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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 and precipitation is one of the most speculative components of integrated assessment models of climate change. Whether detrimental effects of temperature change on economic prosperity are most significant for countries with low incomes or those with high temperatures is still an unresolved question in the literature, while changes in precipitation are widely regarded as not having any significant productivity effects. 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 154 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. Our preferred specifications suggest that a temporary (permanent) 1°C rise in temperature is associated with a reduction in income per capita of 1.3% (14%) in high-temperature countries, with the long-run effects substantially larger than those commonly suggested in the literature. We find weaker differential effects by income-group. We further highlight that changes in precipitation levels can influence short-run and long-run agricultural output per worker in high-temperature or low-income countries, albeit to a very modest extent.

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 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 estimation of Integrated Assessment Models (IAMs), which show how carbon emissions link climate change and economic growth and which provide ways to think about suitable policy 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 3-3.5°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 as measured using weather data (Kolstad & Moore 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, for a recent review): 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 investigations 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

[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) and Kalkuhl & Wenz (2020) 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 growth but reject systematic differences favouring differentiation by either average temperature or income, while Letta & Tol (2019) find evidence for detrimental effects of temperature change on total factor productivity in both hot and poor countries.

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. Deschênes & Greenstone 2007, for US agriculture), since they allow for parameters to differ across groups of countries, depending on their income or temperature levels, respectively. Nevertheless, these *ex ante* imposed constraints 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). Multiple reasons for such heterogeneity suggest themselves, including differential nature of temperature or precipitation increases (e.g. simply more rain fall is unlikely to be harmful whereas temporally more concentrated rainfall could increase flood risk, river silting, land slides, etc.) or differential speed of adaptation to climate change across countries (see, for instance, Malikov et al. 2020, for US agriculture). 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. Second, in the presence of parameter heterogeneity, i.e. a differential weather-growth nexus across countries, the dynamic fixed effects estimator is inconsistent, even for large T (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] Furthermore, causal identification may require the inclusion of lagged outcome and treatment variables (temperature and precipitation) to allow for feedback effects and avoid omitted variable bias (Imai & Kim 2019). Third, in pooled regressions time fixed effects capture global shocks affecting all countries *in the same way*, but cannot deal with global shocks affecting each country differently, 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. Prime

[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 control for initial conditions (Durlauf et al. 2005).

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).

Figure 1 illustrates our approach and summarises our key findings with reference to the debate in the literature: 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 154 countries (on the y-axis) against the country mean temperature in panel (a) and the country average income per capita in panel (b);[5] 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 countries at high temperatures the conditional *contemporaneous* temperature effect is negative and between -1% and -2%. In panel (b) we see a much smaller negative temperature effect for low-income countries. The overlapping of findings is not surprising given that the cross-section correlation between income per capita and temperature (in 2019) is around -0.49 —see also Table 1. Nevertheless, these headline results for aggregate per capita GDP data spell out that we find stronger evidence for a temperature-productivity effect *differentiated by average temperature* ('hot countries suffer the most') than for such an effect *differentiated by average income* ('poor countries suffer the most'). For reference, a temperature increase of 0.6°C to 1°C is the upper bound for estimates of average global heating since the 1960s (Hsiang & Kopp 2018).

In our analysis below we consider a wide range of alternative specifications adopting output, aggregate factor inputs or total factor productivity, and sectoral equivalents for agriculture[6] as dependent variables as well as alternative lag structures to capture the dynamics. Additional analysis breaks new ground by shedding light on the heterogeneous effects of precipitation on agricultural output. In order to 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 (2FE) and standard heterogeneous Mean Group (MG) estimates (Pesaran & Smith 1995)[7] 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 154 countries.[8]

[5] Our results are qualitatively identical if we adopt 1993 as the base year. See footnote 15.

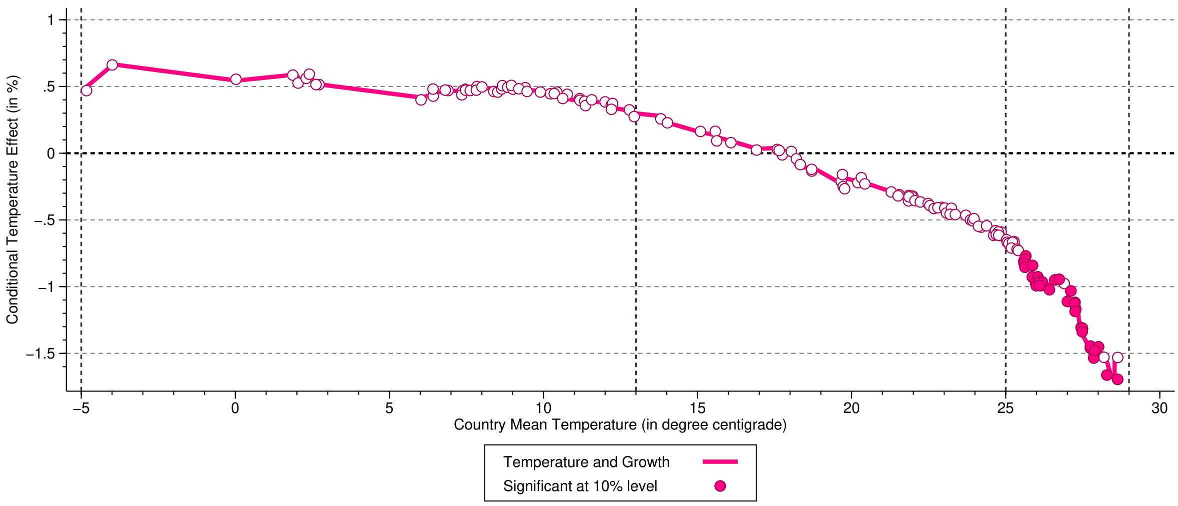
[6] The focus on the agricultural sector is warranted given the significance of agricultural productivity in structural change and hence economic development (e.g. Barrett et al. 2010, Herrendorf et al. 2014, Huneeus & Rogerson 2020).

[7] These are in essence the same as the CCE models but exclude cross-section averages, hence fail to account for any global shocks with heterogeneous impact across countries.

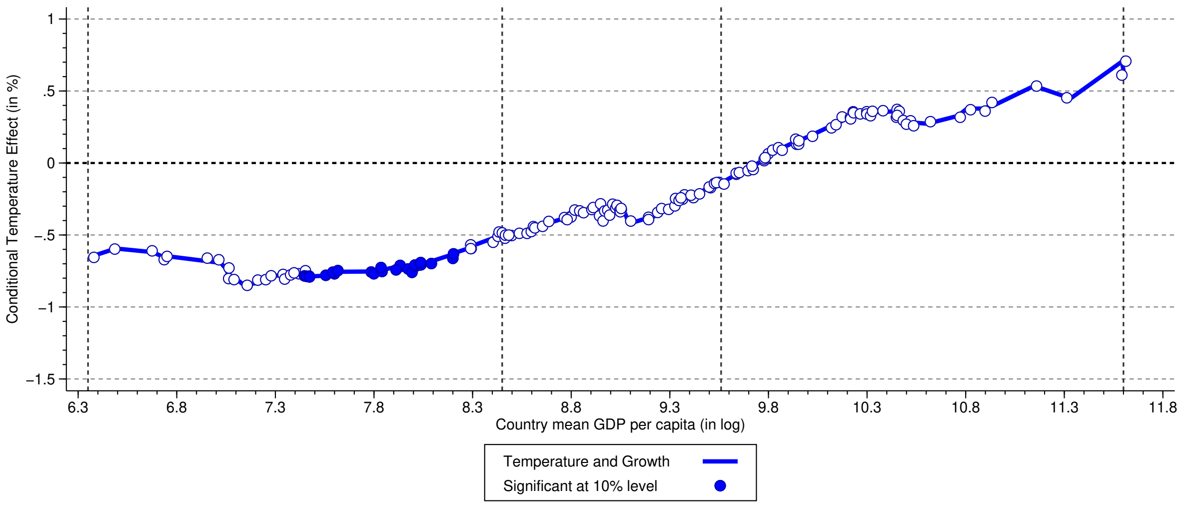
[8] For the 2FE approach we capture heterogeneity via interaction effects, while for the heterogeneous MG and CCE estimates we follow the literature and calculate the outlier-robust means, and their (heteroscedasticity-

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 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 columns (4) and (8) of Panel (c) in Table 2 (contemporaneous temperature variable). 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 Appendix Figure A-1.

