farm size across countries



(a) Raw average farm size

(b) Endowment-adjusted farm size

Notes: Panel (a) plots the ND-GAIN adaptive capacity index against average farm size (hectares per holding). Panel (b) uses an endowment-adjusted farm size measure that scales each country's average farm size by the ratio of its agricultural land per capita to that of the United States, so that the horizontal axis reflects the implied farm size if all countries had the same agricultural land per capita as the United States. The adaptive capacity index is from the ND-GAIN Country Index; farm size and agricultural land are from FAOSTAT.

4 Model

We develop a model of structural transformation between agriculture and non-agriculture, building on Gollin et al. (2002) and Restuccia et al. (2008). The model incorporates production heterogeneity in agriculture as in Adamopoulos and Restuccia (2014) and introduces productivity losses from climate change. Farmers choose whether to adopt climate adaptation technologies. We examine how technological and institutional factors that shape farm size influence climate adaptation decisions and their aggregate consequences for agricultural productivity.

4.1 Economic Environment

Technologies. At each date, a homogeneous agricultural good is produced by farms indexed by i. The production function of farm i is given by

$$y_i = A\kappa(s_i z)^{1-\gamma}\ell_i^{\gamma},\ \gamma \in (0,1),$$

where y_i denotes agricultural output, ℓ_i is land input, A represents economy-wide productivity, κ is sector-specific agricultural productivity, and $s_i^{1-\gamma}$ captures the farm's idiosyncratic productivity. The term $z^{1-\gamma}$ reflects the productivity component determined by the exogenous climate shock D and the farmer's endogenous investment choices in climate adaptation technology x. We describe below how the climate adaptation choices are made.

Non-agricultural output is produced by a representative firm using labor as the only input according to the following constant returns to scale production function:

$$Y_n = AN_n,$$

where A is economy-wide productivity and N_n is the labor input.

Market structure. We assume competitive markets in both sectors and normalize the price of agriculture to one (numeraire). We denote by p_n the relative price of non-agriculture, q the rental rate of land, and w the wage rate in non-agriculture.

Preferences and endowments. The economy is populated by a unit mass of individuals. Each individual owns a fixed share of the aggregate land stock. Total land supply is exogenous and fixed at L, and is supplied inelastically to farms for agricultural production. Land rents are rebated equally to individuals.

Households have Price-Independent Generalized Linear (PIGL) preferences over agricultural and non-agricultural consumption (Boppart, 2014). Indirect utility as a function of the non-agricultural price p_n and income E is

$$v(p_n, E) = \frac{1}{1-\varphi}E^{1-\varphi} - \frac{\alpha}{1-\rho}p_n^{1-\rho} - \frac{1}{1-\varphi} + \frac{\alpha}{1-\rho},$$

where α is the preference weight on agricultural consumption, φ is the income elasticity, and ρ is the price elasticity to p_n.

The implied Hicksian demands for agricultural and non-agricultural goods are

$$c_a = \alpha E^{\varphi}, \qquad c_n = \frac{E - c_a}{p_n} = \frac{E - \alpha E^{\varphi}}{p_n},$$

where c_a and c_n denote consumption of the agricultural and non-agricultural good, respectively.

Occupational choice. Before choosing an occupation, all individuals are ex-ante identical and do not observe their farm operating ability. In equilibrium, the expected value of operating a farm equals the non-agricultural wage, so that individuals are indifferent between becoming farmers or wage workers. Formally, with $V(s)$ denoting the value from operating a farm for ability s and w the non-agricultural wage, an interior occupational allocation requires

$$\mathbb{E}_s[V(s)] = w. \tag{4}$$

Similar to Adamopoulos and Restuccia (2014), we abstract from occupational selection, which has been extensively studied in the literature, in order to focus on the farm size distribution and heterogeneity *within* the agricultural sector.

After choosing to operate a farm, individuals observe their farm operating ability $s_i \sim F(s)$. Realized income for a farmer is given by the farm value $V(s_i)$, while an individual working in non-agriculture earns the wage w. In addition, all individuals receive their share of aggregate land rents qL, so that individual income is the sum of sectoral income (farm profit or wage) and land income.

4.2 Equilibrium

The model is static and we consider a competitive equilibrium in which households, farms, and firms take prices as given, and prices clear the markets.

Incumbent farms. An incumbent farm i is characterized by idiosyncratic productivity s_i and its choice of technology z. The farm's expected per-period profit is given by

$$\pi(s_i z) = \max_{\ell \geq 0} \quad A\kappa(s_i z)^{1-\gamma}\ell^{\gamma} - q\ell$$

The optimal land choice and output of an incumbent farm is given by

$$\ell(s_i z) = \left(\frac{\gamma}{q}\right)^{\frac{1}{1-\gamma}} (A\kappa)^{\frac{1}{1-\gamma}} s_i z,$$
$$y(s_i z) = \left(\frac{\gamma}{q}\right)^{\frac{\gamma}{1-\gamma}} (A\kappa)^{\frac{1}{1-\gamma}} s_i z.$$

The optimal expected profit of an incumbent farm is given by

$$\pi(s_i z) = (1-\gamma)\left(\frac{\gamma}{q}\right)^{\frac{\gamma}{1-\gamma}} (A\kappa)^{\frac{1}{1-\gamma}} s_i z,$$

Climate damage and climate adaptation technology. Each farm i is subject to an exogenous climate damage shock $D_i \geq 0$ that lowers productivity. We capture the climate component of productivity by a scalar $z_i \in (0,\infty)$, which multiplies the farm's idiosyncratic productivity s_i in the production function. By investing $x_i \geq 0$ in adaptation technologies (e.g. irrigation, heat-tolerant varieties, soil conservation), the farm can partially offset the impact of climate damage and, more generally, raise productivity. We model the resulting climate-adjusted productivity as

$$z_i \;=\; g(D_i, x_i),$$

where the function $g : \mathbb{R}_+^2 \to (0,\infty)$ satisfies

$$g_D(D,x) < 0, \qquad g_x(D,x) > 0, \qquad g_{xx}(D,x) \leq 0,$$

so that damage reduces productivity and adaptation raises it with diminishing marginal returns.

