The economic impact of weather and climate

Richard S.J. Tol[a,b,c,d,e,f,1,*]

[a] *Department of Economics, University of Sussex, Falmer, United Kingdom*

[b] *Institute for Environmental Studies, Vrije Universiteit, Amsterdam, The Netherlands*

[c] *Department of Spatial Economics, Vrije Universiteit, Amsterdam, The Netherlands*

[d] *Tinbergen Institute, Amsterdam, The Netherlands*

[e] *CESifo, Munich, Germany*

[f] *Payne Institute for Earth Resources, Colorado School of Mines, Golden, CO, USA*

Abstract

I propose a new conceptual framework to disentangle the impacts of weather and climate on economic activity and growth: A stochastic frontier model with climate in the production frontier and weather shocks as a source of technical inefficiency. I test it on a sample of 160 countries over the period 1950-2014. Results reconcile inconsistencies in previous studies: climate determines production possibilities in both rich and poor countries, whereas weather anomalies enhance inefficiency only in poor countries. In a long-run perspective, the climate effect dominates over the weather effect: simulations suggest that, in the worst-case scenario with unmitigated warming, climate change will curb global output by 13% by 2100, and that a large share of these damages would be avoided if warming were limited to 2°C.

Keywords: climate change; weather shocks; economic growth; stochastic frontier analysis
JEL codes: D24; O44; O47; Q54

[*] Jubilee Building, BN1 9SL, UK
Email address: r.tol@sussex.ac.uk (Richard S.J. Tol)
URL: http://www.ae-info.org/ae/Member/Tol_Richard (Richard S.J. Tol)

[1] Marco Letta expertly assisted with data collection and regressions. Peter Dolton, Jurgen Doornik, Bill Greene, David Greene, David Hendry, Andrew Martinez, Pierluigi Montalbano and Felix Pretis had excellent comments on earlier versions of this work. I also thank seminar participants at the EMCC-III conference, University of Sussex, UNU-MERIT University, the 2019 IAERE conference, Cambridge University, London School of Economics, Sapienza University of Rome, Shanghai Lixin University, Edinburgh University, and CESifo. MATTHEW KOTCHEN: NO INEFFICIENCY, NIKO JAAKKOLLA: BOTH PARABOLAS HIT ZERO AT SAME POINT, BROOKS KAISER: INTERACT WITH AG SHARE

1. Introduction – in the middle of a rewrite

Climate matters to the economy. Not in the way that classical thinkers such as Guan Zhong, Hippocrates or Ibn Khaldun or modern thinkers such as Huntingdon or Diamond argue it does. Climate is not destiny. Environmental determinism is inconsistent with the observations. There are thriving economies in the desert, in the tropics, and in the polar circle. There is destitution, too, in all these places.

The prevailing view among economists is that climate does not matter for economic development, only institutions do. Some argue that climate and geography partly shaped institutions in the past, but have become irrelevant since. Institutional determinism is inconsistent with the observations too. The two halves of the Korean Peninsula and the island of Hispaniola are a powerful reminder of the importance of institutions, but climate obviously matters for agriculture, for energy demand, for tourism, for labour productivity, and for health.

First principles have that climate matters but it has been an empirical challenge to demonstrate this. Climate changes only slowly over time, its signal is swamped by confounders, many of which change more quickly. Climate varies substantially over space, but so do a great many other things that we know are important for development.

Although the impact of climate is hard to identify, the impact of weather can be identified—or so people have argued. Identification rests on weather being random from the perspective of the economy. The problem with this argument is that by now many different economic activities have been found to be affected by the weather, and these activities of course impact one another.

Weather matters too, but cannot readily be extrapolated.

Therefore, simultaneous model of climate and weather.

Empirical estimates of the impact of climate change are problematic. The literature on climate and development suggests that climate may or may not be important, or that it used to be important but not any longer. The literature on weather and growth, when extrapolating to climate change, assumes that short-term elasticities are valid in the long-term. I here propose a new way to simultaneously model the impact of climate and weather, show that both matter and that previous work is misspecified. I report new evidence that rich and poor countries respond differently to weather shocks, but not to climate.

It is easy to estimate the impact of weather on economic activity. Weather varies a lot, and good data are plentiful. The impact of weather on the economy is identified, or so it is argued, because it is like a random assignment to a treatment (Heal and Park, 2016). However, weather has been found to affect many different economic activities (Deschenes and Greenstone, 2007, Burke et al., 2015, Hsiang et al., 2017, Burke et al., 2018, Zhang et al., 2018), which are known to affect each other. Identification is therefore not as clear-cut as sometimes suggested.

The impact of a weather shock is not the same as the impact of climate change (Dell et al., 2014). Climate is what you expect, weather is what you get. Put differently, weather outcomes are draws from an probability distribution. Climate is that distribution. Climate change is best thought of as shifts in the moments of the weather distribution (Auffhammer, 2018b). Therefore, adaptation to weather shocks is limited to immediate responses—put up an umbrella when it rains, close the flood gates when it pours. Adaptation to climate change extends to changes in the capital stock—buy an umbrella, build flood gates—and to updates of the expectations for weather. In other words, weather studies estimate the short-run elasticity, whereas the long-run elasticity is needed to estimate the impact of climate change. Hence, while climate impact estimates account for changes in the capital stock and expectations, weather impact estimates do not. Extrapolating the impact of weather shocks will therefore not lead to credible results for the impact of climate change.

We are not the first to note the difficulties in deriving the impact of climate change from estimated weather effects (Dell et al., 2014, Kolstad and Moore, 2019). Lemoine (2017) highlights the importance of expectations. Adaptation may anticipate future climate change. Truly surprising weather would have a large impact. Bakkensen and Barrage (2018) estimate the weather-sensitive parameters of a structural growth model, Costinot et al. (2016) of a static computable general equilibrium one. Auffhammer (2018a), echoing earlier work by Bigano et al. (2006), proposes the Climate Adaptive Response Estimation (CARE), which is a two-level hierarchical model with the impact of weather at the bottom and its interaction with climate at the top. Lemoine (2018) formally supports Auffhammer's intuition, noting that the *average* weather effect, rather than the *marginal* one, should be carried from the bottom to the top level. This matters because Auffhammer advocates non-linear models.

Hsiang (2016) and Deryugina and Hsiang (2017) take a different route, arguing that the marginal effect of a weather shock equals the marginal climate effect under assumptions elaborated below. While climate change is not marginal, the total effect is of course an integral of marginals. Their assumptions, however, are quite restrictive. Economic agents need to be (1) rational and their adaptation investments (2) optimized. Adaptation needs to be (3) private and adaptation options (4) continuous. The economy needs to be in a (5) spatial equilibrium and (6) markets complete. Adaptation investments are often long-lived, so it is not just spot markets that need to be complete; future markets should be too. Spatial zoning and transport facilities distort the spatial equilibrium. Adaptation is often lumpy, be it air conditioning or irrigation. Some adaptation options, such as coastal protection, are public goods. Agents are not always rational, and decisions suboptimal. The result by Deryugina and Hsiang is almost an impossibility theorem.

Agents have heterogeneous adaption rules at the intensive and extensive margin, in the short- and long-run, and may base their actions on expected rather than historical climate Auffhammer (2018b). Severen et al. (2016) find that ignoring expectations could bias the effects of a climate change on the market for land by 36% to 66%. Academics construct climate as the 30-year average weather. Economic agents may form their expectations differently than analysts assume they do, and may well be influenced by the recent weather.

If we cannot use weather data, it is hard to estimate the impact of climate and climate change. Climate varies slowly over time, and not much at all in the short period for which we have high-quality data. In empirical studies, the identification of the impact of climate therefore comes from cross-sectional variation (see Mendelsohn et al., 1994, Sachs, 2003, Schlenker et al., 2005, for studies of particular sectors), with few exceptions (Barrios et al., 2010). Some studies find an effect (Nordhaus, 2006, Henderson et al., 2018), other studies find no effect (Easterly and Levine, 2003, Rodrik et al., 2004, Andersen et al., 2016), and yet others only an historical one (Acemoglu et al., 2001, Alsan, 2015). Cross-sections are problematic as so many other things vary over space too. Panel data are no panacea as some confounders do not change much over time. Furthermore, while the global climate responds with a considerable delay to greenhouse gas emissions and can thus be considered exogenous, the local climate responds rapidly to urbanisation, land cover change and emissions of aerosols, and thus to economic activity. We do not solve these problems here.

To overcome the external validity gap, one of the more common empirical techniques is the use of long differences. Long difference estimates allow to study the impacts of longer-term (decadal or more) temperature trends on the economic outcome of interest and compare the results with estimates from annual panels. Interesting examples of this approach can be found in Dell et al. (2012), Burke and Emerick (2016) and Burke and Tanutama (2019). While we agree with Auffhammer (2018b) that this is a promising route for further research, the problem with long differences is that it gets rid of all the short-term variability, making impossible to simultaneously investigate and disentangle the effects of weather *and* climate.

Instead, I focus on the interplay between climate and weather. Weather affects economic activity, and so the measurement of the impact of climate on economic activity. Weather can be seen as noise, but that noise may well be correlated with climate, the right-hand-side variable of interest.

The impact of climate and weather should therefore be jointly estimated while controlling for the expectations/adaptation indirect channel. Our empirical strategy rests on the following assumptions. Climate affects production possibilities. This is obvious for agriculture: Holstein cows do well in Denmark but jasmine rice does not; the reverse is true in Thailand. Climate also affects energy and transport, and thus all other sectors of the economy. Weather affects the realization of the production potential. Hot weather may slow down workers, frost may damage crops, floods may disrupt transport and manufacturing. Conceptualized thus, climate affects the production frontier, and weather the distance from that frontier. The econometric specification is therefore a stochastic frontier analysis with weather variables in the inefficiency parameter and climate variables in the frontier. The inefficiency parameter not only reflects by inefficiency[2] but also by production risk and risk preferences. Disentangling inefficiency and risk is beyond the scope of the present work. The issue is complicated by the need to make assumptions about the distribution of the error

[2]Applied to micro data, Stochastic Frontier Analysis measures productive inefficiency. Applied to aggregate data, as we do here, SFA also measures allocative and cross inefficiency.

term representing production risk and about attitudes toward risk in an utility function (Kumbhakar, 2002).

