Climate Change and Economic Prosperity: Evidence from a Flexible Damage Function*

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Abstract: The climate damage function used to assess the economic impact of secular changes in temperature is one of the most speculative components of integrated assessment models of climate change. Existing work informing this debate is based on pooled empirical models incorporating simple interaction terms with 'low income' or 'high temperature', which further give little regard to long-term dynamics. We use aggregate and agricultural data for 151 countries over the past six decades to estimate dynamic heterogeneous models which (a) allow the weather-output nexus to differ freely across countries, (b) help distinguish short-run from long-run effects, and (c) account for unobserved time-varying heterogeneity. Overall, we find that, in low-income or high-temperature countries, a permanent 1°C rise in temperature is associated with a fall in income per capita of about 1.3% in the short-run and 8.5% in the long run in high-temperature countries. The long-run effects are substantially larger than those commonly suggested in the literature and can be traced in the analysis of aggregate Total Factor Productivity (TFP) as well as sectoral output and TFP in agriculture.

Keywords: temperature, weather, climate change, economic development, economic growth

JEL codes: E23, O13, Q54, Q56

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1 Introduction

There is now little doubt that climate change will have a substantial impact on ecosystems and people's livelihoods.[1] A key contribution of the Economics discipline to the quantification of these effects has been the development of Integrated Assessment Models (IAMs), which show how carbon emissions link climate change to economic growth and help identifying the required policies to tackle climate change (Nordhaus 2013). The cost-benefit analysis underlying the 'optimal' amount of global warming relies on climate damages and abatement (mitigation) costs and seeks to find the temperature increase associated with the minimum sum of these two costs. In his Nobel Prize lecture, Nordhaus (2019) suggests that a 3 to 3.5°C rise in temperature by the turn of the next century relative to pre-industrial levels may be 'optimal'. However, this result is contingent on the parameters underlying it, notably the expected magnitude of the economic damages caused by a rise in temperature (Dietz & Stern 2015, Hänsel et al. 2020). In recent years, new estimates of the damage function have been provided by fixed effects panel data studies, relying on weather shocks in annual data for identification (see Auffhammer (2018) and Kolstad & Moore (2020) for recent reviews): Dell et al. (2012) conclude that economic prosperity in low-income countries is much more affected by temperature shocks than that in richer countries ('poor countries suffer the most'), while Burke et al. (2015) suggest that the detrimental effect of temperature shocks rises with the country-specific level of temperature ('hot countries suffer the most').[2] Once the respective temperature-GDP per capita estimates of Dell et al. (2012) and Burke et al. (2015) are fed into revised damage functions of standard IAMs (Moore & Diaz 2015, Glanemann et al. 2020), the 'optimal' limit for temperature increases falls below 2°C (in line with the Paris Climate Agreement), indicating that the estimated climate-induced economic damages are much higher than those conventionally assumed. Hence, panel estimates of the temperature-growth relationship have crucial implications in terms of the speed and strength of policy responses to climate change and therefore require further investigation to assess their validity (Diaz & Moore 2017, Auffhammer 2018).

In this paper we ask whether these important empirical estimates are based on sufficiently general specifications to capture the complex heterogeneous relationship between local climate and prosperity in the context of global shocks. One way to think about the panel data approaches by Dell et al. (2012) and Burke et al. (2015) is to view them as relaxing the strong homogeneity assumption underlying conventional pooled fixed effects estimations (e.g. for US agriculture, see Deschênes & Greenstone 2007), since they allow for parameters to differ across groups of countries, depending on their income or temperature levels, respectively. Nevertheless, these

[1]For a comprehensive survey of the literature on this issue, see the reports of the Intergovernmental Panel on Climate Change, available at `https://www.ipcc.ch/reports/`

[2]Focusing on cross-country analysis, other studies in the latter strand of the literature include Diffenbaugh & Burke (2019), Henseler & Schumacher (2019), Kalkuhl & Wenz (2020), Acevedo et al. (2020), Nath et al. (2023) while Newell et al. (2021) suggest, in line with Dell et al. (2012), that income levels play an important role in the distribution of the negative effects of temperature changes. Adopting the Dell et al. (2012) empirical specification, Meierrieks (2021) concludes that the adverse effects of higher temperatures for health outcomes are disproportionally felt in poorer economies, while Miller et al. (2021) find that heat waves have a more damaging economic effect in poorer countries. Additional studies on agriculture (e.g. Ortiz-Bobea et al. 2021, Huang & Sim 2018) have typically sided with the narrative in one or the other of these two camps. Investigating both alternatives, Kahn et al. (2021) find substantial heterogeneity in the effect of weather on economic growth but reject systematic differences favouring differentiation by either average temperature or income, Letta & Tol (2019) uncover evidence for detrimental effects of temperature change on total factor productivity in both hot and poor countries, Acevedo et al. (2020) conclude that 'hot' areas in rich countries may suffer less from weather shocks than high-temperature regions in developing countries.

constraints imposed *ex ante* are still highly restrictive.[3] First, if the underlying equilibrium relationship differs across countries then the fixed effects estimator is a weighted average of country-specific estimates, with weights defined by unit-specific sample size and variance of the variable of interest (Chernozhukov et al. 2013, Gibbons et al. 2019). By giving more weight to countries affected by larger shocks, the fixed effects estimator can yield different results from a more relevant parameter of interest, such as a simple unweighted average of country-specific estimates (Carter et al. 2018, Gibbons et al. 2019). Hence, the fixed effect estimator may not yield a representative *average* effect. In addition, its aggregative nature obscures cross-country heterogenous responses to weather shocks. Second, the appropriate specification for both causal identification and economic interpretation may require the inclusion of lagged outcomes and 'treatment' variables (e.g. temperature) to allow for feedback effects and avoid omitted variable bias (Imai & Kim 2019). However, in the presence of a differential weather-growth nexus across countries (parameter heterogeneity), the dynamic fixed effects estimator is inconsistent, even for a large time series dimension, leading to an underestimation of the coefficient on an explanatory variable of interest and an overestimation of the coefficient on the lagged dependent variable (Pesaran & Smith 1995).[4] Third, in pooled regressions time fixed effects capture global shocks affecting all countries *in the same way* but cannot deal with global shocks affecting (some) countries differentially, which can lead to biased estimators (Pesaran 2006, Bai 2009). Given that climate change is a global phenomenon, it is important to ensure that the first-order effects on economic performance attributed to local weather shocks do not in fact capture the local influence of other global shocks, such as the global economic cycle.

In response to these potential shortcomings of static pooled fixed effects models, we estimate dynamic heterogeneous panel data models accounting for the cross-sectional dependence induced by global shocks — these common correlated effects (CCE) models augment the country regression with cross-section averages of the dependent and independent variables (Pesaran 2006, Chudik & Pesaran 2015). The CCE estimators enable us to obtain country-specific short-run and long-run estimates of the weather-prosperity relationship which are not subject to bias from spillovers and other unobserved time-varying heterogeneities.[5] Figure 1 illustrates the core of our approach: adopting aggregate income per capita data from 1961 to 2019 we present country-specific predictions from flexible running line regressions of the temperature-productivity CCE estimates in 151 countries (on the y-axis) against the country mean temperature in panel (a) and the country average income per capita in panel (b); filled (hollow) markers indicate statistically (in)significant difference from zero (at the 10% level). Country predictions, i.e. the markers, are minimally perturbed to aid illustration. In panel (a) we can see that, for high-temperature countries, the conditional *contemporaneous* temperature effect of a 1°C rise is negative and between -1% and -2%. In panel (b) we see a relatively similar temperature effect for low-income countries. The consistency of findings is not surprising given that the cross-section correlation between income per capita and temperature is around -0.48 — see also Table 1.

In our analysis below we consider a wide range of alternative dynamic specifications adopting output per capita or total factor productivity and sectoral equivalents for agriculture.[6] In order to

[3]See also Rosen (2019) for a less generous assessment of pooled empirical models.

[4]This is an obvious issue in cross-country growth regressions, which usually adopt a conditional convergence framework and control for initial income levels (Durlauf et al. 2005).

[5]Prime examples of existing work employing these models capturing unobserved heterogeneity in productivity analysis are in the context of knowledge spillovers (Blazsek & Escribano 2010, Eberhardt et al. 2013), total factor productivity (Calderón et al. 2015, Eberhardt & Presbitero 2015, Chirinko & Mallick 2017, Chudik et al. 2017, Madsen et al. 2021) and absorptive capacity (De Visscher et al. 2020, Mazzanti & Musolesi 2020).

[6]The focus on the agricultural sector is warranted, not only because this may be one of the economic activities

make the presentation of this myriad of results as parsimonious as possible (while at the same time contrasting our findings to those from standard two-way fixed effects models we introduce three respective groupings, highlighted in the two plots in Figure 1 using vertical dashed lines, for low, medium and high temperature or income countries — these are not *ad hoc* cut-offs but the terciles of the respective distributions across all 151 countries.[7]

Using these three groupings, our benchmark results for aggregate income per capita confirm that high-temperature countries *and* low-income countries are negatively affected by a rise in temperature: a temporary 1°C rise in temperature reduces income per capita by about 1.3% (1.1-1.5%). These findings are in line with previous research, respectively Dell et al. (2012) and Burke et al. (2015). Additional results indicate that these results are driven by a subset of countries that are 'poor' *and* 'hot'. For other country groups, results are ambiguous. For instance, we cannot conclude that low-temperature or high-income countries would *benefit* from climate change as is sometimes suggested in existing research (Burke et al. 2015, Acevedo et al. 2020, Nath et al. 2023). All of the above results, as well as those routinely reported in the literature, correspond to the short-run effect of a weather shock. However, the use of dynamic models also allows us to estimate long-run long-run effects of a permanent rise in temperature, i.e. climate change. Here, our findings are much starker: the long-run effect of a permanent 1°C rise in temperature is expected to reduce income per capita in high-temperature or low-income countries by about 8.5% (7-10%). Although not strictly comparable, this estimate is substantially higher than those reported in recent meta-analyses (e.g. Howard & Sterner 2017, Rennert et al. 2022).[8] In line with recent studies such as Acevedo et al. (2020) and Ortiz-Bobea et al. (2021), we also find that agricultural outcomes are negatively affected by a temperature rise and positively influenced by higher precipitation, especially in high-temperature countries.

Our study makes three contributions to the literature on climate change and economic prosperity. First, using substantially more flexible empirical models, we provide a systematic assessment of recent panel research investigating the income effects of climate change. In a bottom-up manner, we build on and extend the seminal studies of Dell et al. (2012) and Burke et al. (2015) by permitting each country to have its own weather-income relationship, allowing for many more nuances and avoiding the main results being driven by an unknown subset of observations as is the case when adopting squared temperature terms (e.g. Burke et al. 2015, among others). Second, we employ heterogeneous parameter models in the context of dynamic empirical specifications. This means we can easily estimate long-run effects of a permanent change in temperature levels on income per capita levels, without additional assumptions about future economic paths (as required in Burke et al. 2015, among others). We carefully explain why it makes more economic and econometric sense to interpret existing evidence on climate change as having a permanent 'level' effect rather than a 'growth' effect. Third, throughout our empirical analysis we systematically compare and contrast the primary patterns in our findings for countries differentiated by average temperature or average income. Existing work frequently favours one over the other on the basis of initial benchmark regressions but fails to revisit

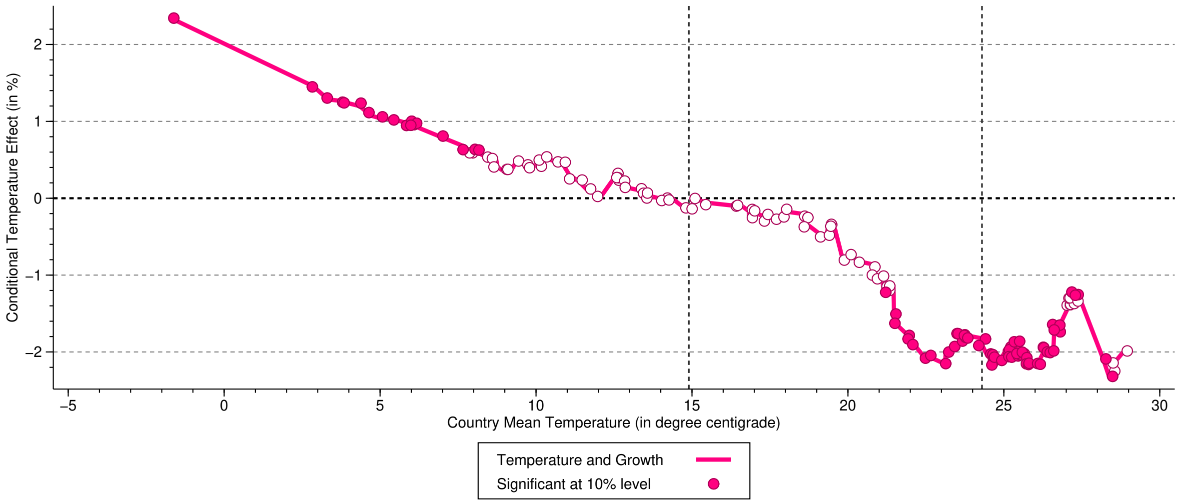
the most exposed to climate change (Ortiz-Bobea et al. 2021) but also because of the significance of agricultural productivity in structural change and hence economic development (e.g. Barrett et al. 2010, Herrendorf et al. 2014, Huneeus & Rogerson 2020).

[7]For the 2FE approach we capture heterogeneity via interaction effects, while for the heterogeneous CCE estimates we follow the literature and calculate the outlier-robust means using an M-estimator (Rousseeuw & Leroy 1987).

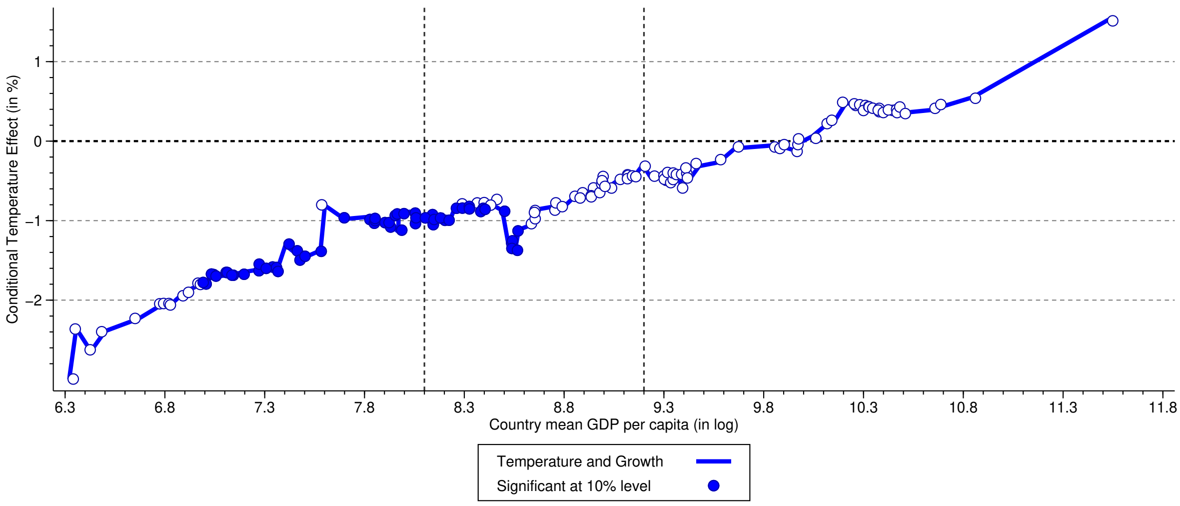
[8]Nath et al. (2023) use an innovative local projections approach accounting for persistence of a temperature shock and find that, in high-temperature countries, a 1°C temperature increase reduces income per capita by about 5% over a ten-year horizon.

Figure 1: The heterogeneous effects of temperature shocks on income per capita

(a) Temperature-Income Effect and Average Country Temperature



(b) Temperature-Income Effect and Average Country Income per Capita



Notes: We present predictions from running line regressions — local linear regressions for k nearest neighbours where $k = N^{0.67}$ — for the estimated short-run effect of temperature on per capita GDP (y-axis) on average country temperature and income per capita in Panels (a) and (b), respectively. These estimates are based on the regressions in column (6) of Tables 2 and 3 (contemporaneous temperature impact). Filled (hollow) markers indicate statistically (in)significant difference from zero (10% level). Predicted effects (the markers) are minimally perturbed to ease illustration. Dashed vertical lines delimit low-, medium- and high-average temperature or -average income country groupings, respectively (these are the full sample terciles, i.e. each segment contains roughly the same number of countries). These plots are for predicted country effects, the equivalent plots showing the raw country estimates can be found in Figure A2 of Appendix A.2.

the relationship in more elaborate specifications. While we tend to find stronger evidence for heterogeneity along existing temperature patterns than by income, at least in the short run, it is very likely that theses differentiated estimates are not independent, given that 'hot' countries are often 'poor'. Indeed, when we combine these categories, it is only the group of countries with above-median temperature and below-median income that are substantially affected by a rise in temperature: a permanent $1°$C temperature rise would induce about a 1.3% income loss in the short-run and a 10% income loss in the long-run. Overall, our findings support studies calling for a much more stringent damage function in IAMs (Moore & Diaz 2015, Glanemann et al. 2020, Rising et al. 2022), especially for low-income countries where parts or all of their (populated) territories are already subject to relatively high, and likely rising, temperature levels.[9]

The remainder of the paper proceeds as follows. In Section 2 we introduce our econometric model and data. We also explain how the short-run and long-run effects are estimated and interpreted. In Section 3, we present our results and discuss them. Section 4 concludes.

2 Econometric model, interpretation and data

2.1 Econometric model

A typical 'growth regression' (Eberhardt & Teal 2011, Barro 2015) is specified as

$$Y_{it} - Y_{it-1} = \gamma Y_{it-1} + X_{it}\iota + \tau_i + \varsigma_t + \varepsilon_{it}, \tag{1}$$

where Y_{it} is the log of income per capita in country i at time t, X a vector of determinants of economic growth, α_i and η_t are country and time fixed effects respectively, ε_{it} is an error term. As highlighted by Caselli et al. (1996), the interpretation of equation (1) depends on the value of the coefficient on the lagged dependent variable. If $\gamma = 0$, the determinants of differences in *steady-state growth rates* are investigated. On the other hand, if $\gamma < 0$, it is the determinants of differences in *steady-state output levels* which are explored. Neoclassical growth theory predicts such a phenomenon of conditional convergence, whereby poorer countries grow faster than richer countries holding other factors constant, and this growth pattern has been found in many studies (Johnson & Papageorgiou 2020). Statistical significance and sign of γ can be tested by not omitting the lagged dependent variable from equation (1).

