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Weather, climate and total factor productivity[1]

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Abstract: Recently it has been hypothesized that climate change will affect total factor productivity growth. Given the importance of TFP for long-run economic growth, if true this would entail a substantial upward revision of current impact estimates. Using macro TFP data from a recently developed dataset in Penn World Tables, we test this hypothesis by directly examining the nature of the relationship between annual temperature shocks and TFP growth rates in the last decades. The results show a negative relationship only in poor countries. While statistically significant, the estimate upper bound is a reduction of TFP growth is less than 0.1%, i.e., climate change will decelerate but not reverse economic growth. This finding increases concerns over the distributional issues of future impacts, and restates the case for complementarity between climate policy and poverty reduction.

JEL classification: O44, O47, Q54

Key words: weather variability; climate change; total factor productivity; economic growth

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Introduction

Since the path-breaking work of Nordhaus (1991), economists have argued in favour of a modest carbon tax. Although frequently challenged in favour of more stringent climate policy, estimates of the social cost of carbon have not increased over the years (Tol, 2015). Three independent author teams (Moore & Diaz, 2015; Dietz & Stern 2015; Moyer, Woolley, Matteson, Glotter & Weisbach, 2014) have recently hypothesized that, should climate change negatively affect total factor productivity, then the estimate of the Pigou tax increases drastically. In this paper, we present econometric evidence of the impact of weather and climate on total factor productivity growth. While not disputing the sign of the hypothesized effect, we show the effect size is small.

Most impact studies of climate change have taken the form of comparative statics impact estimates. These studies show that climate change would have a modest negative impact of human welfare, i.e., a few percent over a century (Tol, 2015), have been criticized because they could not fully capture the potential damage by future climate change (Pindyck, 2012 & 2013; Stern, 2013).

Besides static impacts on welfare, there are also dynamic ones: climate change affects the growth rate of the economy (Fankhauser & Tol, 2005; Hallegatte, 2005). The distinction between static, or "level" effects, and dynamic, or "growth" effects of climate change on economic activity is of first order importance in terms of the magnitude of future impacts. While the so-called *level* effects are temporary and intrinsically reversible, *growth* effects compound over time and permanently reduce output. An impact of hot temperatures on a given year's agricultural yields would represent a *level* effect, while an impact on investments or institutions would affect the economy's ability to *grow*, altering its future path. Fankhauser and Tol argue that climate change may affect labour supply, capital depreciation and productivity (rather than productivity growth). They find that, if these effects are negative, economic growth would be suppressed. The resulting welfare loss would be similar in size to the estimates of the static welfare losses.

Since the onset of growth economics and the pioneering Solow model (Solow, 1956) TFP has been considered a key element to explain long-run development. TFP, as is widely known, represents a combination of labour and capital productivity, which accounts for increase in total output not due to labour or capital inputs, and traditionally has been seen as a rough measure of technological progress. Recently, a number of theoretical studies have hypothesized a future impact of global warming on TFP growth (Stern, 2013; Moore & Diaz, 2015; Dietz & Stern 2015; Moyer, Woolley, Matteson, Glotter & Weisbach, 2014). Given the preeminent importance of TFP for long-run economic growth, if climate change will really harm TFP growth rates, this would entail a radical revision of impact estimates.

Dietz and Stern (2015) change the workings of DICE, one of the most used IAMs, to allow climate impacts to affect TFP growth.[1] They find a much stronger case for stringent emission abatement. Similarly, Moyer, Woolley, Matteson, Glotter and Weisbach (2014) argue that the IAMs used by the US federal Interagency Working Group (IWG)[2] on the Social Cost of Carbon may not capture the full range of consequences of climate change, and contest the fact that "(IAMs) implicitly assume that society will grow far wealthier in the future even if temperatures increase by amounts that many scientists believe may cause substantial hardships". Consequently they change DICE and allow climate impacts to directly affect TFP growth, finding, consistently with Dietz and Stern (2015) large effects on future growth and a much higher value of the SCC than the IWG one.[3]

However, these works do not provide any empirical evidence for this claim and the consequent simulations (Tol, 2015). In fact, while these calibrated models are very sensitive to assumptions about the impact of climate change on TFP growth, the assumptions are just that: they are not grounded in observations. The current paper estimates the impact of weather variability and climate change on total factor productivity growth.