Dell et al. (2012) and Letta and Tol (2018) find heterogeneity in the response of economic growth to weather shocks, specifically that *poorer* countries are hit harder. Burke et al. (2015) instead find that *hotter* countries are hit harder, a find adopted by Pretis et al. (2018). Kahn et al. (2019) reject heterogeneity. Within sample, it is difficult to distinguish between these two specifications as hotter countries tend to be poorer. However, out of sample, a hotter, richer world would be *more* vulnerable to weather shocks according to Burke, but *less* vulnerable according to Dell. Newell et al. (2018), in a cross-validation study, conclude that temperature non-linearly affects the level of GDP, but not its growth rate, and that that temperature disproportionately affects poor countries, with no significant effects in richer ones. We here revisit the question of heterogeneity in the response to weather and climate.

The paper proceeds as follows. Section 2 describes methods and data. Section 3 presents the baseline results. Section 4 conducts the sensitivity analysis. Section **??** discusses the implications for climate change. Section 5 concludes.

2. Methods and data

2.1. Methods

We assume a Cobb-Douglas production function:

$$Y_{c,t} = A_{c,t} K_{c,t}^{\beta} L_{c,t}^{1-\beta} \tag{1}$$

Total factor productivity $A_{c,t}$ is the Solow residual in country c at time t: It captures everything that affects output $Y_{c,t}$ that cannot be explained by capital $K_{c,t}$ or labour $L_{c,t}$.

We concentrate Equation (1) by dividing K and L by labour force L, and denote the resulting variables in lower case.

Taking natural logarithms, the standard reduced form equation to be estimated is:

$$\ln y_{c,t} = \alpha_0 + \beta \ln k_{c,t} \tag{2}$$

We assume that total factor productivity is a function of moving averages of climatic variables (average temperature, $\bar{T}_{c,t}$, and precipitation, $\bar{P}_{c,t}$), whereas weather shocks affect the variance of the stochastic component of permanent income. Hence, Equation (2) becomes:

$$\ln y_{c,t} = \beta_0 + \beta_1 \ln k_{c,t} + \beta_2 \bar{T}_{c,t} + \beta_3 \bar{T}_{c,t}^2 + \beta_4 \bar{P}_{c,t} + \beta_5 \bar{P}_{c,t}^2 + \mu_c + t + v_{c,t} - u_{c,t} \tag{3}$$

where $\bar{T}_{c,t}$ and $\bar{P}_{c,t}$ are the average temperature c.q. precipitation in country c in the thirty years preceding year t, μ_c is a full set of country fixed effects, t is a linear time trend, $v_{c,t} \sim \mathcal{N}(0, \sigma_v^2)$ and

$$u_{c,t} \sim \mathcal{N}^+(0, \sigma_{c,t}^2) = \mathcal{N}^+ \left(0, \gamma_c + \gamma_1 \left| \frac{T_{c,t} - \bar{T}_{c,t}}{\tau_{c,t}} \right| + \gamma_2 \left| \frac{P_{c,t} - \bar{P}_{c,t}}{\pi_{c,t}} \right| \right) \tag{4}$$

where τ and π are the standard deviations of temperature and rainfall, respectively.

We use the True Fixed-Effect (TFE) model (Greene, 2005) to estimate a one-step stochastic frontier model in a fixed-effect setting with explanatory variables in the inefficiency parameter. We use the SFMODEL package for Stata, developed by Kumbhakar et al. (2015) to estimate our model.

Equation (3) assumes that both error terms are stationary. This is a tall assumption as all variables are either non-stationary or trend-stationary.[3] We are not aware of any statistical test for stationarity that applies to this particular estimator and these distributional assumptions. We use three remedies. First, we include a time trend in Equations (3) and (4). Second, we show robustness to different specifications choices and to an alternative assumption (the exponential distribution) for the inefficiency parameter in Equation (4). Third, we reformulate the model as an error-correction one:

$$\Delta \ln y_{c,t} = \sigma_1 \Delta \left| \frac{T_{c,t} - \bar{T}_{c,t}}{\tau_{c,t}} \right| + \sigma_2 \Delta \left| \frac{P_{c,t} - \bar{P}_{c,t}}{\pi_{c,t}} \right| + \mu_c + \eta_{c,t} + \sigma_3 V_{c,t} + w_{c,t} \tag{5}$$

where

$$V_{c,t} = \ln y_{c,t} - \mu_c - \theta_1 \ln k_{c,t} - \theta_2 \bar{T}_{c,t} - \theta_3 \bar{T}_{c,t}^2 - \theta_4 \bar{P}_{c,t} - \theta_5 \bar{P}_{c,t}^2 \tag{6}$$

and $\eta_{c,t}$ are time dummies which act as a non-parametric time trend.[4] We use this alternative estimation strategy to show that our findings are robust to the inclusion of non-parametric time trends and continuous interactions with per capita income. This alternative specification is also better suited to explicitly model the path of convergence towards the long-term equilibrium in a stochastic setting and provide empirical evidence for the speed of recovery after weather perturbations. We of course also perform the usual stationarity tests on the error-correction model.

We test for heterogeneity by interacting the variables of interest with dummies for poor countries and hot countries. We define a country as "poor" if its GDP per capita was below

[3] Although taking first-differences of all variables would get rid of unit roots and directly address non-stationarity, a stochastic frontier analysis in changes would require completely different assumptions and identification choices. More importantly, we are not aware of any empirical work using growth rates to estimate a production function.

[4] The use of a non-parametric time trend was not possible in the baseline SFA model because the inclusion of so many time dummies caused convergence issues in an already computationally cumbersome maximum likelihood estimation.

the 25th percentile of the distribution in the year 1990.[5] In the robustness checks, we also adopt an alternative grouping in terms of affluence, and adopt the World Bank classification of high-income *vs* low-and-middle-income economies.[6] As a final test for heterogeneity with respect to income, in the ECM estimates we drop fixed classifications between rich and poor countries and directly interact our climate and weather variables with continuous GDP per capita. As to heterogeneity with respect to heat, a "hot" country is defined as a country whose average annual temperature is above the 75th percentile of the distribution.

2.2. Data

Our dataset is an unbalanced panel consisting of 160 countries over the period 1950-2014. Data for this study come from two sources. Economic data on output, capital and labour force are taken from the latest version of the Penn World Table (PWT), PWT 9.0 (Feenstra et al., 2015). Weather data are from the University of Delaware's *Terrestrial air temperature and precipitation: 1900-2014 gridded time series, (V 4.01)* (Matsuura and Willmott, 2015). These gridded data have a resolution of 0.5×0.5 degrees, corresponding roughly to 55×55 kilometers at the equator. Following previous literature (Dell et al., 2014, Burke et al., 2015, Auffhammer et al., 2013), we aggregate these grid cells at the country-year level, weighting them by population density in the year 2000 using population data from Version 4 of the *Gridded Population of the World*.[7], with the only exception of Singapore.[8] We use these weather data to construct both our climate and weather variables as defined in Section 2.1. Table 1 presents descriptive statistics for the key variables.[9]

3. Results

Table 2 shows the results of the base specification outlined in Equations 3 and 4. Four variants are presented. In Column 1, we report homogeneous effects in both the frontier and the inefficiency. In the frontier, capital per worker has a significant and stable impact on output per worker. The output elasticity is around 0.61, in line with previous estimates.

[5]1990 is the first year for which we have complete data on PPP GDP per capita for all countries. We choose the 25th percentile of the income distribution because, after testing the 25th, 50th and 75th percentiles, the specification using the 25th percentile resulted the best one according to two criteria: 1) it gives the highest Wald Test χ^2 value (since we assume heteroskedasticity and use clustering, log-likelihoods are actually log-pseudolikelihoods, so the Wald Test has to be used in place of the standard Likelihood-Ratio test for model selection); 2) it maximizes (minimizes) the level of inefficiency (efficiency) according to the (Battese and Coelli, 1988) efficiency index. In any case, qualitative results were unchanged and not driven by this particular poverty threshold, as shown by the robustness tests below.

[6]The WB classification of high-income economies is available here.

[7]Available here.

[8]Singapore has a surface smaller than the size of the weather grids. Given it is one of the few countries that are both rich and hot and thus increase the statistical power of the analysis, we kept it in the sample by attributing to it the weather data of the grid cell in which it is situated.

[9]Cf. subsection A.3 in the Appendix for a complete list of countries and regions in our sample.

Long-run temperature (i.e. climate) has a significant impact on the production frontier. The temperature optimum, the place with the highest output *ceteris paribus* is around 17℃. The effects of long-term rainfall are insignificant at the frontier. Short-term weather anomalies (either temperature or precipitations) are not significant in determining inefficiency. The Battese and Coelli (1988) Efficiency Index is around 81%, in this and all the other baseline specifications.

Moving across the table, Columns 2-4 show heterogeneous impacts between rich and poor countries. The underlying hypothesis is that very poor countries are disproportionately affected by climate and weather, as economic activity is concentrated in agriculture and public investment in protective measures is limited. In Column 2, we check heterogeneity only in the production frontier. That is, we interact climate variables with the poor country dummy defined in Subsection 2.1. Climate affects production potential in both rich and poor countries. The relationship is concave and significant at the 1% level. However, climate has a larger impact in poor countries.[10] The optimum temperature for poor countries is much higher, around 23℃, than for rich ones, where the optimum lies close to 16℃.[11] This matters when extrapolating with respect to climate change.

In Column 3, we test for heterogeneity in inefficiency too. Results for the production frontier are almost unchanged. Impacts on inefficiency sharply differ among rich and poor countries: the latter suffer from a positive, large and strongly significant effect of temperature and rainfall anomalies on inefficiency levels, whereas the impact is negative, smaller and even insignificant (for temperature) in rich countries. In short, temperature anomalies reduce efficiency only in poor countries.

This could, at least partially, be due to the large overlap between poor countries and hot ones. Therefore, in Column 4 we also check for heterogeneity in inefficiency by interacting weather anomalies with the 'hot country' dummy defined in Section 2.1. Previous conclusions (e.g. Dell et al., 2012, Letta and Tol, 2018) remain: weather anomalies do not hit hot countries, they hit poor ones.