It is possible that the error term in equation (1) is serially correlated such as $\varepsilon_{it} = \phi\varepsilon_{it-1} + e_{it}$. Wilkins (2018) demonstrates that neglecting this issue leads to biased coefficient estimates, especially if the X variables are also autocorrelated. Using $\varepsilon_{it-1} = (Y_{it-1} - Y_{it-2}) - \gamma Y_{it-2} - X_{it-1}\kappa - \tau_i - \varsigma_t$, the correct model to be estimated to purge this serial correlation is

$$\begin{aligned} Y_{it} - Y_{it-1} = {} & (1+\gamma+\phi)Y_{it-1} - (\phi\gamma)Y_{it-2} + X_{it}\iota - X_{it-1}\iota\phi + \\ & (1-\phi)\tau_i + (1-\phi)\varsigma_t + e_{it}, \end{aligned} \tag{2}$$

where e_{it} is no more serially correlated. Equation (2) is a special case of an autoregressive distributed lag model, ARDL(2,1)

$$\begin{aligned} Y_{it} - Y_{it-1} = {} & \rho_1 Y_{it-1} + \rho_2 Y_{it-2} + X_{it}\beta_1 + X_{it-1}\beta_2 + \\ & \alpha_i + \eta_t + e_{it}, \end{aligned} \tag{3}$$

[9] It is notable that a $1°$C local rise in temperature would add five additional countries (representing about 600 million people in 2019), to the high-temperature group, including Brazil and the Democratic Republic of Congo.

in which, for example, β_2 is no longer constrained to be equal to $\iota\phi$ or, more generally, $\beta_2^2 + \beta_1\beta_2\rho_1 - \rho_2\beta_1^2 = 0$. It may indeed be the case that the second-order lagged dependent variable and the first lag of the independent variables have independent effects beyond correcting for error persistence (Cook & Webb 2021). Hendry (1995), De Boef & Keele (2008) or Beck & Katz (2011) recommend estimating a general model, such as the ARDL(2,1), adding further lags of the dependent variable if there is still evidence of serial correlation in the residuals.

In the context of the weather-income nexus, such a general model is

$$\begin{aligned}\Delta Y_{it} = &= \rho_1 Y_{it-1} + \rho_2 Y_{it-2} + h(T_{it}) + h(T_{it-1}) + g(PP_{it}) + g(PP_{it-1}) \\ &\quad + \pi_{i1}t + \pi_{i2}t^2 + \alpha_i + \eta_t + e_{it},\end{aligned} \tag{4}$$

where $\Delta Y_{it} = Y_{it} - Y_{it-1}$ and the X variables correspond to current and lagged functions h($\cdot$) of temperature T and g($\cdot$) of precipitation PP, as well as country-specific linear and quadratic time trends. Following Hsiang et al. (2013) and Burke et al. (2015), this model *only* includes linear and quadratic country-specific time trends as time-varying control variables. Their presence reduces the risk of spurious regression, accounts for slow-changing determinants of income per capita (e.g. demography, educational attainment, political institutions, economic policies) whose effects are allowed to vary across countries, and may avoid any risk of 'overcontrolling', by not including variables themselves affected by climatic events (Dell et al. 2014).[10]

The econometric models estimated in the literature can be interpreted as constrained variants of equation (4) with some limited cross-country heterogeneity allowed in the temperature and precipitation coefficients. For example, the models estimated by Dell et al. (2012) impose $\rho_1 = \rho_2 = \pi_{i2} = 0$, and in their preferred specification assume that the marginal effects of temperature and precipitation vary systematically between developed and developing (DEV) countries: the contemporaneous impact of a change in temperature in their model without lagged temperature is captured by $\delta_{i,1} = \delta_1 + \delta_{11} \times DEV_i$, where DEV_i is a dummy for countries with below-median income per capita in the base year.[11] The models estimated by Burke et al. (2015) impose $\rho_1 = \rho_2 = 0$, while they further drop the lags of temperature and precipitation. They capture heterogeneity across countries in the temperature and precipitation effect on growth by adopting squared terms for these variables, substituting the step-function of Dell et al. (2012) with a quadratic function, which implies a contemporaneous impact of a change in temperature of $\delta_{i,1} = \delta_1 + 2 \times \delta_{11} \times T_{i0}$, where δ_1 and δ_{11} are the coefficients on the levels and squared temperature terms and T_{i0} is the base year temperature of country i.

In this paper, we suggest going further than existing research by estimating a general model in which we do not impose pooling constraints on *any* of the coefficients estimated:

$$\begin{aligned}\Delta Y_{it} &= \rho_{i,1} Y_{i,t-1} + \rho_{i,2} Y_{i,t-2} + \delta_{i,1} T_{it} + \delta_{i,2} T_{i,t-1} + \kappa_{i,1} PP_{it} + \kappa_{i,2} PP_{i,t-1} \\ &\quad + \pi_{i,1}t + \pi_{i,2}t^2 + \alpha_i + \sum_{s=t-k}^{t} \lambda_{i,s} f_s + e_{it},\end{aligned} \tag{5}$$

where f_s are current and lagged unobserved common factors with associated country-specific factor loadings λ_{is}.[12]

[10] The lagged dependent variable terms may also partly control for omitted variables since, by definition, they tend to be determined by the latter (Beck & Katz 2011).

[11] These authors also estimate models for a HOT interaction of countries above median average temperature in 1950 but find this not to yield any statistically significant results and they therefore do not investigate this alternative source of heterogeneity in their more elaborate dynamic specifications.

[12] Year dummies are accommodated within this 'multi-factor error structure'.

When moving from a pooled model to a heterogeneous parameter model estimated at the country level (e.g. Pesaran & Smith 1995), we introduce a great deal of flexibility into the relationship between dependent and independent variables. At the same time, however, we assign any variation in the outcome variable of country i to variation in the independent variables of country i exclusively — there is no scope for global (economic, social, cultural or climatic) shocks, or spillovers between countries. This is clearly an extremely strong assumption, and the common factor setup (Pesaran 2006, Bai 2009) seeks to marry the heterogeneous equilibrium relationship with the possibility for global shocks and spillovers affecting countries differentially (e.g. the magnitude of productivity spillovers is in part determined by recipient-country absorptive capacity, see De Visscher et al. 2020). The common factor framework represents a flexible means to capture such heterogeneity, which explains its popularity in studies of productivity and its determinants (e.g. Eberhardt et al. 2013, Calderón et al. 2015, De Visscher et al. 2020, Mazzanti & Musolesi 2020). Following Pesaran (2006) and Chudik & Pesaran (2015), the unobserved common factors are proxied using lagged and contemporaneous cross-section averages of all observed variables in the model (dependent and independent variables).[13] Formally, we estimate the following cross-section average augmented model

$$\begin{aligned} \Delta Y_{it} \quad &= \quad \rho_{i,1} Y_{i,t-1} + \rho_{i,2} Y_{i,t-2} + \delta_{i,1} T_{it} + \delta_{i,2} T_{i,t-1} + \kappa_{i,1} PP_{it} + \kappa_{i,2} PP_{i,t-1} \\ &\quad + \pi_{i,1} t + \pi_{i,2} t^2 + \alpha_i + \sum_{s=t-3}^{t} \left(\zeta^1_{i,s} \overline{\Delta Y_s} + \zeta^2_{i,s} \overline{T_s} + \zeta^3_{i,s} \overline{PP_s} \right) + e_{it}, \end{aligned} \tag{6}$$

where bars indicate unweighted cross-section averages across all countries in the sample. Following a recommended rule of thumb (Chudik & Pesaran 2015) we include three lags of the cross-section averages in addition to their contemporaneous values.

Output and the weather are not only determined by local factors but also global factors. Given economic globalisation and the differential exposure of countries to external shocks, it is imperative to account for the country-specific effects of global income shocks. Deliberately controlling for heterogeneous sensitivities to global climate shocks is a more difficult undertaking. The CCE specification in (6) includes the cross-section averages for the weather variables at the appropriate lag lengths — however, it is difficult to suppress the notion that this may 'throw out the baby with the bath water': weather and climate are *local* phenomena but within a *global* framework (e.g. the influence of the Gulf Stream or El Niño). On the one hand, local climate shocks are partly driven by global shocks and we therefore may not wish to eliminate the country-specific effects of the latter. On the other hand, a global climate shock could have an indirect impact on the economy through international economic spillovers (e.g. lower agricultural yields in country i may boost demand for the agricultural exports of country j). In order to acknowledge the possibility that the standard CCE estimator may perfectly account for global climate shocks, we also estimate a variant of equation (6) where only cross-section averages (CA) of the productivity (dependent) variable are included, i.e. $\zeta^2 = \zeta^3 = 0 \, \forall i, s$ — we refer to the latter as CCE1 and the implementation with all three CA as CCE3 in the results tables.[14]

For a more parsimonious presentation of the results we compute robust short-run and long-run mean estimates by tercile,[15] for instance for the short-run temperature effect

$$\hat{\delta}_{i,1} \quad = \quad \tau_1 \text{Low}_i + \tau_2 \text{Medium}_i + \tau_3 \text{High}_i + \epsilon_i, \tag{7}$$

[13] In Appendix A.1, we discuss the mechanics of the CCE approach. Note that lags of income levels are not included since this would generate collinearity: $\Delta Y_{it} = Y_{it} - Y_{it-1}$ and average differences equal differences in averages.

[14] All Mean Group estimators are implemented using Jan Ditzen's `xtdcce2` command in Stata.

[15] There are two ways of estimating the long-run relationship: (i) estimating robust means for the δ and ρ

where Low_i, Medium_i, and High_i indicate whether country-average temperature for the period 1950-1960 or country-average per capita GDP for the period 1990-2000 belong to the first, second, or third tercile of the respective sample distribution.[16] Given that the dependent variables can include extreme observations, we use an estimator robust to outliers, an M-estimator, to obtain robust means (Rousseeuw & Leroy 1987).

We also consider a hybrid (partially pooled) model in which the temperature variables (but not the other variables) are constrained to have the same short-run coefficients within each group of countries. In this way, we may obtain more precise long-run estimates.[17]

2.2 Dynamic effects, interpretation, data

2.2.1 Short-run and long-run estimates

In equation (4) the 'short-run' contemporaneous (year t) and delayed (year $t-1$) impact of a temperature rise correspond to $\delta_{i,1}$ and $\delta_{2,1}$ respectively. Furthermore, the presence of lagged dependent variables implies that the effects of a *permanent* rise in temperature on income per capita persist beyond $t+1$. For example, over three years, the effect of a one-unit increase in temperature on the log of income per capita is

- $\delta_{i,1}$ in Year 1;
- $(1+\rho_{i,1})\delta_{i,1}+\delta_{i,2}$ in Year 2; and
- $(1+\rho_{i,1})^2\delta_{i,1}+\rho_{i,2}\delta_{i,1}+(1+\rho_{i,1})\delta_{i,2}$ in Year 3.

With $-1<(\rho_{i,1}+\rho_{i,2})<0$, it is clear that a change in the value of a variable in year 1 still exerts an impact in year 3 and subsequent years. This impact decreases over time, with geometrically declining weights given by the powers of $(1+\rho_{i,1})$ and $\rho_{i,2}$. In other words, even in the absence of explanatory variables lagged two time periods (or more), the ARDL(2,1) model still allows the past values of these variables to influence the dependent variable two years later (and beyond). It can therefore be understood as a constrained distributed lags model including an *infinite* number of lags of temperature. Key benefits here are that sample size is less constrained by a parsimonious lag specification and the avoidance of any issues related to multicollinearity. The drawback is that the constraints imposed on the lag distribution may be too strong, although it seems reasonable to assume that the change in the value of a variable exerts an effect over time, with the maximal impact of a shock taking place in the first or second year (Beck & Katz 2011).

The long-run effect can be found by assuming, in equation (6) that $\tilde{Y_{it}}=Y_{i,t-1}=Y_{i,t-2}$ and that the explanatory variables are also in equilibrium. Focusing only on the effect of temperature for a given country, we then obtain

$$\begin{aligned}
0 &= \rho_{i,1}\tilde{Y}_{i,i}+\rho_2\tilde{Y}_i+\delta_{i,1}\tilde{T}_i+\delta_{i,2}\tilde{T}_i+\ldots \\
-(\rho_{i,1}+\rho_{i,2})\tilde{Y}_i &= (\delta_{i,1}+\delta_{i,2})\tilde{T}_i \\
\tilde{Y}_i &= -\frac{(\delta_{i,1}+\delta_{i,2})}{(\rho_{i,1}+\rho_{i,2})}\tilde{T}_i. \qquad (8)
\end{aligned}$$

coefficients across all countries i and then computing the long-run (long run average, LRA, see Phillips & Moon 1999), and (ii), as implied by our notation here, computing the long-run for each country i and then estimating the robust mean (average long run, ALR, see Pesaran & Smith 1995). We adopt the latter strategy.

[16]We use the period 1990-2000 for baseline income per capita because income data for some (recently formed) countries was not available before.

[17]A downside is that the computed short-run estimates are not outlier-robust.

Equation (8) provides the long-run effect of a permanent rise in temperature. It is the cumulative sum of the time-specific effects of temperature on income per capita over an infinite number of time periods.

It has sometimes been suggested that long-run effects could be recovered from a long-difference model in which changes in average income per capita between two periods (e.g. 1970-1985 and 1986-2000) are regressed on changes in temperature between the same periods (see Dell et al. 2014, Burke & Emerick 2016). Dell et al. (2012) obtain estimates similar to their short-run estimates whereas Kalkuhl & Wenz (2020) fail to find supporting evidence of long-run effects. A key econometric issue with this approach is that it implicitly assumes that medium-run trends in weather are exogenous (Kolstad & Moore 2020).[18] However, these may be correlated with omitted variables determining income per capita and varying across time and space. Unfortunately, once a long-difference model is adopted, the small number of observations prevents the mitigation of any potential omitted variable bias because country fixed effects and flexible country-specific time trends cannot be included, as is routinely done in the literature with high-frequency panel data. Most importantly in the context of this paper, drastically reducing the sample size would forbid us to apply heterogenous panel data estimators since they require running country-by-country regressions to obtain country-specific estimates.[19]

2.2.2 Interpretation

Like most of the panel data literature, we draw inference on the causal effects of climate change on economic prosperity by studying the impact of year-on-year variability of key weather statistics, such as annual average temperature, on economic output.[20] Assuming that meteorological events are random 'weather' draws from a 'climate' distribution, this approach has strong identification properties to estimate the short-run economic impact of weather shocks, especially after adjusting for potential confounders (Dell et al. 2014).[21] However, it is unclear how informative these short-run estimates are to assess the long-run effects of a permanent rise in temperature. Over a longer time horizon, economic agents are likely to adapt their behaviour in order to mitigate the consequences of climate change, general equilibrium adjustments take place (e.g. change in capital stock; inter-sectoral factor reallocation) and the climate effects may generate negative feedback loops (e.g. progressive water resources depletion) leading to greater economic damages over time (Dell et al. 2014, Kalkuhl & Edenhofer 2016, Auffhammer 2018, Kolstad & Moore 2020). Depending on whether *adaptation* processes or *intensification* forces dominate, the effects of climate change may be smaller or larger than those of weather shocks.

By its very nature, our model can be understood as assuming that some form of intensification takes place, leading to long-run effects typically larger than the short-run effect; adaptation is mostly neglected, although a coefficient on the delayed impact with the opposite sign of that on

[18]Such an assumption is more likely to hold in the case of annual weather 'shocks'. Another issue may be that the 'long-difference' model is misspecified in the sense that a 'conditional convergence' model, controlling for initial conditions, ought to be adopted (Bloom et al. 2014).

[19]One may also wonder how informative past and relatively limited climate changes are about future long-run effects of a permanent temperature rise.

[20]Weather and climate statistics differ in their temporal coverage. For example, annual average temperature is the 'weather', the thirty-year period temperature average is the 'climate', and a substantial shift in this medium-run average is 'climate change'.

[21]This perspective is well summarised by Blanc & Schlenker (2017) who suggest that "weather anomalies make ideal right-hand side variables in panel regressions with fixed effects because, as mentioned earlier, they are random and exogenous" (p.262).

the immediate impact could be interpreted as evidence of such a phenomenon. While there is no guarantee that these transition dynamics are accurate, they are in line with the assumption found in many growth models of a partial adjustment process lasting several periods to a long-run equilibrium defined by the determinants of steady-state output/TFP levels (Jones 1995, Temple & Wößmann 2006, Johnson & Papageorgiou 2020, Nath et al. 2023).[22] Intensification forces also emerge naturally in IAMs which allow climate change to directly influence not only current output but also capital stock accumulation (e.g. accelerated depreciation of the existing capital stock due to its destruction, abandonment, or increased wear and tear; diversion of investment towards less productivity-enhancing adaptation measures) or total factor productivity levels (Moyer et al. 2014, Dietz & Stern 2015, Tsigaris & Wood 2019).

A conservative interpretation of our results is that the short-run estimates of weather shocks are likely to be well identified whereas the long-run estimates, while consistent with the dynamics implied by our (fairly standard) growth model, are inherently much more fragile since they involve extrapolation, much like other studies of the future economic effects of climate change (e.g. Burke et al. 2015, Moore & Diaz 2015). We also report long-run effects which omit, in their calculation, the estimated coefficient on the first lag of temperature. Inclusion of this term helps identifying the contemporaneous impact of a weather shock but its coefficient could capture a reversal (or intensifying) effect associated with a transitory shock which would not occur with a long-lasting temperature rise.

Our model also implies that a permanent weather shock, i.e. climate change, influences long-run *income levels* but not long-run *income growth rates*. This level vs. growth issue has been debated for the past decade, notably because the projected global impact of climate change on GDP varies tremendously depending on the stance adopted (Newell et al. 2021, Chang et al. 2023). As previously indicated, the model estimated drives the interpretation. In equation (1), omitting the lagged dependent variable implies that a 'growth equation' rather than a 'level equation' is estimated. However, the implicit constraint imposed that $\gamma = 0$ may be erroneous, and this assumption ought to be tested. Indeed, initial income per capita is one of the most robust determinants of economic growth (Fernandez-Arias & Montiel 2001, Magnus et al. 2010, Eicher et al. 2011, Rockey & Temple 2016), with a negative coefficient suggesting conditional convergence. Of course, as long as a new equilibrium is not reached, economic growth will be temporarily affected, deviating from its steady-state value (Romer 2019). A permanent level effect could be mistaken for a permanent growth effect, especially when the appropriate dynamics are omitted (Hendry 1995, Casey et al. 2023). In the spirit of Bond et al. (2010), some studies have tried to disentangle the growth effects of climate change from their level effects (Kalkuhl & Wenz 2020, Newell et al. 2021, Casey et al. 2023, Nath et al. 2023). Their joint results suggest that the latter are much more likely than the former in the long-run.

2.2.3 Data

Weather Data Data on *weather* come from the Climatic Research Unit at the University of East Anglia, UK.[23] For each month-year, we calculate population-weighted country averages,

[22] Even if adjustments at the unit-level are discrete, occasional, and asynchronous, a smooth partial adjustment process can still hold at the aggregate level (King & Thomas 2006). It is also interesting to note that an adaptative expectations model, in which agents revise their expectations based on the discrepancy between what they anticipated and what actually happened, would lead the same dynamics as a partial adjustment model (Dougherty 2016).