There is a large and growing body of empirical literature which focuses on the relationship between climate and economic activity. Jared Diamond (Diamond, 1999) revived the spirit of Ellsworth Huntington (Huntington, 1922), arguing that geography and climate are the fundamental drivers of economic development. Olsson and Hibbs (2005) provide empirical support. Gallup, Sachs, and Mellinger (1999) argue that geography and climate are important, but that their impact can be modified by technology. In sharp contrast to this environmental determinism, (Acemoglu, Johnson, & Robinson, 2000; Easterly & Levine, 2003; Rodrik, Subramanian, & Trebbi, 2004) argue for institutional determinism and find that, in a direct statistical contest, institutional variables have predictive power but climate and geography variables do not. The institutional view has been challenged by Alsan (2014) and Andersen, Dalgaard and Selaya (2016). Alsan (2014) shows that the tse-tse fly is a major factor in the underdevelopment in Sub-Saharan Africa. Andersen, Dalgaard and

[1] Further changes to the DICE framework they undertake are allowing for convexity of the damage function (Weitzman, 2010) and for high values of the climate sensitivity parameter (Weitzman, 2009 & 2011).
[2] DICE (Nordhaus, 2008), FUND (Anthoff, Tol, & Yohe, 2009) and PAGE (Hope, 2006).
[3] Also, they notice how impacts on growth would contribute to settle the debate on the discount rate sparked after the publication of the Stern Review (Stern, 2007). See also Nordhaus (2007), Stern (2013) and Tol et al. (2006).

Selaya (2016) show that UV radiation (but not climate) plays a role in explaining the pattern of development across the world.

These cross-section analyses of the climate-income relationship suffer from a range of endogeneity and confounders problems. A literature has emerged that uses robust panel studies that try to isolate the effect of temperature or other meteorological variables on economic activity and growth.[4] A comprehensive review is carried out in Dell, Jones, and Olken (2014).

As far as climate change is concerned, though, this literature is problematic for a number of reasons. First, as emphasized by Tol (2015), weather impacts are assumed to be informative about climate impacts; put differently, short-term elasticities are used to assess long-term effects. Second, since the Industrial Revolution global temperature has risen of almost 1°C (IPCC, 2013) while increases in temperature during the 21st century will very likely be of 2°C or more (IPCC, 2013) which means these studies extrapolate far beyond historical experience. Third, it is by no means guaranteed that historical relationships will continue to hold in the future as technologies and institutions evolve. However, while external validity is debatable, there are techniques, as for example long differences, that can alleviate these concerns. Thus, these *caveats* notwithstanding, recently panel methods have been employed to disentangle level effects from growth effects.

For example, in a global sample from 1950-2003, Dell, Jones, and Olken (2012) find temperature shocks have significant negative effects on GDP growth of poor countries, but not of rich ones. Interestingly, using weather lags and long differences, they find evidence for persistence of impacts, which suggests temperature shocks are only slowly absorbed by the economy and have long-lasting effects in poor countries, leading them to conclude that temperature also affects the growth rate of GDP in poor countries, other, or rather, than output level. Bansal and Ochoa (2011) do not exploit country-specific temperature shocks, but global average temperature shocks, and find tropical countries are the most vulnerable and that on average a 1°C global increase reduces growth by 0.9%. A study on windstorms by Hsiang and Jina (2014) for 28 Caribbean countries over the 1970-2006 period shows similar results. Burke, Hsiang, and Miguel (2015), studying 166 countries between 1960 and 2010, find that productivity peaks at about 13°C and declines non-linearly thereafter, leading them to predict impacts much larger than previously estimated[5].