For the quantitative analysis we parameterize the climate–adaptation multiplier in logs as

$$\log z(D,x) = -D + \big(\eta_0 + \eta_1 D\big)\,\log(1+x), \tag{5}$$

so that

$$z(D,x) = e^{-D}\,(1+x)^{\eta_0+\eta_1 D}, \qquad \eta_0 \geq 0,\ \eta_1 \geq 0. \tag{6}$$

In the absence of adaptation ($x = 0$) we have $z(D,0) = e^{-D}$, so D captures the pure damage component. The parameter η_0 governs the productivity effect of adaptation in normal conditions, while η_1 controls how the marginal effect of adaptation scales with the level of climate damage. When $\eta_0 > 0$, adaptation raises productivity even in the absence of damage ($D = 0$); when $\eta_1 > 0$, adaptation becomes more effective in mitigating damage as D increases.

We assume a convex adaptation cost function $k : \mathbb{R}_+ \to \mathbb{R}_+$,

$$k(x) = \frac{\psi}{1+\nu}\, x^{1+\nu}, \qquad \psi > 0,\ \nu \geq 0, \tag{7}$$

where ψ is a scale parameter and ν controls the curvature of costs.

Given the profit function $\pi(sz) = \Omega sz$ derived above, an incumbent farm with productivity s facing damage D chooses adaptation x to solve

$$\Pi(s, D, x) \;=\; \Omega s\, z(D, x) - k(x) \;=\; \Omega s\, e^{-D}\, (1 + x)^{\eta_0+\eta_1 D} - \frac{\psi}{1+\nu} x^{1+\nu}. \tag{8}$$

The first-order condition for an interior solution $x > 0$ is

$$\frac{\partial \Pi}{\partial x} = \Omega s\, e^{-D} \big(\eta_0 + \eta_1 D\big)\, (1 + x)^{\eta_0+\eta_1 D-1} - \psi x^{\nu} = 0. \tag{9}$$

Because (9) is nonlinear in x and involves both $(1 + x)$ and x raised to powers, it does not admit a simple closed-form solution for $x^*(s, D)$. In the quantitative analysis we therefore solve (9) numerically for $x^*(s, D)$, imposing the Kuhn–Tucker conditions $x \geq 0$ and complementary slackness, and then set

$$z(s, D) \equiv z\big(D, x^*(s, D)\big), \qquad V(s, D) = \Omega s\, z(s, D) - k\big(x^*(s, D)\big).$$

Definition of equilibrium. A competitive equilibrium consists of prices (p_n, w, q); agricultural and non-agricultural employment shares (N_a, N_n); farm-level decision rules for land demand $\ell(s, D)$, adaptation choice $x(s, D)$, climate-adjusted productivity $z(s, D)$, output $y(s, D)$, profit $\pi(s, D)$, and farm value $V(s, D)$; and individual consumption allocations for farmers $\{c_a^F(s), c_n^F(s)\}$ and workers (c_a^W, c_n^W) such that:

(i) **Non-agricultural firm problem.** Given prices (p_n, w), N_n solves the representative non-agricultural firm's problem.

(ii) **Farm problem.** Given prices (q, w, p_n), policy functions $x(s, D)$ and $\ell(s, D)$ solve the incumbent farm with ability s facing climate damage D, yielding the optimal per-period profit $\pi(s, D)$ and value net of adaptation cost $V(s, D)$.

(iii) **Occupational choice (no selection).** Before choosing an occupation, individuals do not observe s_i. In equilibrium, an interior agricultural employment share $N_a \in (0, 1)$ requires that the expected value of operating a farm equals the non-agricultural wage:

$$\mathbb{E}_s\big[V(s, D)\big] = w. \tag{10}$$

A fraction N_a of individuals become farmers and a fraction $N_n = 1 - N_a$ work in non-agriculture.

(iv) **Individual consumption.** Given income $I^F(s)$ and the relative price p_n, the pair $(c_a^F(s), c_n^F(s))$ solves the consumption problem of a farm operator with ability s. Given wage w and p_n, the pair (c_a^W, c_n^W) solves the worker's consumption problem.

(v) **Final goods markets clear.** Market clears for the agricultural and non-agricultural goods:

$$C_a + X = Y_a, \qquad C_n = Y_n,$$

where (C_a, C_n) denote the aggregate consumption of agricultural and non-agricultural goods; (Y_a, Y_n) denote the aggregate agricultural and non-agricultural output; and X denote the aggregate investment cost of adapation:

$$C_a = N_a \int_s c_a^F(s)\, dF(s) + N_n\, c_a^W, \qquad C_n = N_a \int_s c_n^F(s)\, dF(s) + N_n\, c_n^W,$$

$$Y_a = N_a \int_s y(s, D)\, dF(s), \qquad Y_n = AN_n.$$

$$X = N_a \int c\big(x(s, D)\big)\, dF(s).$$

(vi) **Land and labor market clears.** The land market clears:

$$N_a \int \ell(s, D)\, dF(s) = L,$$

and the labor market clears:

$$N_a + N_n = 1.$$

4.3 Model implications

Recall that, given climate-adjusted productivity z, the optimal per-period profit of a farm with idiosyncratic productivity s is

$$\pi(sz) = (1-\gamma)\left(\frac{\gamma}{q}\right)^{\frac{\gamma}{1-\gamma}} (A\kappa)^{\frac{1}{1-\gamma}} sz.$$

For notational convenience define

$$\Omega \;\equiv\; (1-\gamma)\left(\frac{\gamma}{q}\right)^{\frac{\gamma}{1-\gamma}} > 0,$$

so that

$$\pi(sz) = \Omega\, (A\kappa)^{\frac{1}{1-\gamma}} sz.$$

With the climate–adaptation multiplier

$$z(D, x) = e^{-D}\, (1+x)^{\eta_0 + \eta_1 D}, \qquad \eta > 0,$$

and a convex per-period cost of adaptation

$$k(x) = \frac{\psi}{1+\nu} x^{1+\nu}, \qquad \psi > 0,\ \nu \geq 0,$$

a farm with productivity s and damage D chooses x to maximize

$$\Pi(s, D, x) = \Omega\,(A\kappa)^{\frac{1}{1-\gamma}} s\, e^{-D}\,(1+x)^{\eta_0+\eta_1 D} - \frac{\psi}{1+\nu} x^{1+\nu}, \qquad x \geq 0.$$