[23] These can be downloaded from: `https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.05/crucy.2103081329.v4.05/`

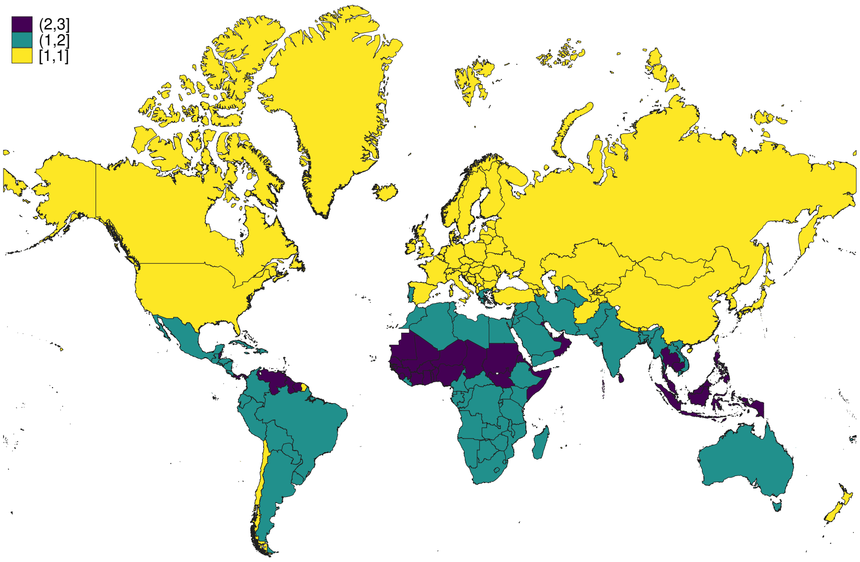
Table 1: Country Groupings (Table)

	Income $\longrightarrow$		
Temperature $\downarrow$	*Low*	*Medium*	*High*
Low	BIH, LSO, MNG, TJK	ALB, ARM, AZE, BGR, CHN, GEO, KAZ, KGZ, MDA, MKD, ROU, TKM, UKR, UZB	AUT, BLR, CAN, CHE, CHL, CZE, DEU, DNK, ESP, EST, FIN, FRA, GBR, GRC, HRV, HUN, IRL, ISL, ITA, JPN, KOR, LTU, LVA, NLD, NOR, NZL, POL, RUS, SVK, SVN, SWE, TUR, USA
Medium	AGO, BDI, BOL, COD, ETH, HND, KEN, MDG, MOZ, MWI, NPL, PAK, RWA, SLV, SYR, TZA, UGA, ZMB	BRA, BTN, BWA, COL, DOM, DZA, ECU, EGY, FJI, GTM, IRN, IRQ, JOR, LBN, MAR, NAM, PER, PRY, SWZ, TUN, ZAF, ZWE	ARG, AUS, BHS, CYP, ISR, MEX, PRT, SAU, TWN, URY
High	BEN, BFA, BGD, CAF, CIV, CMR, COG, DJI, GHA, GIN, GMB, GNB, HTI, IND, KHM, LAO, LBR, MLI, MMR, MRT, NER, NGA, SDN, SEN, SLE, TCD, TGO, VNM, YEM	BLZ, CRI, GAB, GNQ, GUY, IDN, JAM, LKA, NIC, PAN, PHL, SUR, THA, VEN	ARE, BRN, KWT, MYS, OMN, QAT, TTO

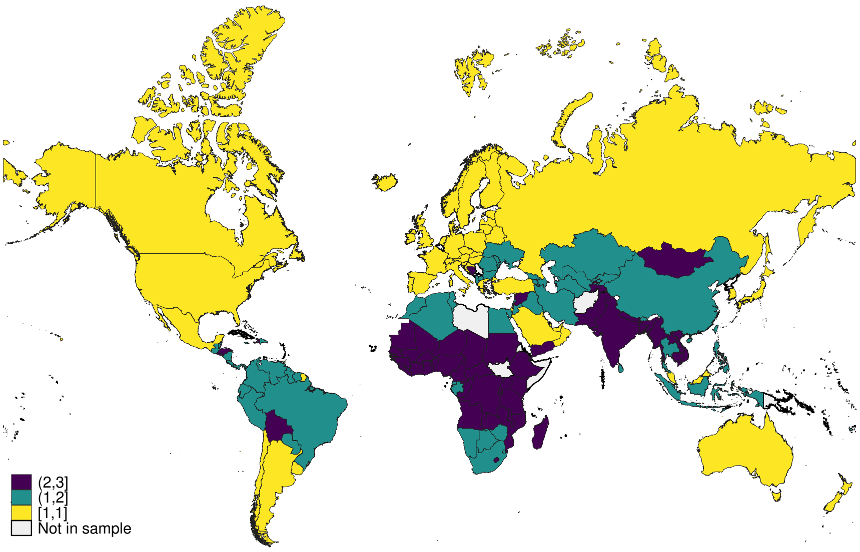
Notes: The table reports the group membership of the countries (using 3-digit iso codes) in our sample by income and temperature terciles.

Figure 2: Country Groupings (Maps)

(a) Countries grouped by Average Temperature (terciles)



(b) Countries grouped by Average Income per capita (terciles)



Notes: We illustrate the distribution of low, medium and high temperature/income groups in our sample in Panels (A) and (B), respectively. Darker shading implies warmer/poorer country groups. The Spearman's rank correlation between the two country group variables is -0.50.

where the weights correspond to the cell-specific population in 1990, as in Dell et al. (2012).[24] Geospatial population data come from the HYDE 3.2 database, with a grid cell size of about 85 km^2 at the equator.[25] Alternative population weights are adopted in robustness checks. In line with the literature, we use the annual average temperature (°C) as our key variable of interest and include annual average precipitation (mm/1000) as control variable.[26]

Aggregate Income Data Data on *income per capita* come from the Penn World Tables (PWT).[27] We use real GDP at constant 2017 national prices in million US$ (*rgdna*) as advised by Pinkovskiy, Maxim and Sala-i-Martin, Xavier (2020) and construct per capita values using the population data (in million, *L*). We also calculate total factor productivity, based on a simple production function, following Casey et al. (2023): $Y = \text{TFP} \times (K)^{\alpha} L^{(1-\alpha)}$, with $\alpha = \frac{1}{3}$.[28]

Agricultural Sector Data In additional regressions we adopt measures of output and total factor productivity in the agricultural sector as respective dependent variables. Data for total output (constant 2015 US$) and TFP (index, 2015=100) come from the U.S. Department of Agriculture (Fuglie 2012, 2015)[29] and cover the same 1961-2019 country sample as that income analysis.

Terciles Most of our results will be presented as robust mean estimates for Low, Medium, and High Temperature/Income groupings. We provide details of the group membership for these temperature and income per capita terciles in Table 1. Maps in Figure 2 similarly indicate which countries belong to which temperature and income group.

3 Results

In each Table, we group countries according to their reference *temperature levels* or their reference *income per capita levels* ('low', 'medium' and 'high'). Each column corresponds to (i) different estimators (pooled two-way fixed effects [2FE]; mean group estimators augmented with only cross-section averages of growth [CCE1] or all cross-section averages [CCE3]; partially pooled mean group estimators [Hybrid CCE1 and Hybrid CCE3]) and (ii) specifications (linear [Y] or quadratic [YQ] time trends). Our preferred specifications are the fully flexible and partially pooled CCE3 approaches with quadratic trends since these are the most in agreement with the methodological choices of previous studies. For this reason, we primarily focus on results in columns (6) and (10). All dependent variables are expressed in logs.[30]

[24] Burke et al. (2015) use as weights the cell-specific population in 2000.

[25] These can be downloaded from: https://easy.dans.knaw.nl/ui/datasets/id/easy-dataset:74467

[26] In Section 3.3., we investigate whether precipitation shocks matter.

[27] Available at https://www.rug.nl/ggdc/productivity/pwt/?lang=en

[28] Gollin (2002) shows that, after some necessary adjustments, labour income shares tend to be roughly constant across time and space with a mean value of about 0.66, implying an average capital share value α of about $\frac{1}{3}$ with constant returns to scale.

[29] Available at the USDA ERS website: https://www.ers.usda.gov/data-products/international-agricultural-productivity/

[30] At the bottom of each table, we report a first-order serial correlation test (Born & Breitung 2016). It indicates that inclusion of two lags of the dependent variable is required to diagnose the absence of error auto-correlation in our pooled 2FE model. In addition, the joint sum of the coefficients on these lags is always statistically significant (and estimated to be between -1 and 0).[31] Taken together, these two observations justify the adoption of our general model and a 'levels' interpretation of our results.

Table 2: Temperature shocks and income per capita, by temperature group

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
			Mean Group Estimates							
Estimator	2FE	2FE	CCE1	CCE1	CCE3	CCE3	CCE1	CCE1	CCE3	CCE3
Variant							Hybrid	Hybrid	Hybrid	Hybrid
Lagged dependent variable estimates (summed)										
All countries	-10.01***	-16.70***								
	(1.134)	(2.350)								
Low Temp			-13.91***	-24.51***	-13.60***	-29.06***	-9.586***	-21.58***	-12.37***	-23.61***
			(1.346)	(1.547)	(1.540)	(2.401)	(0.981)	(1.563)	(1.385)	(1.773)
Medium Temp			-9.953***	-20.03***	-9.958***	-21.67***	-9.631***	-18.79***	-9.419***	-19.60***
			(1.061)	(1.823)	(1.100)	(2.051)	(0.895)	(1.573)	(0.923)	(1.781)
High Temp			-9.989***	-22.84***	-10.37***	-26.89***	-8.843***	-24.07***	-8.941***	-22.64***
			(1.137)	(1.924)	(1.252)	(2.582)	(1.049)	(2.140)	(1.098)	(1.901)
Short-run estimates (summed)										
Contemporaneous										
Low Temp	0.469*	0.315	0.443**	0.411**	0.541**	0.495*	0.221	0.166	0.476	0.273
	(0.244)	(0.201)	(0.181)	(0.175)	(0.264)	(0.269)	(0.189)	(0.172)	(0.324)	(0.358)
Medium Temp	-0.984**	-0.482	-0.221	-0.430	-0.110	-0.630*	-0.605	-0.639	-1.298***	-1.279**
	(0.472)	(0.462)	(0.315)	(0.310)	(0.367)	(0.368)	(0.547)	(0.558)	(0.492)	(0.616)
High Temp	-2.233***	-1.991***	-1.443***	-1.446***	-1.307***	-1.471***	-0.615	-0.762	-1.898**	-2.257***
	(0.692)	(0.650)	(0.359)	(0.346)	(0.433)	(0.434)	(0.551)	(0.521)	(0.785)	(0.873)
First lag										
Low Temp	-0.156	-0.229	0.101	0.0903	0.485**	0.502**	-0.154	-0.190	0.243	0.0648
	(0.214)	(0.202)	(0.147)	(0.169)	(0.240)	(0.250)	(0.163)	(0.156)	(0.278)	(0.312)
Medium Temp	-0.0790	0.406	0.0809	0.181	0.369	0.184	0.161	0.227	0.816*	0.871**
	(0.479)	(0.420)	(0.193)	(0.232)	(0.308)	(0.325)	(0.316)	(0.342)	(0.444)	(0.407)
High Temp	0.982***	0.948***	-0.267	-0.341	-0.286	-0.739*	-0.235	-0.362	0.800	0.0528
	(0.321)	(0.349)	(0.215)	(0.250)	(0.340)	(0.397)	(0.395)	(0.391)	(0.734)	(0.834)
Long-run estimates										
Low Temp	3.130	0.515	3.482	2.851*	3.948	3.012	0.780***	-0.124***	5.000***	1.449***
	(3.205)	(1.624)	(2.651)	(1.489)	(3.502)	(2.007)	(0.0818)	(0.00861)	(0.613)	(0.107)
Medium Temp	-10.63**	-0.453	-6.585*	-1.351	-10.38*	-0.144	-6.098***	-2.769***	-5.189***	-2.704***
	(4.535)	(2.054)	(3.911)	(2.046)	(5.766)	(3.020)	(0.577)	(0.230)	(0.531)	(0.247)
High Temp	-12.50	-6.246	-14.25***	-7.120***	-10.82	-8.328***	-9.148***	-5.021***	-12.52***	-9.975***
	(7.873)	(4.743)	(5.408)	(2.418)	(7.063)	(3.184)	(1.199)	(0.460)	(1.732)	(0.871)
Long-run estimates, computed with first lag omitted										
Low Temp	4.689*	1.886	6.874***	2.729***	4.305	1.294	2.563***	0.875***	3.309***	1.171***
	(2.427)	(1.215)	(2.143)	(0.924)	(2.855)	(1.163)	(0.269)	(0.0606)	(0.406)	(0.0868)
Medium Temp	-9.837*	-2.885	-6.121	-1.914	-11.46**	-2.755	-8.318***	-4.292***	-13.99***	-8.485***
	(5.065)	(2.893)	(4.177)	(1.780)	(4.927)	(2.006)	(0.786)	(0.357)	(1.433)	(0.774)
High Temp	-22.31***	-11.92***	-11.76**	-6.366***	-8.044	-5.032**	-6.619***	-3.404***	-21.65***	-10.21***
	(6.760)	(4.248)	(4.775)	(1.960)	(5.587)	(2.014)	(0.867)	(0.312)	(2.995)	(0.892)
Trends	Y	YQ	Y	YQ	Y	YQ	Y	YQ	Y	YQ
Time FE	Y	Y								
AR1(0) (p)	0.000	0.000								
AR1(1) (p)	0.000	0.000								
AR1(2) (p)	0.915	0.346								

Notes: *** p<0.01 ** p<0.05 * p<0.10. Cluster-robust standard errors are in parentheses. 2FE: two-way fixed effects. CCE1: mean group-common correlated effects estimator with one common factor proxy (cross-sectional average of dependent variable). CCE3: mean group-common correlated effects estimator with three common factor proxies (cross-sectional averages of dependent variable and weather variables). 'Hybrid': coefficients of temperature variables constrained to be the same within each group. All regressions include annual average precipitation (and its lag). Country-specific trends: Y (yes, linear), YQ (yes, quadratic). AR1(*): residual serial correlation AR(1) test with 0, 1, 2 lagged dependent variable terms. Underlying econometric models are as follows (models augmented with linear *and* quadratic country trends):

2FE in (2) $$\Delta Y_{it} = \rho_1 Y_{i,t-1} + \rho_2 Y_{i,t-2} + \delta_1 T_{it} + \delta_2 T_{i,t-1} + \kappa_1 PP_{it} + \kappa_2 PP_{i,t-1} + \pi_{i,1} t + \pi_{i,2} t^2 + \alpha_i + e_{it}$$

CCE1 in (4) $$\Delta Y_{it} = \rho_{i,1} Y_{i,t-1} + \rho_{i,2} Y_{i,t-2} + \delta_{i,1} T_{it} + \delta_{i,2} T_{i,t-1} + \kappa_{i,1} PP_{it} + \kappa_{i,2} PP_{i,t-1} + \pi_{i,1} t + \pi_{i,2} t^2 + \alpha_i + \sum_{s=t-3}^{t} \left(\zeta^1_{i,s} \overline{\Delta Y_s}\right) + e_{it}$$

CCE3 in (6) $$\Delta Y_{it} = \rho_{i,1} Y_{i,t-1} + \rho_{i,2} Y_{i,t-2} + \delta_{i,1} T_{it} + \delta_{i,2} T_{i,t-1} + \kappa_{i,1} PP_{it} + \kappa_{i,2} PP_{i,t-1} + \pi_{i,1} t + \pi_{i,2} t^2 + \alpha_i + \sum_{s=t-3}^{t} \left(\zeta^1_{i,s} \overline{\Delta Y_s} + \zeta^2_{i,s} \overline{T_s} + \zeta^3_{i,s} \overline{PP_s}\right) + e_{it}$$

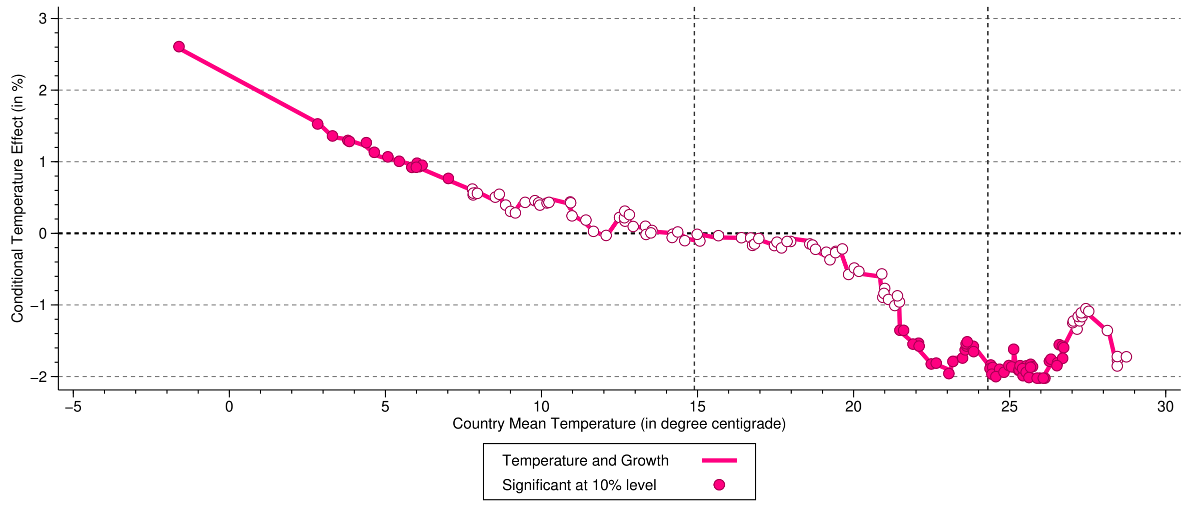
Table 3: Temperature shocks and income per capita, by income group