Using these three groupings, our benchmark results for aggregate income per capita confirm that high-temperature countries are negatively affected by a rise in temperature: a temporary 1°C rise in temperature reduces income per capita by about 1.3%. All of the above results, as well as those routinely (though not necessarily exclusively) reported in the existing literature, are for static models, yet our estimation of dynamic models allows us to calculate long-run effects, assuming, through exponentially declining lag weights, that countries adapt to climate change over time. 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 countries by 14% — this estimate is substantially higher than those reported in recent meta-analyses (e.g. Howard & Sterner 2017, Rennert et al. 2022). Groupings according to average income per capita, as in Dell et al. (2012), appear much less relevant: estimates are smaller and less stable across specifications. Additional results suggest that the non-linear relationship between temperature and aggregate income per capita is not simply driven by the response of agricultural output to weather shocks.

While the existing literature on climate change and income cited above disagrees about the patterns underlying the temperature-growth nexus, there is a quasi-unanimous agreement that the effects for precipitation are insignificant. A notable exception here is Damania et al. (2020), who demonstrate that in a standard two-way fixed effects model an insignificant precipitation effect at the country level turns statistically significant and following an inverted-U shape once more granular data are employed, pointing to the relative significance of the agricultural sector within the economy as the driving force of this effect.[9] While our results for aggregate GDP per capita are in line with those in the broader literature (no effect), our findings for the agricultural sector find indeed a significant and positive role for precipitation increases in countries with medium or high average temperature. A 100mm increase in precipitation is associated with an average short-run effect of 0.7-0.9% and an average long-run effect of around 2.7% increase in income per capita. However, to put these figures into perspective: in medium/high-temperature countries, for a nearly balanced sample, median precipitation declined from 1,218mm in 1971 to 1,187mm in 2019.[10] Hence, over the 1971-2019 period, the decline in precipitation may have contributed to a long-run fall in agricultural output of just 0.85% in these countries.

robust) standard errors, using an M-estimator (Rousseeuw & Leroy 1987).

[9]The economic effects reported in Damania et al. (2020), e.g. +0.7% (-1.6%) change in aggregate income per capita growth for a sample standard deviation increase in precipitation (temperature) relative to mean per capita GDP growth of 2.1% (cell level data), make for difficult interpretation vis-à-vis the effect of climate change: the cross-country standard deviation of temperature for this period is around 8°C while that for precipitation is around 800mm (based on our country-level sample restricted to 1990-2014) — global heating-induced temperature change is believed to be 0.6 to 1°C while the change in precipitation over time is non-uniform and amounts to perhaps 20-30mm. Hence, the economic magnitudes reported by these authors mimic taking a country with the precipitation level of temperate-continental Austria (1,139mm, sample mean) and moving it to the level of tropical Honduras (1,969mm), or taking a country with the average temperature of Malta (19°C, sample mean) and moving it to the level of the United Arab Emirates (27.7°C).

[10]The agricultural data start in 1961, but using 1971 provides a much better coverage across countries.

Our study makes three main 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 replicate 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. Second, we employ our heterogeneous parameter models in the context of dynamic empirical specifications. This means that we can easily estimate long-run effects of a permanent change in temperature levels on GDP levels, without additional assumptions about future economic paths.[11] Third, throughout our empirical analysis we systematically compare and contrast the primary patterns in our heterogeneous 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 relationship in more elaborate specifications (e.g. Dell et al. 2012, with respect to studying the effects in hot countries). We consistently find stronger evidence for heterogeneity along existing temperature patterns than by income.

Our findings support those studies calling for a much more stringent damage function in IAMs, especially for countries where part or all of their (populated) territories are subject to already relatively high, and likely increasing, temperature levels. It is notable that a 1°C local rise in temperature would add eleven additional countries to the high-temperature group (representing 1.6 billion people in 2019), including India and the Democratic Republic of Congo, with substantial detrimental productivity effects from temperature changes.

The remainder of the paper proceeds as follows. In Section 2 we introduce our econometric model and data. In Section 3, we present our results and discuss them. Section 4 concludes.

2 Econometric model and data

2.1 Econometric model and implementation

Consider the following dynamic pooled model:

$$\begin{aligned} Y_{it} &= \gamma Y_{it-1} + h(T_{it}) + h(T_{i,t-1}) + g(PP_{it}) + g(PP_{i,t-1}) \\ &\quad + \beta_1' X_{it} + \beta_2' X_{it-1} + \alpha_i + \eta_t + \pi_{i1} t + \pi_{i2} t^2 + \varepsilon_{it}, \end{aligned} \tag{1}$$

[11] There is a debate about whether climate change has a permanent impact on income 'levels' or 'growth rates' (e.g. Kalkuhl & Wenz 2020, Newell et al. 2021, among others). Ultimately, our long-run estimates correspond to *permanent* impacts on GDP levels. Given that this transition to a new equilibrium is not instantaneous, the growth rate will be *temporarily* affected, too.

where the log of income per capita in country i at time t, Y_{it}, depends on past economic performance, current and lagged functions h($\cdot$) of temperature T and g($\cdot$) of precipitation PP, current and lagged values of control variables X, country and time fixed effects α_i and η_t, as well as country-specific linear and quadratic trends. ε_{it} is a white noise error term. Simplifying that $h(T_{it}) = \delta_{i,1}T_{it}$ and $h(T_{i,t-1}) = \delta_{i,2}T_{it-1}$, with coefficient δ allowed to vary across countries and similarly for $g(\cdot)$, this autoregressive distributed lag (ARDL) model can be re-written in its equivalent error correction form as:

$$\begin{aligned} \Delta Y_{it} &= \theta Y_{i,t-1} + \delta_{i,1}T_{it} + \delta_{i,2}T_{i,t-1} + \kappa_{i,1}PP_{it} + \kappa_{i,2}PP_{i,t-1} \\ &\quad +\beta_1' X_{it} + \beta_2' X_{it-1} + \alpha_i + \eta_t + \pi_{i1}t + \pi_{i2}t^2 + \varepsilon_{it}, \end{aligned} \tag{2}$$

where Δ is the first difference operator and $\theta = (\gamma - 1)$.

The econometric models estimated in the literature can be interpreted as constrained variants of equation (2) with some limited cross-country heterogeneity allowed in the temperature and precipitation coefficients. For example, the models estimated by Dell et al. (2012) impose $\theta = \beta_1 = \beta_2 = \pi_{i2} = 0$, and in their preferred specification assume that the marginal effects of temperature and precipitation vary systematically between developed and developing (DEV) countries, i.e. the short-run 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 — in analogy for models also including lagged temperature and for equivalent analysis of precipitation.[12] The models estimated by Burke et al. (2015) also impose $\theta = \beta_1 = \beta_2 = 0$, while they further drop the lags of temperature and precipitation ($\delta_{i,2} = 0$, $\kappa_{i,2} = 0$). 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 short-run 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 analogy for precipitation.

In this paper, we suggest going further by not *ex ante* imposing any pooling constraints on any of the coefficients estimated:

$$\begin{aligned} \Delta Y_{it} &= \theta_i Y_{i,t-1} + \delta_{i,1}T_{it} + \delta_{i,2}T_{i,t-1} + \kappa_{i,1}PP_{it} + \kappa_{i,2}PP_{i,t-1} \\ &\quad +\alpha_i + \sum_{s=t-k}^{t} \lambda_{i,s} f_s + \pi_{i1}t + \pi_{i2}t^2 + \epsilon_{it}, \end{aligned} \tag{3}$$

where f_s are current and lagged unobserved common factors with associated country-specific

[12] 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.

factor loadings λ_{is}.[13]

Factors and factor loadings are unknown, and the panel time series literature has two alternative ways of tackling identification of model parameters $(\theta, \delta, \kappa, \beta)$ in this setup: first, following Bai (2009), the factors and loadings can be estimated from model residuals via principal component analysis, which involves repeated iteration until estimates converge. However, this approach is not presently extended to an explicitly dynamic setup and we therefore apply a second implementation following Pesaran (2006) and Chudik & Pesaran (2015): here, the unobserved common factors are proxied using lagged and contemporaneous cross-section averages of all observed variables in the model (dependent and independent variables).[14] The heterogeneous parameters are captured by construction given the country-specific regression models in this common correlated effects (CCE) estimator. Formally,

$$\begin{aligned}\Delta Y_{it} &= \theta_i Y_{i,t-1} + \delta_{i1} T_{it} + \delta_{i2} T_{i,t-1} + \kappa_{i,1} PP_{it} + \kappa_{i,2} PP_{i,t-1} \\ &\quad + \alpha_i + \sum_{s=t-k-2}^{t} (\zeta_{is}^1 \overline{\Delta Y_{is}} + \zeta_{is}^2 \overline{T_{i,s}} + \zeta^4 3_{is} \overline{PP_{i,s}} + \zeta_{is}^4 \overline{X_{i,s}}) + \pi_{i1} t + \pi_{i2} t^2 + \epsilon_{it},\end{aligned} \tag{4}$$

where bars indicate cross-section averages across all countries in the sample. For comparative purposes we also estimate a standard Pesaran & Smith (1995) Mean Group estimator, a heterogeneous parameter estimator which excludes the set of cross-section averages.