The first-order condition (FOC) for an interior optimum $x > 0$ is

$$\frac{\partial \Pi}{\partial x} = \Omega\,(A\kappa)^{\frac{1}{1-\gamma}} s\, e^{-D}\,\eta D\,(1+x)^{\eta_0+\eta_1 D-1} - \psi x^{\nu} = 0, \tag{11}$$

which can be written as

$$\frac{\Omega\,(A\kappa)^{\frac{1}{1-\gamma}} s\, e^{-D}\,\eta D}{\psi} = \frac{x^{\nu}}{(1+x)^{\eta_0+\eta_1 D-1}}.$$

5 Quantitative Analysis

We calibrate a benchmark economy to match data moments for Italy. We then perform a series of counterfactual experiments to assess the role of factors that shape farm sizes on climate adaptation decisions and aggregate consequences on agricultural productivity.

5.1 Calibration

We calibrate a benchmark economy to micro, sectoral, and aggregate data for the Italy. Endowed farming ability s is assumed to be drawn from the lognormal distribution with normalized mean 0 and standard deviation σ_s. The model features nine parameters to calibrate: the decreasing returns to land γ, the dispersion in endowed farming ability σ_s, the curvature parameters of climate adaptation benefits and costs (η, ν), the agricultural consumption weight α, the price elasticity ρ, the income elasticity φ, relative productivity in agriculture κ, economy-wide productivity A, and the aggregate land endowment L.

A set of three parameters are either normalized or disciplined by outside evidence. First, we set the decreasing-returns parameter to $\gamma = 0.65$, consistent with agricultural factor income shares reported by Valentinyi and Herrendorf (2008) and standard in the misallocation literature. We set the price-elasticity parameter to $\rho = 0$ and the income-elasticity parameter to $\varphi = 0.30$, following Boppart (2014). Aggregate productivity terms are normalized to one, $A = \kappa = 1$.

We calibrate σ_s to match the size distribution of farms in the Italy. The land endowment L is chosen to match land per worker in agriculture. We calibrate the preference parameters the level of agricultural employment in the Italian data.

Climate damage and adaptation parameters. The key new ingredients of the model are the parameters governing climate damage and adaptation. We parameterize the climate–adaptation multiplier as

$$\log z(D, x) = -D + \eta_0 \log(1 + x) + \eta_1 D \log(1 + x), \qquad z(D, x) = e^{-D}(1 + x)^{\eta_0 + \eta_1 D}, \quad (12)$$

where $D \geq 0$ is a reduced-form damage and $\eta > 0$ captures how strongly adaptation x mitigates damage. In the production function

$$y = A\kappa(sz)^{1-\gamma}\ell^{\gamma},$$

the farm-level TFP term that multiplies land is proportional to $(sz)^{1-\gamma}$. Holding s fixed, the climate component of log TFP is therefore $(1 - \gamma) \log z(D, x)$.

In the empirical implementation, we map D to temperature T via a linear index

$$D(T) = \delta T,$$

so that

$$\log z(D(T), x) = -\delta T + \eta_0 \log(1 + x) + \delta\eta_1 T \log(1 + x),$$

and the climate contribution to log TFP is

$$(1 - \gamma) \log z(D(T), x) = -(1 - \gamma)\delta T + (1 - \gamma)\delta\eta\, T \log(1 + x). \tag{13}$$

At the micro level, we estimate the reduced-form regression

$$\log \mathrm{TFP}_{it} = \beta_0 + \beta_1 T_{it} + \beta_2 \log(1 + x_{it}) + \beta_3 T_{it} \times \log(1 + x_{it}) + \text{controls} + \varepsilon_{it}, \tag{14}$$

where T_{it} is (demeaned) temperature and x_{it} is the measure of adaptation (e.g. irrigated area). Comparing (13) and (14) with $D(T) = \delta T$ yields the mapping

$$\beta_1 = -(1 - \gamma)\,\delta, \qquad \beta_2 = \eta_0 \qquad \beta_3 = (1 - \gamma)\,\delta\eta_1. \tag{15}$$

Hence

$$\delta = -\frac{\beta_1}{1 - \gamma}, \qquad \eta_0 = \beta_2, \qquad \eta_1 = -\frac{\beta_3}{\beta_1},$$

so the curvature parameter η_1 is identified by the *ratio* β_3/β_1 and does not depend on γ, while the scale of the damage index δ scales with $(1 - \gamma)^{-1}$.

Using our baseline regression estimates $\hat{\beta}_1 = -0.126$, $\hat{\beta}_2 = 0.045$ and $\hat{\beta}_3 = 0.184$, and $\gamma = 0.65$ (so $1 - \gamma = 0.35$), equations (15) imply

$$\hat{\delta} = -\frac{\hat{\beta}_1}{1 - \gamma} = \frac{0.126}{0.35} \approx 0.36, \qquad \hat{\eta_1} = -\frac{\hat{\beta}_3}{\hat{\beta}_1} = \frac{0.126}{0.184} \approx 0.68.$$

Thus a one-unit increase in T generates a damage index of about $D(T) \approx 0.17T$, and the marginal effectiveness of adaptation increases with damage at rate $\eta \approx 0.05$.

Disciplining cost curvature. We discipline the curvature parameter ν using the reduced-form regression of adaptation on farm size and Heat Shocks,

$$\text{Adapt}_{it} \;=\; \gamma_1 \log \text{FarmSize}_i + \gamma_2 \text{HeatShock}_{it} + \gamma_3 \big(\log \text{FarmSize}_i \times \text{HeatShock}_{it} \big) + \text{FE} + u_{it}, \tag{16}$$

where Adopt_{it} is (approximately) $\log x_{it}$ and $\log \text{FarmSize}_i$ is the initial farm size. We calibrate cost curvature η to match the elasticity of adaptation intensity with respect to farm size.