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
			Mean Group Estimates							
Estimator	2FE	2FE	CCE1	CCE1	CCE3	CCE3	CCE1	CCE1	CCE3	CCE3
Variant							Hybrid	Hybrid	Hybrid	Hybrid
Lagged dependent variable estimates (summed)										
All countries	-10.08*** (1.153)	-16.81*** (2.363)								
High Income			-12.71*** (1.063)	-25.53*** (1.407)	-12.84*** (1.111)	-30.30*** (1.944)	-7.621*** (0.756)	-20.25*** (1.203)	-8.442*** (0.998)	-21.41*** (1.680)
Medium Income			-12.11*** (1.286)	-19.14*** (1.873)	-12.20*** (1.516)	-20.33*** (2.306)	-12.88*** (1.245)	-20.79*** (2.019)	-14.77*** (1.816)	-21.66*** (2.149)
Low Income			-8.577*** (1.093)	-22.94*** (2.026)	-8.428*** (1.205)	-25.66*** (2.507)	-8.538*** (0.993)	-22.70*** (1.946)	-7.233*** (0.867)	-22.11*** (2.017)
Short-run estimates (summed)										
Contemporaneous										
High Income	-0.180 (0.275)	0.136 (0.248)	0.187 (0.238)	0.235 (0.217)	0.394 (0.290)	0.701*** (0.268)	-0.163 (0.321)	-0.203 (0.309)	0.0415 (0.281)	-0.0691 (0.341)
Medium Income	-0.0801 (0.536)	-0.316 (0.499)	-0.861*** (0.329)	-0.865*** (0.311)	-0.542 (0.410)	-1.025** (0.396)	-0.737 (0.524)	-0.937* (0.522)	-0.188 (0.671)	-0.246 (0.653)
Low Income	-1.042* (0.562)	-1.113** (0.450)	-0.242 (0.318)	-0.539 (0.326)	-0.513 (0.397)	-1.140*** (0.404)	-0.566 (0.482)	-0.736 (0.453)	-1.402 (0.889)	-1.538* (0.798)
First lag										
High Income	-0.383** (0.170)	-0.0825 (0.155)	0.159 (0.135)	0.161 (0.148)	0.381* (0.214)	0.419** (0.207)	-0.111 (0.176)	-0.169 (0.171)	-0.106 (0.202)	-0.122 (0.248)
Medium Income	0.439 (0.459)	0.313 (0.402)	0.0893 (0.204)	0.0989 (0.223)	1.055*** (0.314)	0.809** (0.334)	0.303 (0.389)	0.208 (0.398)	0.679 (0.536)	0.682 (0.481)
Low Income	0.333 (0.428)	0.208 (0.517)	-0.344* (0.206)	-0.361 (0.244)	-0.931** (0.369)	-1.385*** (0.395)	-0.431 (0.431)	-0.556 (0.431)	-0.0766 (0.840)	-0.196 (0.813)
Long-run estimates										
High Income	-5.582 (3.554)	0.317 (1.889)	-0.647 (2.761)	1.305 (1.344)	4.522 (3.275)	5.260*** (1.826)	-4.587*** (0.454)	-2.063*** (0.123)	-0.810*** (0.0940)	-0.896*** (0.0704)
Medium Income	3.564 (4.667)	-0.0204 (2.404)	-5.748 (4.318)	-3.017 (2.530)	-11.12** (5.403)	-4.215 (3.355)	-3.848*** (0.394)	-4.063*** (0.383)	4.113*** (0.489)	1.998*** (0.197)
Low Income	-7.034 (5.901)	-5.382* (3.149)	-8.419 (5.087)	-3.058 (2.218)	-10.76 (6.763)	-6.865** (2.972)	-14.27*** (1.671)	-6.698*** (0.596)	-19.38*** (2.456)	-8.496*** (0.776)
Long-run estimates, computed with first lag omitted										
High Income	-1.783 (2.703)	0.807 (1.455)	2.170 (2.569)	1.146 (0.940)	2.393 (2.877)	3.540*** (1.177)	-2.722*** (0.269)	-1.126*** (0.0670)	0.525*** (0.0609)	-0.324*** (0.0254)
Medium Income	-0.795 (5.352)	-1.882 (3.022)	-6.698* (3.791)	-3.887** (1.801)	-15.56*** (4.690)	-7.414*** (2.139)	-6.529*** (0.668)	-5.223*** (0.492)	-1.575*** (0.187)	-1.125*** (0.111)
Low Income	-10.34* (5.528)	-6.622** (2.710)	-2.474 (4.390)	-1.456 (1.650)	-0.604 (5.371)	-3.348* (1.797)	-8.101*** (0.949)	-3.814*** (0.339)	-18.37*** (2.329)	-7.538*** (0.689)
Trends	Y	YQ	Y	YQ	Y	YQ	Y	YQ	Y	YQ
Time FE	Y	Y								
AR1(0) (*p*)	0.000	0.000								
AR1(1) (*p*)	0.000	0.000								
AR1(2) (*p*)	0.911	0.334								

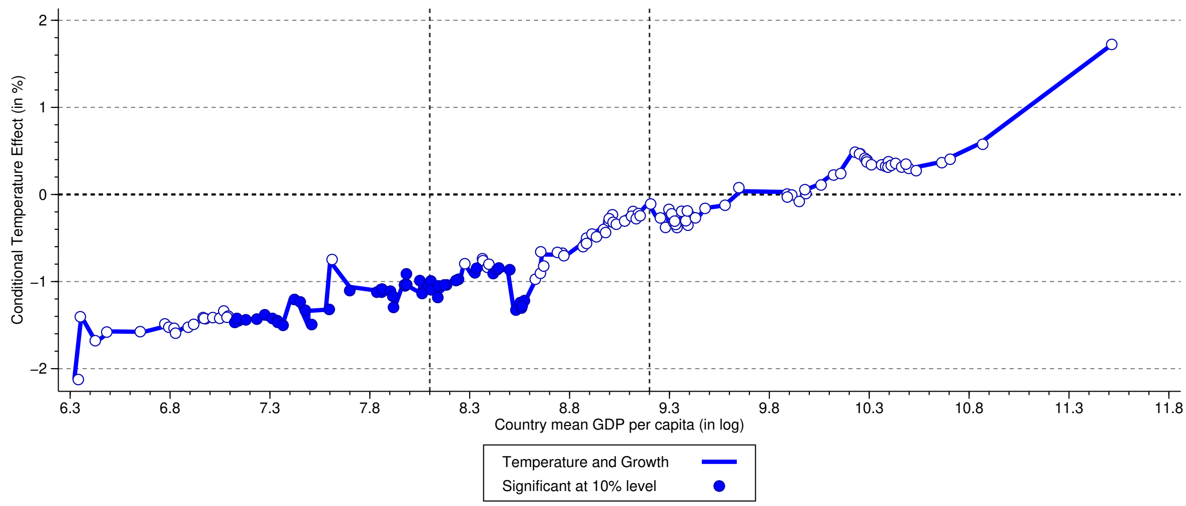
Notes: *** p<0.01 ** p<0.05 * p<0.10. Cluster-robust standard errors are in parentheses. 2FE: two-way fixed effects. CCE1: mean group-common correlated effects estimator with one common factor proxy (cross-sectional average of dependent variable). CCE3: mean group-common correlated effects estimator with three common factor proxies (cross-sectional averages of dependent variable and weather variables). Hybrid: coefficients of temperature variables constrained to be the same within each group. All regressions include yearly average precipitation. Country-specific trends: Y (yes, linear), YQ (yes, quadratic). AR1(*): residual serial correlation AR(1) test with 0, 1, 2 lagged dependent variable terms. See notes to Table 2 for detailed empirical specifications.

Figure 3: The heterogeneous effects of temperature shocks on Total Factor Productivity

(a) Temperature-TFP Effect and Average Country Temperature



(b) Temperature-TFP Effect and Average Country Income per Capita



Notes: We present predictions from running line regressions for the estimated short-run effect of temperature on log TFP (y-axis) on average country temperature and income per capita in Panels (a) and (b), respectively. These estimates are based on the regression in column (6) of Tables 2 and 3 (contemporaneous temperature impact). Filled (hollow) markers indicate statistically (in)significant difference from zero (10% level). Predicted effects (the markers) are minimally perturbed to ease illustration. Dashed vertical lines delimit low-, medium- and high-average temperature or -average income country groupings, respectively (these are the full sample terciles, i.e. each segment contains roughly the same number of countries). These plots are for predicted country effects, the equivalent plots showing the raw country estimates can be found in Figure A2 of Appendix A.2.

3.1 Aggregate economy

In Table 2, we group countries according to their reference *temperature levels* and estimate the impact of a weather shock on income per capita. Across columns (1)-(10), we tend to find that a positive temperature shock has statistically significant negative short-run and long effects on income per capita in high-temperature countries. Focusing on columns (6) and (10), a 1°C rise would reduce income per capita by 1.6-2.5% in the short-run and 8-10% in the long-run. Furthermore, medium-temperature countries may also be negatively affected by a permanent temperature increase whereas the opposite could happen in low-temperature countries. In Table A1 in Appendix A.3, we use total factor productivity (TFP) as dependent variable. Given that our econometric approach relies on the presence of unexpected and temporary weather shocks, TFP is the income component most likely to be affected, possibly allowing us to obtain more precisely identified effects. Our results are broadly similar to those previously obtained, although the slightly smaller size of the estimated coefficients suggests that a positive temperature shock may also be associated with a fall in tangible factor inputs (capital).

In Table 3, we group countries according to their reference *income per capita levels* and estimate the impact of a weather shock on income per capita. The split of countries by income tends to generate much less stable and statistically significant coefficients across columns. The clearest picture again emerges for low-income countries. Columns (6) and (10) suggest that a 1°C rise would reduce income per capita by about 1.1-1.5% in the short-run and 7-8% in the long-run. It is much less clear whether other countries would gain or lose from global warming, although it seems that high-income countries would be those least impacted. In Table A2 in Appendix A.3, using total factor productivity (TFP) as dependent variable keeps our results unchanged. Figure 3 provides running line estimates for the Temperate-TFP effect relative to mean temperature or income per capita.

3.2 Agricultural Sector

The agricultural sector is frequently argued to represent the key sector impacted by climate change (Nordhaus 1993, Ortiz-Bobea et al. 2021). We therefore investigate the impact of a temperature shock on agricultural output per capita and agricultural TFP.

In Tables 4 and A3 in Appendix A.3, when splitting our country sample according to reference *temperature levels*, we tend to find a large, negative, and statistically significant short-run impact of a temperature rise on agricultural outcomes in medium or high-temperature countries, notably when considering TFP. Size and statistical significance of the long-run effects are strongly influenced by the coefficient on the first lag of temperature, which is often positive and large, (partly) offsetting any negative immediate impact. However, if we constrain the temperature coefficients to be the same across country groups, we estimate in column (10) of Table 4 that a 1°C rise would, in the long-run, reduce agricultural output by about 7% in high-temperature countries, 4.0% in medium-temperature countries, and boost agricultural output by 3% in low-temperature countries. If, furthermore, we assume, as we previously suggested, that the lagged temperature effect may not be relevant when estimating the long-run impact of climate change, the estimated impacts would be -14%, -7%, and + 0.8%. TFP long-run effects are broadly similar in column (10) of Table A3.

In Tables 5 and A4 in Appendix A.3, when splitting our country sample according to reference *per capita income levels*, we tend to detect a negative, and statistically significant short-run

Table 4: Temperature shock and agricultural output, by temperature group

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
			Mean Group Estimates							
Estimator	2FE	2FE	CCE1	CCE1	CCE3	CCE3	CCE1	CCE1	CCE3	CCE3
Variant							Hybrid	Hybrid	Hybrid	Hybrid
Lagged dependent variable estimates (summed)										
All countries	-18.77***	-30.05***								
	(2.218)	(2.736)								
Low Temp			-27.38***	-39.70***	-40.68***	-54.66***	-25.99***	-39.72***	-22.30***	-31.53***
			(2.537)	(3.117)	(3.277)	(3.944)	(2.745)	(3.568)	(2.413)	(3.561)
Medium Temp			-25.67***	-39.25***	-32.71***	-45.02***	-24.78***	-36.78***	-23.44***	-38.88***
			(2.090)	(2.579)	(2.613)	(3.167)	(2.192)	(2.344)	(2.141)	(2.765)
High Temp			-20.19***	-29.18***	-25.49***	-37.48***	-19.84***	-28.46***	-22.10***	-28.57***
			(1.725)	(1.855)	(2.314)	(2.484)	(1.730)	(1.854)	(1.967)	(2.223)
Short-run estimates (summed)										
Contemporaneous										
Low Temp	0.777**	0.609*	0.863***	0.736**	0.340	-0.00639	0.105	0.0911	0.548	0.246
	(0.316)	(0.310)	(0.326)	(0.337)	(0.511)	(0.521)	(0.325)	(0.355)	(0.751)	(0.983)
Medium Temp	-2.051***	-1.722***	-1.359***	-1.434***	-0.462	-1.252*	-2.189***	-2.062***	-3.031***	-2.680***
	(0.601)	(0.546)	(0.442)	(0.479)	(0.668)	(0.640)	(0.813)	(0.754)	(0.916)	(0.836)
High Temp	-2.364***	-1.967**	-2.331***	-2.213***	-1.249**	-0.864	-2.264**	-2.391**	-3.620**	-3.873
	(0.772)	(0.803)	(0.428)	(0.485)	(0.589)	(0.611)	(0.886)	(1.148)	(1.845)	(2.664)
First lag										
Low Temp	0.669**	0.551	0.281	0.393	1.268**	1.673***	0.243	0.212	0.866	0.643
	(0.325)	(0.334)	(0.391)	(0.370)	(0.532)	(0.533)	(0.426)	(0.395)	(0.608)	(0.622)
Medium Temp	1.361**	1.760***	0.375	0.428	1.832***	1.204**	0.399	0.365	0.853	0.996
	(0.530)	(0.562)	(0.514)	(0.468)	(0.567)	(0.595)	(0.655)	(0.667)	(0.720)	(0.705)
High Temp	0.898	1.078*	1.353***	1.082**	1.541**	1.428**	1.599**	1.235*	2.813**	1.984
	(0.640)	(0.636)	(0.514)	(0.483)	(0.686)	(0.680)	(0.711)	(0.700)	(1.353)	(1.382)
Long-run estimates										
Low Temp	7.706***	3.862***	2.687	3.492**	0.301	2.165	1.660***	0.862***	6.706***	3.044***
	(2.447)	(1.492)	(1.950)	(1.352)	(1.983)	(1.377)	(0.182)	(0.0738)	(0.713)	(0.341)
Medium Temp	-3.680	0.128	-4.042	-2.898*	3.638	2.390	-9.548***	-5.154***	-11.32***	-4.485***
	(3.302)	(1.944)	(2.730)	(1.639)	(2.699)	(2.087)	(0.866)	(0.319)	(1.028)	(0.287)
High Temp	-7.807*	-2.958	-6.098*	-5.404**	1.150	-0.127	-4.658***	-4.724***	-4.581***	-6.992***
	(4.519)	(3.374)	(3.361)	(2.241)	(3.224)	(2.574)	(0.434)	(0.314)	(0.413)	(0.515)
Long-run estimates, computed with first lag omitted										
Low Temp	4.140**	2.028*	2.343	3.148***	0.311	0.827	0.502***	0.259***	2.599***	0.842***
	(1.757)	(1.038)	(1.571)	(1.197)	(1.488)	(1.019)	(0.0551)	(0.0222)	(0.276)	(0.0942)
Medium Temp	-10.93***	-5.731***	-7.370***	-5.057***	-2.181	-1.608	-11.68***	-6.263***	-15.75***	-7.136***
	(3.286)	(1.803)	(2.232)	(1.440)	(2.183)	(1.452)	(1.059)	(0.387)	(1.430)	(0.456)
High Temp	-12.59***	-6.547**	-12.23***	-7.447***	-4.064	-1.888	-15.85***	-9.767***	-20.55***	-14.34***
	(4.274)	(2.682)	(2.509)	(1.799)	(2.506)	(1.670)	(1.477)	(0.648)	(1.853)	(1.056)
Trends	Y	YQ	Y	YQ	Y	YQ	Y	YQ	Y	YQ
Time FE	Y	Y								
AR1(0) (p)	0.000	0.000								
AR1(1) (p)	0.006	0.373								
AR1(2) (p)	0.455	0.240								

Notes: *** p<0.01 ** p<0.05 * p<0.10. Cluster-robust standard errors are in parentheses. 2FE: two-way fixed effects. CCE1: mean group-common correlated effects estimator with one common factor proxy (cross-sectional average of dependent variable). CCE3: mean group-common correlated effects estimator with three common factor proxies (cross-sectional averages of dependent variable and weather variables). Hybrid: coefficients of temperature variables constrained to be the same within each group. All regressions include annual average precipitation (and its lag). Country-specific trends: Y (yes, linear), YQ (yes, quadratic). AR1(*): residual serial correlation AR(1) test with 0, 1, 2 lagged dependent variable terms. See notes to Table 2 for detailed empirical specifications.

Table 5: Temperature shock and agricultural output, by income group

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
			Mean Group Estimates							
Estimator	2FE	2FE	CCE1	CCE1	CCE3	CCE3	CCE1	CCE1	CCE3	CCE3
Variant							Hybrid	Hybrid	Hybrid	Hybrid
Lagged dependent variable estimates (summed)										
All countries	-18.81***	-30.13***								
	(2.243)	(2.755)								
High Income			-23.49***	-34.23***	-27.68***	-36.97***	-25.18***	-38.95***	-27.52***	-33.68***
			(2.042)	(2.401)	(2.450)	(3.017)	(2.589)	(3.273)	(2.434)	(2.683)
Medium Income			-24.48***	-34.73***	-33.53***	-46.27***	-23.90***	-34.57***	-31.31***	-48.46***
			(2.273)	(2.686)	(3.074)	(3.635)	(2.309)	(2.673)	(2.952)	(3.520)
Low Income			-25.17***	-38.58***	-36.31***	-53.18***	-22.19***	-32.78***	-30.17***	-48.55***
			(2.280)	(2.949)	(2.890)	(3.737)	(1.962)	(2.045)	(2.856)	(4.197)
Short-run estimates (summed)										
Contemporaneous										
High Income	0.127	0.309	0.129	0.327	0.225	0.504	-0.124	0.0186	-0.347	-0.0737
	(0.328)	(0.281)	(0.333)	(0.346)	(0.514)	(0.548)	(0.301)	(0.298)	(0.536)	(0.573)
Medium Income	-0.884	-0.985*	-1.556***	-1.577***	-1.120*	-1.288**	-0.910	-1.037	-1.243	-0.813
	(0.586)	(0.551)	(0.478)	(0.482)	(0.598)	(0.580)	(0.759)	(0.717)	(0.846)	(0.800)
Low Income	-1.505	-1.549	-1.293***	-1.523***	-0.494	-1.230*	-1.651*	-1.672*	-2.550*	-2.646*
	(1.002)	(0.950)	(0.463)	(0.483)	(0.650)	(0.638)	(0.961)	(0.876)	(1.406)	(1.593)
First lag										
High Income	0.178	0.401	0.873**	0.975**	2.045***	2.439***	0.494	0.604*	0.670	0.816
	(0.263)	(0.252)	(0.400)	(0.379)	(0.534)	(0.594)	(0.313)	(0.360)	(0.593)	(0.581)
Medium Income	1.761***	1.739***	0.976*	0.811*	1.651**	1.562**	0.767	0.609	0.918	1.335
	(0.562)	(0.604)	(0.515)	(0.473)	(0.667)	(0.639)	(0.805)	(0.773)	(0.765)	(0.812)
Low Income	1.316**	1.176*	0.126	-0.0157	0.928	0.368	0.558	0.515	1.689**	1.817**
	(0.558)	(0.645)	(0.456)	(0.422)	(0.609)	(0.589)	(0.690)	(0.759)	(0.775)	(0.908))
Long-run estimates										
High Income	1.622	2.354*	3.192	2.786*	3.273	4.119**	1.899***	2.079***	1.016***	1.927***
	(2.467)	(1.261)	(2.395)	(1.493)	(2.310)	(1.637)	(0.199)	(0.172)	(0.103)	(0.168)
Medium Income	4.661	2.502	-4.422	-1.862	-2.424	-0.876	-0.798***	-1.419***	-1.110***	1.238***
	(3.671)	(2.422)	(2.877)	(1.736)	(2.709)	(2.035)	(0.079)	(0.109)	(0.109)	(0.0909)
Low Income	-1.003	-1.239	-5.531	-5.195**	4.664	1.077	-6.662***	-3.771***	-3.807***	-2.644***
	(4.992)	(3.269)	(3.441)	(2.109)	(3.335)	(2.317)	(0.616)	(0.239)	(0.333)	(0.193)
Long-run estimates, computed with first lag omitted										
High Income	0.673	1.025	-1.031	1.034	-0.675	0.755	-0.635***	0.0622***	-1.095***	-0.191***
	(1.753)	(0.939)	(1.677)	(1.116)	(1.529)	(1.102)	(0.067)	(0.005)	(0.110)	(0.0167)
Medium Income	-4.700	-3.268*	-9.652***	-5.246***	-5.356**	-2.734*	-5.077***	-3.435***	-4.243***	-1.927***
	(3.163)	(1.832)	(2.609)	(1.595)	(2.079)	(1.406)	(0.499)	(0.265)	(0.418)	(0.141)
Low Income	-8.000	-5.142*	-6.044**	-4.953***	1.017	-0.441	-10.06***	-5.452***	-11.28***	-8.447***
	(5.295)	(3.104)	(2.533)	(1.607)	(2.468)	(1.609)	(0.931)	(0.345)	(0.985)	(0.616)
Trends	Y	YQ	Y	YQ	Y	YQ	Y	YQ	Y	YQ
Time FE	Y	Y								
AR1(0) (p)	0.000	0.000								
AR1(1) (p)	0.000	0.336								
AR1(2) (p)	0.463	0.235								

Notes: *** p<0.01 ** p<0.05 * p<0.10. Cluster-robust standard errors are in parentheses. 2FE: two-way fixed effects. CCE1: mean group-common correlated effects estimator with one common factor proxy (cross-sectional average of dependent variable). CCE3: mean group-common correlated effects estimator with three common factor proxies (cross-sectional averages of dependent variable and weather variables). Hybrid: coefficients of temperature variables constrained to be the same within each group. All regressions include annual average precipitation (and its lag). Country-specific trends: Y (yes, linear), YQ (yes, quadratic). AR1(*): residual serial correlation AR(1) test with 0, 1, 2 lagged dependent variable terms. See notes to Table 2 for detailed empirical specifications.

impact of a temperature shock on agricultural output in low-income countries. In addition, in column (10) of Table 5, we also find some evidence of a statistically significant long-run negative effect in low-income countries, especially if we do not take into account the delayed impact. In comparison to the country split by reference temperature levels, the short-run and long-run effects are smaller and the statistical significance of the short-run TFP impacts is much more fragile.