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[4] As they explain: "panel data exploit the exogeneity of cross-time weather variation, allowing for causative identification".
[5] Burke et al. reasonably assume (but do not test) that the log of per capita income has a unit root. They regress its presumably stationary first difference on the level of temperature. However, temperatures are either trend-stationary (Gay-Garcia, Estrada, & Sánchez, 2009) or integrated of order one (Kaufmann, Kauppi, & Stock, 2010). In other words, Burke,

These studies focus on the recent past, which saw only limited climate change. This could, on the one hand, lead one to speculate that these impacts could be exacerbated by further increases or non-linear effects which lie outside historical experience and, on the other, that weather impacts must be interpreted with caution given both the difference between a 1°C shock in a given year and place and a permanent 1°C global increase, and the fact that in the long-run adaptation may take place and substantially mitigate negative impacts. It is the controversial but ultimately difficult to solve "intensification vs adaptation" debate over which of these two long-term effects will eventually outweigh the other (Dell, Jones & Olken, 2014).

A first consequence of this new wave of empirical studies on climate and growth has been to induce practitioners to use these new estimates to derive empirically-based projections and implement them in IAMs to see how these respond to the relaxation of assumptions about exogenous economic growth. Moore and Diaz (2015) show that if DICE is modified and calibrated on Dell, Jones and Olken (2012), the predicted impacts go up, and so the consequent SCC, compared to the baseline scenario in which climate change does not affect growth. Lemoine and Kapnick (2015) convert estimates of past economic costs of regional warming into projections of the economic costs of future global warming. They do recognize, though, that this is mostly relevant only for relatively small changes in climate.

Using TFP data from the most recent version of the Penn World Table, we use a panel dataset for 60 countries, covering the period 1960 – 2006, to test the hypothesis of a causal relationship between temperature shocks and annual TFP growth rates. What emerges from our analysis is that temperature shocks affect annual TFP growth rates only in poor countries. Of course this conclusion is subjected to *caveats* and must be interpreted with caution. Nonetheless, it basically confirms the results of Dell, Jones and Olken (2012) and rejects the conclusions of Burke, Hsiang, and Miguel (2015). We also show that the assumptions of Dietz and Stern (2015), Moore and Diaz (2015) and Moyer, Woolley, Matteson, Glotter and Weisbach (2014) have no empirical grounding.

The contributions of this paper are the following: first, it provides a useful empirical test for the plausibility of the recent hypothesis of an impact of climate change on TFP growth. Second, to our knowledge this is the first study to examine the macro relationship between temperature shocks and

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Hsiang, and Miguel (2015) regress an I(0) process on an I(1) series, but they also include year-fixed effects. The implicit time-trend must therefore co-integrate with the temperature trend, so they essentially regress income innovations on the co-integrating vector of year dummies and temperature.
We do not fully understand the implications of this unconventional estimating strategy.

TFP growth. Third, unlike other works on temperature and economic growth, this analysis can provide direct, and not just indirect, evidence on the persistence of weather impacts on economic activity in the medium or long-run, since it focuses on TFP, and not GDP, growth rate.

The outline of the rest of this paper is as follows. Section 1 provides a theoretical background on the potential TFP-climate change relationship. Section 2 presents data and descriptive statistics. Section 3 describes the identification strategy. Section 4 presents empirical results. Section 5 performs robustness checks. Section 6 discusses the implications of the results with regard to climate change. Section 7 sums up, illustrates some *caveats* and concludes.

Section 1
Background on the TFP impact channel

We follow Dietz and Stern (2015) to show how climate change could affect technological progress. Consider the standard DICE model: a Ramsey-Cass-Koopmans growth model with an added climate externality and emission abatement costs:

$$Y_t = (1 - \Omega_t^Y)(1 - \Lambda_t)[A_t N_t^{1-\alpha} K_t^{\alpha}] \tag{1}$$

where A_t and N_t are specified exogenously, K_t evolves according to the standard equation:

$$K_{t+1} = K_t(1-\delta) + sY_t \tag{2}$$

Λ_t are emission abatement costs and Ω_t^Y is a quadratic damage function of the change in global temperature relative to the global mean in 1900[6]:

$$\Omega_t^Y = 1 - \frac{1}{1+\pi_1 \triangle T_t + \pi_2 \triangle T_t^2} \tag{3}$$

Equation (1) represents the impact function in case of only level effects: in this model, a portion of output in each time period is simply "thrown away" due to the impacts of climate change Ω_t^Y .