Rainfall anomalies increase inefficiency in poor countries, as expected. Rainfall anomalies *decrease* inefficiency in rich countries. This is harder to explain. This may reflect the restoration effort after floods—recall that we use GDP rather than NDP—while droughts have little effect as agriculture is such a small share of output.

The coefficients for inefficiency are hard to interpret as these are not marginal effects (Kumbhakar et al., 2015). First, inefficiency is multiplicative (as we took the natural logarithm of per capita output) so that the marginal effect depends on the frontier. Second, we use a half-normal distribution so that the expectation is $\sigma_u\sqrt{\frac{2}{\pi}}$. The coefficients further affect the

[10] The total net effects of long-term rainfall in poor countries are not reported in this or the following tables, with the exception of the specification using the exponential distribution of the inefficiency parameter. Overall, however, there is no robust and statistically significant impact.

[11] Average long-run temperature is 23.7℃ in poor countries and 16.9℃ in rich countries.

variance of the technical inefficiency, $\sigma_u^2 \left(1 - \frac{2}{\pi}\right)$. Table 3 reports marginal effects of weather variables on the mean and variance of the inefficiency, with bootstrapped standard errors and p-values.[12] Signs and significance are as in Table 2. Weather anomalies affect both the *mean* and the *variance* of economic output in countries that are poor.

4. Robustness

We implement three different types of robustness checks: sensitivity to different specifications and identification choices in the SFA model; an alternative distributional assumption for the inefficiency parameter; and an error-correction model to formally test for non-stationarity. For all these sensitivity tests, with the exception of the error-correction model, we only report estimates of our preferred specification, column 3 of Table 2.

4.1. Alternative specifications

This first set of robustness checks implements the same baseline model described in Equations 3 and 4 but adopts a broad set of different specification choices for key variables and interactions.

4.1.1. High-income vs other economies

First, we test whether our core findings are driven by the somewhat arbitrary discrimination we introduce between rich countries and poor and middle-income ones. To do so, we replace the distinction between rich and poor countries with a classification taken from the World Bank[13] and interact our climate and weather variables with dummy which takes value 0 if a country is a "High-Income Economy" and 1 otherwise. Results for this specification are presented in columns 1 of Tables 4 and 5, respectively, for frontier and the inefficiency. For the production frontier, results are qualitatively the same as in Table 2. Quantitatively, the temperature effects have shifted: the quadratic temperature effect is more pronounced, heterogeneity between rich and poor countries less pronounced. Temperature optima are lower. As for the inefficiency, results for precipitation are qualitatively similar to the baseline model. Coefficients are different but not significantly so. However, the impact of temperature anomalies is now significant for richer countries as well. In Table 2, only rainfall anomalies positively affect rich countries. In Table 4, both precipitation and temperature anomalies positively affect rich countries (by reducing their average inefficiency towards the production frontier). Finally, the log-pseudolikelihood is higher that in the corresponding baseline specification.

[12] We implemented the bootstrapping procedure suggested by Kumbhakar et al. (2015) with 1000 replications; p-values assume normality per the central limit theorem.

[13] Available here.

4.1.2. *Squared anomalies*

Second, we replace *absolute* weather anomalies in the inefficiency term with *squared* anomalies. This place a heavier weight on larger anomalies, i.e., we check for non-linearity by focusing on weather *extremes*. Columns 2 of Tables 4 and 5 report estimates for this alternative specification. The results for the production frontier are largely unaffected, and the qualitative results for the inefficiency are as above. The log-pseudolikelihood is somewhat higher for the absolute anomalies, so linearity is our preferred specification.

4.1.3. *Linear anomalies*

The weather anomalies in Equation 4 are absolute anomalies. Cold and hot weather, wet and dry spells are assumed to equally increase technical inefficiency. We test this functional form, replacing absolute anomalies with their original values, thus introducing both positive and negative deviations. See column 3 of Tables 4 and 5. Estimates for the production frontier are almost unaltered. Results for inefficiency are very different. Only the interaction between temperature and poverty is weakly significant. Linear anomalies do not capture the impacts of weather on technical inefficiency. Economies are affected by unusual weather, rather than by the weather *per se*. Adaptation matters.

4.1.4. *Asymmetric anomalies*

Additionally, we also test for asymmetric anomalies, i.e., we disentangle negative and positive weather shocks in the inefficiency parameter. Specifically, we split the weather anomalies into two series, one (the other) positive if above (below) the mean and zero otherwise. Results are in column 4 of Tables 4 and 5. The frontier is unaffected. Cold and drought reduce efficiency in all countries. This removes the earlier puzzling effect of rainfall anomalies in rich countries. Temperature and rainfall shocks, whether positive or negative, significantly affect inefficiency in poor countries but the coefficients do not significantly differ from each other or from those in Table 2. While there is some evidence for asymmetry between the impact of wet and dry spells, cold and hot spells, the increase in the log-pseudolikelihood is minimal (3 points) for the six additional parameters estimated.

4.1.5. *Excluding rainfall*

In the cross-validation exercise of Newell et al. (2018), the best-performing models only include temperature, leaving precipitation out. In our baseline model, we include rainfall in both the frontier and the inefficiency because we follow recommendations in previous literature (Auffhammer et al., 2013, Dell et al., 2014) stressing the strong correlation between temperature and precipitation and the consequent risk of omitted variable bias in case of exclusion of one of the two. Rainfall is insignificant in the frontier but significant in inefficiency. We re-estimate the baseline model excluding rainfall. See column 5 in Tables 4 and 5. The results for the production frontier are largely unaffected. However, temperature shocks now significantly reduce technical inefficiency in rich countries. This could be because the exclusion of rainfall anomalies leads the model to ascribe to temperature anomalies the negative impact of rainfall shocks on inefficiency.

4.1.6. Weather in the frontier

As a placebo test, we also look at weather effects on productivity. That is, we move weather anomalies from the inefficiency parameter to the production frontier. Results are in column 6 of Table 4. As expected, coefficients of weather variables are individually insignificant, but the aggregate effect of temperature anomalies on poor countries is significant and negative, albeit an order of magnitude smaller than the impact of the average temperature. However, the log-pseudolikelihood is sharply lower than the baseline model. This specification, variations of which are often used in literature, is not the preferred one.

4.1.7. Capital as a substitute for climate

Like previous papers (Sachs, 2003, Schlenker et al., 2005, Nordhaus, 2006, Henderson et al., 2018), we find a significant association between climate and economic performance. In the concentrated Cobb-Douglas production function, Equation (1), there are two determinants of output per worker: climate and capital per worker. In this specificatin, capital is a *de facto* substitute for climate, and with a constant elasticity. We test the latter assumption, and so answer the question whether sufficient capital would make a country immune from the influence of its climate. We therefore interact long-run temperature variables with capital per worker in the production frontier. See Table 6, Column 1. Temperature is significant and so are the interactions with capital. The interactions have the opposite signs. That is, climate's influence on output shrinks as capital deepens. See Figure 1. The marginal effects of squared temperature turns to zero at a capital stock of \$6.8 million dollar per worker. In our sample, the United Arab Emirates in 1970 has the highest value: \$0.8 million per worker. Capital is a substitute for climate, but an imperfect one, and the impact of climate will remain.

4.1.8. Institutions vs climate

In the debate on the long-run determinants of growth and development, some find that climate plays a fundamental role in shaping long-run development (Sachs, 2003, Andersen et al., 2016), whereas others argue that the impact of climate disappears when accounting for institutions (Acemoglu et al., 2001, 2002, Easterly and Levine, 2003, Rodrik et al., 2004, Alsan, 2015). We test this in Table 6. As a proxy for institutional quality, we use the Polity 2 Score.[14] This categorical variable is an aggregate score which ranges from -10 (hereditary monarchy) to 10 (consolidated democracy). While this is not the best indicator for institutional quality, it is correlated with other indicators. Historical depth is the key advantage of Polity 2 over other indicators, which are available only for recent years. We

[14] The Polity Project Database, annual national data for the period 1800-2017, can be downloaded here.

interact it with long-run temperature and precipitation in the production frontier. See Table 6, Column 2.

The effect of temperature on the production frontier remains when controlling for institutional quality, and actually becomes stronger. The interaction between the institutional variable and squared temperature is positive and significant at the 1% level. Better institutions dampens the negative effect of high average temperatures. However, the effect is small: The coefficient falls from -0.0068 for a country with the best Polity score to -0.0074 for the worst score. Figure 2 shows the marginal effects of long-run temperature at different institutional quality levels. The slope is almost flat. There is no statistically significant difference between countries, and even countries with the highest Polity 2 Score experience significant effects of temperature shocks.

4.2. Exponential distribution of the inefficiency parameter

In Equation 4, we assume a half-normal distribution of the inefficiency parameter. We could have assumed a truncated-normal distribution or an exponential distribution instead (Greene, 2005, Kumbhakar et al., 2015, Belotti et al., 2013). Unfortunately, truncated-normal models with fixed-effects are known to suffer severe convergence issues, and our case was no exception. Columns 7 of Tables 4 and 5 show results for the exponential distribution. The estimates for the frontier are similar as above, except that the interaction between rainfall and poverty is significant. Poor economies in arid areas fare worse. The temperature optimum in poor countries is much higher. The Battese and Coelli (1988) Efficiency Index is similar to the baseline model. Poor countries are hit harder by weather anomalies.

4.3. Results by decade

Non-stationarity is a key concern in any long panel of economic data. To the best of our knowledge, there is no test for the stationary of the residuals of an SFA model. Figure A.4 shows the residuals of the frontier, inefficiency, and the total error, all averaged across countries. Although there is no trend, these residuals do not pass a stationarity test. Panel stationarity tests require that the residuals of every country are stationary. Equation (3) has a common trend for all countries. It should therefore not come as a surprise that the model fails every test for panel cointegration.

We therefore perform two robustness checks. Below, we estimate an error-correction model. Here, we split our sample into the 7 decades it covers. The model re-estimated for the shorter periods is unlikely to suffer from non-stationarity and spurious results. The sample split also allows us to test for parameter stability. Note that the panel is unbalanced. Potential parameter instability is thus over time as well as over the countries for which data is available at that time.