Overall, as illustrated by Figure 4, our results indicate that a positive temperature shock has a negative impact on agricultural TFP in medium/high-temperature countries and low/medium-income countries, supporting the notion that agriculture is one of the most sectors the most likely to be directly affected by climate change.

3.3 Robustness checks

3.3.1 Alternative Weights for Temperature and Precipitation Data

Previous results are for a range of different estimators and specifications. However, the underlying data remained the same (population-weighted average using data for 1990) and mean-group estimates corresponded to (outlier-free) simple averages of country-specific estimates. We therefore examine in Table 6 whether using (i) 1950 population-weighted country temperature averages (T1950); (ii) 2010 population-weighted country temperature averages (T2010); or (iii) 2010 log population-weighted mean-group estimates (POP2010), alter our key results.[32] Reporting our preferred specifications (CCE3 and Hybrid CCE3), this does not appear to be the case. Results confirm that high-temperature or low-income countries are adversely affected by a temperature shock. A 1°C rise would reduce income per capita by about 1.2-2.3% in the short-run and 8-10% in the long-run. In Appendix A.4, we conduct the same exercise using agricultural output per capita. Our findings are qualitatively similar to those presented in Tables 4 and 5 and also suggest that high-temperature or low-income countries are most adversely affected by a temperature shock in the short and long run.

3.3.2 Country Groups

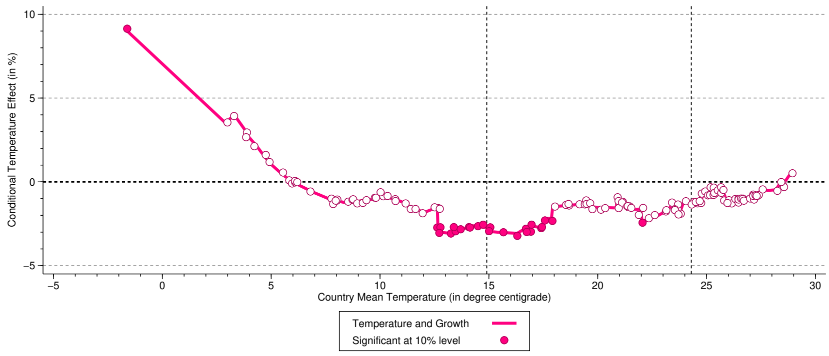
In Table 7, we examine the sensitivity of our results to changes in country grouping. Results in the first four results columns suggest that countries above median reference temperature or below median reference income may equally suffer from a permanent 1°C temperature rise: about a 1% income loss in the short-run and a 6% income loss in the long-run.[33] Columns (3)-(4) suggest that these heterogenous effects are not independent. When we group countries into four categories, combining income and temperature, it is solely the countries with above-median temperature *and* below-median income that are affected by weather changes (in a consistent and statistically significant manner). A permanent 1°C temperature rise would induce about a 1.3% income loss in the short-run and a 10% income loss in the long-run. When using agricultural output per capita as dependent variable, estimates reported in Table A6 in Appendix A.4 lead to the same conclusion.

[32]Note that the short-run hybrid CCE3 estimates could not be weighted as the use of weights was not possible with the -xtdcce2- command.

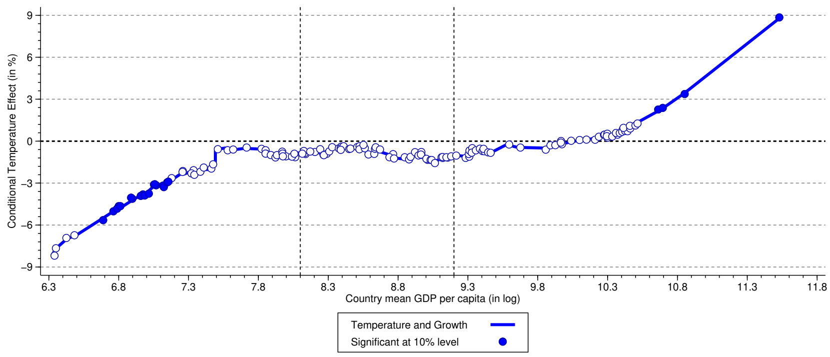
[33]These results are very similar albeit attenuated compared with our findings when we adopt three country groups.

Figure 4: The heterogeneous effects of temperature shocks on agricultural output and TFP

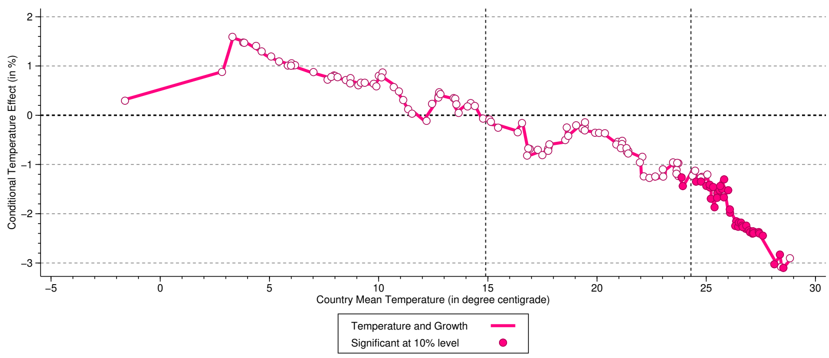
(a) Temperature-Agricultural Output Effect and Average Country Temperature



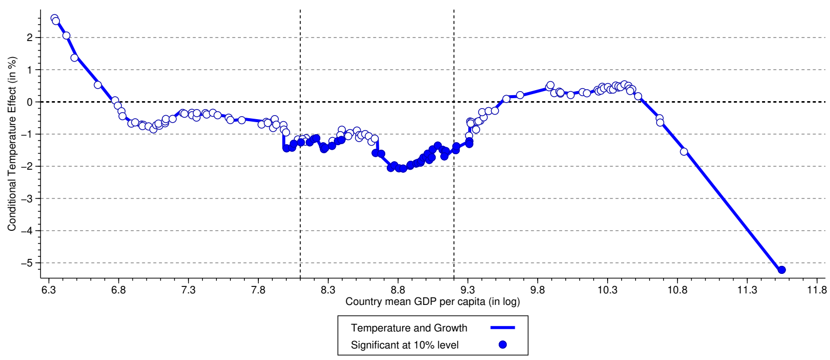
(b) Temperature-Agricultural Output Effect and Average Country Income pc



(c) Temperature-Agricultural TFP Effect and Average Country Temperature



(d) Temperature-Agricultural TFP Effect and Average Country Income pc



Notes: We present predictions from running line regressions for the estimated short-run effect of temperature on agricultural output or agricultural TFP (y-axis) on average country temperature (in red) and income per capita (in blue), respectively. Filled (hollow) markers indicate statistically (in)significant difference from zero (10% level). Predicted effects (the markers) are minimally perturbed to ease illustration. Dashed vertical lines delimit low-, medium- and high-average temperature or -average income country groupings, respectively (these are the full sample terciles, i.e. each segment contains roughly the same number of countries).

Table 6: Temperature Shocks and income per capita: robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)			(7)	(8)	(9)	(10)	(11)	(12)
	Analysis for Temperature Groups								Analysis for Income per capita Groups					
Estimator	CCE3	CCE3	CCE3	CCE3	CCE3	CCE3			CCE3	CCE3	CCE3	CCE3	CCE3	CCE3
Variant	Hybrid		Hybrid		Hybrid					Hybrid		Hybrid		Hybrid
Raw Data Weights	T1950	T1950	T2010	T2010	POP2010	POP2010			T1950	T1950	T2010	T2010	POP2010	POP2010
Contemporaneous estimates								***Contemporaneous estimates***						
Low Temperature	0.358	0.173	0.503*	0.267	0.485*	0.273		High Income	0.696***	-0.0623	0.701***	-0.0794	0.738***	-0.0691
	(0.272)	(0.366)	(0.270)	(0.354)	(0.268)	(0.358)			(0.256)	(0.347)	(0.267)	(0.339)	(0.267)	(0.341)
Medium Temperature	-0.668*	-1.516**	-0.642*	-1.277**	-0.609	-1.279**		Medium Income	-0.989**	-0.229	-1.024**	-0.256	-0.992**	-0.246
	(0.380)	(0.677)	(0.369)	(0.614)	(0.368)	(0.616)			(0.382)	(0.662)	(0.397)	(0.651)	(0.389)	(0.653)
High Temperature	-1.226***	-2.107**	-1.477***	-2.271**	-1.378***	-2.257***		Low Income	-1.195***	-1.550*	-1.153***	-1.529*	-1.079***	-1.538*
	(0.441)	(0.890)	(0.436)	(0.881)	(0.438)	(0.873)			(0.391)	(0.814)	(0.404)	(0.804)	(0.406)	(0.798)
Long-run estimates								***Long-run estimates***						
Low Temperature	0.724	0.274***	3.546*	1.454***	2.882	1.453***		High Income	5.259***	-0.855***	5.234***	-0.913***	5.464***	-0.910***
	(2.074)	(0.0205)	(2.061)	(0.110)	(2.022)	(0.107)			(1.843)	(0.0664)	(1.824)	(0.0718)	(1.757)	(0.0699)
Medium Temperature	0.305	-3.022***	-0.0580	-2.677***	-0.0188	-2.751***		Medium Income	-5.702*	2.133***	-3.700	1.911***	-4.284	2.015***
	(2.883)	(0.257)	(3.062)	(0.244)	(3.071)	(0.253)			(3.344)	(0.211)	(3.413)	(0.196)	(3.421)	(0.205)
High Temperature	-7.608**	-9.698***	-8.294**	-10.18***	-7.924**	-9.889***		Low Income	-7.216**	-8.455***	-6.830**	-8.510***	-6.609**	-8.523***
	(3.276)	(0.810)	(3.179)	(0.895)	(3.146)	(0.909)			(3.014)	(0.774)	(2.991)	(0.777)	(2.961)	(0.790)
Trends	YQ	YQ	YQ	YQ	YQ	YQ	YQ		YQ	YQ	YQ	YQ	YQ	YQ

Notes: *** $p<0.01$ ** $p<0.05$ * $p<0.10$. Cluster-robust standard errors are in parentheses. T1950/T2010: population-weighted temperature levels using population distribution in 1950 or 2010 (instead of 1990). POP2010: population-weighted estimates, using log of population in 2010. CCE3: mean group-common correlated effects estimator with three common factor proxies (cross-sectional averages of dependent variable and weather variables). Hybrid: coefficients of temperature variables constrained to be the same within each group. All regressions include annual average precipitation (and its lag). Country-specific trends: YQ (yes, quadratic).

Table 7: Temperature shocks and income per capita: alternative country groups

	(1) Temperature Groups	(2)		(1)' Income pc Groups	(2)'		(3) Income pc × Temperature	(4)
Estimator	CCE3	CCE3		CCE3	CCE3		CCE3	CCE3
Variant		Hybrid			Hybrid			Hybrid
Contemporaneous estimates								
Low Temp	0.168	-0.201	High Income	0.129	-0.309	Low Temp × High income	0.373	-0.148
	(0.268)	(0.308)		(0.283)	(0.299)		(0.270)	(0.412)
High Temp	-1.145***	-1.470**	Low Income	-0.987***	-0.963	Low Temp × Low income	-0.405	-0.315
	(0.361)	(0.621)		(0.330)	(0.675)		(0.579)	(0.729)
						High Temp × High income	-0.741	-0.195
							(0.715)	(0.979)
						High Temp × Low income	-1.270***	-1.852***
							(0.404)	(0.676)
Long-run estimates								
Low Temp	2.495	-0.881***	High Income	2.983	-1.773***	Low Temp × High income	1.762	-1.226***
	(1.876)	(0.0596)		(2.065)	(0.100)		(2.183)	(0.0954)
High Temp	-5.867**	-7.680***	Low Income	-5.549**	-4.277***	Low Temp × Low income	3.930	-5.676***
	(2.584)	(0.584)		(2.408)	(0.363)		(3.761)	(0.836)
						High Temp × High income	6.659	-1.478***
							(5.096)	(0.227)
						High Temp × Low income	-10.41***	-9.180***
							(3.059)	(0.869)
Trends	YQ	YQ		YQ	YQ		YQ	YQ

Notes: *** p<0.01 ** p<0.05 * p<0.10. Cluster-robust standard errors are in parentheses. CCE3: mean group-common correlated effects estimator with three common factor proxies (cross-sectional averages of dependent variable and weather variables). Hybrid: coefficients of temperature variables constrained to be the same within each group. All regressions include yearly average precipitation. Country-specific trends: YQ (yes, quadratic). We only present short-run and long-run estimates.

3.4 Precipitation Shocks

Lastly, in Appendix A.5, we investigate whether precipitation shocks matter.[34] A consistent picture only emerges for agricultural output per capita.[35] Tables A9 and A10 indicate that 100 mm in additional precipitation in high-temperature or low-income countries would increase agricultural output per capita by 0.5% in the short-run and possibly 1% in the long-run. These effects are small in comparison to those associated with a 1°C temperature rise, especially when considering the observed changes in global average precipitation over the past half-century.

4 Concluding Remarks

In this paper, we adopted dynamic heterogenous panel data models with common factors to estimate the short-run and long-run effects of climate change as reflected by short-run temperature shocks. In line with previous research pleading for the consideration of more realistic damage functions, our less restrictive analysis of historical data suggests that permanent climate change can have a large negative effect on the prosperity of countries, especially those characterised by

[34]Note that for our sample of countries, the median precipitation levels have been stable over the 1961-2019 period, hovering around 800 mm, whereas the median temperature levels have increased by about 0.63 °C.

[35]Regarding income per capita, studies (e.g. Dell et al. 2012, Burke et al. 2015, Kalkuhl & Wenz 2020, Acevedo et al. 2020) have frequently reported a statistically insignificant effect of precipitation shocks at the country-level. However, Damania et al. (2020) show that an effect can be recovered, especially on agricultural output in developing countries, by explicitly acknowledging within-country spatial variability in rainfall through the use of sub-national data. A positive (negative) precipitation shock tends to be associated with higher (lower) output. Kotz et al. (2022) confirm and extend this finding.

low-income levels or high-temperature location. We find that a permanent 1°C rise in temperature in these groups of countries is associated with a short-run fall in income per capita of about 1.3% and a long-term reduction of about 8.5% — the latter effect is more substantial than what previous research indicates. Of course, caution is warranted when extrapolating these results into a future in which global temperature is much higher than now and may involve yet-to-be observed tipping points and catastrophic outcomes (Weitzman 2012, Pindyck 2013, Stern 2013, Lemoine & Traeger 2016, Dietz et al. 2021, Kemp et al. 2022). Our findings ought rather be interpreted as a warning signal: even moderate climate change *already* has substantial negative economic implications in hot (and often poor) countries.

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A Appendices

A.1 The CCE approach

For an illustration of the mechanics of the CCE approach we assume a simplified empirical model with the dependent variable y_{it}, a single observable x_{it} and a single unobserved common factor f_t with country-specific factor loadings λ_i:

$$y_{it} \;=\; \alpha_i + \beta_i x_{it} + u_{it} \qquad u_{it} = \lambda_i f_t + \varepsilon_{it} \tag{A2}$$

where α_i is a country intercept (fixed effect)[2] and ε_{it} is assumed white noise. The common factor f_t can be linear or nonlinear, stationary or nonstationary. Recall that the purpose of the common factor is to capture global effects and that we want to account for these in a flexible manner, with country-specific impacts. In a pooled regression (imposing $\beta_i = \beta$) we could simply replace the f_t with a set of $T-1$ year dummies, however this would assume that their effect is common across countries ($\lambda_i = \lambda$). An equivalent specification of the global shocks with common impact can be achieved in a heterogeneous model by transforming the model variables prior to estimation: if we take variables in deviations from the cross-section mean, $y_{it} = y_{it} - y_t$ (note: y_t, not y_i as in the 'within' transformation) and similarly for x, then this accounts for the common shocks f_t but again imposes a common coefficient λ — see Eberhardt & Teal (2011) for more details on pooled and heterogeneous models with unobserved heterogeneity. The CCE estimator instead achieves accounting for *common* shocks with *heterogeneous* impact across countries.