[6] The damage function is usually calibrated *ad hoc* on the basis of impact studies of climate change. The quadratic form has been criticized because it does not allow for convexity of damages [*sic*] (Stern, 2013; Weitzman, 2010).

In this framework, climate impacts affect long-run economic growth as climate change reduces current output, and hence savings and investment, which in turn reduce future capital and future output. The savings rate may also be affected, as the returns to investment fall. Both effects have been shown to be quantitatively small (Fankhauser & Tol, 2005; Moyer, Woolley, Matteson, Weisbach & Glotter, 2014).

If, instead, climate change also affects TFP, things change substantially. Specifically, TFP is endogenous and grows according to the following law of motion:

$$A_{t+1} = (1 - \Omega_t^A)(1 - \delta_t^A) A_t + \alpha(I_t) \quad (4)$$

where δ_t^A is the net depreciation rate for productivity, $\alpha(I_t)$ is a "spillover function" that converts the flow of capital investment in each period into a flow of capital externalities, and Ω_t^A are the impacts of climate change on TFP, while the remaining share of damages still affects output level.
Damages are then partitioned between output and TFP:

$$\Omega_t^A = f^A \cdot \Omega_t \quad (5)$$

$$\Omega_t^Y = 1 - \frac{(1-\Omega_t)}{(1-\Omega_t^A)} \quad (6)$$

where f^A is the fraction of impacts of climate change that harms TFP growth.

Of course the effects of this modification depend on the share of impacts directly affecting TFP, but even a small share leads to a radically different consumption growth path: Dietz and Stern (2015) assume that $f^A = 0.05$ and find that consumption per capita in year 2205 is reduced from more than 15 times the 2005 level to 11.4 times higher. Moyer, Woolley, Matteson, Glotter and Weisbach (2014) explore the consequences of different values of f^A between 1% and 100%. They show that $f^A = 0.05$ leads to a 70% drop in consumption per capita in 2300 relative to the no climate change case. Similar qualitative results are obtained by Moore and Diaz (2015) when they alter the DICE model to let climate change affect TFP growth on the basis of parameters calibrated on the estimates of Dell, Jones and Olken (2012). As Dietz and Stern (2015) sum up: "in this formulation some part of the instantaneous impacts of climate change falls on TFP, permanently reducing future output possibilities".

Section 2

Data and Descriptive Statistics

A. Data

Data for this paper are taken from a range of different sources.

TFP Data

Data on total factor productivity of countries come from the most recent version of the Penn World Table, PWT 8.1 (PWT 8.1, 2016). In particular, in our study we use $RTFP^{NA}$ data[7]. $RTFP^{NA}$, where the prefix R stays for "real", is a country-specific index of TFP where in the benchmark year, 2005, $RTFP^{NA}$ is 1 for all countries. $RTFP^{NA}$ can be used to study within-country productivity growth over time. In our specifications, we use the natural logarithm of the $RTFP^{NA}$ index. This means that the 2005 benchmark value is 0 for all countries in the logarithmic specification. We calculate annual $RTFP^{NA}$ growth rates by first-differencing, and check for stationarity[8]. Henceforth, from now on, "TFP growth rate" it is intended as the annual growth rate of the natural logarithm of the $RTFP^{NA}$ index as taken from PWT 8.1. For further information on the $RTFP^{NA}$ index and data, see Appendix (1).

Temperature and Precipitation Data

These data are taken from the *Terrestrial Air Temperature and Precipitation: 1900 – 2006 Monthly Time Series* (Matsuura & Willmott, 2007), from the University of Delaware (UDEL), as aggregated to the country-year level by (Dell, Jones & Olken, 2012), using population weights, where the weights are constructed from 1990 population data at 30 arc second resolution from the *Global Rural Urban Mapping Project* (Balk et al., 2004). Importantly, given temperature levels are trend-stationary, in order to exclude potentially spurious results and ensure stationary residuals in our regressions, we transform data by first-differencing and check for stationarity. We do the same with precipitation data.

GDP Data

We use per capita GDP data in order to distinguish between impacts in rich and poor countries. These data come from the Maddison Project ('Maddison Project', 2016.).