Table 7 shows the results, shrinking the decadal estimates to their average. The results for the whole sample are shown too (repeating Table 2) as well as the differences between the two estimates. The estimates for the frontier are largely unaffected. The capital elasticity of output is smaller if the sample if split, but although the difference is statistically significant it is not economically: 0.62 v 0.59. There is a statistically significant difference for the interaction between poverty and rainfall, but this is a difference between two insignificant estimates.

With regard to the determinants of inefficiency, the interaction between poverty and temperature loses significance. No parameter is significantly affected.

Although the stochastic frontier model does not pass stationarity tests, the results for the variables of interest are not affected.

4.4. Error-correction model

As a further empirical test, we estimate the error-correction model (ECM) defined in Equations (5) and (6). We assume here that weather anomalies cause short-term deviations from the long-run equilibrium, while climate affects the long-run equilibrium growth path of the economy. The error-correction model is dynamic, unlike the stochastic frontier models above, tracking the time needed to absorb the perturbation caused by weather anomalies. The ECM specification allows to test for stationarity of the residuals, which is not possible in the stochastic frontier model. It also allows us to relax the dichotomous approach—poor vs rich countries—and test a continuous interactions with lagged GDP per capita levels.

Table 8 presents the results for the long-run co-integrating vector, Table 9 for the short-run error-correction.[15]

The estimates of the co-integrating vector confirm that temperature is significantly associated with output per worker. We find an optimal temperature, 15.6℃, that is close to the one above, 16.3℃. The continuous interaction with lagged GDP per capita shows that income dampens the negative effect of climate on GDP level. Figure 3 shows that the level of income required to insulate countries from the impact of an adverse climate is by far out of sample, just as in the case of the interaction with capital per worker. Long-term rainfall is not significant, but its interaction with GDP per capita is. All else equal, more rain means lower income; this effect tapers off at higher rainfall, but does not reverse in-sample; the effect is stronger in richer countries.

In the stochastic frontier model, poorer countries are more prone to weather-induced inefficiency. In the error-correction model, rainfall shocks reduce growth in poor countries and temperature shocks in poor and hot countries. See Table 9.

Tables A1 and A2 report results of Fisher-type panel unit-root tests based on the Augmented Dickey-Fuller tests. These stationarity tests strongly reject the null hypothesis that the panel

[15] In the short-run error-correction estimates, V is the residual of Table 8, Column 3, since this specification is by far the best among the co-integrating vector models.

contains unit roots, making us confident that we are not getting spurious results caused by non-stationarity.

In conclusion, the error-correction model results suggest that, even when accounting for non-stationarity concerns and including non-parametric time trends and continuous interactions, our qualitative insights are confirmed: climate is a determinant of economic activity in all countries; weather shocks affect growth rates predominantly in poor and hot countries.

The foregoing has established that the key findings of this paper are, by and large, robust to alternative specification choices and identification strategies.

5. Conclusion

We use stochastic frontier analysis to jointly model the impacts of weather and climate on economic activity in most countries over 65 years. A key feature is that we distinguish production potential, affected by climate, and the realisation of economic output, affected by weather. Weather shocks thus have a transient effect, climate change a permanent impact. Temperature affects production potential in both rich and poor countries, but more so in poor ones. This is not surprising since they are on average hotter and closer to biophysical limits. Temperature and rainfall shocks induce inefficiency in poor countries only, especially hotter ones. These results are qualitatively and quantitatively robust to alternative specifications, controls, and estimators.

We find that poor, rather than hot, countries are particularly sensitive to the weather. This confirms Dell et al. (2012) and Letta and Tol (2018), but contradicts Burke et al. (2015). Hot and poor countries overlap, and the empirical distinction between heat and poverty is fragile. However, the cross-validation study of Newell et al. (2018) further confirms that it is poverty, rather than heat, that raises vulnerability to weather variability. The implications are different. We expect a hotter and richer future. In the Burke (Dell) specification, countries would grow more (less) vulnerable to unusual weather. Reducing outdoor work, decreasing the weight of the agricultural sector in national production and increasing adaptive capacity (e.g. through the diffusion of air conditioning) would help poorer countries to dampen the negative effects of weather shocks.

But we also find that neither higher income and capital nor better institutions insulate countries from the influence of their climate. This confirms some earlier studies, but contradicts others. We explicitly model heteroskedasticity due to weather shocks, and show that this heteroskedasticity systematically varies between rich and poor countries. Previous studies did not do this and so may be biased. The discrepancies between Dell et al. (2012) and Burke et al. (2015) may thus be due to an omitted variable bias with respect to climate, rather than to a linear *vs* non-linear functional form of annual temperature. Finally, we find that the weather effect is small compared to the climate effect, especially in the long-run.

The GDP-maximizing long-run temperature in our baseline specification is 17.26 degrees Celsius. In the last year of our sample, 2014, the 30-year average temperature for the period

1984-2013 is 18.68 °C. We are already well past the global temperature optimum. The implication is that a permanently hotter climate will make most countries poorer than they would be without climate change. Indeed, our simulations suggest that, in the worst case scenario of unmitigated warming, climate change will reduce global output per worker by up to 13 % by 2100, whereas in a 2°C warming scenario consistent with a stabilization pathway total economic losses would be considerably lower.

We do not include all impacts of climate change. We omit direct impacts on human welfare, such as biodiversity and health. Our model does not capture the range of events which could be triggered by climate change but lie outside the current range of historical experience, such as thawing permafrost, a thermohaline circulation shutdown or unprecedented sea level rise (Dell et al., 2014). Because of data availability, we use democracy as a proxy for high-quality government. We limit our attention to aggregate economic activity. Adaptation and expectations are implicit in our model. However, we do not explicitly model either production risk or risk preferences. This prevents us to disentangle weather effects on efficiency from those on production risk. In line with (Newell et al.), we find that the temperature peak, a key parameter to quantify climate change damages, is very sensitive to specification. Finally, our projections with respect to climate change are static, not dynamic.

Our numerical results are therefore far from final. The simulation results only illustrate the effect size. The methodological advancement in this work is more important: the joint, simultaneous estimation of the impact of two different, but often confused, phenomena: weather and climate. We defer to future research the task of refining the theoretical and empirical framework proposed here, and applying it to other macro contexts and, crucially, household and firm data.

References

D. Acemoglu, S. Johnson, and J. A. Robinson. The colonial origins of comparative development: An empirical investigation. *American Economic Review*, 91(5):1369–1401, December 2001. doi: 10.1257/aer.91.5.1369.

D. Acemoglu, S. Johnson, and J. A. Robinson. Reversal of fortune: Geography and institutions in the making of the modern world income distribution. *The Quarterly Journal of Economics*, 117(4):1231–1294, 2002.

M. Alsan. The effect of the tsetse fly on african development. *American Economic Review*, 105(1):382–410, January 2015. doi: 10.1257/aer.20130604. URL http://www.aeaweb.org/articles?id=10.1257/aer.20130604.

T. B. Andersen, C.-J. Dalgaard, and P. Selaya. Climate and the emergence of global income differences. *The Review of Economic Studies*, 83(4):1334–1363, 2016. doi: 10.1093/restud/rdw006. URL http://dx.doi.org/10.1093/restud/rdw006.

M. Auffhammer. Climate adaptive response estimation: Short and long run impacts of climate change on residential electricity and natural gas consumption using big data. Working Paper 24397, National Bureau of Economic Research, March 2018a. URL http://www.nber.org/papers/w24397.

M. Auffhammer. Quantifying economic damages from climate change. *Journal of Economic Perspectives*, 32(4):33–52, 2018b.

M. Auffhammer, S. M. Hsiang, W. Schlenker, and A. Sobel. Using weather data and climate model output in economic analyses of climate change. *Review of Environmental Economics and Policy*, 7(2):181–198, 2013.

L. Bakkensen and L. Barrage. Climate shocks, cyclones, and economic growth: Bridging the micro-macro gap. Working Paper 24893, National Bureau of Economic Research, August 2018. URL http://www.nber.org/papers/w24893.

S. Barrios, L. Bertinelli, and E. Strobl. Trends in rainfall and economic growth in africa: A neglected cause of the african growth tragedy. *The Review of Economics and Statistics*, 92(2):350–366, 2010. doi: 10.1162/rest.2010.11212. URL https://doi.org/10.1162/rest.2010.11212.

G. E. Battese and T. J. Coelli. Prediction of firm-level technical efficiencies with a generalized frontier production function and panel data. *Journal of Econometrics*, 38(3):387 – 399, 1988. ISSN 0304-4076. doi: https://doi.org/10.1016/0304-4076(88)90053-X. URL http://www.sciencedirect.com/science/article/pii/030440768890053X.

F. Belotti, S. Daidone, G. Ilardi, and V. Atella. Stochastic frontier analysis using stata. *The Stata Journal*, 13(4):719–758, 2013.

A. Bigano, J. M. Hamilton, and R. S. J. Tol. The impact of climate on holiday destination choice. *Climatic Change*, 76:389–406, 2006.

M. Burke and K. Emerick. Adaptation to climate change: Evidence from us agriculture. *American Economic Journal: Economic Policy*, 8(3):106–40, 2016.

M. Burke and V. Tanutama. Climatic constraints on aggregate economic output. Technical report, National Bureau of Economic Research, 2019.

M. Burke, S. M. Hsiang, and E. Miguel. Global non-linear effect of temperature on economic production. *Nature*, 527(7577):235–239, 2015.

M. Burke, W. M. Davis, and N. S. Diffenbaugh. Large potential reduction in economic damages under un mitigation targets. *Nature*, 557(7706):549–553, 2018.

A. Costinot, D. Donaldson, and C. Smith. Evolving comparative advantage and the impact of climate change in agricultural markets: Evidence from 1.7 million fields around the world. *Journal of Political Economy*, 124(1):205–248, 2016. doi: 10.1086/684719. URL https://doi.org/10.1086/684719.

M. Dell, B. F. Jones, and B. A. Olken. Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, 4(3):66–95, July 2012. doi: 10.1257/mac.4.3.66. URL http://www.aeaweb.org/articles?id=10.1257/mac.4.3.66.

M. Dell, B. F. Jones, and B. A. Olken. What do we learn from the weather? the new climate-economy literature. *Journal of Economic Literature*, 52(3):740–798, 2014.