How does the Pesaran (2006) CCE augmentation identify the coefficient of interest in this setup, given that the factors are unobserved and the variable transformation suggested above still cannot capture heterogeneous λ_i? We start with the model in (A2) and compute its cross-section average (denoted by bars)

$$\bar{y}_t = \bar{\alpha} + \bar{\beta}\bar{x}_t + \bar{\lambda} f_t, \tag{A3}$$

where the error term drops out since $\bar{\varepsilon}_t = 0$ by assumption. Now solve this equation for the common factor, i.e. $f_t = (1/\bar{\lambda})(\bar{y}_t - \bar{\alpha} - \bar{\beta}\bar{x}_t)$, and substitute this back into our model

$$\begin{aligned} y_{it} &= \alpha_i + \beta_i x_{it} + \lambda_i f_t + \varepsilon_{it} && \text{(A4)} \\ &= [\alpha_i - (\bar{\alpha}/\bar{\lambda})] + \beta_i x_{it} - (\lambda_i/\bar{\lambda})\bar{y}_t - (\lambda_i/\bar{\lambda})\bar{\beta}\bar{x}_t + \varepsilon_{it} && \text{(A5)} \\ &= \alpha_i^\star + \beta_i x_{it} + \lambda_{1i}^\star \bar{y}_t + \lambda_{2i}^\star \bar{x}_t + \varepsilon_{it}, && \text{(A6)} \end{aligned}$$

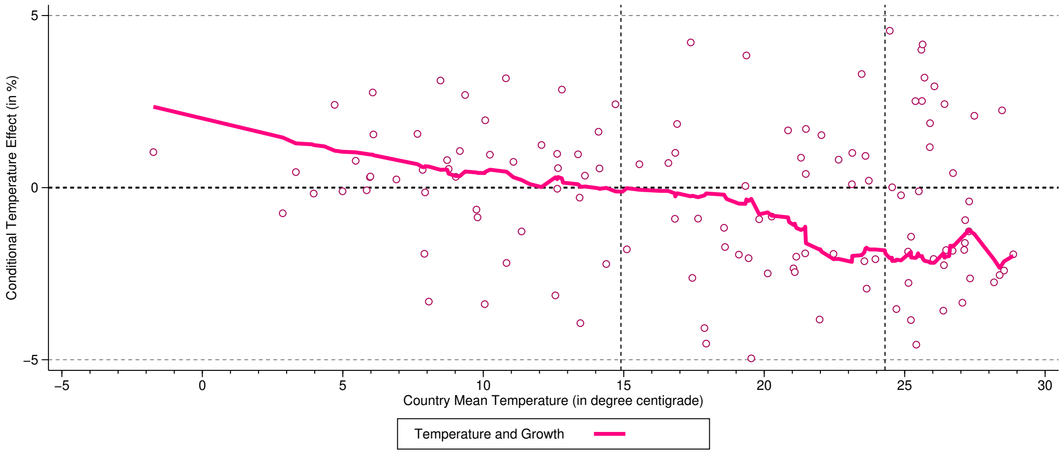
where in the final step we simply re-parameterise. It can be easily seen that we were able to account for the unobserved common factor f_t with heterogeneous factor loadings λ_i by a combination of (i) cross-section averages of observable variables ($\bar{y}_t, \bar{x}_t$) and (ii) heterogeneous parameters $\lambda_{1i}^\star$ and $\lambda_{2i}^\star$ — we use $\star$ to highlight that these parameters are different from that on the factor and the intercept in Equation (A2). Crucially, the parameter of interest, β_i, *is* identifiable via this approach. Theoretical work and simulations have shown that this augmentation using cross-section averages of the dependent and independent variables is extremely powerful, providing consistent estimates of β_i in the presence of non-stationary factors, structural breaks, and whether the model variables (and unobservables) are cointegrated or not (Kapetanios et al. 2011, Chudik & Pesaran 2013). The extension to a dynamic empirical model we follow in this paper is provided in Chudik & Pesaran (2015) and amounts to the inclusion of $int(T^{1/3}) = 3$ additional lags of cross-section averages.

[2]In a multi-factor error structure we can argue that one of the factors f_t could be a vector of 1s and hence the country intercept can be omitted as it is accommodated by the factor structure.

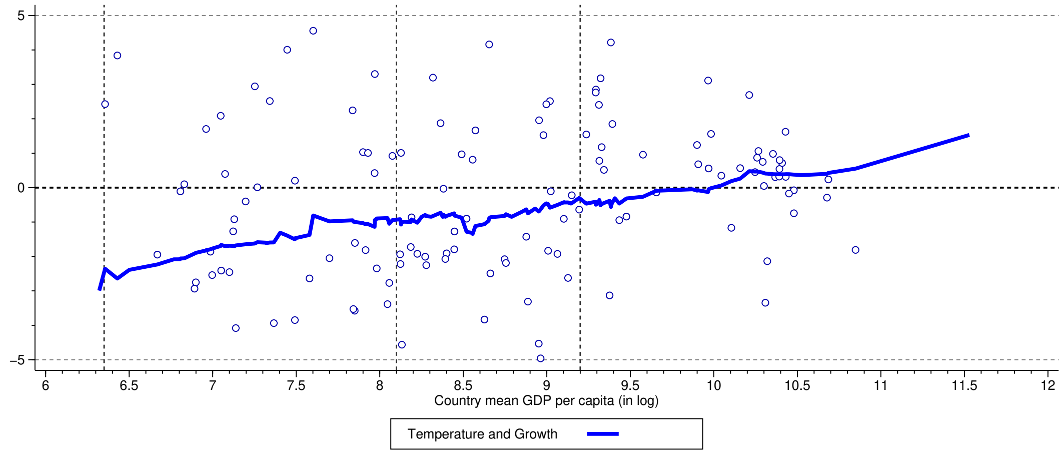
A.2 Raw estimates

Figure A1: The heterogeneous effects of temperature shocks on income per capita

(a) Temperature-Income Effect and Average Country Temperature



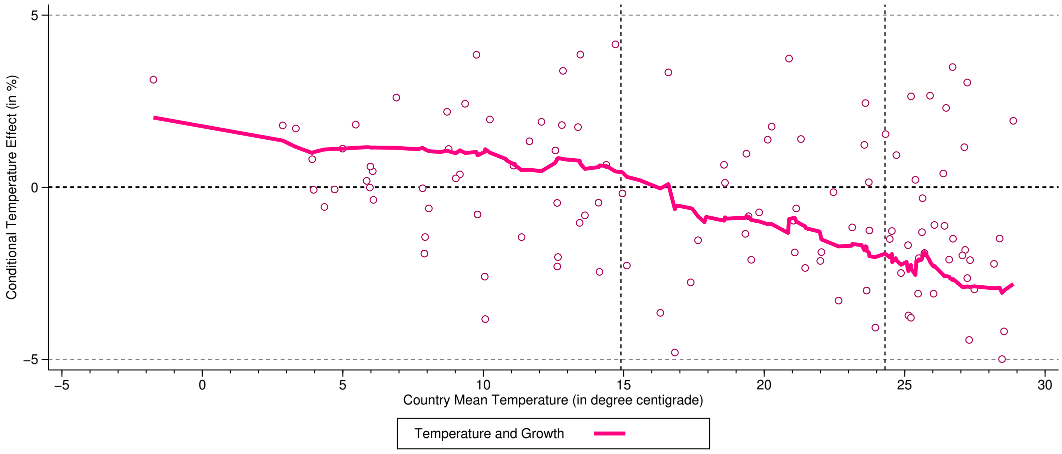
(b) Temperature-Income Effect and Average Income per Capita



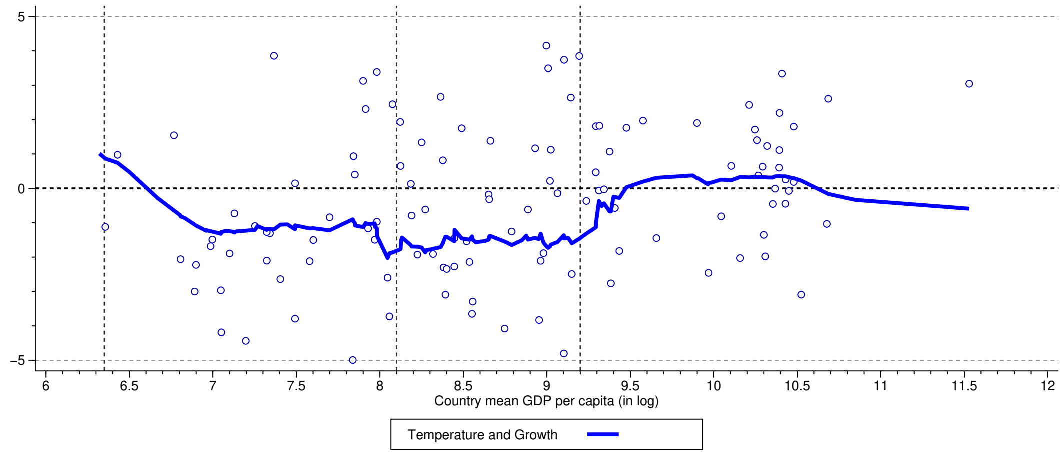
Notes: We present raw estimates of contemporaneous temperature from dynamic (ARDL) regressions temperature of per capita GDP (y-axis) plotted against average country temperature and average income per capita in Panels (a) and (b), respectively. These estimates are based on the regression in column (6) of Tables 2 and 3 (contemporaneous temperature impact) in the main text. Dashed vertical lines delimit low-, medium- and high-average temperature or -average income country groupings, respectively (these are the full sample terciles). For ease of illustration, country estimates above |10| are not reported.

Figure A2: The heterogeneous effects of temperature shocks on agricultural TFP

(a) Temperature-TFP Effect and Average Country Temperature



(b) Temperature-TFP Effect and Average Income per Capita



Notes: We present raw estimates of contemporaneous temperature from dynamic (ARDL) regressions temperature of per capita GDP (y-axis) plotted against average country temperature and average income per capita in Panels (a) and (b), respectively. These estimates are based on the regression in column (6) of Tables A3 and A4 (contemporaneous temperature impact). Dashed vertical lines delimit low-, medium- and high-average temperature or -average income country groupings, respectively (these are the full sample terciles). For ease of illustration, country estimates above |10| are not reported.

A.3 TFP effects of weather shocks

Table A1: Temperature shock and TFP, by temperature group

	2FE	2FE	MGCCE1	MGCCE1	MGCCE3	MGCCE3	MGCCE1 3 groups	MGCCE1 3 groups	MGCCE3 3 groups	MGCCE3 3 groups
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Short-run										
Contemporaneous										
TEMPLOW	0.482**	0.305	0.475***	0.491***	0.457*	0.456	0.240	0.189	0.437	0.308
	(0.235)	(0.188)	(0.172)	(0.166)	(0.269)	(0.289)	(0.179)	(0.161)	(0.307)	(0.341)
TEMPMED	-0.962**	-0.582	-0.352	-0.574*	-0.131	-0.515	-0.725	-0.820	-1.530***	-1.461**
	(0.445)	(0.450)	(0.321)	(0.299)	(0.343)	(0.375)	(0.520)	(0.535)	(0.470)	(0.585)
TEMPHIGH	-2.049***	-1.844***	-1.187***	-1.246***	-1.038**	-1.186***	-0.381	-0.534	-1.523*	-1.823**
	(0.681)	(0.647)	(0.372)	(0.351)	(0.419)	(0.444)	(0.593)	(0.555)	(0.820)	(0.878)
First lag										
TEMPLOW	-0.171	-0.265	0.146	0.122	0.506**	0.485**	-0.116	-0.144	0.208	0.0357
	(0.203)	(0.190)	(0.157)	(0.158)	(0.254)	(0.238)	(0.154)	(0.145)	(0.260)	(0.258)
TEMPMED	0.123	0.485	0.142	0.267	0.460	0.330	0.242	0.271	0.861*	0.964*
	(0.475)	(0.413)	(0.213)	(0.226)	(0.343)	(0.321)	(0.331)	(0.363)	(0.513)	(0.493)
TEMPHIGH	0.944***	0.873***	-0.362	-0.408*	-0.393	-0.569	-0.302	-0.392	0.422	-0.124
	(0.302)	(0.315)	(0.223)	(0.223)	(0.368)	(0.362)	(0.417)	(0.383)	(0.616)	(0.708)
Long-run										
TEMPLOW	2.528	0.213	4.814**	3.970***	3.302	1.463	1.264***	0.225***	5.897***	1.394***
	(2.520)	(1.362)	(2.192)	(1.264)	(3.494)	(1.889)	(0.111)	(0.0154)	(0.643)	(0.0980)
TEMPMED	-6.822*	-0.522	-5.030*	-0.676	-3.397	-0.583	-4.956***	-2.906***	-6.165***	-2.488***
	(3.649)	(1.957)	(2.859)	(1.462)	(4.684)	(2.584)	(0.396)	(0.192)	(0.543)	(0.185)
TEMPHIGH	-8.983	-5.239	-5.854	-5.147**	-17.45***	-7.041**	-5.588***	-3.861***	-8.178***	-7.969***
	(6.242)	(4.122)	(4.529)	(2.064)	(5.474)	(2.918)	(0.642)	(0.338)	(0.848)	(0.653)
Long-run, first lag omitted										
TEMPLOW	3.921**	1.643	5.978***	2.989***	-0.278	1.767	2.443***	0.938***	3.994***	1.249***
	(1.888)	(1.010)	(1.714)	(0.863)	(2.372)	(1.222)	(0.214)	(0.0642)	(0.436)	(0.0878)
TEMPMED	-7.819**	-3.137	-3.212	-1.950	-4.347	-1.738	-7.432***	-4.342***	-14.11***	-7.305***
	(3.954)	(2.555)	(2.782)	(1.463)	(3.125)	(1.782)	(0.594)	(0.287)	(1.242)	(0.543)
TEMPHIGH	-16.65***	-9.943***	-6.779*	-4.920***	-7.012**	-4.327**	-3.117***	-2.225***	-11.31***	-7.460***
	(5.444)	(3.702)	(3.603)	(1.721)	(3.403)	(1.793)	(0.358)	(0.195)	(1.173)	(0.612)
Lagged dependent variables										
LDV (sum)	-12.30***	-18.55***								
	(1.264)	(2.013)								
TEMPLOW			-15.09***	-25.00***	-15.15***	-28.16***	-10.80***	-21.88***	-13.19***	-24.16***
			(1.275)	(1.653)	(1.940)	(2.531)	(0.962)	(1.592)	(1.492)	(1.817)
TEMPMED			-12.98***	-23.03***	-13.10***	-24.14***	-12.10***	-21.70***	-12.56***	-24.18***
			(1.215)	(1.741)	(1.352)	(2.132)	(0.968)	(1.442)	(1.097)	(1.771)
TEMPHIGH			-12.16***	-24.84***	-14.38***	-28.26***	-12.31***	-27.55***	-13.88***	-26.62***
			(1.279)	(2.031)	(1.594)	(2.614)	(1.320)	(2.336)	(1.422)	(2.239)
Trends	Y	YQ	Y	YQ	Y	YQ	Y	YQ	Y	YQ
Time FE	Y	Y								
LAGLD0AR1 p-value	0	0								
LAGLD1AR1 p-value	0	0								
LAGLD2AR1 p-value	0.865	0.280								

Notes: *** $p<0.01$ ** $p<0.05$ * $p<0.10$. Cluster-robust standard errors are in parentheses. 2FE: two-way fixed effects. MGCCE1: mean group-common correlated effects estimator with one common factor proxy (cross-sectional average of dependent variable). MGCCE3: mean group-common correlated effects estimator with three common factor proxies (cross-sectional averages of dependent variable and weather variables). Three groups: coefficients of temperature variables constrained to be the same within each group. All regressions include yearly average precipitation. Country-specific trends: Y (yes, linear), YQ (yes, quadratic). LAGLD*AR1: serial correlation AR(1) test with 0,1,2 lagged dependent variable terms.

Table A2: Temperature shock and TFP, by income group

	2FE (1)	2FE (2)	MGCCE1 (3)	MGCCE1 (4)	MGCCE3 (5)	MGCCE3 (6)	MGCCE1 3 groups (7)	MGCCE1 3 groups (8)	MGCCE3 3 groups (9)	MGCCE3 3 groups (10)
Short-run										
No lag										
GDPPCHIGH	-0.181	0.0758	0.200	0.265	0.407	0.720***	-0.176	-0.175	0.0325	-0.0487
	(0.261)	(0.238)	(0.221)	(0.193)	(0.275)	(0.274)	(0.306)	(0.286)	(0.278)	(0.329)
GDPPCMED	-0.0364	-0.370	-0.814***	-0.802***	-0.525	-0.972**	-0.608	-0.874*	-0.133	-0.272
	(0.501)	(0.478)	(0.297)	(0.270)	(0.358)	(0.376)	(0.509)	(0.487)	(0.681)	(0.610)
GDPPCLOW	-0.976*	-1.017**	-0.124	-0.532*	-0.471	-1.015**	-0.501	-0.691	-1.421*	-1.514**
	(0.557)	(0.441)	(0.309)	(0.313)	(0.380)	(0.411)	(0.516)	(0.447)	(0.830)	(0.772)
First lag										
GDPPCHIGH	-0.365**	-0.118	0.148	0.164	0.362*	0.451**	-0.107	-0.142	-0.0798	-0.0992
	(0.165)	(0.147)	(0.134)	(0.138)	(0.203)	(0.195)	(0.157)	(0.148)	(0.200)	(0.239)
GDPPCMED	0.573	0.339	0.0434	0.0232	1.142***	0.790**	0.435	0.330	0.713	0.686
	(0.441)	(0.385)	(0.205)	(0.215)	(0.310)	(0.312)	(0.452)	(0.475)	(0.537)	(0.495)
GDPPCLOW	0.361	0.263	-0.335	-0.280	-0.997***	-1.141***	-0.398	-0.499	-0.114	-0.152
	(0.418)	(0.512)	(0.220)	(0.248)	(0.362)	(0.362)	(0.448)	(0.456)	(0.912)	(0.872)
Long-run										
GDPPCHIGH	-4.413	-0.226	1.460	1.484	6.000*	4.775***	-3.126***	-1.663***	-0.451***	-0.724***
	(2.765)	(1.614)	(2.142)	(1.102)	(3.258)	(1.649)	(0.240)	(0.0911)	(0.0392)	(0.0534)
GDPPCMED	4.337	-0.164	-2.803	-0.680	-9.614**	-6.131**	-1.232***	-2.574***	4.028***	1.632***
	(3.568)	(2.152)	(3.154)	(1.714)	(4.766)	(2.947)	(0.110)	(0.208)	(0.421)	(0.160)
GDPPCLOW	-4.976	-4.043	-3.510	-1.414	-15.06***	-6.120**	-10.79***	-5.754***	-16.43***	-7.388***
	(4.701)	(2.738)	(4.038)	(1.699)	(5.438)	(2.760)	(1.145)	(0.471)	(1.774)	(0.640)
Long-run, first lag omitted										
GDPPCHIGH	-1.466	0.406	2.317	1.431*	2.932	3.177***	-1.943***	-0.918***	0.310***	-0.238***
	(2.106)	(1.264)	(1.733)	(0.861)	(2.225)	(1.110)	(0.149)	(0.0503)	(0.0269)	(0.0176)
GDPPCMED	-0.294	-1.981	-4.013	-3.009**	-13.61***	-5.952***	-4.335***	-4.137***	-0.925***	-1.072***
	(4.061)	(2.631)	(2.578)	(1.439)	(3.385)	(2.015)	(0.385)	(0.335)	(0.0967)	(0.105)
GDPPCLOW	-7.894*	-5.451**	0.913	-0.981	-2.193	-2.821	-6.013***	-3.340***	-15.21***	-6.715***
	(4.475)	(2.343)	(3.297)	(1.551)	(3.277)	(1.797)	(0.638)	(0.273)	(1.642)	(0.581)
Lagged dependent variables										
LDV (sum)	-12.37***	-18.65***								
	(1.285)	(2.017)								
GDPPCHIGH			-15.16***	-26.38***	-16.06***	-30.70***	-10.46***	-21.07***	-11.67***	-22.07***
			(1.008)	(1.484)	(1.366)	(2.018)	(0.801)	(1.150)	(1.017)	(1.710)
GDPPCMED			-14.28***	-21.74***	-14.35***	-22.07***	-15.96***	-23.21***	-16.02***	-25.20***
			(1.349)	(1.901)	(1.858)	(2.520)	(1.429)	(1.882)	(1.781)	(2.399)
GDPPCLOW			-10.09***	-24.85***	-11.66***	-26.65***	-10.10***	-25.47***	-10.26***	-25.50***
			(1.137)	(2.065)	(1.526)	(2.546)	(1.054)	(2.068)	(1.102)	(2.235)
Trends	Y	YQ	Y	YQ	Y	YQ	Y	YQ	Y	YQ
Time FE	Y	Y								
LAGLD0AR1 p-value	0	0								
LAGLD1AR1 p-value	0	0								
LAGLD2AR1 p-value	0.858	0.270								

Notes: *** p<0.01 ** p<0.05 * p<0.10. Cluster-robust standard errors are in parentheses. 2FE: two-way fixed effects. MGCCE1: mean group-common correlated effects estimator with one common factor proxy (cross-sectional average of dependent variable). MGCCE3: mean group-common correlated effects estimator with three common factor proxies (cross-sectional averages of dependent variable and weather variables). Three groups: coefficients of temperature variables constrained to be the same within each group. All regressions include yearly average precipitation. Country-specific trends: Y (yes, linear), YQ (yes, quadratic). LAGLD*AR1: serial correlation AR(1) test with 0,1,2 lagged dependent variable terms.