Parameter	Description	Value	Source		
Literature, normalizations, and micro estimates					
φ	Price elasticity	0.00	Boppart (2014)		
σ	Income elasticity	0.30	Boppart (2014)		
γ	Span-of-control	0.65	Valentinyi and Herrendorf (2008)		
A	Economy-wide productivity	1.00	Normalization		
κ	Ag-specific productivity	1.00	Normalization		
η_0	Returns to adaptation	0.045	IV regression estimate		
η_1	Returns to adaptation	0.68	IV regression estimate		
D	Climate damage (BE)	0.20	Estimated damage		
Calibrated			Target	Model	Data
α	Pref. weight for agriculture	0.27	Italian ag. employment share	5.0%	5.0%
ν	Adaptation cost curvature	2.43	Adaptation–size elasticity	0.09	0.09
ψ	Adaptation cost scale	1.89	Average adaptation level	0.30	0.30
σ_s	Farming ability dispersion	1.98	Italian farm size distribution	–	–
L	Land endowment	0.38	Italian average farm size (ha)	7.5	7.5

Calibrating the cost scale ψ. We choose ψ so that the model reproduces the average level of adaptation observed in the data. Let $\overline{\text{Adapt}}$ denote the sample mean of Adapt_{it} (our measure of $\log(1 + x_{it})$), and let (s_i, D_{it}) denote the farm–damage pairs used in the second-stage regression. Given (δ, η, ν), we select ψ to solve

$$\overline{\text{Adapt}} \approx \frac{1}{N} \sum_{i,t} \log(1 + x(s_i, D_{it})),$$

This targets the average intensity of adaptation, while the curvature parameter ν is disciplined by the cross-sectional response of adaptation to farm size and temperature. Average of $\log(1 + x)$ is around 0.3 in the data.

5.2 Quantitative Experiments

Work in progress.

This section uses the calibrated model to quantify how climate damages to agricultural productivity translate into (i) endogenous climate adaptation, (ii) structural transformation, (iii) aggregate productivity losses, and (iv) food insecurity, and how these effects differ across countries at different development levels.

Across all experiments, we will report: (i) the average adaptation level, (ii) realized agricultural TFP losses (with and without adaptation), (iii) the agricultural employment share, (iv) aggregate labor productivity, (v) average farm size, and (vi) the share of the population under food insecurity. For each experiment, we present a compact table of levels (baseline vs. shocked economy) and a table of changes relative to baseline. We also report the share of damages mitigated by adaptation,

$$\text{Mitigated share} \equiv 1 - \frac{\text{realized ag. loss with adaptation}}{\text{exogenous damage } D}.$$

In the cross-country exercises (Experiments 3–4), we additionally report cross-sectional dispersion (p10–p90 or deciles) of income, agricultural employment shares, and food insecurity.

5.2.1 Experiment 1: Responses to a Common Climate Damage

We first compare a benchmark ("rich") economy to a "poorer" economy obtained by lowering aggregate and agricultural productivity parameters. Specifically, we set $(A, \kappa) = (0.4, 0.6)$ for the poorer economy while holding all other parameters fixed. In the no-shock equilibrium ($D = 0$), the poor economy features dramatically lower agricultural productivity: agricultural TFP is about 24% of the rich level. This lower productivity is associated with much smaller farms and a substantially larger agricultural employment share (about 40% versus 5% in the rich economy). Food insecurity is already pervasive in the poor equilibrium (around 70% of the population), while it remains close to zero in the rich benchmark.

We then expose both economies to the same climate shock $D = 0.3$. Given the exponential damage structure, this corresponds to an exogenous productivity decline of about 26% in the absence of adaptation.

Main results. The rich economy adapts significantly more: average adaptation effort is more than twice as large as in the poor economy (0.32 versus 0.13), and roughly 21% of the exogenous damage is mitigated, compared to about 8% in the poor case. Consequently, realized agricultural TFP declines less in the rich economy. In the rich economy, the agricultural employment share increases only moderately (from about 5% to 6%), and food insecurity rises slightly (from 0.7% to 1.5%). In contrast, the poor economy experiences a sharp structural reversal: the agricultural employment share jumps from about 40% to more than 60%, average farm size contracts markedly (from 0.93 to 0.62), and food insecurity increases from roughly 70% to about 90%.

Overall, the same climate shock generates limited aggregate effects in the rich economy but triggers large reallocation toward low-productivity agriculture and severe welfare losses in the poor economy.

Table 5: Benchmark economy vs. poorer economy: no climate shock ($D = 0$)

	Rich	Poor
Agricultural TFP	1.00	0.24
Agricultural employment share (%)	5.00	40.30
Average farm size	7.50	0.93
Food insecurity (pop. share, %)	0.66	70.45

Notes: The poor economy sets $(A, \kappa) = (0.4, 0.6)$.

Table 6: Experiment 1: Richer economies adapt more and mitigate climate damage ($D = 0.3$)

Climate damage shock	$D = 0.3$	
	Rich	Poor
Average adaptation	0.32	0.13
Ag. prod. loss without adaptation (%)	25.92	25.92
Ag. prod. loss with adaptation (%)	20.43	23.84
Share of damage mitigated (%)	*21.19*	*8.03*

Notes: "Without adaptation" uses $TFP_a = (1 - D)$; "with adaptation" uses realized equilibrium agricultural TFP net of endogenous adaptation. The mitigated share is $1 - \frac{\text{realized loss with adaptation}}{D}$.

Table 7: Experiment 1: Climate damages affect poorer economies much more

	Rich		Poor	
Climate damage shock	$D = 0$	$D = 0.3$	$D = 0$	$D = 0.3$
Agricultural TFP	1.00	0.89	0.24	0.19
Agricultural employment share (%)	5.00	5.93	40.30	60.62
Average farm size	7.50	6.33	0.93	0.62
Food insecurity (pop. share, %)	0.66	1.54	70.45	90.14

Notes: Food insecurity is the population share with consumption below the subsistence threshold in the model.

5.2.2 Experiment 2: Heterogeneous Climate Damages by Income Group.

We discipline the magnitude of climate damages using cross-country projections from the GFDL scenario. Countries are split at the median level of real GDP per capita, and we compute the average projected agricultural yield ratio for each group. This implies an exogenous agricultural TFP damage of $D^H = 0.27$ (corresponding to an average yield loss of approximately 23.9%) for high-income economies and $D^L = 0.34$ (corresponding to an average yield loss of approximately 29.0%) for low-income economies.