T. Deryugina and S. Hsiang. The marginal product of climate. Working Paper 24072, National Bureau of Economic Research, November 2017. URL http://www.nber.org/papers/w24072.

O. Deschenes and M. Greenstone. The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather. *American Economic Review*, 97(1):354–385, 2007.

W. Easterly and R. Levine. Tropics, germs, and crops: how endowments influence economic development. *Journal of Monetary Economics*, 50(1):3–39, 2003. ISSN 0304-3932. doi: https://doi.org/10.1016/S0304-3932(02)00200-3.

R. C. Feenstra, R. Inklaar, and M. P. Timmer. The next generation of the penn world table. *American economic review*, 105(10):3150–82, 2015.

W. Greene. Fixed and random effects in stochastic frontier models. *Journal of productivity analysis*, 23(1): 7–32, 2005.

G. Heal and J. Park. Reflectionstemperature stress and the direct impact of climate change: A review of an emerging literature. *Review of Environmental Economics and Policy*, 10(2):347–362, 2016. doi: 10.1093/reep/rew007. URL http://dx.doi.org/10.1093/reep/rew007.

J. V. Henderson, T. Squires, A. Storeygard, and D. Weil. The global distribution of economic activity: Nature, history, and the role of trade. *The Quarterly Journal of Economics*, 133(1):357–406, 2018. doi: 10.1093/qje/qjx030. URL http://dx.doi.org/10.1093/qje/qjx030.

S. Hsiang. Climate econometrics. *Annual Review of Resource Economics*, 8(1):43–75, 2016. doi: 10.1146/annurev-resource-100815-095343. URL https://doi.org/10.1146/annurev-resource-100815-095343.

S. Hsiang, R. Kopp, A. Jina, J. Rising, M. Delgado, S. Mohan, D. J. Rasmussen, R. Muir-Wood, P. Wilson, M. Oppenheimer, K. Larsen, and T. Houser. Estimating economic damage from climate change in the united states. *Science*, 356(6345):1362, 2017.

M. E. Kahn, K. Mohaddes, R. N. C. Ng, M. H. Pesaran, M. Raissi, and J.-C. Yang. Long-term macroeconomic effects of climate change: A cross-country analysis. Working paper, University of Cambridge, 2019.

C. D. Kolstad and F. C. Moore. Estimating the economic impacts of climate change using weather observations. Technical report, National Bureau of Economic Research, 2019.

S. C. Kumbhakar. Specification and estimation of production risk, risk preferences and technical efficiency. *American Journal of Agricultural Economics*, 84(1):8–22, 2002.

S. C. Kumbhakar, H. Wang, and A. P. Horncastle. *A practitioner's guide to stochastic frontier analysis using Stata*. Cambridge University Press, 2015.

D. Lemoine. Expect above average temperatures: Identifying the economic impacts of climate change. Working Paper 23549, National Bureau of Economic Research, June 2017. URL http://www.nber.org/papers/w23549.

D. Lemoine. Sufficient statistics for the cost of climate change. Working Paper 25008, National Bureau of Economic Research, September 2018. URL http://www.nber.org/papers/w25008.

M. Letta and R. S. J. Tol. Weather, climate and total factor productivity. *Environmental and Resource Economics*, Jun 2018. ISSN 1573-1502. doi: 10.1007/s10640-018-0262-8. URL https://doi.org/10.1007/s10640-018-0262-8.

K. Matsuura and C. Willmott. Terrestrial air temperature and precipitation: 1900–2014 gridded time series (version 4.01), 2015.

R. Mendelsohn, W. D. Nordhaus, and D. Shaw. The impact of global warming on agriculture: A ricardian analysis. *The American Economic Review*, 84(4):753–771, 1994. ISSN 00028282. URL http://www.jstor.org/stable/2118029.

R. Newell, B. Prest, and S. Sexton. The gdp-temperature relationship: Implications for climate change damages. Technical report, RFF Working Paper. Available at: http://www. rff. org/research/publications , 2018.

R. G. Newell, B. C. Prest, and S. Sexton. The gdp temperature relationship: Implications for climate change damages. Technical report, Resources for the Future, 2018/07/05/ .

W. D. Nordhaus. Geography and macroeconomics: New data and new findings. *Proceedings of the National Academy of Science*, 103(10):3510–3517, 2006. URL www.pnas.org/cgi/doi/10.1073/pnas.

0509842103.

F. Pretis, M. Schwarz, K. Tang, K. Haustein, and M. R. Allen. Uncertain impacts on economic growth when stabilizing global temperatures at 1.5°c or 2°c warming. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 376(2119):20160460, 2018. doi: 10.1098/rsta.2016.0460.

D. Rodrik, A. Subramanian, and F. Trebbi. Institutions rule: The primacy of institutions over geography and integration in economic development. *Journal of Economic Growth*, 9(2):131–165, Jun 2004. ISSN 1573-7020. doi: 10.1023/B:JOEG.0000031425.72248.85. URL https://doi.org/10.1023/B:JOEG.0000031425.72248.85.

J. D. Sachs. Institutions don't rule: Direct effects of geography on per capita income. Working Paper 9490, National Bureau of Economic Research, February 2003. URL http://www.nber.org/papers/w9490.

W. Schlenker, W. M. Hanemann, and A. C. Fisher. Will us agriculture really benefit from global warming? accounting for irrigation in the hedonic approach. *American Economic Review*, 95(1):395–406, 2005.

C. Severen, C. Costello, and O. Deschenes. A forward looking ricardian approach: Do land markets capitalize climate change forecasts? Working Paper 22413, National Bureau of Economic Research, July 2016. URL http://www.nber.org/papers/w22413.

P. Zhang, O. Deschenes, K. Meng, and J. Zhang. Temperature effects on productivity and factor reallocation: Evidence from a half million chinese manufacturing plants. *Journal of Environmental Economics and Management*, 88:1 – 17, 2018. ISSN 0095-0696. doi: https://doi.org/10.1016/j.jeem.2017.11.001. URL http://www.sciencedirect.com/science/article/pii/S0095069617304588.

Table 1: Descriptive statistics

Variable	Unit	Mean	Var	sd	Min	Max	Obs
Output per worker	ln($)	9.768	1.399	1.183	6.047	13.318	7753
Capital per worker	ln($)	10.831	1.937	1.392	5.650	14.524	7753
Temp	℃	18.505	52.839	7.269	-1.833	29.021	7753
Temp^2	$℃^2$	395.257	60913.587	246.807	0.363	842.222	7753
Pre	cm/month	9.375	32.199	5.674	0.299	32.710	7753
Pre^2	$(\text{cm/month})^2$	120.084	21896.750	147.976	0.089	1069.974	7753
ΔTemp	℃	0.961	0.543	0.737	0.000	7.395	7753
ΔPre	cm/month	0.876	0.502	0.709	0.001	6.717	7753

Table 2: Baseline results

	Dependent variable: output per worker			
	(1)	(2)	(3)	(4)
Frontier				
Capital per worker	0.613***	0.613***	0.616***	0.613***
	(0.00806)	(0.00814)	(0.00826)	(0.00821)
Temp	0.189***	0.183***	0.181***	0.183***
	(0.0236)	(0.0238)	(0.0238)	(0.0237)
Temp^2	-0.00547***	-0.00556***	-0.00563***	-0.00568***
	(0.000692)	(0.000680)	(0.000686)	(0.000673)
Pre	0.000544	0.00725	0.00689	0.00987
	(0.0112)	(0.0113)	(0.0113)	(0.0113)
Pre^2	-0.0000150	-0.000542	-0.000525	-0.000599
	(0.000367)	(0.000395)	(0.000395)	(0.000385)
Poor x Temp		0.329**	0.325**	0.371**
		(0.151)	(0.147)	(0.151)
Poor x Temp^2		-0.00540*	-0.00513*	-0.00621**
		(0.00310)	(0.00301)	(0.00309)
Poor x Pre		0.0131	0.0244	0.0181
		(0.0359)	(0.0358)	(0.0358)
Poor x Pre^2		0.000803	0.000540	0.000638
		(0.000972)	(0.000965)	(0.000958)
Usigma				
ΔTemp	0.0246	0.0226	-0.0531	-0.0622
	(0.0329)	(0.0331)	(0.0358)	(0.0382)
ΔPre	0.00243	0.00342	-0.0859**	-0.109***
	(0.0360)	(0.0361)	(0.0409)	(0.0399)
Poor x ΔTemp			0.193***	0.183***
			(0.0583)	(0.0596)
Poor x ΔPre			0.272***	0.257***
			(0.0657)	(0.0682)
Hot x ΔTemp				0.0709
				(0.0589)
Hot x ΔPre				0.0981
				(0.0716)
N	7753	7753	7753	7753
Log-pseudolikelihood	2041.7	2049.3	2106.0	2112.0
BC Efficiency Index	0.814	0.816	0.814	0.814
Opt.Temp.	17.26	16.49	16.12	16.11
Opt. Temp. in poor countries		23.39	23.56	23.28
Poor total Temp		0.512***	0.507***	0.554***
		(0.149)	(0.145)	(0.149)
Poor total Temp^2		-0.0110***	-0.0108***	-0.0119***
		(0.00305)	(0.00295)	(0.00302)
Poor total ΔTemp			0.140***	0.121**
			(0.0505)	(0.0570)
Poor total ΔPre			0.186***	0.149**
			(0.0578)	(0.0688)
Hot total ΔTemp				0.00867
				(0.0581)
Hot total ΔPre				-0.0106
				(0.0719)
Poor and hot total ΔTemp				0.191***
				(0.058)
Poor and hot total ΔPre				0.247***
				(0.068)

Notes: all specifications include country fixed effects and a time trend. * p<0.1, ** p<0.05, *** p<0.01.