These empirical implementations provide us with N estimates for the short-run effect of temperature and precipitation on growth ($\hat{\delta}_{i,1}$ and $\hat{\kappa}_{i,1}$) as well as N estimates for the long-run effects $(\hat{\delta}_{i,1} + \hat{\delta}_{i,2})/-\hat{\theta}_i$ and $(\hat{\kappa}_{i,1} + \hat{\kappa}_{i,2})/-\hat{\theta}_i$. In the presence of a lagged dependent variable, we are effectively estimating a rational distributed lag model, where the effects of a permanent rise in temperature on income per capita persists beyond $t+1$, but with lower influence over time (with implicit geometrically declining weights, that would be in line with the progressive implementation of adaptation policies). For a more parsimonious presentation of the results we compute robust mean estimates by tercile, for instance for the short-run temperature effect

$$\hat{\delta}_{i,1} = \tau_1 \text{Low}_i + \tau_2 \text{Medium}_i + \tau_3 \text{High}_i + \epsilon_i \tag{5}$$

where Low_i, Medium_i, and High_i indicate whether country-average temperature or country-average per capita GDP belong to the first, second, or third terciles of the respective sample distribution.[15] Similarly for the κ coefficients and the respective implied long-run estimates

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

[14] We include three lags of the cross-section averages in addition to their contemporaneous values. 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.

[15] We use the sample average values for the period 1961-2019 for several reasons. First, our panel is unbalanced: we only reach our full sample of countries in 1993 and therefore do not have a common base year. Second, for initially 'poor' countries having experienced significant economic development (e.g. South

for temperature and precipitation.[16] Given that these dependent variables can include extreme observations, we use an estimator robust to outliers, an M-estimator, to obtain robust means and their (heteroscedasticity and outlier robust) standard errors (Rousseeuw & Leroy 1987).

The CCE specification in (4) 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. influence of Gulf Stream or El Niño). The standard application of the CCE estimator typically separates macroeconomic policies at the country level from the consequences of global macroeconomic tendencies, but this setup does not fit the weather-productivity nexus very well. In order to acknowledge the possibility that the standard CCE estimator would perfectly account for global climate shocks, we also estimate a variant of equation (4) where only cross-section averages of the productivity (dependent) variable are included, i.e. $\zeta^3 = \zeta^4 = 0\, \forall i, s$ — we refer to the latter as CCE$^\sharp$ and the standard implementation as CCE in the results tables.[17]

Finally, the presentation of our estimates by income or temperature terciles below highlights the productivity implications of a 1°C increase in temperature or a 100mm increase in precipitation — the former represents an upper bound for estimates of global heating over the past six decades, the latter is almost an order of magnitude larger than the observed average increase, although country-specific change in precipitation is not uniformly positive or negative (Hsiang & Kopp 2018, Damania et al. 2020).

2.2 Intuition

Above we introduced the common factor setup and the implementation by Pesaran (2006) to identify the parameters of interest on the observed temperature and precipitation variables in the face of unobserved time-varying heterogeneity. In the following we lay out why this is necessary in the first place and the intuition how the CCE approach works.

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 equilibrium 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

Korea), the income averages capture the fact that these countries may have possibly become *less sensitive* to climate change if the temperature-growth relationship is mediated by higher income levels. Note that we find qualitatively similar results for the effects of a temperature shock on aggregate economic development when we use 1993 values of income per capita as base year.

[16]There are two ways of estimating the long-run relationship: (i) estimating robust means for the δ, κ and θ 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.

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

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).

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:

$$y_{it} = \alpha_i + \beta_i x_{it} + u_{it} \qquad u_{it} = \lambda_i f_t + \varepsilon_{it} \tag{6}$$

where α_i is a country intercept (fixed effect)[18] 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, $\tilde{y}_{it} = y_{it} - y_t$ (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 (6) and compute its cross-section average (denoted by bars)

$$\bar{y}_t = \bar{\alpha} + \bar{\beta}\bar{x}_t + \bar{\lambda} f_t, \tag{7}$$

where the error term drops out since $\bar{\varepsilon}_t = 0$ by assumption. Now solve this equation for the

[18] 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.

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

$$\begin{aligned} y_{it} &= \alpha_i + \beta_i x_{it} + \lambda_i f_t + \varepsilon_{it} && (8)\\ &= [\alpha_i - (\bar{\alpha}/\bar{\lambda})] + \beta_i x_{it} - (\lambda_i/\bar{\lambda})\bar{y}_t - (\lambda_i/\bar{\lambda})\bar{\beta}\bar{x}_t + \varepsilon_{it} && (9)\\ &= \alpha_i^\star + \beta_i x_{it} + \lambda_{1i}^\star \bar{y}_t + \lambda_{2i}^\star \bar{x}_t + \varepsilon_{it}, && (10) \end{aligned}$$

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 (6). 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.

2.3 Preferred Specification

There are inferential costs to estimating unduly restricted models, such as static models instead of dynamic models, since the inclusion of lags avoids an omitted variable bias and modifies the interpretation of the results (De Boef & Keele 2008). For example, the presence of a lagged dependent variable can account for convergence effects, omitted variables, and allows for the calculation of the long-run effects associated with a distributed lag model. Hence, estimates of dynamic models ought to be preferred to those derived from static models.

Besides the weather variables, the models do not include any control variables. Including country-specific time trends in a flexible way (in our case, linear and quadratic trends)[19] reduces the risk of spurious regression and accounts for slow-changing (and relatively predictable) determinants of income per capita such as demography or educational attainment, political institutions or economic policies (Burke et al. 2015).

In the presence of heterogeneous slopes, the dynamic fixed effects estimator is biased and inconsistent. In addition, common time fixed effects cannot account for the heterogeneous impact of global shocks. Hence, estimates of heterogeneous models (MG) with common factors (CCE) ought to be preferred to those derived from pooled fixed effects models (2FE).

[19] In additional results available on request we estimated pooled and heterogeneous models with country-specific linear or quadratic trends along with a benchmark case without any such deterministic components.

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. On the one hand, local climate shocks are partly driven by global shocks and we may not wish therefore to eliminate the country-specific effects of the latter ($\text{CCE}^\sharp$). On the other hand, a global climate shock could have an indirect impact on the economy through international economic spillovers; for instance, lower agricultural yields in one foreign country may boost demand for the agricultural exports of another country. At the risk of under-estimating the effects of climate change, our preferred specification controls for all shocks (CCE).

2.4 Data

We follow the literature in drawing inference on the causal effects of climate change on economic prosperity by studying the variability of weather variables (annual average temperature and total precipitation) in their effect on various measures of (sectoral) economic output (Kolstad & Moore 2020).[20] Hence, the identification here and in the literature is based on temporary, unexpected weather shocks. Short-term estimates based on these data assume that agents do not change their beliefs about the underlying distribution of weather they face, whereas long-term estimates factor in such adjustments (e.g. change in investment behaviour, factor input use, etc), under the premise that opportunities for adaptation represent small steps rather than cataclysmic game-changers (Deryugina & Hsiang 2017). Our long-run estimates implicitly capture this partial adjustment behaviour by giving less weight over time to a permanent weather change.

Weather Data Data on *weather* come from the Climatic Research Unit at the University of East Anglia, UK.[21] In line with the literature we use the annual average temperature (°C). We also include, in the same manner as temperature, annual average precipitation (mm/100). These measures are area-weighted.[22]

Aggregate Income Data Data on *income per capita* come from the Penn World Tables (PWT).[23] 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, *pop*). We also decompose the log of income per capita

[20] These authors define climate change as "a change in the probability distribution from which the weather statistic [e.g. annual temperature] is drawn in each time period" (3).

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

[22] Other studies, e.g. Dell et al. (2012), have used population-weighted measures and found little difference with the use of area-weighted measures. Furthermore, while the use of the latter may under-estimate the impact of climate change, it is also less likely to be endogenous to outcomes.