We solve the model separately for a rich (baseline) economy and for a poor economy (characterized by lower $A = 0.4$ and $\kappa = 0.6$), both under no shock and under their respective income-group-specific shock. All equilibria are computed with identical structural parameters except for (A, κ) and the exogenous damage parameter D. We then compare adaptation, realized agricultural losses, structural change, aggregate productivity, and food insecurity outcomes.

Results. Under heterogeneous damages, the gap between rich and poor economies widens sharply. The rich economy adapts substantially more (0.32 vs. 0.13), mitigating about 21.27% of the exogenous damage, compared to only 7.91% in the poor economy. As a result, realized agricultural productivity losses are smaller in the rich economy (5.14%) than in the poor one (7.92%), despite the latter facing a larger initial shock.

The shock induces a moderate increase in agricultural employment in the rich economy (from 5.00% to 5.85%), while the poor economy experiences a dramatic reallocation toward agriculture (from 40.3% to 64.4%). Aggregate labor productivity declines modestly in the rich economy (from 1.00 to 0.99, relative to the benchmark), but collapses in the poor economy (from 0.28 to 0.19). Food insecurity increases in both cases, but the rise is disproportionately large in the poor economy (from 70.45% to 91.40%), compared to the rich one (from 0.66% to 1.44%).

Overall, allowing climate damages to vary by income group substantially amplifies cross-country inequality relative to a common-shock benchmark.

Table 8: Experiment 2: income-group-specific climate damages

	High-income (Rich)		Low-income (Poor)	
Climate damage shock (% ag. prod.)	No shock	$D^H = 23.9\%$	No shock	$D^L = 29.0\%$
Average adaptation level	–	0.32	–	0.13
Realized ag. prod. loss with adaptation (%)	–	5.14	–	7.91
Share of damage mitigated (%)	–	21.27	–	7.91
Agricultural employment share (%)	5.00	5.85	40.30	64.40
Aggregate labor productivity	1.00	0.99	0.28	0.19
Food insecurity (pop. share, %)	0.66	1.44	70.45	91.40

Notes: High- and low-income economies are defined relative to the median level of real GDP per capita. D^H and D^L are computed from average projected yield losses under the GFDL scenario. Aggregate labor productivity is measured relative to the rich no-shock benchmark.

5.2.3 Experiment 3: Cross-Country Calibration and Inequality under Common Climate Damage

WORK IN PROGRESS... We calibrate the model country-by-country using observed land endowments and endogenous productivity parameters. For each country c, land endowment L_c is fixed using land per capita relative to Italy, while (A_c, κ_c) are calibrated at $D = 0$ to jointly match the agricultural employment share $N_{a,c}$ and income per worker relative to Italy under a fixed-price income definition. Preference parameters and the ability distribution are held constant across countries. We then impose a uniform agricultural productivity shock of $D = 0.2$ and solve the general equilibrium separately for each country. Because the shock is identical across economies, all cross-country differences in outcomes reflect structural heterogeneity rather than differential exposure. The shock generates a marked increase in global dispersion. The cross-country 90–10 income ratio rises from 8 in the baseline to above 10 under the climate shock. Losses are concentrated in the lower tail of the distribution: countries in the bottom income decile experience income declines of roughly 3–4 percent, compared to less than 1 percent in the top decile. Reallocation toward agriculture is substantially stronger in low-income economies. Agricultural employment in the bottom decile increases by approximately 18 percentage points, compared to roughly 3 percentage points in middle-income economies. Food insecurity also rises disproportionately in the lower tail, increasing by 8–10 percentage points in the poorest deciles. Table **??** summarizes baseline levels and post-shock changes for bottom, median, and top income deciles.

Table 9: Experiment 4 (work in progress): country-specific projected damages

Outcome (change from baseline)	Mean	p10	p90	Share worse than baseline (%)
Realized agricultural prod. loss (%)				
Aggregate labor productivity (%)				
Agricultural employment share (pp)				
Food insecurity (pp)				

Notes: *Work in progress.* Country-specific shocks D_c will be taken from projected climate damages; outcomes are computed in general equilibrium.

5.2.4 Experiment 4: Cross-country income distribution under heterogeneous projected climate damage.

We combine the country-specific calibration in Experiment 3 with country-specific projected climate damages D_c. This allows the model to map projected climate impacts into a global distribution of winners and losers, where some high-latitude/high-income countries may face small damages (or even benefits) while many low-income countries face large damages.

Expected results. Introducing heterogeneity in D_c should substantially increase cross-country dispersion in outcomes relative to Experiments 2–3. We expect a pronounced right tail of adverse outcomes concentrated among poorer countries: very large increases in food insecurity, sharp reversals of structural transformation (labor reallocation into agriculture), and large declines in aggregate productivity. Conversely, a subset of rich countries may show negligible impacts or modest gains, generating a "two-sided" distribution of climate impacts.

Figures/tables to report. (i) A map or binned scatter of realized damages vs. income; (ii) decile plots of changes in food insecurity and aggregate productivity; (iii) a table decomposing cross-sectional dispersion into: baseline heterogeneity, heterogeneity in D_c, and endogenous adaptation (mitigation).

Implementation notes (to ensure comparability across experiments). (i) We keep preferences and technology parameters fixed across economies and vary only (A, κ, L) and the shock D; (ii) for each counterfactual, we recompute the stationary equilibrium, including the endogenous adaptation decision rule; (iii) we report both level outcomes and changes relative to each economy's own baseline; and (iv) we verify that targeted calibration moments remain matched in the baseline (no-shock) equilibria for Experiments 1 and 3 by construction.