Table 3: Marginal effects of the inefficiency variables - Baseline results

	(1)	(2)	(3)	(4)
Marginal effects on E(u)				
ΔTemp	0.00277	0.00276	-0.00601	-0.00722
	(0.00387)	(0.00395)	(0.0358)	(0.00457)
ΔPre	0.000525	0.000458	-0.00977**	-0.0128***
	(0.00429)	(0.00432)	(0.00482)	(0.00486)
Poor x ΔTemp			0.0219***	0.0210***
			(0.00671)	(0.00683)
Poor x ΔPre			0.0308***	0.0299***
			(0.00767)	(0.00780)
Hot x ΔTemp				0.00857
				(0.00727)
Hot x ΔPre				0.0110
				(0.00862)
Marginal effects on V(u)				
ΔTemp	0.000701	0.000733	-0.00157	-0.00195
	(0.000986)	(0.00106)	(0.00111)	(0.00124)
ΔPre	0.000127	0.000117	-0.00258**	-0.00348**
	(0.00109)	(0.00115)	(0.00129)	(0.00139)
Poor x ΔTemp			0.00578***	0.00565***
			(0.00178)	(0.00184)
Poor x ΔPre			0.00812***	0.00808***
			(0.00210)	(0.0217)
Hot x ΔTemp				0.00236
				(0.00204)
Hot x ΔPre				0.00305
				(0.00242)

Notes: * p<0.1, ** p<0.05, *** p<0.01.

Table 4: Alternative specifications - Frontier

	Dependent variable: output per worker						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	WB classification	Squared anomalies	Linear anomalies	Asymmetric anomalies	No rainfall	Weather in the frontier	Exponential dist.
Frontier							
Capital per worker	0.620***	0.614***	0.612***	0.616***	0.615***	0.613***	0.632***
	(0.00842)	(0.00816)	(0.00818)	(0.00826)	(0.00808)	(0.00812)	(0.00822)
Temp	0.172***	0.182***	0.183***	0.176***	0.181***	0.183***	0.151***
	(0.0309)	(0.0238)	(0.0241)	(0.0239)	(0.0234)	(0.0238)	(0.0236)
Temp^2	-0.0102***	-0.00556***	-0.00564***	-0.00565***	-0.00542***	-0.00553***	-0.00453***
	(0.00173)	(0.000681)	(0.000683)	(0.000686)	(0.000653)	(0.000681)	(0.000662)
Pre	0.00310	0.00698	0.00766	0.00781		0.00698	0.0179
	(0.0228)	(0.0113)	(0.0114)	(0.0114)		(0.0113)	(0.0118)
Pre^2	-0.000347	-0.000505	-0.000552	-0.000587		-0.000524	-0.000472
	(0.00113)	(0.000396)	(0.000396)	(0.000398)		(0.000395)	(0.000389)
Poor x Temp	0.135**	0.329**	0.342**	0.326**	0.324**	0.329**	0.352**
	(0.0583)	(0.148)	(0.151)	(0.147)	(0.148)	(0.149)	(0.157)
Poor x Temp^2	0.00255	-0.00527*	-0.00583*	-0.00513*	-0.00621**	-0.00545*	-0.00308
	(0.00193)	(0.00304)	(0.00311)	(0.00302)	(0.00301)	(0.00306)	(0.00304)
Poor x Pre	0.0166	0.0191	0.00765	0.0266		0.00926	0.112***
	(0.0271)	(0.0359)	(0.0375)	(0.0368)		(0.0360)	(0.0371)
Poor x Pre^2	-0.00000697	0.000627	0.000908	0.000545		0.000866	-0.00154
	(0.00120)	(0.000970)	(0.00100)	(0.000986)		(0.000961)	(0.000939)
ΔTemp						-0.00200	
						(0.00298)	
Poor x ΔTemp						-0.00912	
						(0.00675)	
ΔPre						0.00111	
						(0.00278)	
Poor x ΔPre						-0.00331	
						(0.00773)	
N	7753	7753	7753	7753	7753	7753	7753
Pseudo loglikelihood	2122.5	2087.3	2058.1	2109.3	2084.9	2051.5	2497.9
BC Efficiency Index	0.826	0.815	0.814	0.816	0.815	0.813	0.840
Opt. Temp.	8.424	16.37	16.20	15.57	16.69	16.51	16.63
Poor Opt. Temp.	19.97	23.61	22.85	23.29	21.71	23.27	33.03
Poor total Temp	0.307***	0.511***	0.524***	0.502***	0.505***	0.511***	0.503***
	(0.0495)	(0.146)	(0.149)	(0.145)	(0.146)	(0.147)	(0.154)
Poor total Temp^2	-0.00769***	-0.0108***	-0.0115***	-0.0108***	-0.0116***	-0.0110***	-0.00761***
	(0.00120)	(0.00298)	(0.00306)	(0.00296)	(0.00296)	(0.00301)	(0.00296)
Poor total ΔTemp						-0.0111*	
						(0.00610)	
Poor total ΔPre						-0.00220	
						(0.00722)	

Notes: all specifications include country fixed effects and a time trend. In Column 1 'Poor' stands for a 'non-high-income' country. In Column 3 absolute anomalies are replaced with their original values. Standard errors are clustered at the country level. * p<0.1, ** p<0.05, *** p<0.01.

Table 5: Alternative specifications - Inefficiency

	Dependent variable: output per worker						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	WB classification	Squared anomalies	Linear anomalies	Asymmetric anomalies	No rainfall	Weather in the frontier	Exp. dist.
Inefficiency							
ΔTemp	-0.208***		0.00122		-0.0928***		-0.0313
	(0.0671)		(0.0256)		(0.0358)		(0.0395)
ΔPre	-0.194**		0.00533				-0.0820*
	(0.0863)		(0.0259)				(0.0425)
Poor x ΔTemp	0.292***		0.0957*		0.321***		0.195***
	(0.0760)		(0.0559)		(0.0536)		(0.0633)
Poor x ΔPre	0.271***		-0.0386				0.290***
	(0.0932)		(0.0542)				(0.0684)
$(\Delta\text{Temp})^2$		-0.0186					
		(0.0114)					
Poor x $(\Delta\text{Temp})^2$		0.0675***					
		(0.0179)					
$(\Delta\text{Pre})^2$		-0.0334**					
		(0.0141)					
Poor x $(\Delta\text{Pre})^2$		0.0981***					
		(0.0251)					
ΔTemp_+				-0.0275			
				(0.0385)			
Poor x ΔTemp_+				0.171***			
				(0.0644)			
ΔTemp_-				0.136**			
				(0.0562)			
Poor ΔTemp_-				-0.256***			
				(0.0902)			
ΔPre_+				-0.0801			
				(0.0492)			
Poor x ΔPre_+				0.260***			
				(0.0907)			
ΔPre_-				0.102**			
				(0.0474)			
Poor x ΔPre_-				-0.289***			
				(0.0782)			
Poor total ΔTemp	0.0835**		0.0969*		0.228***		0.164***
	(0.0379)		(0.0516)		(0.0466)		(0.0558)
Poor total ΔPre	0.0767*		-0.0333				0.208***
	(0.0424)		(0.0477)				(0.0606)
Poor total $(\Delta\text{Temp})^2$		0.0489***					
		(0.0144)					
Poor total $(\Delta\text{Pre})^2$		0.0647***					
		(0.0213)					
Poor total Poor ΔTemp_+				0.143***			
				(0.0552)			
Poor total Poor ΔPre_+				0.180**			
				(0.0797)			
Poor total Poor ΔTemp_-				-0.119			
				(0.0754)			
Poor total Poor ΔPre_-				-0.187***			
				(0.0683)			

In Column 1 'Poor' stands for a 'non-high-income' country. In Column 3 absolute anomalies are replaced with their original values. Standard errors are clustered at the country level. * p<0.1, ** p<0.05, *** p<0.01.

Table 6: Capital and institutions

	Dependent variable: output per worker	
	(1)	(2)
Frontier		
Capital per worker	0.883***	0.647***
	(0.0219)	(0.00854)
Temp	0.666***	0.310***
	(0.0479)	(0.0247)
Temp^2	-0.0194***	-0.00709***
	(0.00137)	(0.000704)
Capital per worker x Temp	-0.0405***	
	(0.00320)	
Capital per worker Temp^2	0.00123***	
	(0.000101)	
Pre	-0.0152	0.00483
	(0.0112)	(0.0118)
Pre^2	0.000548	-0.0000469
	(0.000355)	(0.000350)
Polity2 x Temp		-0.000489
		(0.000343)
Polity2 x Temp^2		0.0000296***
		(0.00000970)
Polity2		-0.00528*
		(0.00298)
Usigma		
ΔTemp	0.0277	0.0258
	(0.0318)	(0.0330)
ΔPre	0.00348	-0.00183
	(0.0354)	(0.0381)
N	7753	7753
Log-pseudolikelihood	2123.1	2123.3
BC Efficiency Index	0.811	0.798
Opt. Temp.	17.17	21.84

Notes: all specifications include country fixed effects and a linear time trend. Standard errors are clustered at the country level. * p<0.1, ** p<0.05, *** p<0.01.

Table 7: Split sample

	Dependent variable: output per worker		
	(1)	(2)	(3)
	whole sample	split sample	difference
Frontier			
Capital per worker	0.616***	0.587***	0.029**
	(0.008)	(0.012)	(0.012)
Temp	0.181***	0.169***	0.012
	(0.024)	(0.036)	(0.036)
Temp^2	-0.00563***	-0.00532***	-0.00031
	(0.00069)	(0.00128)	(0.00128)
Pre	0.00689	0.00264	0.00425
	(0.01130)	(0.01322)	(0.01328)
Pre^2	-0.000525	-0.000013	-0.000512
	(0.000395)	(0.000423)	(0.000423)
Poor x Temp	0.325**	0.382**	-0.057
	(0.147)	(0.122)	(0.134)
Poor x Temp^2	-0.00513	-0.00002	-0.00511
	(0.00301)	(0.00342)	(0.00343)
Poor x Pre	0.0244	-0.1034	0.01278**
	(0.0358)	(0.0549)	(0.0553)
Poor x Pre^2	0.000540	0.001603	-0.001063
	(0.00965)	(0.001634)	(0.001634)
Inefficiency			
ΔTemp	-0.0531	-0.0347	-0.0184
	(0.0358)	(0.0655)	(0.0668)
ΔPre	-0.0859**	-0.1251**	0.0392
	(0.0409)	(0.0570)	(0.0567)
Poor x ΔTemp	0.193***	0.101	0.092
	(0.058)	(0.092)	(0.093)
Poor x ΔPre	0.272***	0.429***	-0.157
	(0.066)	(0.092)	(0.094)