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

into the log of two components, inputs and TFP, based on the following, simple equation: $Y/POP = \text{TFP} \times (Y/K)^{\alpha/(1-\alpha)} e^{\phi S}$, where Y is income, POP is total population, K is the capital stock, S is the average years of education in the population aged 15 and over, and we set technology parameters to $\alpha = 1/3$ and $\phi = 0.09$.[24] These data are available for 154 countries over the 1961-2019 period.[25]

Agricultural Sector Data In additional regressions we adopt measures of output, inputs and total factor productivity in the agricultural sector as respective dependent variables. Data for the log of agricultural output per worker, a factor input index and an agricultural TFP index come from the U.S. Department of Agriculture (Fuglie 2012, 2015)[26] and cover the same 1961-2019 country sample as that in our 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.

[24] Data on capital stock come from the PWT and data on schooling attainment are taken from the Wittgenstein Centre (http://dataexplorer.wittgensteincentre.org/wcde-v2/).

[25] We omit countries with fewer than 25 observations.

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

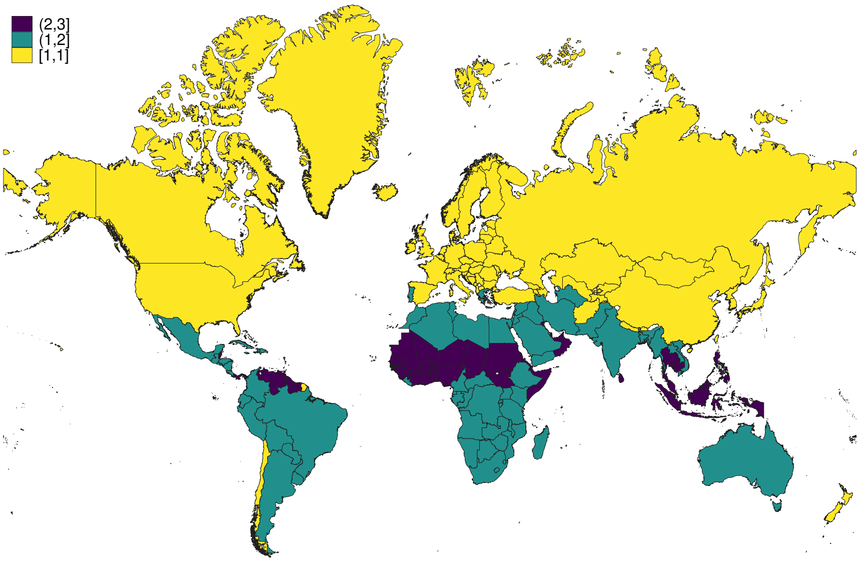
Table 1: Country Groupings (Table)

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

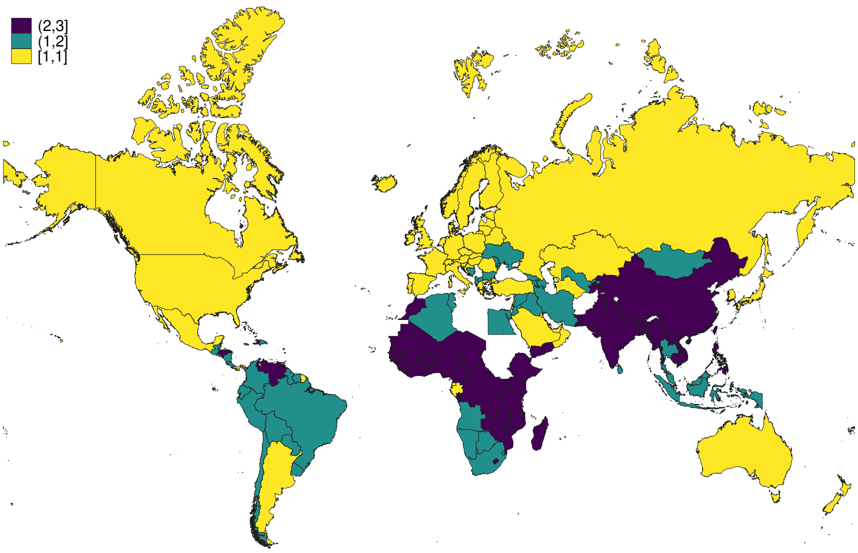
Notes: The table reports the group membership of the countries (using 3-digit iso codes) in our sample by income and temperature terciles.

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 cross-section correlation coefficient between the two raw variables (average temperature, average log GDP pc) is -0.48.

Table 2: Temperature Effects on Aggregate Economic Development

	Split by Temperature Group					Split by Income Group			
	(1)	(2)	(3)	(4)		(5)	(6)	(7)	(8)
Estimator	2FE	MG	CCE$^\sharp$	CCE		2FE	MG	CCE$^\sharp$	CCE
Panel (a) Static Models									
Low	0.572	0.428	0.762	0.338	High	0.419	-0.003	0.203	0.102
	(0.273)**	(0.265)	(0.224)***	(0.229)		(0.186)**	(0.269)	(0.249)	(0.264)
Medium	-0.278	0.0199	-0.190	-0.102	Medium	-0.200	-0.450	-0.351	-0.643
	(0.450)	(0.353)	(0.305)	(0.324)		(0.339)	(0.398)	(0.394)	(0.398)
High	-1.747	-0.746	-1.010	-0.994	Low	-0.622	0.207	-0.101	-0.0689
	(0.719)**	(0.465)	(0.476)**	(0.495)**		(0.241)**	(0.432)	(0.372)	(0.429)
Panel (b) Models with lagged weather variables									
— Coefficient on Contemporaneous Temperature (T_{it})									
Low	0.585	0.611	0.860	0.551	High	0.169	0.039	0.162	0.093
	(0.266)**	(0.240)**	(0.212)***	(0.242)**		(0.295)	(0.228)	(0.226)	(0.254)
Medium	-0.298	-0.133	-0.237	-0.119	Medium	-0.093	-0.372	-0.274	-0.457
	(0.458)	(0.337)	(0.313)	(0.335)		(0.555)	(0.442)	(0.408)	(0.388)
High	-1.729	-0.951	-1.231	-1.195	Low	-0.505	-0.035	-0.232	-0.174
	(0.676)**	(0.444)**	(0.491)**	(0.515)**		(0.452)	(0.398)	(0.375)	(0.440)
— Coefficient on Lagged Temperature ($T_{i,t-1}$)									
Low	-0.209	-0.0540	0.412	0.475	High	-0.664	-0.416	-0.059	0.020
	(0.221)	(0.276)	(0.252)	(0.266)*		(0.236)***	(0.245)*	(0.218)	(0.222)
Medium	0.125	0.411	-0.015	-0.066	Medium	0.296	0.313	0.049	0.104
	(0.422)	(0.399)	(0.437)	(0.445)		(0.359)	(0.337)	(0.381)	(0.412)
High	-0.166	0.305	-0.113	-0.247	Low	0.686	0.799	0.377	0.157
	(0.405)	(0.319)	(0.346)	(0.457)		(0.357)*	(0.366)**	(0.417)	(0.503)
Panel (c) Models with lagged weather and dependent variables (ARDL)									
– Coefficient on Contemporaneous Temperature (T_{it})									
Low	0.547	0.713	0.596	0.241	High	0.394	0.344	0.385	0.821
	(0.231)**	(0.249)***	(0.183)***	(0.285)		(0.290)	(0.223)	(0.233)	(0.311)***
Medium	-0.159	-0.409	-0.312	0.221	Medium	-0.172	-0.634	-0.543	-0.577
	(0.478)	(0.339)	(0.361)	(0.473)		(0.499)	(0.400)	(0.381)	(0.436)
High	-1.391	-0.994	-1.298	-1.230	Low	-0.667	-0.320	-0.658	-0.926
	(0.578)**	(0.455)**	(0.406)***	(0.440)***		(0.419)	(0.413)	(0.358)*	(0.382)**
– Coefficient on Lagged Temperature ($T_{i,t-1}$)									
Low	-0.043	0.102	0.189	0.466	High	-0.373	-0.285	-0.0236	0.383
	(0.217)	(0.264)	(0.215)	(0.304)		(0.198)*	(0.213)	(0.197)	(0.281)
Medium	0.178	0.230	-0.0952	0.316	Medium	0.281	0.161	-0.163	-0.158
	(0.368)	(0.355)	(0.323)	(0.501)		(0.368)	(0.347)	(0.333)	(0.510)
High	-0.203	-0.153	-0.491	-0.770	Low	0.467	0.350	-0.128	-0.187
	(0.386)	(0.301)	(0.364)	(0.602)		(0.370)	(0.378)	(0.380)	(0.547)