6 Conclusion

TBW

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Online Appendix

A Empirical Findings: Robustness

Table A.1: First-stage regressions: adaptation and temperature interaction

	(1) IV at $t-1$	(2) IV at t
Panel A: Dependent variable = log(Adaptation)		
IV(Adaptation)	0.283***	0.291***
	(0.054)	(0.052)
IV(Adaptation) × HeatShock	0.015	0.002
	(0.030)	(0.031)
HeatShock	−0.225	−0.114
	(0.272)	(0.275)
First-stage F (excluded instruments)	17.9	25.6
R^2	0.25	0.27
Observations	3,079	3,270
Year, sector, altitude FE	✓	✓
Panel B: Dependent variable = HeatShock × log(Adaptation)		
IV(Adaptation)	0.026	−0.001
	(0.018)	(0.030)
IV(Adaptation) × HeatShock	0.286***	0.281***
	(0.069)	(0.056)
HeatShock	−1.158**	−1.062***
	(0.483)	(0.369)
First-stage F (excluded instruments)	9.6	21.4
R^2	0.44	0.46
Observations	3,079	3,270
Year, sector, altitude FE	✓	✓

Notes: The table reports first-stage regressions corresponding to the IV (2SLS) specifications in Table 4. In Panel A, the dependent variable is log(Adaptation$_{it}$); in Panel B, the dependent variable is HeatShock$_{it}$ × log(Adaptation$_{it}$). The excluded instruments are the log of EU environmental funds received by the farm ("IV(Adaptation)") and its interaction with the Heat Shock HeatShock$_{it}$ × IV(Adaptation)$_{it}$. Column (1) uses instruments measured at $t-1$; column (2) uses instruments measured at t. All regressions include year, sector, and altitude fixed effects. Standard errors are clustered at the province level. Reported first-stage F-statistics are for the joint significance of the excluded instruments.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (two-sided tests).

Table A.2: Robustness: Climate Shocks × $FarmSize_{i,0}$ Without Main Effect of $FarmSize_{i,0}$

	(1)	(2)
	Dependent variable: log(Drip irrigation + 1)	
Temperature (t)	-0.00933	
	(0.0156)	
Temp(t) × log farm size$_{i,0}$	0.00695***	
	(0.000977)	
Temperature (t–1)		-0.0115
		(0.0174)
Temp(t–1) × log farm size$_{i,0}$		0.00670***
		(0.00101)
Constant	0.130	0.183
	(0.295)	(0.328)
N	99,102	70,359
Year FE	✓	✓
Sector FE	✓	✓

Standard errors clustered at the province level in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: This appendix table reports robustness checks corresponding to the mechanism specification in Table 3. Each column estimates a model in which the effect of climate shocks on adaptation is allowed to vary with farm size, but the main effect of log(Farm Size$_{i0}$) is intentionally excluded. The dependent variable is $\log(1 + \text{Drip Irrigation}_{it})$.

Column (1) uses the contemporaneous temperature measure Temp$_{it}$ and its interaction with farm size, while Column (2) uses the lagged temperature measure Temp$_{it-1}$ and its interaction with farm size. As a robustness check, we replaced initial farm size with contemporaneous log farm size; coefficients in both panels remain virtually identical in magnitude and significance.

Table A.3: Determinants of Log TFP: Farm Size, Temperature, and Adaptation

	(1) Log TFP	(2) Log TFP	(3) Log TFP
Log Farm Size	0.0562		0.0411
	(0.107)		(0.101)
Temperature	-0.0343**	-0.0217*	-0.0456**
	(0.0164)	(0.0124)	(0.0204)
Temperature × Log Farm Size	0.00387		0.00842
	(0.00585)		(0.00552)
Log Adaptation		0.246*	-0.444
		(0.125)	(0.344)
Temperature × Log Adaptation		0.000358	0.0381**
		(0.00631)	(0.0166)
Log Farm Size × Log Adaptation			0.266**
			(0.102)
Temp × Log Size × Log Adaptation			-0.0152***
			(0.00490)
Constant	7.569***	7.604***	7.529***
	(0.282)	(0.227)	(0.371)
Observations	99,072	99,071	99,071
Adj. R^2	0.369	0.465	0.488

All specifications control for year×sector and year×altitude fixed effects.

Standard errors clustered at the province level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4: Climate Adaptation, $TFP_{i,0}$ and Temperature Shocks (Robustness)

	(1)	(2)	(3)
		Dependent variable: log(Drip irrigation + 1)	
$TFP_{i,0}$	0.174***	0.172***	0.111***
	(0.00312)	(0.0271)	(0.0334)
Temperature shock (dtemp)		-0.0221	
		(0.0140)	
$TFP_{i,0}$ × Temperature shock		-0.00566	
		(0.00624)	
Hot days			0.00178
			(0.00202)
$TFP_{i,0}$ × Hot days			0.00179**
			(0.000780)
Constant	0.299***	0.295***	0.240***
	(0.00238)	(0.0403)	(0.0749)
N	85,514	61,069	85,514
Year FE	✓	✓	✓
Sector FE	✓	✓	✓

Robustness: replacing initial farm size with initial farm-level productivity ($TFP_{i,0}$) yields consistent results. Baseline effects remain positive and statistically significant, and the interaction with heat exposure is preserved, supporting the interpretation that more productive farms are more responsive in adapting through drip irrigation. Standard errors clustered at the province level in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5: Marginal effect of temperature shocks by farm-size quintile

	(1) log(days > 30)	(2) log(days > 35)
Q1 (small)	-0.120**	-0.045*
	(0.052)	(0.024)
Q2	-0.064**	-0.020
	(0.027)	(0.019)
Q3	-0.069*	-0.018**
	(0.037)	(0.009)
Q4	-0.090	0.008
	(0.079)	(0.019)
Q5 (large)	0.004	0.000
	(0.062)	(0.025)
$Q5 - Q1$	0.123*	0.045
	(0.069)	(0.031)
Year × Sector FE	✓	✓
Year × Altitude FE	✓	✓
Obs.	85,515	73,052

Notes: Entries report average marginal effects of temperature shocks on log(TFP) by farm-size quintile. Standard errors (clustered at the province level) are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