Table A3: Temperature shock and agricultural TFP, by temperature group

	2FE	2FE	MGCCE1	MGCCE1	MGCCE3	MGCCE3	MGCCE1 3 groups	MGCCE1 3 groups	MGCCE3 3 groups	MGCCE3 3 groups
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Short-run										
Contemporaneous										
TEMPLOW	0.700***	0.573**	0.922***	0.855***	0.963***	0.606**	0.317	0.225	0.437	0.396
	(0.248)	(0.248)	(0.269)	(0.299)	(0.291)	(0.290)	(0.241)	(0.282)	(0.358)	(0.489)
TEMPMED	-1.497**	-1.150*	-1.078**	-0.933*	-1.045*	-0.987*	-1.449**	-1.006	-2.163**	-1.504*
	(0.651)	(0.632)	(0.455)	(0.478)	(0.572)	(0.569)	(0.697)	(0.705)	(0.902)	(0.905)
TEMPHIGH	-1.248	-1.323	-2.112***	-2.376***	-1.980***	-2.146***	-1.867***	-2.669***	-2.957***	-3.833***
	(0.903)	(0.820)	(0.416)	(0.428)	(0.518)	(0.515)	(0.694)	(0.636)	(1.109)	(1.283)
First lag										
TEMPLOW	0.00704	-0.140	-0.164	-0.153	-0.0221	0.383	-0.146	-0.284	-0.250	-0.391
	(0.254)	(0.249)	(0.260)	(0.244)	(0.342)	(0.343)	(0.312)	(0.296)	(0.448)	(0.459)
TEMPMED	1.410***	1.672***	0.644	0.471	0.411	0.461	0.700	0.903**	0.942	1.459**
	(0.421)	(0.415)	(0.401)	(0.362)	(0.476)	(0.473)	(0.439)	(0.438)	(0.624)	(0.666)
TEMPHIGH	1.658***	1.311**	1.910***	1.437***	1.613***	1.374**	2.429***	1.213**	3.349***	1.933**
	(0.630)	(0.588)	(0.419)	(0.384)	(0.549)	(0.542)	(0.729)	(0.562)	(1.205)	(0.898)
Long-run										
TEMPLOW	4.128**	1.520	2.083	1.931*	3.002	0.599	1.004***	-0.173***	0.964***	0.0121***
	(1.707)	(1.058)	(1.724)	(1.071)	(1.901)	(1.411)	(0.110)	(0.0146)	(0.111)	(0.00112)
TEMPMED	-0.512	1.832	-1.876	-1.139	0.289	0.724	-3.798***	-0.329***	-5.449***	-0.122***
	(3.696)	(2.194)	(2.497)	(1.749)	(2.808)	(2.148)	(0.274)	(0.0234)	(0.411)	(0.00964)
TEMPHIGH	2.392	-0.0449	-2.473	-2.649	-1.293	0.829	3.640***	-6.765***	2.189***	-8.237***
	(5.567)	(2.870)	(2.911)	(2.233)	(3.625)	(2.898)	(0.243)	(0.468)	(0.187)	(0.690)
Long-run, first lag omitted										
TEMPLOW	4.087***	2.010**	2.918**	3.228***	2.108*	1.048	1.865***	0.660***	2.245***	1.127***
	(1.497)	(0.899)	(1.157)	(0.870)	(1.172)	(0.934)	(0.204)	(0.0558)	(0.260)	(0.104)
TEMPMED	-8.744**	-4.032*	-4.197**	-2.688*	-3.320*	-2.644*	-7.342***	-3.237***	-9.651***	-4.088***
	(3.760)	(2.205)	(1.947)	(1.377)	(1.988)	(1.577)	(0.529)	(0.230)	(0.727)	(0.324)
TEMPHIGH	-7.290	-4.642	-12.45***	-10.37***	-8.319***	-8.228***	-12.08***	-12.40***	-16.52***	-16.62***
	(5.464)	(2.934)	(2.150)	(1.668)	(2.505)	(2.018)	(0.807)	(0.857)	(1.410)	(1.393)
Lagged dependent variables										
LDV (sum)	-17.12***	-28.51***								
	(1.398)	(1.935)								
TEMPLOW			-26.35***	-46.33***	-30.43***	-52.02***	-22.80***	-43.36***	-23.11***	-45.82***
			(2.645)	(3.750)	(3.184)	(4.423)	(2.445)	(3.642)	(2.558)	(4.061)
TEMPMED			-25.30***	-38.68***	-30.00***	-41.49***	-23.70***	-38.04***	-26.60***	-43.54***
			(1.811)	(2.745)	(2.405)	(3.321)	(1.655)	(2.731)	(2.009)	(3.483)
TEMPHIGH			-18.50***	-25.82***	-19.43***	-26.87***	-17.12***	-25.97***	-20.47***	-28.84***
			(1.478)	(2.012)	(1.976)	(2.300)	(1.141)	(1.853)	(1.683)	(2.354)
Trends	Y	YQ	Y	YQ	Y	YQ	Y	YQ	Y	YQ
Time FE	Y	Y								
LAGLD0AR1 p-value	0	0								
LAGLD1AR1 p-value	0	0.056								
LAGLD2AR1 p-value	0.689	0.227								

Notes: *** p<0.01 ** p<0.05 * p<0.10. Cluster-robust standard errors are in parentheses. 2FE: two-way fixed effects. MGCCE1: mean group-common correlated effects estimator with one common factor proxy (cross-sectional average of dependent variable). MGCCE3: mean group-common correlated effects estimator with three common factor proxies (cross-sectional averages of dependent variable and weather variables). Three groups: coefficients of temperature variables constrained to be the same within each group. All regressions include yearly average precipitation. Country-specific trends: Y (yes, linear), YQ (yes, quadratic). LAGLD*AR1: serial correlation AR(1) test with 0,1,2 lagged dependent variable terms.

Table A4: Temperature shock and agricultural TFP, by income group

	2FE	2FE	MGCCE1	MGCCE1	MGCCE3	MGCCE3	MGCCE1 3 groups	MGCCE1 3 groups	MGCCE3 3 groups	MGCCE3 3 groups
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Short-run										
No lag										
GDPPCHIGH	0.643**	0.566**	0.362	0.428	0.353	0.237	0.0915	0.103	0.357	0.323
	(0.304)	(0.273)	(0.334)	(0.341)	(0.402)	(0.380)	(0.263)	(0.295)	(0.475)	(0.383)
GDPPCMED	-0.515	-0.456	-0.947**	-1.118**	-1.220**	-1.539***	-0.374	-0.612	-0.689	-0.572
	(0.480)	(0.467)	(0.449)	(0.449)	(0.552)	(0.510)	(0.647)	(0.611)	(0.774)	(0.720)
GDPPCLOW	-1.026	-1.089	-1.379***	-1.484***	-0.735	-0.881	-1.185	-1.230	-0.739	-0.829
	(0.881)	(0.829)	(0.433)	(0.435)	(0.609)	(0.578)	(0.765)	(0.829)	(1.285)	(1.488)
First lag										
GDPPCHIGH	0.520**	0.420*	0.818**	0.982***	0.620	1.279***	0.697**	0.730**	1.105*	1.136*
	(0.249)	(0.232)	(0.320)	(0.303)	(0.410)	(0.447)	(0.350)	(0.339)	(0.629)	(0.617)
GDPPCMED	0.328	0.286	0.590	0.140	0.566	0.471	0.560	0.0393	0.719	0.600
	(0.424)	(0.422)	(0.382)	(0.348)	(0.427)	(0.412)	(0.548)	(0.560)	(0.680)	(0.717)
GDPPCLOW	0.722	0.577	0.695*	0.401	0.620	0.351	0.277	0.286	0.729	1.031
	(0.560)	(0.614)	(0.412)	(0.371)	(0.492)	(0.465)	(0.540)	(0.510)	(0.828)	(0.858)
Long-run										
GDPPCHIGH	6.803***	3.456***	2.696	4.363***	3.783	3.208*	4.449***	2.422***	6.699***	3.941***
	(1.741)	(1.192)	(2.210)	(1.532)	(2.379)	(1.683)	(0.449)	(0.204)	(0.746)	(0.363)
GDPPCMED	-1.095	-0.595	-3.030	-3.330**	-1.417	-0.0733	1.192***	-2.378***	0.185***	0.104***
	(2.273)	(2.041)	(2.231)	(1.539)	(3.106)	(2.083)	(0.107)	(0.186)	(0.0173)	(0.00822)
GDPPCLOW	-1.781	-1.795	-0.931	-1.856	0.134	-1.854	-5.088***	-3.207***	-0.0423***	0.625***
	(3.494)	(2.879)	(2.751)	(1.939)	(3.007)	(2.277)	(0.413)	(0.230)	(0.00340)	(0.0511)
Long-run, first lag omitted										
GDPPCHIGH	3.763**	1.984**	-0.533	1.330	0.346	-0.418	0.516***	0.300***	1.635***	0.874***
	(1.746)	(0.945)	(1.557)	(1.137)	(1.481)	(1.179)	(0.0521)	(0.0253)	(0.182)	(0.0806)
GDPPCMED	-3.011	-1.597	-4.065*	-2.632*	-5.388**	-4.007**	-2.390***	-2.540***	-4.253***	-2.153***
	(2.821)	(1.631)	(2.157)	(1.553)	(2.349)	(1.685)	(0.214)	(0.199)	(0.398)	(0.169)
GDPPCLOW	-6.002	-3.817	-6.876***	-6.015***	-1.587	-3.540*	-6.642***	-4.177***	-3.314***	-2.570***
	(5.040)	(2.829)	(2.067)	(1.590)	(2.600)	(1.848)	(0.539)	(0.299)	(0.266)	(0.210)
Lagged dependent variables										
LDV (sum)	-17.10***	-28.53***								
	(1.383)	(1.931)								
GDPPCHIGH			-25.31***	-42.14***	-29.20***	-46.15***	-23.38***	-41.99***	-23.07***	-42.83***
			(2.514)	(3.534)	(3.076)	(4.177)	(2.340)	(3.456)	(2.406)	(3.854)
GDPPCMED			-22.74***	-32.53***	-25.54***	-34.97***	-19.91***	-29.56***	-21.54***	-29.98***
			(1.904)	(2.680)	(2.504)	(3.226)	(1.753)	(2.318)	(2.018)	(2.440)
GDPPCLOW			-22.42***	-33.63***	-25.53***	-35.63***	-21.94***	-34.49***	-26.58***	-36.07***
			(1.830)	(2.716)	(2.416)	(3.135)	(1.711)	(2.481)	(2.195)	(2.941)
Trends	Y	YQ	Y	YQ	Y	YQ	Y	YQ	Y	YQ
Time FE	Y	Y								
LAGLD0AR1 p-value	0	0								
LAGLD1AR1 p-value	0	0.0455								
LAGLD2AR1 p-value	0.698	0.223								

Notes: *** p<0.01 ** p<0.05 * p<0.10. Cluster-robust standard errors are in parentheses. 2FE: two-way fixed effects. MGCCE1: mean group-common correlated effects estimator with one common factor proxy (cross-sectional average of dependent variable). MGCCE3: mean group-common correlated effects estimator with three common factor proxies (cross-sectional averages of dependent variable and weather variables). Three groups: coefficients of temperature variables constrained to be the same within each group. All regressions include yearly average precipitation. Country-specific trends: Y (yes, linear), YQ (yes, quadratic). LAGLD*AR1: serial correlation AR(1) test with 0,1,2 lagged dependent variable terms.

A.4 Agricultural output: robustness checks

Table A5: Agricultural output per capita: robustness checks

	MGCCE3	MGCCE3 3 groups	MGCCE3	MGCCE3 3 groups	MGCCE3	MGCCE3 3 groups			MGCCE3	MGCCE3 3 groups	MGCCE3	MGCCE3 3 groups	MGCCE3	MGCCE3 3 groups
BY TEMP	T1950	T1950	T2010	T2010	POP2010	POP2010		BY GDPPC	T1950	T1950	T2010	T2010	POP2010	POP2010
	(1)	(2)	(3)	(4)	(5)	(6)			(1)'	(2)'	(3)'	(4)'	(5)'	(6)
Contemporaneous								*Contemporaneous*						
TEMPLOW	-0.233	-0.0620	-0.0197	0.239	0.0195	0.246		GDPPCHIGH	0.472	-0.0566	0.507	-0.0900	0.431	-0.0737
	(0.501)	(0.892)	(0.524)	(1.004)	(0.497)	(0.983)			(0.522)	(0.554)	(0.545)	(0.584)	(0.531)	(0.573)
TEMPMED	-0.991	-2.189**	-1.297**	-2.704***	-1.363**	-2.680***		GDPPCMED	-1.297**	-0.829	-1.296**	-0.838	-1.301**	-0.813
	(0.652)	(1.055)	(0.646)	(0.831)	(0.636)	(0.836)			(0.560)	(0.799)	(0.578)	(0.808)	(0.580)	(0.800)
TEMPHIGH	-0.945	-3.872	-0.875	-3.841	-0.897	-3.873		GDPPCLOW	-1.248**	-2.582	-1.275**	-2.652*	-1.256**	-2.646*
	(0.606)	(2.617)	(0.615)	(2.665)	(0.608)	(2.664)			(0.615)	(1.612)	(0.631)	(1.581)	(0.632)	(1.593)
Long-run								*Long-run*						
TEMPLOW	2.273*	1.432***	2.018	3.076***	2.067	3.100***		GDPPCHIGH	4.138**	1.933***	4.017**	1.907***	3.683**	1.913***
	(1.356)	(0.170)	(1.378)	(0.346)	(1.318)	(0.345)			(1.650)	(0.168)	(1.605)	(0.167)	(1.571)	(0.165)
TEMPMED	2.688	-3.313***	2.181	-4.483***	2.043	-4.515***		GDPPCMED	-0.691	1.119***	-1.108	1.172***	-1.013	1.249***
	(2.164)	(0.210)	(2.106)	(0.288)	(2.101)	(0.293)			(2.060)	(0.0792)	(2.015)	(0.0853)	(1.987)	(0.0943)
TEMPHIGH	0.263	-6.443***	-0.0475	-6.738***	-0.343	-7.000***		GDPPCLOW	1.663	-2.390***	1.028	-2.639***	1.059	-2.676***
	(2.558)	(0.475)	(2.615)	(0.483)	(2.561)	(0.534)			(2.317)	(0.176)	(2.280)	(0.192)	(2.360)	(0.199)
Trends	YQ	YQ	YQ	YQ	YQ	YQ	YQ		YQ	YQ	YQ	YQ	YQ	YQ

Notes: *** p<0.01 ** p<0.05 * p<0.10. Cluster-robust standard errors are in parentheses. T1950/T2010: population-weighted temperature levels using population distribution in 1950 or 2010 (instead of 1990). POP2010: population-weighted estimates, using log of population in 2010. MGCCE3: mean group-common correlated effects estimator with three common factor proxies (cross-sectional averages of dependent variable and weather variables). Three groups: coefficients of temperature variables constrained to be the same within each group. All regressions include yearly average precipitation. Country-specific trends: YQ (yes, quadratic).

Table A6: Agricultural output per capita: two or four groups of countries

	MGCCE2	MGCCE2 2 groups		MGCCE2	MGCCE2 2 groups		MGCCE2	MGCCE2 4 groups
BY TEMP			BY GDPPC			BY TEMP*GDDPC		
VARIABLES	(1)	(2)		(1)'	(2)'		(3)	(4)
Contemporaneous								
TEMPLOW	-0.331	-0.547	GDPPCHIGH	0.120	-0.306	TEMPLOW*GDPPCHIGH	0.173	-0.646
	(0.461)	(0.451)		(0.445)	(0.742)		(0.496)	(0.795)
TEMPHIGH	-1.031**	-2.666**	GDPPCLOW	-1.534***	-1.226	TEMPLOW*GDPPCLOW	-1.808	0.803
	(0.484)	(1.295)		(0.519)	(0.897)		(1.112)	(1.287)
						TEMPHIGH*GDPPCHIGH	-0.0182	-2.536
							(0.978)	(2.811)
						TEMPHIGH*GDPPCLOW	-1.422**	-3.848***
							(0.586)	(1.075)
Long-run								
TEMPLOW	2.983**	-0.0599***	GDPPCHIGH	1.511	1.488***	TEMPLOW*GDPPCHIGH	2.116	-1.568***
	(1.287)	(0.00411)		(1.361)	(0.0944)		(1.381)	(0.125)
TEMPHIGH	-0.324	-2.480***	GDPPCLOW	1.675	2.408***	TEMPLOW*GDPPCLOW	5.029*	4.023***
	(1.957)	(0.151)		(1.837)	(0.144)		(2.807)	(0.450)
						TEMPHIGH*GDPPCHIGH	-0.206	6.786***
							(3.389)	(0.684)
						TEMPHIGH*GDPPCLOW	-0.376	-10.15***
							(2.432)	(0.824)
Trends	YQ	YQ		YQ	YQ		YQ	YQ

Notes: *** p<0.01 ** p<0.05 * p<0.10. Cluster-robust standard errors are in parentheses. MGCCE3: mean group-common correlated effects estimator with three common factor proxies (cross-sectional averages of dependent variable and weather variables). Two/four groups: coefficients of temperature variables constrained to be the same within each group. All regressions include yearly average precipitation. Country-specific trends: YQ (yes, quadratic).