Notes: We present robust mean estimates and associated standard errors of country-specific temperature-development coefficients by (temperature or income) group: low, medium, high (in rows). We reverse the order of presentation for the analysis by income group to ease comparison of 'high temperature' vs 'low income' results (now in the same row). The columns are for alternative underlying empirical models of the weather-growth relationship (all models include temperature and precipitation): 2FE – pooled two-way fixed effects estimator; MG – simple Pesaran & Smith (1995) Mean Group estimator; CCE – standard Pesaran (2006) Common Correlated Effects estimator; CCE$^\sharp$ – dto but only including cross-section averages of the dependent variable. All of these underlying models further include country-specific linear and quadratic trends. Different panels of the table are for different specification: (a) static, (b) with lagged weather variables (partial adjustment model), (c) with lagged weather and dependent variables (autoregressive distributed lag model). The sample (static model) is for 154 countries with 8,020 observations. Outlier-robust standard errors in parentheses (cluster-robust for 2FE). *** p<0.01, ** p<0.05, * p<0.1

3 Results

3.1 Aggregate Income per capita

Table 2 presents estimates for the temperature-productivity relationship at the aggregate economy level. Here and in all following results tables we present robust mean estimates for the weather-productivity effect. The columns are for different estimators, separated into two blocks: analysis by temperature group and by income group. We reverse the order of presentation (high, medium, low) for the analysis by income group to ease the direct comparison of 'high temperature' vs 'low income' results. 'Low', 'Medium' and 'High' present robust mean estimates, with the exception of the pooled two-way fixed effects (2FE) estimator in (1) and (5).[27] Panels (a) to (c) present coefficients from static, partial adjustment and dynamic (ARDL) models, respectively.[28]

The static model results in Panel (a) indicate that our 2FE estimates are in line with the findings of both Burke et al. (2015) ('hot countries suffer most')[29] and Dell et al. (2012) ('poor countries suffer most'),[30] but once we move away from assuming a common weather-productivity nexus only the former result remains robust. In column (4), the average low-temperature country effect on income per capita is smaller compared with the 2FE results and not statistically significant while that for high-temperature countries is moderated to -1%.

Our results for the *contemporaneous* temperature variable in Panel (b) replicate the patterns from the static models: there is no evidence for a link to income but strong evidence for a link to average temperature.[31] Adding the first lag of the weather variables captures the effects of a temperature (results presented here) and precipitation shock (results available on request) *after one year*. Most coefficients for these *lagged* effect are small and not statistically significant across models: this suggests that we do not find persistence of the temperature shock but the short-run effect is also not reversed, implying a net output loss or gain over the two-year period. The exception here are the 'income split' pooled 2FE and the simple MG models, for which (insignificant) immediate effects are notably reversed after one year.

Panel (c) then provides results for the fully dynamic model. The estimates are broadly similar to those presented in Panel (b) for the 'temperature split', while we find a negative impact of a temperature shock on low-income countries in the CCE results in (7) and (8). Fully dynamic specifications, such as the ARDL from which results in Panel (c) are derived,

[27] The pooled 2FE model includes precipitation and precipitation^2.

[28] Long-run estimates derived from the dynamic model are presented in Table 3 below.

[29] The coefficient on $High$ (Low) is statistically significant and implies that a 1°C rise in temperature reduces (increases) income per capita by 1.7% (0.6%) in high-temperature (low-temperature) countries.

[30] The coefficient on Low ($High$) is statistically significant and suggests that a 1°C rise in temperature would reduce (increase) income per capita by about 0.6% (0.42%) in poor (rich) countries.

[31] Low temperature countries benefit to the tune of 0.6% higher income per capita for a 1°C rise in temperature, while for high temperature countries the effect is a reduction by 1.2%.

allow us to estimate the long-run effects of a permanent temperature change, which we present in Table 3.[32] We can see, in columns (4) and (8), that a permanent 1°C rise in temperature is associated with a decline in per capita GDP of 14% in high-temperature countries and a weaker decline, both in statistical and economic terms, of 6% in low-income countries.

Overall, our fully flexible estimations provide more support for a temperature-productivity effect differentiated by average temperature ('hot countries suffer the most') than for an effect differentiated by average income ('poor countries suffer the most').

Table 3: Cumulative Temperature Effects on Aggregate Economic Development

	Split by Temperature Group					Split by Income Group			
	(1)	(2)	(3)	(4)		(5)	(6)	(7)	(8)
Estimator	2FE	MG	CCE$^\sharp$	CCE		2FE	MG	CCE$^\sharp$	CCE
Low	3.843	7.348	6.185	2.034	High	0.159	0.685	3.429	6.689
	(2.671)	(3.114)**	(2.575)**	(2.931)		(2.691)	(3.141)	(2.694)	(3.475)*
Medium	0.138	-1.178	-4.199	4.366	Medium	0.828	-4.627	-5.573	-8.760
	(3.403)	(4.594)	(4.005)	(5.680)		(4.757)	(5.005)	(4.972)	(5.688)
High	-12.15	-12.06	-7.498	-14.40	Low	-1.522	-0.394	-2.542	-5.727
	(6.352)*	(5.636)**	(4.845)	(5.054)***		(4.943)	(4.798)	(3.822)	(4.385)

Notes: We present robust mean long-run estimates and associated standard errors of country-specific temperature-development coefficients by (temperature or income) group: low, medium, high (in rows). The columns are for alternative underlying empirical models of the weather-growth relationship (all models include temperature and precipitation): 2FE – pooled two-way fixed effects estimator; MG – simple Pesaran & Smith (1995) Mean Group estimator; CCE – standard Pesaran (2006) Common Correlated Effects estimator; CCE$^\sharp$ – dto but only including cross-section averages of the dependent variable. All of these underlying models further include country-specific linear and quadratic trends. The sample is for 154 countries. Outlier-obust standard errors in parentheses (cluster-robust for 2FE). *** p<0.01, ** p<0.05, * p<0.1.

3.2 Aggregate TFP and Factor Inputs

In Table 4 we present the robust mean estimates from ARDL specifications adopting aggregate Total Factor Productivity (TFP) in Panel (a) or a Factor Input Index in Panel (b) as the dependent variable. Columns (4) and (8) suggest that 60% of the negative effect of a temperature shock on high-temperature/low-income countries on aggregate income (presented in Table 2 above) is captured by a fall in TFP and 40% by a fall in inputs. Long-run estimates are presented in Table 5. Most of these are imprecisely estimated (except for 2FE) but they suggest the same TFP/input effect decomposition and a preference for a temperature-productivity effect *differentiated by average temperature*.

[32]These are computed as average long-run estimates (see discussion in section 2.1) and under the assumption of exponentially declining lag weights.

Table 4: Temperature Effects on Aggregate TFP and Factor Inputs (ARDL Models)