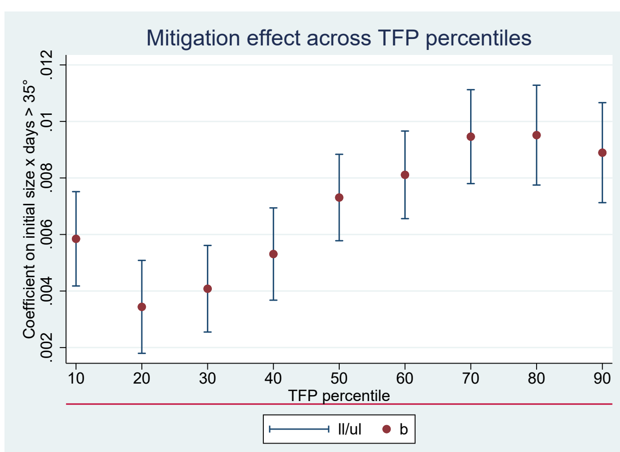

Figure A.1: Quantile regression (deciles): mitigation effect of baseline farm size. Coefficient estimates for the interaction term avgsize × veryhot across deciles of the TFP distribution. A positive coefficient indicates that larger farms experience a weaker productivity loss from very hot days (> 35°C). Vertical bars denote 95% confidence intervals.

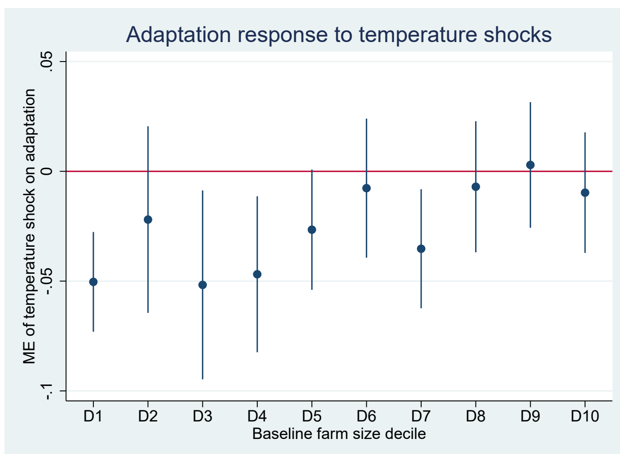

Figure A.2: Adaptation response to Heat Shocks by baseline farm-size decile. The figure reports the marginal effect of Heat Shocks (*dtemp*) on technology adoption, measured as log(Drip irrigation + 1), estimated separately across deciles of baseline farm size. The negative response to heat shocks is concentrated among smaller farms (D1–D4) and attenuates substantially for larger farms (D8–D10), where the effect becomes close to zero. Vertical bars denote 95% confidence intervals.

B Other functional forms of climate adaptation $g(D, x)$

We consider several parametric specifications for the damage–adaptation function $g(D, x)$.

(i) Exponential damage with full mitigation. We first consider an exponential form in which adaptation can, in principle, fully offset climate damage. Let $D \in [0, 1)$ denote the productivity loss in the absence of adaptation, so that $g(D, 0) = 1 - D$. We set

$$g(D, x) \; = \; 1 - De^{-\eta x}, \qquad \eta > 0. \tag{B.1}$$

This specification satisfies

$$g(D, 0) = 1 - D, \qquad g(0, x) = 1 \;\; \forall x, \qquad \lim_{x \to \infty} g(D, x) = 1,$$

so that a farm with $x = 0$ bears the full damage D, while arbitrarily large adaptation $(x \to \infty)$ restores productivity to its no-damage level. Moreover,

$$g_x(D, x) = D\eta e^{-\eta x} > 0, \qquad g_{xx}(D, x) = -D\eta^2 e^{-\eta x} < 0,$$

so adaptation exhibits diminishing returns.

Under the linear profit specification $\pi(sz) = \Omega sz$ derived above and linear cost $c(x) = x$, the first-order condition (**??**) becomes

$$\Omega s_i D_i \eta e^{-\eta x_i} = 1,$$

which yields the interior optimal adaptation level

$$x(s_i, D_i) \; = \; \frac{1}{\eta} \log \big(\Omega s_i D_i \eta \big), \tag{B.2}$$

whenever $\Omega s_i D_i \eta > 1$, and $x(s_i, D_i) = 0$ otherwise. This implies that larger and more climate-exposed farms invest more in adaptation.

A convenient feature of (B.1) is that it delivers a simple log-linear representation of $\log g(D, x)$ around the data, which maps directly into reduced-form regressions of $\log \text{TFP}$ on temperature, adaptation, and their interaction. A limitation is that this specification allows full mitigation: for any given D, sufficiently large x restores $g(D, x)$ arbitrarily close to 1.

(ii) Exponential damage with partial mitigation. To allow for residual climate damages even under very high adaptation, we introduce a parameter $\underline{\phi} \in (0,1)$ capturing the minimal damage share that cannot be mitigated. We set

$$g(D,x) \;=\; 1 - \left[\underline{\phi} + (1-\underline{\phi})e^{-\eta x}\right] D, \qquad 0 < \underline{\phi} < 1,\ \eta > 0. \tag{B.3}$$

This form satisfies

$$g(D,0) = 1 - D, \qquad g(0,x) = 1 \ \ \forall x, \qquad \lim_{x\to\infty} g(D,x) = 1 - \underline{\phi} D,$$

so that only a fraction $1-\underline{\phi}$ of the damage D can be eliminated, and a residual share $\underline{\phi} D$ remains even as $x \to \infty$. Adaptation remains increasing and concave:

$$g_x(D,x) = (1-\underline{\phi})D\eta e^{-\eta x} > 0, \qquad g_{xx}(D,x) = -(1-\underline{\phi})D\eta^2 e^{-\eta x} < 0.$$

The parameter $\underline{\phi}$ has a transparent interpretation,

$$\underline{\phi} \;=\; \frac{\text{residual damage under arbitrarily high adaptation}}{\text{damage with no adaptation}},$$

and we therefore treat $\underline{\phi}$ as an externally calibrated parameter, using quantitative estimates of the maximal fraction of climate damages that can be avoided through adaptation in the agricultural sector. Given $\underline{\phi}$, the remaining parameters (δ, η) can be estimated by matching the model-implied response of log TFP to temperature, adaptation, and their interaction to the reduced-form coefficients.