B. Descriptive Statistics

[7] Note that this series has only recently become available. Previous studies of the impact of climate change on economic growth, reviewed above, therefore did not have access to these data.
[8] For the panel unit root tests for annual TFP growth, temperature change and precipitation change, see Appendix (2), Table A.1 – A.6.

The main dataset is composed of 60 countries[9] and covers the period 1960 – 2006. Figure 1 is a scatterplot of TFP and temperature levels in 2006, and the linear prediction. As can be seen, there is a negative correlation between the two. This correlation is not a causal relationship, but could be due to confounding factors such as institutions. There is no reverse causality.
Table 1 provides some descriptive statistics for the main variables. There is a huge variation both in the annual growth rates of TFP, with an average of about 5% annual increase but a minimum and a maximum that are respectively -56% and 27%, and in terms of temperature changes as well, where the mean annual change in temperature is very small but the extremes are between 2°C and 3°C. Finally, precipitation exhibits even greater variability.

Section 3
Empirical Strategy

We use a fixed-effect panel as the estimation method to isolate the impact of weather shocks on the growth rate of total factor productivity[10]. Our identification strategy is straightforward and follows Dell, Jones, and Olken (2012). The baseline specification of our model is the following:

$$TFP_{it} = \alpha + \beta \Delta Temp_{it} + \gamma \Delta Pre_{it} + \mu_i + \theta_{rt} + \varepsilon_{it} \qquad (7)$$

Where TFP_{it} represents the annual growth rate of TFP, and $\Delta Temp_{it}$ is annual temperature change. ΔPre_{it} represents annual change in precipitation levels, which is used only as a control variable following the recommendation in Auffhammer, Hsiang, Schlenker and Sobel (2013). By excluding precipitation we would run the risk of omitted variable bias. Furthermore, in order to investigate for heterogeneous effects of temperature shocks, we follow Dell, Jones and Olken (2014) and interact the vector of temperature changes with dummies that capture the heterogeneity of interest, in particular dummies for being a "poor" or a "hot" country.

As for the other elements in the equation, μ_i are country fixed effects, θ_{rt} are region x time fixed effects, where this interaction allows for differentiated trends in different regions, as recommended by Dell, Jones and Olken (2014), in order to isolate idiosyncratic local shocks[11]. Finally, ε_{it} are error terms adjusted for clustering at the country level.

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[9] The choice of the countries has been made on the basis of data availability. For the list of countries, see Appendix (5).
[10] For rthe appriopirateness of the FE approach compared to a random effects (RE) specification, see Appendix (2), Table A.7.
[11] For the list of regions, see Appendix (6).

There is no reason to be concerned about reverse causality. Confounding variables are a minor worry. TFP is constructed rather than observed. If weather variations would cause mismeasurement in the size of the labour force or the capital stock, then we would wrongly attribute this to TFP. We are not aware of a way to test this for our data.

TFP is total factor productivity. By construction, when measured at a national, annual resolution, TFP is a mix of a wide range of factors. Changes in TFP can be due to technological change, the standard but flawed interpretation. Changes in TFP can also be due to managerial or behavioural change, changes in the structure of the economy or company entry and exit within sectors, changes in regulation or taxation, changes in the provision of public goods, changes in market power, or changes in international trade. The results below show that temperature variations affect TFP growth, but our data do not allow us to identify the channel through which TFP is affected. That said, our approach is a step forward compared to previous studies which looked at economic growth, an even more convoluted measure.

Section 4
Empirical Results

Table 2 reports the results for the baseline specification of equation (7). Column (1) only includes annual changes in temperature and precipitation levels. A first inspection shows that the coefficient for the annual change in temperatures, ΔTemp, is negative and significant at the 5% level, suggesting that a 1°C annual increase in temperature would lower TFP growth rates of countries by 0.49%. Column (2), however, reveals that adding an interaction between temperature change and a dummy for being poor – with "poor" being defined as having a below median GDP per capita in the initial year of our panel, 1960 – substantially changes the picture: this interaction in fact is negative and strongly significant, while the coefficient for temperature changes is now negative but statistically insignificant, which suggests the negative effects of temperature on TFP growth rates are concentrated in poor countries.