	Split by Temperature Group					Split by Income Group			
	(1)	(2)	(3)	(4)		(5)	(6)	(7)	(8)
Estimator	2FE	MG	CCE$^\sharp$	CCE		2FE	MG	CCE$^\sharp$	CCE
Panel (a) Temperature Effect on Aggregate TFP									
– Coefficient on Contemporaneous Temperature (T_{it})									
Low	0.323**	0.426***	0.281	0.0589	High	0.237	0.261	0.282	0.550
	(0.137)	(0.149)	(0.106)***	(0.138)		(0.171)	(0.119)**	(0.145)*	(0.159)***
Medium	-0.111	-0.292	-0.241	-0.0457	Medium	-0.125	-0.385	-0.304	-0.196
	(0.250)	(0.204)	(0.206)	(0.240)		(0.287)	(0.254)	(0.220)	(0.289)
High	-0.784	-0.626	-0.758	-0.747	Low	-0.368	-0.359	-0.537	-0.822
	(0.365)**	(0.270)**	(0.279)***	(0.390)*		(0.247)	(0.242)	(0.220)**	(0.191)***
– Coefficient on Lagged Temperature ($T_{i,t-1}$)									
Low	-0.0343	0.0439	0.0889	0.213	High	-0.215	-0.171	0.0206	0.301
	(0.131)	(0.147)	(0.137)	(0.178)		(0.130)	(0.122)	(0.117)	(0.176)*
Medium	0.0358	-0.0619	-0.0684	0.131	Medium	0.0457	-0.116	-0.130	0.0568
	(0.217)	(0.198)	(0.208)	(0.289)		(0.234)	(0.224)	(0.214)	(0.337)
High	-0.240	-0.213	-0.215	-0.305	Low	0.263	0.107	-0.0582	-0.287
	(0.283)	(0.215)	(0.241)	(0.322)		(0.211)	(0.220)	(0.232)	(0.285)
Panel (b) Temperature Effect on Aggregate Factor Inputs (Index)									
– Coefficient on Contemporaneous Temperature (T_{it})									
Low	0.217	0.295	0.238	0.067	High	0.107	0.101	0.140	0.364
	(0.113)*	(0.124)**	(0.0840)***	(0.148)		(0.128)	(0.107)	(0.0917)	(0.135)***
Medium	-0.0778	-0.0704	-0.150	0.104	Medium	-0.047	-0.166	-0.180	-0.235
	(0.244)	(0.170)	(0.151)	(0.200)		(0.260)	(0.193)	(0.159)	(0.216)
High	-0.689	-0.232	-0.498	-0.486	Low	-0.277	0.104	-0.277	-0.427
	(0.309)**	(0.242)	(0.180)***	(0.230)**		(0.221)	(0.230)	(0.172)	(0.216)**
– Coefficient on Lagged Temperature ($T_{i,t-1}$)									
Low	-0.056	0.061	0.093	0.246	High	-0.245	-0.088	-0.033	0.269
	(0.102)	(0.130)	(0.108)	(0.140)*		(0.094)***	(0.101)	(0.084)	(0.108)**
Medium	0.153	0.347	0.005	-0.019	Medium	0.275	0.347	-0.017	-0.069
	(0.183)	(0.211)	(0.174)	(0.223)		(0.166)	(0.170)**	(0.160)	(0.235)
High	0.0780	0.211	-0.175	0.022	Low	0.360	0.415	-0.008	-0.025
	(0.184)	(0.146)	(0.157)	(0.291)		(0.200)*	(0.217)*	(0.200)	(0.275)

Notes: We present robust mean estimates and associated standard errors of country-specific temperature-'input' coefficients by (temperature or income) group: low, medium, high (in rows), where 'input' refers to aggregate TFP or an aggregate input index. The columns are for alternative underlying empirical models of the weather-growth relationship (all models include temperature and precipitation): 2FE – pooled two-way fixed effects estimator; MG – simple Pesaran & Smith (1995) Mean Group estimator; CCE – standard Pesaran (2006) Common Correlated Effects estimator; CCE$^\sharp$ – dto but only including cross-section averages of the dependent variable. All of these underlying models further include country-specific linear and quadratic trends. The sample is for 149 countries with 7,406 (7,798) observations in the TFP (factor input) analysis. Outlier-robust standard errors in parentheses (cluster-robust for 2FE). *** p<0.01, ** p<0.05, * p<0.1

Table 5: Cumulative Temperature Effects on Aggregate TFP and Factor Inputs

	Split by Temperature Group					Split by Income Group			
	(1)	(2)	(3)	(4)		(5)	(6)	(7)	(8)
Estimator	2FE	MG	CCE$^\sharp$	CCE		2FE	MG	CCE$^\sharp$	CCE
Panel (a) Temperature Effect on Aggregate TFP									
Low	3.781	3.252	2.580	-1.198	High	-1.364	-0.536	-5.647	-1.309
	(2.863)	(2.338)	(2.012)	(2.205)		(4.972)	(4.976)	(4.859)	(3.129)
Medium	-0.985	-4.921	-4.208	2.697	Medium	-1.039	-9.571*	-4.398	-2.680
	(3.236)	(0.646)	(0.533)	(0.743)		(5.038)	(5.390)	(3.748)	(4.645)
High	-13.400*	-4.699	-5.343	-6.786	Low	0.288	3.460*	3.485	0.282
	(7.935)	(5.375)	(4.875)	(5.494)		(3.049)	(2.065)	(2.222)	(2.684)
Panel (b) Temperature Effect on Aggregate Factor Inputs (Index)									
Low	1.228	2.047	1.695	-1.226	High	-1.050	-0.465	0.166	1.299
	(1.255)	(1.369)	(1.055)	(1.603)		(1.169)	(1.529)	(1.351)	(1.424)
Medium	0.572	1.968	-0.542	1.954	Medium	1.730	2.913	-0.310	-1.250
	(1.926)	(2.765)	(2.038)	(2.746)		(2.314)	(2.580)	(2.250)	(2.957)
High	-4.654	0.521	-3.787	-3.609	Low	0.633	2.826	-1.477	-3.112
	(3.199)	(2.968)	(3.085)	(2.899)		(2.714)	(3.001)	(2.604)	(2.609)

Notes: We present robust mean long-run estimates and associated standard errors of country-specific temperature-productivity coefficients by (temperature or income) group: low, medium, high (in rows). The columns are for alternative underlying empirical models of the weather-growth relationship (all models include temperature and precipitation): 2FE – pooled two-way fixed effects estimator; MG – simple Pesaran & Smith (1995) Mean Group estimator; CCE – standard Pesaran (2006) Common Correlated Effects estimator; CCE$^\sharp$ – dto but only including cross-section averages of the dependent variable. All of these underlying models further include country-specific linear and quadratic trends. The sample is for 149 countries. Outlier-robust standard errors in parentheses (cluster-robust for 2FE). *** p<0.01, ** p<0.05, * p<0.1.

3.3 Agricultural Sector

The agricultural sector is frequently argued to represent the key sector impacted by climate change (Nordhaus 1993, Ortiz-Bobea et al. 2021) and we therefore investigate the log of agricultural output per worker, an agricultural input index and an agricultural TFP index using our dynamic weather-productivity specifications. In Table 6, we observe in panel (a) a large, negative, and often statistically significant short-run impact of a temperature shock on agricultural output per worker in medium/high-temperature and low/medium income countries, which may be fully offset one year later as suggested by the positive and statistically significant lagged effects. Estimates of panels (b) and (c) suggest the temperature shock mainly operates through a decline in TFP, in line with Ortiz-Bobea et al. (2021). The long-run estimates presented in Table 7 are relatively small and not statistically significant and do not really favour a specific country split. Hence, while the association between agriculture and weather is natural, it is unlikely that changes in agricultural output per worker associated with a temperature shock fully drive the changes in output per capita we reported in Table 2.

Table 6: Temperature Effects on Agricultural Output, TFP and Inputs (ARDL models)