A.5 The effects of precipitation shocks

Table A7: Precipitation shocks and income per capita, by temperature group

	2FE (1)	2FE (2)	MGCCE1 (3)	MGCCE1 (4)	MGCCE3 (5)	MGCCE3 (6)	MGCCE1 3 groups (7)	MGCCE1 3 groups (8)	MGCCE3 3 groups (9)	MGCCE3 3 groups (10)
Short-run										
Contemporaneous										
TEMPLOW	0.486	-0.0730	0.249	-0.673	-1.041	-1.973**	0.333	0.284	0.304	-0.00173
	(0.922)	(0.979)	(0.763)	(0.771)	(0.967)	(0.962)	(1.001)	(1.084)	(1.332)	(1.345)
TEMPMED	0.299	0.100	1.773*	0.624	0.774	1.214	0.848	0.683	0.552	0.491
	(0.525)	(0.494)	(0.971)	(0.878)	(0.981)	(0.918)	(1.458)	(1.030)	(1.536)	(1.074)
TEMPHIGH	1.415*	0.797	1.570	0.677	1.986*	0.242	1.092	0.355	0.417	0.163
	(0.830)	(0.891)	(1.082)	(0.903)	(1.148)	(0.973)	(1.279)	(0.874)	(1.184)	(1.093)
First lag										
TEMPLOW	1.282**	0.834	1.924**	0.912	0.279	-1.599	0.617	0.369	0.795	0.616
	(0.649)	(0.709)	(0.809)	(0.937)	(1.087)	(1.109)	(0.751)	(0.861)	(0.993)	(1.442)
TEMPMED	-1.202*	-1.351**	-1.737**	-1.817**	-1.844*	-2.279**	-1.060*	-1.144*	-1.505**	-1.595*
	(0.645)	(0.620)	(0.855)	(0.842)	(1.037)	(0.942)	(0.637)	(0.603)	(0.633)	(0.840)
TEMPHIGH	0.330	-0.229	-0.296	-1.060	-0.996	-1.844	-0.580	-1.248*	-1.180	-1.816
	(0.782)	(0.863)	(0.961)	(1.061)	(1.148)	(1.123)	(1.155)	(0.714)	(1.322)	(1.305)
Long-run										
TEMPLOW	17.55	4.547	5.274	-2.423	5.631	-10.90	11.21***	3.177***	8.053***	2.657***
	(12.31)	(8.503)	(12.39)	(6.969)	(11.63)	(7.058)	(1.230)	(0.226)	(1.137)	(0.226)
TEMPMED	-8.963	-7.479**	-19.50	0.991	-3.031	-1.952	-2.184***	-3.041***	-9.638***	-6.710***
	(6.138)	(3.506)	(14.98)	(6.975)	(14.43)	(8.384)	(0.231)	(0.259)	(1.000)	(0.618)
TEMPHIGH	17.32	3.395	-1.502	-12.75*	9.668	-13.02*	5.780***	-4.005***	-8.319***	-7.514***
	(13.63)	(9.366)	(15.93)	(6.785)	(17.36)	(7.642)	(0.713)	(0.347)	(1.245)	(0.665)
Long-run, first lag omitted										
TEMPLOW	4.820	-0.436	2.497	-2.035	7.177	-4.621	3.926***	1.383***	2.227***	-0.00749***
	(9.118)	(5.854)	(7.961)	(3.539)	(8.724)	(4.000)	(0.431)	(0.0982)	(0.314)	(0.000636)
TEMPMED	2.969	0.598	12.20	6.947	-1.143	3.632	8.739***	4.513***	5.581***	2.982***
	(5.182)	(2.941)	(11.07)	(5.229)	(10.90)	(4.862)	(0.923)	(0.385)	(0.579)	(0.275)
TEMPHIGH	14.05	4.766	8.751	0.945	8.920	-0.289	12.34***	1.589***	4.556***	0.739***
	(8.681)	(5.699)	(11.49)	(4.528)	(11.66)	(4.304)	(1.523)	(0.138)	(0.682)	(0.0654)
Trends	Y	YQ	Y	YQ	Y	YQ	Y	YQ	Y	YQ
Time FE	Y	Y								
LAGLD0AR1 p-value	0	0								
LAGLD1AR1 p-value	0	0								
LAGLD2AR1 p-value	0.938	0.347								

Notes: *** p<0.01 ** p<0.05 * p<0.10. Cluster-robust standard errors are in parentheses. 2FE: two-way fixed effects. MGCCE1: mean group-common correlated effects estimator with one common factor proxy (cross-sectional average of dependent variable). MGCCE3: mean group-common correlated effects estimator with three common factor proxies (cross-sectional averages of dependent variable and weather variables). Three groups: coefficients of temperature variables constrained to be the same within each group. All regressions include yearly average temperature. Country-specific trends: Y (yes, linear), YQ (yes, quadratic). LAGLD*AR1: serial correlation AR(1) test with 0,1,2 lagged dependent variable terms.

Table A8: Precipitation shock and income per capita, by income group

	2FE	2FE	MGCCE1	MGCCE1	MGCCE3	MGCCE3	MGCCE1 3 groups	MGCCE1 3 groups	MGCCE3 3 groups	MGCCE3 3 groups
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Short-run										
No lag										
GDPPCHIGH	-1.232*	-1.098*	-0.838	-1.060	-1.359	-1.916**	-1.182	-1.368*	-1.172	-1.566
	(0.633)	(0.642)	(0.769)	(0.752)	(0.862)	(0.916)	(1.119)	(0.746)	(0.834)	(1.077)
GDPPCMED	0.501	0.354	2.016**	0.474	0.908	0.719	0.540	0.292	0.184	-0.255
	(0.561)	(0.602)	(0.939)	(0.935)	(1.072)	(1.011)	(0.575)	(0.753)	(1.078)	(2.096)
GDPPCLOW	3.191***	1.654	2.417**	1.211	2.163**	0.911	1.204	0.356	-0.293	-0.236
	(0.996)	(1.041)	(0.933)	(0.835)	(1.090)	(1.035)	(0.981)	(1.038)	(1.738)	(1.935)
First lag										
GDPPCHIGH	-0.0527	-0.0779	0.767	0.361	1.270	-0.145	0.0453	-0.476	0.530	-0.129
	(0.532)	(0.541)	(0.719)	(0.750)	(0.971)	(0.980)	(1.393)	(1.150)	(0.703)	(0.483)
GDPPCMED	-0.146	-0.160	1.613*	0.653	0.302	-1.658	-0.208	-0.419	-0.967	-1.324
	(0.674)	(0.734)	(0.832)	(0.864)	(1.155)	(1.027)	(0.953)	(0.487)	(0.665)	(0.983)
GDPPCLOW	-0.624	-2.089**	-2.674***	-3.400***	-4.360***	-4.056***	-2.801***	-3.153***	-3.779***	-3.408**
	(1.079)	(0.915)	(0.979)	(1.005)	(1.208)	(1.149)	(1.010)	(1.130)	(1.390)	(1.698)
Long-run										
GDPPCHIGH	-12.75	-7.027	-4.374	-2.852	7.463	-9.534	-15.63***	-10.98***	-7.539***	-8.156***
	(9.323)	(5.904)	(11.51)	(5.090)	(12.81)	(6.609)	(1.586)	(0.741)	(0.922)	(0.603)
GDPPCMED	3.520	1.159	7.866	-1.506	-4.263	-7.120	2.929***	-0.749***	-6.022***	-7.765***
	(10.15)	(7.017)	(13.65)	(7.533)	(12.88)	(8.532)	(0.312)	(0.0700)	(0.683)	(0.795)
GDPPCLOW	25.46*	-2.597	-19.34	-10.34	9.182	-9.486	-20.76***	-14.27***	-51.84***	-16.59***
	(13.26)	(7.175)	(17.84)	(7.082)	(17.99)	(7.852)	(2.639)	(1.335)	(5.618)	(1.513)
Long-run, first lag omitted										
GDPPCHIGH	-12.22*	-6.562*	-6.576	-3.068	-0.552	-7.086*	-16.26***	-8.145***	-13.76***	-7.534***
	(6.394)	(3.966)	(9.015)	(3.148)	(8.507)	(3.650)	(1.649)	(0.550)	(1.684)	(0.557)
GDPPCMED	4.969	2.114	10.43	0.719	-3.512	0.275	4.765***	1.725***	1.414***	-1.253***
	(5.694)	(3.775)	(10.28)	(5.144)	(10.37)	(5.026)	(0.508)	(0.161)	(0.160)	(0.128)
GDPPCLOW	31.65***	9.886	21.37*	6.981	21.96*	5.442	15.66***	1.814***	-3.733***	-1.073***
	(10.37)	(6.310)	(12.32)	(4.273)	(12.47)	(4.386)	(1.990)	(0.170)	(0.405)	(0.0979)
Trends	Y	YQ	Y	YQ	Y	YQ	Y	YQ	Y	YQ
Time FE	Y	Y								
LAGLD0AR1 p-value	0	0								
LAGLD1AR1 p-value	0	0								
LAGLD2AR1 p-value	0.917	0.345								

Notes: *** p<0.01 ** p<0.05 * p<0.10. Cluster-robust standard errors are in parentheses. 2FE: two-way fixed effects. MGCCE1: mean group-common correlated effects estimator with one common factor proxy (cross-sectional average of dependent variable). MGCCE3: mean group-common correlated effects estimator with three common factor proxies (cross-sectional averages of dependent variable and weather variables). Three groups: coefficients of temperature variables constrained to be the same within each group. All regressions include yearly average temperature. Country-specific trends: Y (yes, linear), YQ (yes, quadratic). LAGLD*AR1: serial correlation AR(1) test with 0,1,2 lagged dependent variable terms.

Table A9: Precipitation shocks and agricultural output per capita, by temperature group

	2FE	2FE	MGCCE1	MGCCE1	MGCCE3	MGCCE3	MGCCE1 3 groups	MGCCE1 3 groups	MGCCE3 3 groups	MGCCE3 3 groups
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Short-run										
Contemporaneous										
TEMPLOW	3.735*	3.358*	5.315***	4.946***	4.819*	1.463	3.185	3.170	1.806	1.551
	(2.039)	(2.004)	(1.681)	(1.730)	(2.508)	(2.488)	(2.400)	(2.326)	(3.203)	(3.721)
TEMPMED	1.354	1.492	3.408**	3.200**	2.365	1.908	0.123	0.361	0.143	0.694
	(1.006)	(0.995)	(1.563)	(1.546)	(1.697)	(1.791)	(1.895)	(1.815)	(1.474)	(1.305)
TEMPHIGH	3.433**	3.586**	6.404***	6.521***	4.900**	4.760**	2.730	2.169	2.138	2.448
	(1.571)	(1.621)	(1.803)	(1.864)	(1.895)	(1.872)	(2.516)	(2.401)	(2.315)	(2.695)
First lag										
TEMPLOW	-0.913	-1.169	-1.654	-1.006	2.910	4.889*	-0.540	-0.206	-1.168	-1.048
	(1.372)	(1.396)	(1.930)	(1.780)	(2.422)	(2.590)	(2.267)	(2.570)	(2.362)	(2.530)
TEMPMED	-2.628***	-2.255**	-0.153	1.332	0.538	0.969	-1.839	-1.483	-2.652	-1.090
	(0.986)	(0.997)	(1.899)	(1.869)	(2.173)	(2.261)	(2.153)	(2.171)	(1.678)	(1.311)
TEMPHIGH	-0.248	0.0278	-0.154	-0.780	-1.047	-2.100	0.172	-0.416	-2.139	-1.707
	(0.947)	(1.018)	(1.603)	(1.560)	(1.889)	(1.844)	(2.473)	(2.228)	(1.521)	(1.516)
Long-run										
TEMPLOW	14.97	7.279	-4.262	10.43	5.133	14.68**	14.48***	9.164***	3.180***	1.484***
	(12.19)	(7.734)	(8.994)	(6.753)	(10.48)	(6.867)	(1.512)	(0.825)	(0.347)	(0.155)
TEMPMED	-6.759	-2.537	2.469	1.335	0.570	5.976	-8.386***	-3.168***	-12.88***	-1.004***
	(7.058)	(4.550)	(11.54)	(6.548)	(9.453)	(6.505)	(0.716)	(0.179)	(1.168)	(0.0626)
TEMPHIGH	16.89**	12.02*	44.57***	21.23***	26.13**	9.972	20.30***	6.734***	-0.004***	2.584***
	(8.350)	(6.166)	(10.80)	(6.179)	(12.27)	(7.565)	(1.761)	(0.460)	(0.0004)	(0.167)
Long-run, first lag omitted										
TEMPLOW	19.81*	11.17*	14.92**	10.15*	10.09	4.441	17.44***	9.802***	8.998***	4.575***
	(11.09)	(6.724)	(7.330)	(5.353)	(7.456)	(5.225)	(1.821)	(0.882)	(0.982)	(0.479)
TEMPMED	7.183	4.962	16.10**	10.89**	8.504	9.547**	0.601***	1.019***	0.736***	1.759***
	(5.454)	(3.387)	(7.528)	(4.422)	(5.934)	(4.396)	(0.0514)	(0.0576)	(0.0668)	(0.110)
TEMPHIGH	18.21**	11.92**	34.23***	21.79***	18.47**	9.405*	19.10***	8.334***	11.27***	8.540***
	(8.371)	(5.390)	(9.648)	(6.240)	(7.937)	(5.444)	(1.657)	(0.569)	(1.067)	(0.553)
Trends	Y	YQ	Y	YQ	Y	YQ	Y	YQ	Y	YQ
Time FE	Y	Y								
LAGLD0AR1 p-value	0	0								
LAGLD1AR1 p-value	0.006	0.357								
LAGLD2AR1 p-value	0.467	0.242								

Notes: *** p<0.01 ** p<0.05 * p<0.10. Cluster-robust standard errors are in parentheses. 2FE: two-way fixed effects. MGCCE1: mean group-common correlated effects estimator with one common factor proxy (cross-sectional average of dependent variable). MGCCE3: mean group-common correlated effects estimator with three common factor proxies (cross-sectional averages of dependent variable and weather variables). Three groups: coefficients of temperature variables constrained to be the same within each group. All regressions include yearly average temperature. Country-specific trends: Y (yes, linear), YQ (yes, quadratic). LAGLD*AR1: serial correlation AR(1) test with 0,1,2 lagged dependent variable terms.

Table A10: Precipitation shocks and agricultural output per capita, by income group

	2FE (1)	2FE (2)	MGCCE1 (3)	MGCCE1 (4)	MGCCE3 (5)	MGCCE3 (6)	MGCCE1 3 groups (7)	MGCCE1 3 groups (8)	MGCCE3 3 groups (9)	MGCCE3 3 groups (10)
Short-run										
No lag										
GDPPCHIGH	1.875	2.137	3.142**	3.540**	2.485	-0.0395	0.329	0.315	-2.286	-2.789
	(1.245)	(1.414)	(1.544)	(1.609)	(1.987)	(2.076)	(1.439)	(1.323)	(1.791)	(2.654)
GDPPCMED	0.537	0.459	4.104**	3.427**	2.768	2.753	-0.487	-0.483	-0.669	-0.337
	(0.996)	(0.980)	(1.617)	(1.634)	(2.132)	(1.972)	(2.594)	(2.246)	(2.067)	(1.676)
GDPPCLOW	7.610***	8.018***	7.742***	7.670***	6.313***	5.552***	5.727***	5.269***	6.448***	6.860***
	(2.206)	(2.160)	(1.731)	(1.817)	(1.976)	(1.979)	(2.165)	(1.928)	(2.477)	(2.466)
First lag										
GDPPCHIGH	1.755	1.950	-0.548	0.0854	1.710	2.617	1.896	1.821	1.754	1.123
	(1.385)	(1.554)	(1.918)	(1.783)	(2.140)	(2.230)	(2.798)	(2.986)	(2.741)	(2.379)
GDPPCMED	-1.504*	-1.458*	2.646	2.774*	5.216**	3.807*	-1.136	-1.140	-0.545	-0.0590
	(0.817)	(0.798)	(1.755)	(1.667)	(2.280)	(2.195)	(2.199)	(2.291)	(2.063)	(1.866)
GDPPCLOW	-3.845***	-2.989**	-4.143**	-3.712**	-4.431**	-3.311	-3.348**	-2.862*	-3.474*	-2.771
	(1.369)	(1.411)	(1.838)	(1.778)	(2.134)	(2.134)	(1.414)	(1.522)	(1.811)	(1.770)
Long-run										
GDPPCHIGH	19.30*	13.59	2.206	8.660	7.775	11.30*	12.10***	6.868***	-1.770***	-4.070***
	(11.49)	(8.580)	(8.260)	(6.603)	(9.014)	(6.344)	(1.236)	(0.563)	(0.148)	(0.309)
GDPPCMED	-5.140	-3.320	15.78	12.07*	3.061	15.58**	-8.627***	-5.411***	-4.258***	-0.894***
	(6.390)	(4.073)	(11.32)	(6.973)	(10.84)	(7.439)	(0.818)	(0.397)	(0.430)	(0.0637)
GDPPCLOW	20.01**	16.72***	25.42**	14.06**	18.73	5.119	14.29***	7.611***	11.55***	12.04***
	(9.166)	(6.309)	(11.02)	(6.477)	(12.35)	(8.363)	(1.393)	(0.470)	(0.974)	(0.858)
Long-run, first lag omitted										
GDPPCHIGH	9.968	7.107	16.50**	6.869	8.632	2.586	1.788***	1.013***	-7.607***	-6.813***
	(6.810)	(4.794)	(7.308)	(4.863)	(6.345)	(4.455)	(0.183)	(0.0831)	(0.634)	(0.518)
GDPPCMED	2.856	1.527	8.721	7.325	1.585	4.902	-2.587***	-1.609***	-2.345***	-0.761***
	(5.307)	(3.265)	(8.280)	(4.880)	(7.153)	(4.733)	(0.245)	(0.118)	(0.237)	(0.0542)
GDPPCLOW	40.46***	26.66***	40.43***	28.69***	26.65***	15.23***	34.41***	16.66***	25.05***	20.19***
	(12.14)	(7.378)	(9.296)	(6.098)	(7.690)	(5.170)	(3.354)	(1.029)	(2.112)	(1.439)
Trends	Y	YQ	Y	YQ	Y	YQ	Y	YQ	Y	YQ
Time FE	Y	Y								
LAGLD0AR1 p-value	0	0								
LAGLD1AR1 p-value	0.006	0.363								
LAGLD2AR1 p-value	0.458	0.236								

Notes: *** p<0.01 ** p<0.05 * p<0.10. Cluster-robust standard errors are in parentheses. 2FE: two-way fixed effects. MGCCE1: mean group-common correlated effects estimator with one common factor proxy (cross-sectional average of dependent variable). MGCCE3: mean group-common correlated effects estimator with three common factor proxies (cross-sectional averages of dependent variable and weather variables). Three groups: coefficients of temperature variables constrained to be the same within each group. All regressions include yearly average temperature. Country-specific trends: Y (yes, linear), YQ (yes, quadratic). LAGLD*AR1: serial correlation AR(1) test with 0,1,2 lagged dependent variable terms.