Table 8: Error-correction model - Long-run co-integrating vector

	Dependent variable: output per worker		
	(1)	(2)	(3)
Capital per worker	0.612***	0.597***	0.171***
	(0.0406)	(0.0423)	(0.0247)
Temp	0.158	0.133	0.295**
	(0.0343)	(0.0921)	(0.120)
Temp^2	-0.00697***	-0.00615***	-0.00947***
	(0.00103)	(0.00206)	(0.00318)
Pre	-0.023	0.00840	0.0287
	(0.0298)	(0.0523)	(0.049)
Pre^2	0.0000157	-0.00108	-0.000283
	(0.00107)	(0.00183)	(0.00165)
Poor x Temp		0.197	
		(0.475)	
Poor x Temp^2		-0.00668	
		(0.00973)	
Poor x Pre		-0.205	
		(0.141)	
Poor x Pre^2		0.00618	
		(0.00381)	
Lagged GDP per capita x Temp			-0.0161*
			(0.00814)
Lagged GDP per capita x Temp^2			0.000548**
			(0.000245)
Lagged GDP per capita x Pre			-0.0147***
			(0.00597)
Lagged GDP per capita x Pre^2			0.000296*
			(0.000165)
Lagged GDP per capita			0.940***
			(0.0689)
N	7753	7753	7753
Adjusted R^2	0.791	0.792	0.939
Opt. Temp.	11.30	10.84	15.57
Opt. Temp. in poor countries		12.86	
Poor total temp		0.330	
		(0.476)	
Poor total Temp^2		-0.0128	
		(0.00969)	

Notes: all the specifications include country and time fixed effects. Standard errors are clustered at the country level.
* p<0.1, ** p<0.05, *** p<0.01.

Table 9: Error-correction model - Short-run error-correction

	Dependent variable: output per worker growth rate			
	(1)	(2)	(3)	(4)
V	0.119***	0.118***	0.118***	0.369***
	(0.0196)	(0.0196)	(0.0195)	(0.0334)
Δ(ΔTemp)	-0.00111	-0.0000309	0.000266	-0.0084*
	(0.000717)	(0.000586)	(0.000692)	(0.00502)
Δ(ΔPre)	-0.00122*	-0.000660	-0.00130*	-0.00297
	(0.000689)	(0.000713)	(0.000683)	(0.00414)
Poor x Δ(ΔTemp)		-0.00388*	-0.00354	
		(0.00213)	(0.00229)	
Poor x Δ(ΔPre)		-0.00225	-0.00283	
		(0.00189)	(0.00198)	
Hot x Δ(ΔTemp)			-0.00139	
			(0.00165)	
Hot x Δ(ΔPre)			0.00291	
			(0.00190)	
GDP per capita x Δ(ΔTemp)				0.000862
				(0.000537)
GDP per capita x Δ(ΔPre)				0.000230
				(0.000458)
GDP per capita				-0.0188***
				(0.00501)
N	7591	7591	7591	7591
Adjusted R^2	0.0213	0.0220	0.0221	0.323
Poor total Δ(ΔTemp)		-0.00391*	-0.00328	
		(0.00205)	(0.00240)	
Poor total Δ(ΔPre)		-0.00291*	-0.00413**	
		(0.00175)	(0.00199)	
Hot total Δ(ΔTemp)			-0.00112	
			(0.00140)	
Hot total Δ(ΔPre)			0.00161	
			(0.00188)	
Poor and hot total Δ(ΔTemp)			-0.00466**	
			(0.00193)	
Poor and hot total Δ(ΔPre)			-0.00122	
			(0.00185)	

Notes: all the specifications include country fixed effects. Standard errors are clustered at the country level.
* p<0.1, ** p<0.05, *** p<0.01.