	Split by Temperature Group					**Split by Income Group**			
	(1)	(2)	(3)	(4)		(5)	(6)	(7)	(8)
Estimator	2FE	MG	CCE$^\sharp$	CCE		2FE	MG	CCE$^\sharp$	CCE
Panel (a) Agricultural Output per Worker (ARDL) – Coefficient on Contemporaneous Temperature (T_{it})									
Low	0.476	0.292	0.207	0.444	High	-1.474	-1.471	-1.619	-1.309
	(0.407)	(0.483)	(0.521)	(0.656)		(0.412)	(0.549)	(0.610)	(0.948)
Medium	-1.407	-1.190	-1.452	0.0376	Medium	-1.285	-1.523	-1.464	-0.115
	(0.701)**	(0.632)*	(0.739)*	(0.888)		(0.730)*	(0.747)**	(0.874)*	(0.778)
High	-1.387	-2.194	-1.671	-0.934	Low	0.549	0.0952	0.381	1.345
	(0.960)	(0.668)***	(0.675)**	(0.813)		(0.830)*	(0.514)***	(0.495)***	(0.690)*
– Coefficient on Lagged Temperature ($T_{i,t-1}$)									
Low	363	0.300	-0.00322	0.690	High	1.533	0.844	0.715	0.618
	(0.389)	(0.467)	(0.456)	(0.663)		(0.347)	(0.421)*	(0.496)*	(0.696)***
Medium	1.834	1.369	1.156	1.721	Medium	0.965	0.994	0.308	0.936
	(0.689)***	(0.505)***	(0.657)*	(0.787)**		(0.785)	(0.763)	(0.673)	(1.088)
High	0.551	0.873	0.857	1.004	Low	0.411	0.752	0.914	1.931
	(0.865)	(0.633)	(0.619)	(0.927)		(0.641)**	(0.450)*	(0.548)	(0.634)
Panel (b) Agricultural TFP (ARDL) – Coefficient on Contemporaneous Temperature (T_{it})									
Low	0.688	0.540	0.461	1.485	High	0.550	0.243	0.385	1.699
	(0.303)**	(0.331)	(0.380)	(0.511)***		(0.277)**	(0.309)	(0.384)	(0.622)***
Medium	-0.872	-0.667	-0.956	-0.252	Medium	-0.765	-0.961	-1.131	-0.606
	(0.612)	(0.581)	(0.603)	(0.614)		(0.607)	(0.570)*	(0.576)*	(0.633)
High	-1.383	-1.518	-1.262**	-0.804	Low	-0.705	-0.771	-1.024	-0.452
	(0.700)**	(0.536)***	(0.486)**	(0.630)		(0.773)	(0.527)	(0.499)**	(0.579)
– Coefficient on Lagged Temperature ($T_{i,t-1}$)									
Low	0.273	0.225	-0.124	0.947	High	0.869	0.861	0.598	0.651
	(0.285)	(0.370)	(0.323)	(0.589)		(0.263)*	(0.372)**	(0.388)**	(0.652)***
Medium	2.000	1.575	1.130	1.624	Medium	1.195	1.337	0.802	1.180
	(0.526)	(0.487)	(0.484)	(0.662)		(0.587)**	(0.574)**	(0.468)*	(0.722)
High	0.829	1.484	1.574	1.479	Low	0.519	0.963	0.988	2.288
	(0.572)	(0.617)	(0.535)***	(0.648)**		(0.545)	(0.465)*	(0.493)	(0.575)
Panel (c) Agricultural Input Index (ARDL) – Coefficient on Contemporaneous Temperature (T_{it})									
Low	0.102	0.089	0.270	0.080	High	-0.099	-0.312	-0.083	-0.241
	(0.204)	(0.182)	(0.269)	(0.306)		(0.198)	(0.197)	(0.253)	(0.323)
Medium	-0.504	-0.292	-0.429	-0.423	Medium	0.080	0.107	0.110	0.021
	(0.242)**	(0.148)*	(0.184)**	(0.246)*		(0.270)	(0.195)	(0.234)	(0.302)
High	-0.256	-0.112	0.049	0.113	Low	-0.556	-0.159	-0.244	-0.126
	(0.305)	(0.255)	(0.254)	(0.403)		(0.344)	(0.186)	(0.229)	(0.331)
– Coefficient on Lagged Temperature ($T_{i,t-1}$)									
Low	0.188	-0.082	0.223	0.040	High	-0.127	-0.225	-0.106	-0.492
	(0.207)	(0.226)	(0.233)	(0.327)		(0.200)	(0.204)	(0.236)	(0.280)*
Medium	0.077	0.022	0.008	0.158	Medium	0.306	-0.043	0.098	0.404
	(0.236)	(0.215)	(0.227)	(0.343)		(0.231)	(0.225)	(0.251)	(0.361)
High	0.0416	-0.230	-0.337	-0.185	Low	0.724	-0.028	-0.095	0.109
	(0.408)	(0.229)	(0.247)	(0.298)		(0.356)**	(0.234)	(0.216)	(0.301)

Notes: We present robust mean estimates and associated standard errors of country-specific temperature-'output' coefficients by (temperature or income) group: low, medium, high (in rows). The columns are for alternative underlying empirical models of the weather-growth relationship (all models include temperature and precipitation): 2FE – pooled two-way fixed effects estimator; MG – simple Pesaran & Smith (1995) Mean Group estimator; CCE – standard Pesaran (2006) Common Correlated Effects estimator; CCE$^\sharp$ – dto but only including cross-section averages of the dependent variable. All of these underlying models further include country-specific linear and quadratic trends. Different panels of the table are for different dependent variables: (a) agricultural output per worker, (b) agricultural TFP, (c) agricultural inputs (index). All results are based on autoregressive distributed lag models. The sample is for 154 countries with 8,020 observations. Outlier-robust standard errors in parentheses (cluster-robust for 2FE). *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7: Cumulative Temperature Effects on Agricultural output

	Split by Temperature Group					Split by Income Group			
	(1)	(2)	(3)	(4)		(5)	(6)	(7)	(8)
Estimator	2FE	MG	CCE$^\sharp$	CCE		2FE	MG	CCE$^\sharp$	CCE
Low	3.010	1.768	1.176	0.354	High	3.430	2.721	3.694	4.045
	(1.891)	(2.329)	(1.961)	(2.179)		(2.219)	(3.011)	(2.670)	(3.508)
Medium	1.533	-1.178	-4.199	4.366	Medium	-1.144	-4.627	-5.573	-8.760
	(2.872)	(2.761)	(2.675)	(3.286)		(3.002)	(3.162)	(2.779)	(3.284)
High	-3.001	-4.277	-3.528	-0.714	Low	0.209	-1.601	-4.416*	-1.661
	(4.931)	(3.518)	(3.402)	(4.210)		(3.087)	(2.371)	(2.527)	(2.958)

Notes: We present robust mean long-run estimates and associated standard errors of country-specific temperature-agricultural development coefficients by (temperature or income) group: low, medium, high (in rows), with the exception of columns (1) and (5) which are pooled estimates using interactions. The columns are for alternative underlying empirical models of the weather-growth relationship (all models include temperature and precipitation): 2FE – pooled two-way fixed effects estimator; MG – simple Pesaran & Smith (1995) Mean Group estimator; CCE – standard Pesaran (2006) Common Correlated Effects estimator; CCE$^\sharp$ – dto but only including cross-section averages of the dependent variable. All of these underlying models further include country-specific linear and quadratic trends. The sample is for 154 countries. Outlier-robust standard errors in parentheses (cluster-robust for 2FE). *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

3.4 Precipitation

Like previous research, we have primarily focused on temperature shocks as a proxy for the effects of climate change. Other studies usually mention that they do not find any impact of precipitation changes on income or its components. In Table 8, we report the ARDL results of precipitation on income per capita and agricultural output per worker. While panel (a) suggests an absence of robust contemporaneous effects on the former outcome, panel (b) shows that agricultural output benefits from higher rainfall in medium/high-temperature and low/high-income countries, with little evidence of a reversal effect one year later. The long-run estimates presented in Table 9 indicate that a permanent 100 mm increase in rainfall is associated with a 2.7% increase in agricultural output per worker in medium/high-temperature or low income countries.[33] Note, however, that in medium/high-temperature countries, for a nearly balanced sample, median precipitation declined from 1,218mm in 1971 to 1,187mm in 2019. Hence, over the period 1971-2019, the decline in precipitation may have contributed to a long-run fall in agricultural output of 0.85%.

Although we found fault with the presentation of the magnitudes of economic effects of precipitation in Damania et al. (2020), their suggestion that regional rather than national data hold the key to the apparent micro-macro puzzle for the economic significance of precipitation is still a useful suggestion worthy of additional research.

[33] Long-run estimates for other dependent variables yield limited insights (insignificant) and are omitted here but available on request.

Table 8: Precipitation Effects on GDP pc and Agricultural Output pw (ARDL Models)