(iii) Hyperbolic damage with partial mitigation. An alternative specification replaces the exponential attenuation with a rational function, which decays more slowly in x:

$$g(D,x) \;=\; 1 - D\left[\underline{\phi} + (1-\underline{\phi})\frac{1}{1+\eta x}\right], \qquad 0 < \underline{\phi} \leq 1,\ \eta > 0. \tag{B.4}$$

Again,

$$g(D,0) = 1 - D, \qquad g(0,x) = 1 \ \ \forall x, \qquad \lim_{x\to\infty} g(D,x) = 1 - \underline{\phi} D,$$

so that only a fraction $1-\underline{\phi}$ of damage can be mitigated. The marginal effect of adaptation is

$$g_x(D,x) = D(1-\underline{\phi})\frac{\eta}{(1+\eta x)^2} > 0,$$

with $g_{xx}(D,x) < 0$, implying diminishing returns to adaptation.

Relative to the exponential case, the hyperbolic form implies that mitigation effects taper off more gradually for large x, which can be desirable in counterfactuals that consider large changes in adaptation. Moreover, expanding $\log g(D, x)$ around the sample mean of (D, x) yields a log-linear approximation in temperature, $\log x$, and their interaction, closely aligned with the empirical specification used in our regressions. As in (B.3), the parameter $\underline{\phi}$ can be calibrated from external evidence on residual damages, while η is disciplined by the estimated elasticity of log TFP with respect to adaptation and its interaction with temperature.

(iv) Regression-consistent wedge. To match the reduced-form specification

$$\log \mathrm{TFP}_{it} = \beta_0 + \beta_1 T_{it} + \beta_2 \log x_{it} + \beta_3 (T_{it} \log x_{it}) + \varepsilon_{it},$$

we assume that the climate–adaptation multiplier takes the form

$$z_i = g(T_i, x_i) = \exp\bigl(-D(T_i)\bigr)\, x_i^{\psi + \eta D(T_i)},$$

so that

$$\log z_i = -D(T_i) + D(T_i)\, \eta \log x_i + \psi \log x_i.$$

With the linear damage index $D(T) = \delta T$, this implies

$$\log \mathrm{TFP}_{it} = \alpha_i - \delta T_{it} + \delta\eta\, T_{it} \log x_{it} + \psi \log x_{it},$$

and therefore

$$\beta_1 = -\delta, \qquad \beta_2 = \psi, \qquad \beta_3 = \delta\eta.$$

The specification has several advantages and disadvantages.

Pros.

- **Direct link to the reduced form.** With a linear damage index $D(T) = \delta T$, the model reproduces exactly the empirical regression

  $$\log \mathrm{TFP}_{it} = \beta_0 + \beta_1 T_{it} + \beta_2 \log x_{it} + \beta_3 \bigl(T_{it} \log x_{it}\bigr) + \varepsilon_{it},$$

  with a one-to-one mapping

  $$\beta_1 = -\delta, \qquad \beta_2 = \psi, \qquad \beta_3 = \delta\eta.$$

  Thus the estimated coefficients $(\beta_1, \beta_2, \beta_3)$ can be interpreted directly as structural parameters (δ, η, ψ).

- **Transparent interpretation.** The term $-D(T)$ captures the pure effect of temperature on productivity, $D(T)\,\eta \log x$ captures the fact that adaptation is more valuable in hotter conditions, and $\psi \log x$ allows for a (possibly small) direct productivity effect of adaptation even in the absence of climate damage.

- **Tractability and closed-form decisions.** Under the linear profit specification $\pi(sz) = \Omega sz$ and linear cost $c(x) = x$, the first-order condition for adaptation,

$$\frac{\partial}{\partial x}\big[\Omega s\, g(T,x)\big] = 1,$$

  becomes

$$\Omega s\ \exp\big(-D(T)\big)\, x^{\psi+\eta D(T)-1}\big(\psi + \eta D(T)\big) = 1,$$

  which yields a closed-form expression for $x(s,T)$ whenever $\psi + \eta D(T) \neq 1$. This facilitates comparative statics and quantitative counterfactuals.

- **Monotonicity in adaptation.** For $D(T) \geq 0$ and $\psi + \eta D(T) > 0$, we have

$$\frac{\partial \log z}{\partial \log x} = \psi + \eta D(T) > 0,$$

  so that an increase in adaptation x always raises climate-adjusted productivity.

Cons.

- **No built-in partial mitigation.** For fixed $T > 0$ and $\psi + \eta D(T) > 0$, we have $z(T,x) \to \infty$ as $x \to \infty$. Hence adaptation can more than fully offset climate damage and raise TFP arbitrarily above the no-damage benchmark. This may be at odds with the idea that even very large adaptation efforts cannot completely undo climate change, or that there is an upper bound on feasible productivity.

- **Marginal effect of temperature can change sign at high adaptation.** The marginal effect of temperature on log productivity is

$$\frac{\partial \log z}{\partial T} = -D'(T) + D'(T)\,\eta \log x = D'(T)\big(\eta \log x - 1\big).$$

  For moderate x (so that $\eta \log x < 1$) this is negative, as desired. However, for sufficiently large x the model implies $\partial \log z/\partial T > 0$, i.e. additional warming becomes beneficial once adaptation is very high. Empirically, the parameter estimates may ensure that this region is far outside the observed support of x, but the possibility is present in the functional form.

- **Adaptation at zero damage if $\psi > 0$.** When $D(T) = 0$, we obtain $z(0, x) = x^{\psi}$. If $\psi > 0$, adaptation has a strictly positive effect on productivity even in the absence of climate damage, and with linear costs the optimal choice $x(0)$ is strictly positive. This violates the normative condition that farms would not invest in climate adaptation when there is no climate risk. One can enforce $x(0) = 0$ by imposing $\psi = 0$ in the structural model and treating a small estimated β_2 as capturing other, unmodelled channels.

- **Unbounded gains in extreme counterfactuals.** Because $z(T, x)$ grows without bound in x for any fixed $T > 0$, aggressive adaptation policies in counterfactual simulations (very large x) can generate unrealistically large productivity gains. If the analysis focuses on moderate changes around the observed range of (T, x), this may be of limited concern, but for large departures from the data a bounded specification (such as the hyperbolic or exponential partial-mitigation forms discussed above) may be more appropriate.