This is confirmed by looking at the net impact of temperature change in poor countries, at the bottom of Column (2), which suggests a 1°C annual increase in temperature in poor countries would decrease TFP growth rates by about 1.5 percentage points, with a significance at the 1% level.

This finding is somewhat weakened when we add an interaction between temperature changes and a dummy for being hot, with "hot" being defined as having an above median average temperature in the 1960s. The results are shown in Column (3): the coefficient of the Poor x ∆Temp interaction is now -1.2 %, and significant at 5%, while the "hot" interaction turns out to be insignificant, and so its net effect. Importantly, the total effect of temperature in poor countries is also diminished both in terms of magnitude and significance[12]. The fact that the negative effect of temperature changes in poor countries is somewhat weakened could be explained in two different ways: the first is that the negative effect of temperature on TFP growth rates comes not only through being poor, but also, partially, through being hot, and the second is that the definitions of "hot" and "poor" overlap to a good extent and thus the inclusion of an "hot" interaction partially offsets the results for poor countries. The distinction matters a great deal when it comes to conclusions with regard to future climate change: it is a completely different picture whether the negative effects of temperature shocks appear only in poor countries or also, even if slightly, in hot countries regardless whether rich or poor.

In order to shed light on the issue, in Column (4) we use an alternative definition of poor, with "poor" being now defined as having a below median GDP per capita. The "poor" interaction is again strongly significant, with the coefficient of Poor_2 x ∆Temp again very similar, with a value of -1.43 percentage points, the "hot" interaction again negative but statistically insignificant (and so its net total impact), and the total impact in poor countries again significant at the 1% level. Therefore, this variation suggests that only TFP growth rates of poor countries are affected by temperature shocks.

Finally, to enhance confidence in this finding, in Column (5) and (6) we consider a different definition of "hot" country, with the dummy for hot that has value 1 for countries with an average temperature in the 1960s above the 75% percentile, and repeat our specifications. The results, while confirming the negative impact of temperature shocks on the TFP growth rate of poor countries, also show that there is a negative and 5% significant impact of temperature shocks in hot countries, with a net effect of about -1 percentage point on the annual TFP growth. In other words, even though the negative effect of annual temperature comes through being poor, there also seems to be weak evidence of an impact in hot countries. Given the importance of this distinction, in Section V we investigate more closely the relationship between temperature shocks and TFP growth, by performing a variety of robustness checks.

[12] Incidentally, it is also worth remarking how precipitation change has a negative and significant effect, but this control variable has proved to be very sensitive to specifications throughout the whole empirical analysis and its results should therefore be interpreted with caution and are no further discussed here.

Section 5
Robustness Checks

Nine robustness checks are performed: the repetition of the baseline specification for a different dataset, comprising 68 countries and covering the period 1970–2006; the repetition of the main specification in both datasets using different weather data; a specification including an interaction between temperature shocks and a dummy for being rich; an investigation of the poor subsample of our dataset; a specification using a joint interaction term for countries which are both poor and hot; two alternative specifications which include respectively an interaction with GDP per capita and one with a measure of institutional quality; a repetition of the main specification in which we use labour productivity growth as the dependent variable in place of TFP growth; regressions on changes in the number of persons employed and capital stock; the use of Driscoll-Kraay (1998) standard errors in place of clustered standard errors for the baseline analysis in both samples.

A. Different sample

We run the same regressions using a different sample of the same dataset, changing the composition of countries and the time period. In particular, we add 8 countries to the main sample: Bulgaria, Hungary, Kuwait, Panama, Paraguay, Poland, Qatar and Saudi Arabia. Some of these countries are hot and rich, increasing the statistical power to distinguish between heat and affluence. The new time period is 1970 – 2006. Table 3 provides some descriptive statistics for the new dataset, Table 4 the results for the main specification.

As for the impact in poor countries, the results are very similar: the previous findings are confirmed in terms of magnitude, sign and significance, and if anything reinforced. This is probably due to the fact that some of the added countries, such as the Arab oil states, are very rich, very hot and with high TFP growth (although concentrated in one sector). The robustness check conducted on Sample B reinforces the main thesis of this work: a negative causal relationship between annual TFP growth rates and temperature shocks only exists in poor countries, while the TFP growth rates of rich countries, regardless whether they are hot or cold, do not appear to suffer from temperature changes. In other words, the impacts of temperature on total factor productivity are conditional on the level of GDP per capita.