	Split by Temperature Group					**Split by Income Group**			
	(1)	(2)	(3)	(4)		(5)	(6)	(7)	(8)
Estimator	2FE	MG	CCE$^\sharp$	CCE		2FE	MG	CCE$^\sharp$	CCE
Panel (a) Precipitation Effect on Aggregate GDP pc									
– Coefficient on Contemporaneous Precipitation (PP_{it})									
Low	-0.0712	-0.121	-0.007	-0.335	High	-0.000	0.184	0.007	-0.041
	(0.108)	(0.097)	(0.092)	(0.115)***		(0.089)	(0.121)	(0.107)	(0.141)
Medium	0.016	0.071	-0.045	-0.074	Medium	0.025	0.104	-0.023	-0.150
	(0.048)	(0.111)	(0.131)	(0.140)		(0.062)	(0.097)	(0.108)	(0.113)
High	0.087	0.201	0.015	0.023	Low	0.081	-0.128	-0.0221	-0.212
	(0.085)	(0.104)*	(0.098)	(0.136)		(0.086)	(0.087)	(0.098)	(0.126)*
– Coefficient on Lagged Precipitation ($PP_{i,t-1}$)									
Low	0.133	0.00416	0.167	-0.0494	High	-0.104	-0.160	-0.133	-0.241
	(0.795)*	(1.518)	(0.925)*	(1.404)		(0.106)	(0.121)	(0.105)	(0.139)*
Medium	-0.181	-0.107	-0.148	-0.186	Medium	0.00730	0.287	0.0471	-0.158
	(0.0601)***	(0.125)	(0.108)	(0.126)		(0.0663)	(0.135)**	(0.116)	(0.124)
High	0.0288	0.0216	-0.0792	-0.215	Low	-0.100	-0.167	0.0261	-0.0663
	(0.0799)	(0.107)	(0.0936)	(0.118)*		(0.0821)	(0.0908)ù	(0.0940)	(0.133)
Panel (b) Precipitation Effect on Agricultural Output per worker									
– Coefficient on Contemporaneous Precipitation (P_{it})									
Low	0.164	0.151	0.353	0.258	High	0.626	0.603	0.688	0.863
	(0.174)	(0.259)	(0.254)	(0.377)		(0.304)**	(0.225)***	(0.258)***	(0.322)***
Medium	0.317	0.732	0.814	0.892	Medium	0.0717	0.216	0.362	0.184
	(0.126)***	(0.234)***	(0.231)***	(0.272)***		(0.0793)	(0.195)	(0.201)*	(0.273)
High	0.331	0.619	0.536	0.689	Low	0.585	0.698	0.735	0.912
	(0.166)**	(0.206)***	(0.205)***	(0.270)**		(0.202)***	(0.249)***	(0.228)***	(0.298)***
– Coefficient on Lagged Precipitation ($PP_{i,t-1}$)									
Low	-0.0543	0.003	-0.293	-0.306	High	0.705	-0.314	-0.351	-0.462
	(0.140)	(0.261)	(0.335)	(0.350)		(0.513)	(0.176)*	(0.205)*	(0.249)*
Medium	-0.434	-0.184	-0.162	-0.050	Medium	-0.207	-1.000	-0.201	0.014
	(0.083)***	(0.212)	(0.246)	(0.292)		(0.084)**	(0.193)	(0.250)	(0.311)
High	0.124	-0.028	0.014	0.092	Low	-0.396	0.256	0.212	0.361
	(0.209)	(0.168)	(0.196)	(0.231)		(0.129)***	(0.219)	(0.277)	(0.324)

Notes: We present robust mean estimates and associated standard errors of country-specific precipitation-'output' coefficients by (temperature or income) group: low, medium, high (in rows), where 'input' refers to aggregate GDP per capita or agricultural output per worker. The columns are for alternative underlying empirical models of the weather-growth relationship (all models include temperature and precipitation): 2FE – pooled two-way fixed effects estimator; MG – simple Pesaran & Smith (1995) Mean Group estimator; CCE – standard Pesaran (2006) Common Correlated Effects estimator; CCE$^\sharp$ – dto but only including cross-section averages of the dependent variable. All of these underlying models further include country-specific linear and quadratic trends. The sample is for 154 countries with (8,020) observations. Outlier-robust standard errors in parentheses (cluster-robust for 2FE). *** p<0.01, ** p<0.05, * p<0.1

Table 9: Cumulative Precipitation Effects on Agricultural output

	Split by Temperature Group					Split by Income Group			
	(1)	(2)	(3)	(4)		(5)	(6)	(7)	(8)
Estimator	2FE	MG	CCE$^\sharp$	CCE		2FE	MG	CCE$^\sharp$	CCE
Low	2.308	0.817	-0.118	-0.109	High	5.625***	1.936*	1.725	1.791*
	(1.431)	(1.277)	(1.242)	(1.087)		(1.589)	(1.064)	(1.088)	(1.035)
Medium	3.221	2.692**	3.260**	2.820**	Medium	0.838	2.149*	1.453	1.188
	(2.312)	(1.324)	(1.417)	(1.276)		(3.307)	(1.143)	(1.292)	(1.131)
High	5.476***	2.716***	2.627**	2.722***	Low	1.617	2.159*	2.831**	2.688**
	(1.453)	(0.946)	(1.098)	(0.974)		(2.569)	(2.371)	(2.527)	(2.958)

Notes: We present robust mean long-run estimates and associated standard errors of country-specific precipitation-agricultural development coefficients by (temperature or income) group: low, medium, high. The columns are for alternative underlying empirical models of the weather-growth relationship (all models include temperature and precipitation): 2FE – pooled two-way fixed effects estimator; MG – simple Pesaran & Smith (1995) Mean Group estimator; CCE – standard Pesaran (2006) Common Correlated Effects estimator; CCE$^\sharp$ – dto but only including cross-section averages of the dependent variable. All of these underlying models further include country-specific linear and quadratic trends. The sample is for 154 countries. Outlier-robust standard errors in parentheses (cluster-robust for 2FE). *** p<0.01, ** p<0.05, * p<0.1.

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 indicates that permanent climate change can have a large negative effect on the prosperity of countries, especially those in high temperature geographic zones. We find that a permanent 1°C rise in temperature in this group of countries is associated with a long-term reduction in income per capita of 14% — this effect is more substantial than previous research has suggested (Burke et al. 2015). Evidence for a strongly differentiated effect across countries by income level (Dell et al. 2012) is less consistent and at worst these specifications suggest a 6% drop in income per capita for poor countries over the six decades analysed. Extrapolation of these results to the future is likely to lack credibility, since we do not know what the shape of the damage function looks like for temperature increases of 1°C or more above pre-industrial levels (Pindyck 2013, 2020). In the absence of counterfactuals in the data, and the possibility of catastrophic outcomes (Weitzman 2012, Stern 2013), history cannot be our guide because our inferences are too model-dependent (King & Zeng 2007). 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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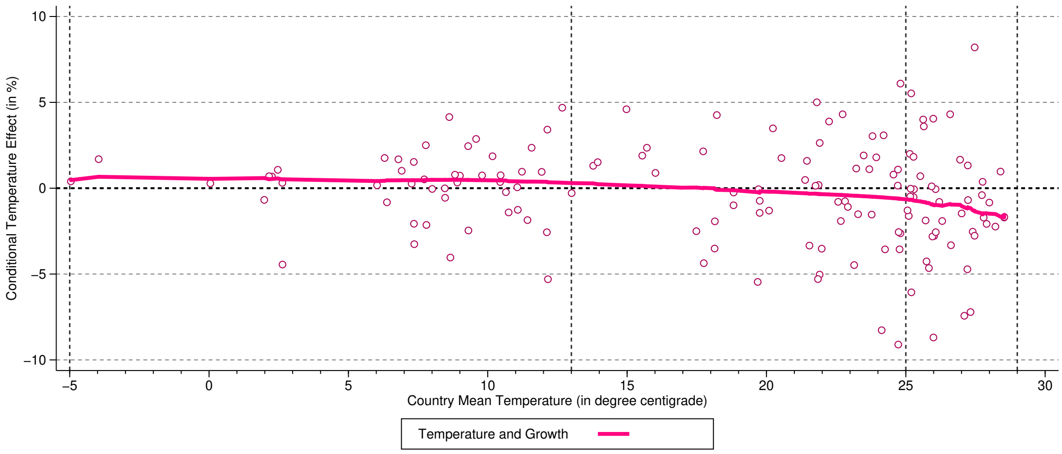
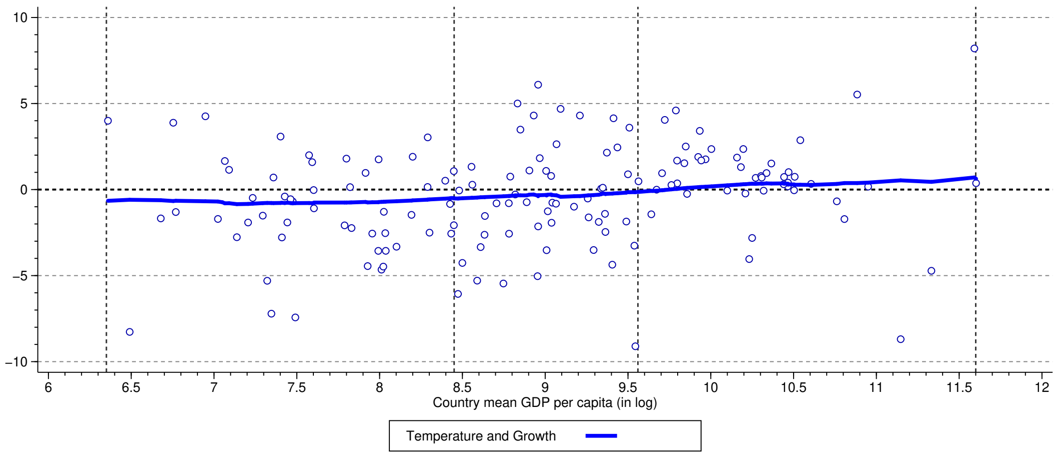
Appendix

Figure A-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 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 regressions in columns [4] and [8] of Panel (c) in Table 2 (contemporaneous temperature variable) 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.