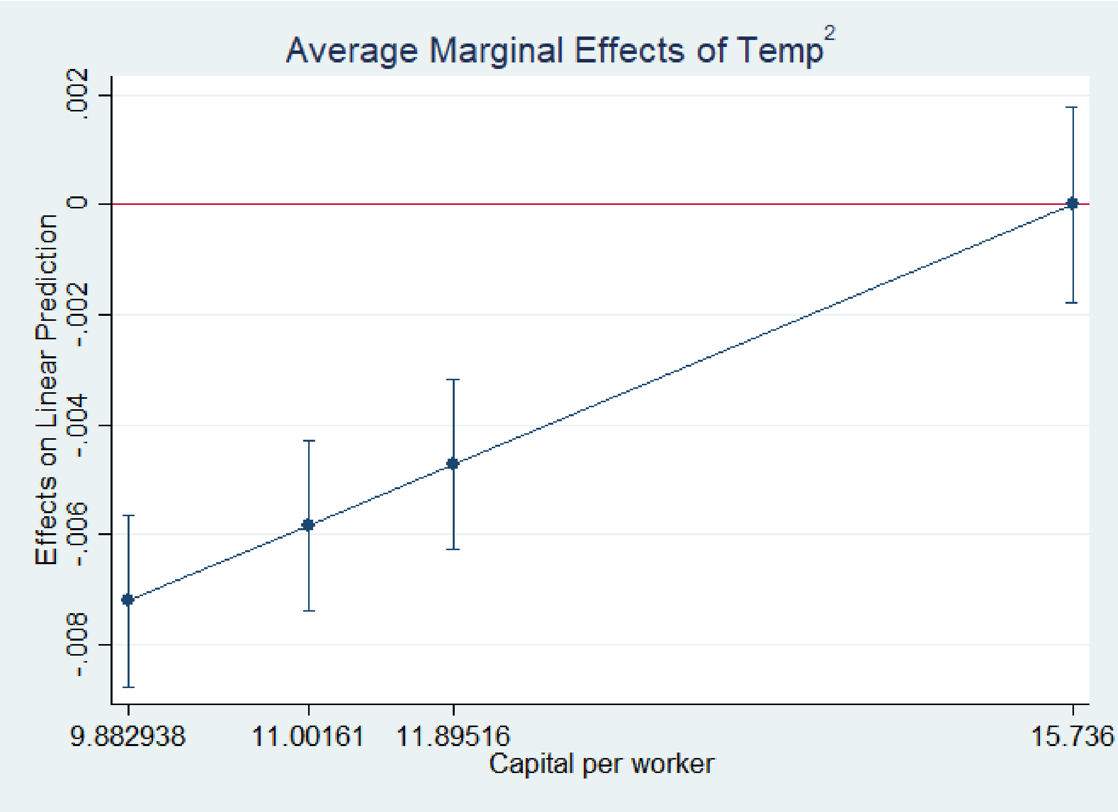

Figure 1: Marginal effects of Temp^2 at different capital levels

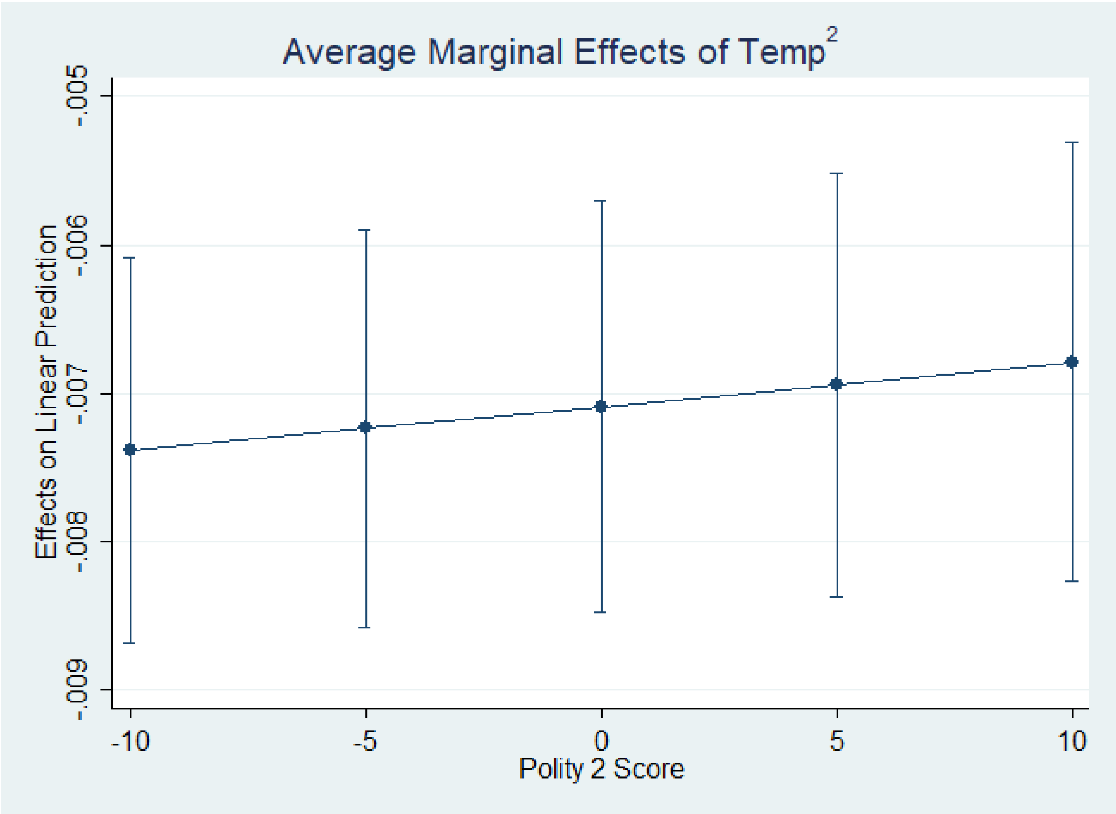

Figure 2: Marginal effects of $Temp^2$ at different institutional quality levels

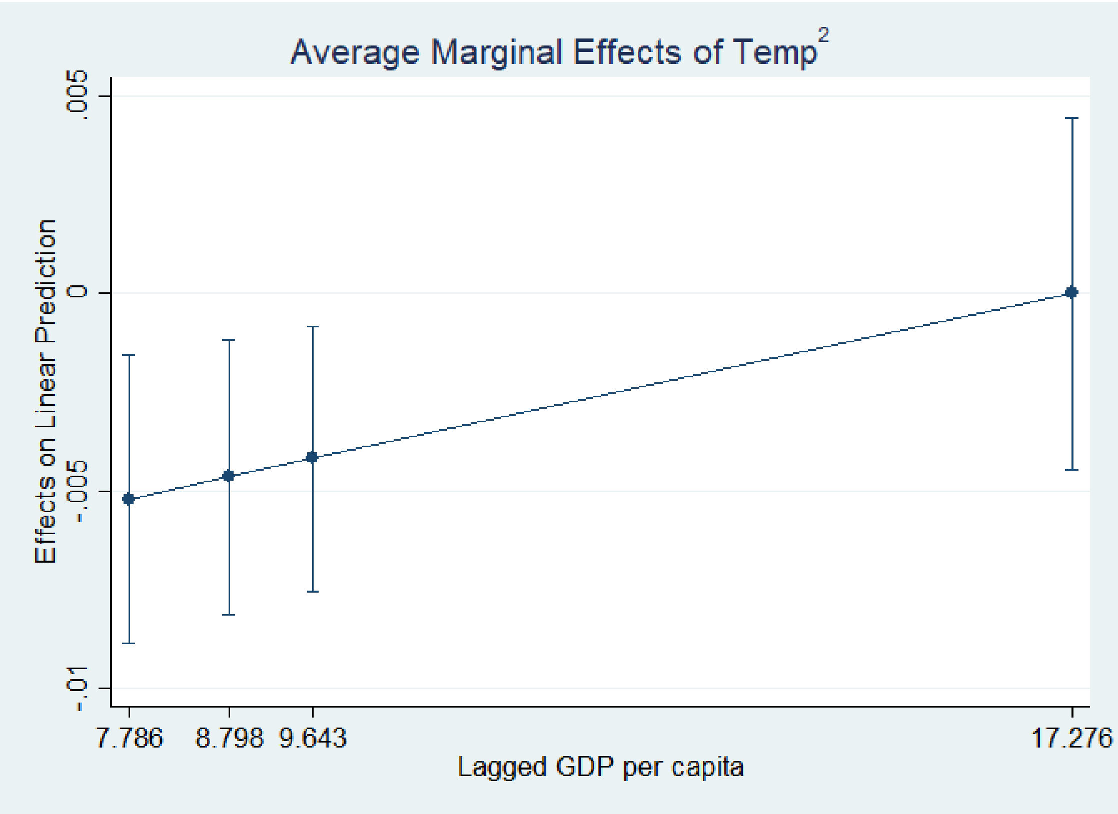

Figure 3: Marginal effects of Temp^2 at different lagged GDP per capita levels (Error-Correction Model, Long-run cointegrating vector)

Appendix A. Stationarity

Appendix A.1. Residuals

Appendix A.2. Panel unit-root tests for the residuals of the error-correction model

Table A1: Fisher-type unit-root test for Table 7, Column 3 residual

Test	Statistic	Value	p-value
Inverse χ^2 (320)	P	1058.5419	0.0000
Inverse Normal	Z	-20.5569	0.0000
Inverse logit t(804)	L*	-21.9939	0.0000
Modified inv. χ^2	Pm	29.1934	0.0000

Notes: Based on Augmented Dickey-Fuller tests. The null hypothesis is that all panels contain unit roots, the alternative hypothesis is that at least one panel is stationary. Cross-sectional means removed and drift trend included. The ADF regressions include 2 lags.

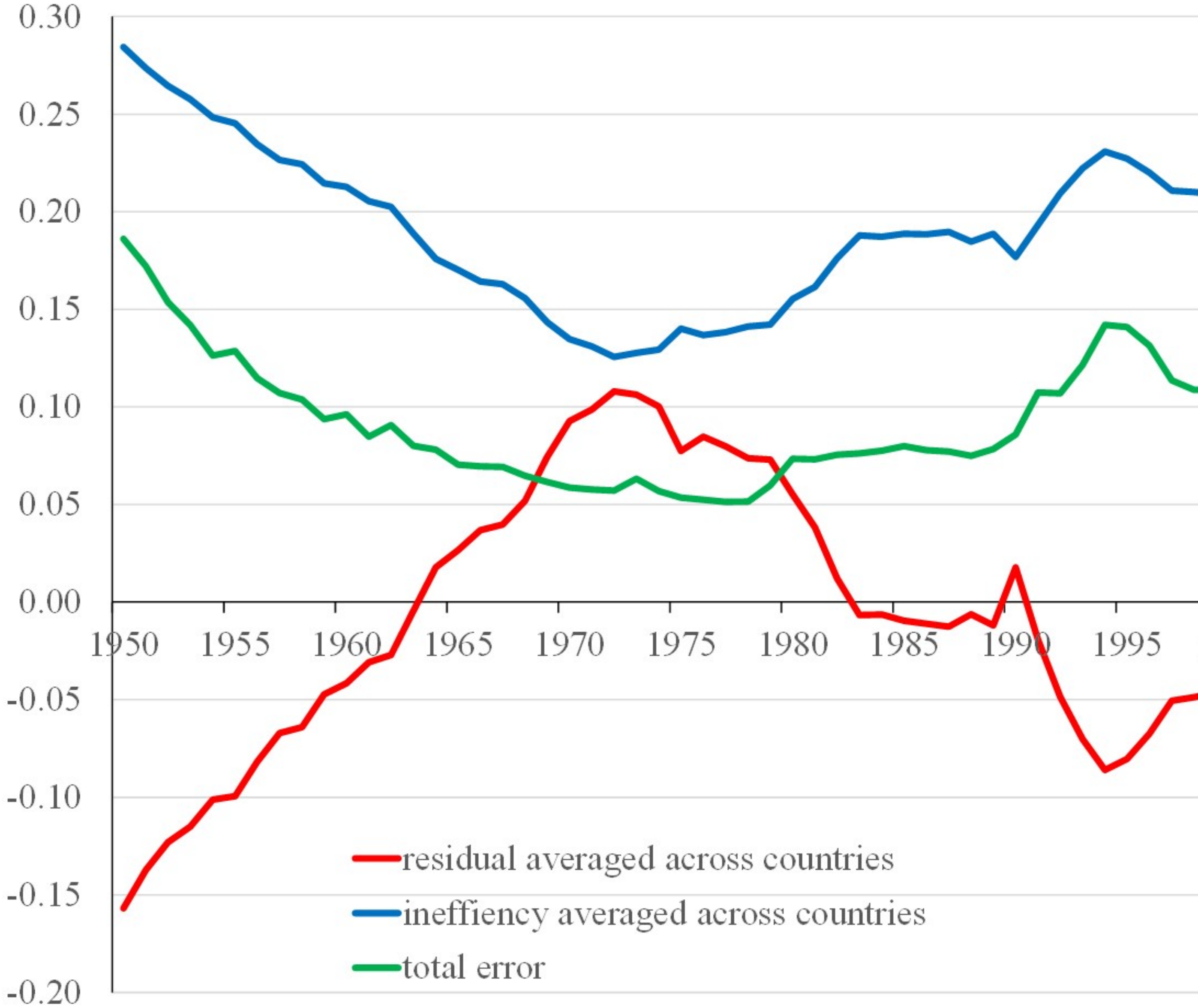

Figure A.4: Annual average residuals of the frontier, average annual inefficiency, and total error term for Column 3 in Table 2.

Table A2: Fisher-type unit-root test for Table 8, Column 4 residual

Test	Statistic	Value	p-value
Inverse χ^2 (320)	P	1461.6599	0.0000
Inverse Normal	Z	-27.4212	0.0000
Inverse logit t(804)	L^*	-31.4722	0.0000
Modified inv. χ^2	Pm	45.1281	0.0000

Notes: Based on Augmented Dickey-Fuller tests. The null hypothesis is that all panels contain unit roots, the alternative hypothesis is that at least one panel is stationary. Cross-sectional means removed and drift trend included. The ADF regressions include 2 lags.

Appendix B. Additional tables

List of countries

Albania
Algeria
Angola
Argentina
Armenia
Australia
Austria
Azerbaijan
Bahamas
Bangladesh
Belarus
Belgium
Belize
Benin
Bhutan
Bolivia
Bosnia and Herzegovina
Botswana
Brazil
Brunei
Bulgaria
Burkina Faso
Burundi
Cabo Verde
Cambodia
Cameroon
Canada
Central African Republic
Chad
Chile
China
Colombia
Comoros
Congo
Costa Rica
Croatia
Cyprus
Czech Republic
D.R. of the Congo

Denmark
Djibouti
Dominican Republic
Ecuador
Egypt
El Salvador
Equatorial Guinea
Estonia
Ethiopia
Fiji
Finland
France
Gabon
Gambia
Georgia
Germany
Ghana
Greece
Guatemala
Guinea
Guinea-Bissau
Haiti
Honduras
Hungary
Iceland
India
Indonesia
Iran
Iraq
Ireland
Israel
Italy
Ivory Coast
Jamaica
Japan
Jordan
Kazakhstan
Kenya
Kuwait
Kyrgyzstan
Lao People's DR
Latvia
Lebanon

Lesotho
Liberia
Lithuania
Luxembourg
Macedonia
Madagascar
Malawi
Malaysia
Mali
Mauritania
Mauritius
Mexico
Mongolia
Montenegro
Morocco
Mozambique
Myanmar
Namibia
Nepal
Netherlands
New Zealand
Nicaragua
Niger
Nigeria
Norway
Oman
Pakistan
Panama
Paraguay
Peru
Philippines
Poland
Portugal
Qatar
Republic of Korea
Republic of Moldova
Romania
Russian Federation
Rwanda
Sao Tome and Principe
Saudi Arabia
Senegal
Serbia

Sierra Leone
Singapore
Slovakia
Slovenia
South Africa
Spain
Sri Lanka
St. Vincent and the Grenadines
Sudan (Former)
Suriname
Swaziland
Sweden
Switzerland
Syria
Taiwan
Tajikistan
Tanzania
Thailand
Togo
Trinidad and Tobago
Tunisia
Turkey
Turkmenistan
Uganda
Ukraine
United Arab Emirates
United Kingdom
United States
Uruguay
Uzbekistan
Venezuela
Vietnam
Yemen
Zambia
Zimbabwe

List of regions

Eastern Europe and Central Asia
Latin America and the Caribbean
Middle East and North Africa
South and East Asia and the Pacific
Sub-Saharan Africa

Western Europe and offshoots