B. Different weather data

Since both TFP and weather data are notably affected by measurement errors, to partially alleviate these concerns we perform exactly the same analysis, in both samples, but using another weather dataset, the *CRUCY Version 3.23* by the Climatic Research Unit (CRU) of the University of East Anglia (CRU, 2016) . Furthermore, this dataset uses a different weighting scheme with respect to our main source of weather data: the CRU data are aggregated at the country levels using area weights, rather than population weights as in the first case, which means that the aggregated data now represent the average weather experienced by a place, as opposed to the average weather experienced by a person (Dell, Jones & Olken, 2014). This is not a trivial difference: in countries like United States, Australia, Canada, China, large and scarcely populated areas will dominate the national average temperature when using area weights. So this double difference, both of source and aggregation method, takes to weather data that are quite different from those used in our main specification[13], and thus we reckon this constitutes a useful and reliable check for the robustness of our findings[14]. Table 5 replicates the specification of Table 2 for the main dataset using the CRU data.

The results are remarkably consistent with those emerged from the baseline analysis: the negative effect of temperature shocks on TFP growth rates only comes through being poor, not through being hot, and there is no such causal relationship in rich countries. This consistency is further confirmed when repeating the same exercise but using Sample B. The table for this check can be found in Appendix (3), Table A.9: results are similar.

C. Exploring the "rich" interaction

We first check whether or not only in poor countries TFP growth is affected by temperature by inspecting its complement. We therefore run exactly the same specification of Table 2, but substitute the "poor" interaction with an interaction between annual temperature changes and a dummy for being rich, with "rich" being defined as having an above average GDP per capita in 1960. Additionally, we also include the alternative definition of "rich", Rich_2, defined as having an above average GDP per capita, and interact it with temperature shocks.

The results are shown in Table 6. Column (1) shows results for the baseline specification which only includes annual temperature and precipitation shocks and the "rich" interaction. Although at a first inspection the coefficient for ΔTemp and Rich*ΔTemp being both strongly significant, but of opposite sign, their linear combination at the bottom of Column (2) makes clear that the total effect of temperature on the TFP growth rate of rich countries is small and statistically insignificant. When

[13] See the Appendix (3), Table A.8 for descriptive statistics of the CRU weather variables.

we add the “hot” interaction in Column (2), the total effect of shocks in rich countries is again very small and insignificant. We repeat the same exercise in Columns (3) and (4), using the alternative definition of “hot”, with analogous results. Finally, in Column (5) and (6), we run two specifications with the different definition of “hot” as having above 75% percentile average temperature in the 1960s. Once again, the net effect in rich countries is again close to zero and insignificant.

D. Investigating the subsample of poor countries

In Table 7 we run a specification using only the subsample of poor countries, “poor” defined as having a below median GDP per capita in 1960. The coefficient for ΔTemp is negative and significant, predicting a -1.8 percentage point decrease in the TFP growth rate for a 1°C increase. This confirms again the negative causal relationship in poor countries, which is shown graphically in Figure 2.

E. Joint interactions with poor and hot dummies

Finally, we run two specifications in which we add in the regressions a double interaction term, namely between temperature changes, a dummy for being poor and a dummy for being hot, and we repeat these for both our definitions of poor and hot countries. Table 8 shows the results. With the joint interaction included, temperature shocks significantly affect TFP growth not only in poor countries but also in hot countries. The effect is larger in poor countries than in hot countries, but the difference is not significant. The joint effect is similar in size as above.

F. Interactions with GDP / per capita and Polity2

Additionally, we investigate two specifications which could affect the interpretation and validity of our findings. First, we run a specification in which we substitute the “poor” interaction with an interaction between temperature shocks and GDP per capita. The previous definitions of poor, in fact, are all based on a fixed classification between who is rich and who is poor. This is fine for estimation, but not for simulation. In almost fifty years countries that were poor in the beginning grew out of poverty, with the notable examples of South Korea, Malaysia and China. We would hope for other countries to follow their lead in the next fifty years. Interacting annual temperature changes with GDP per capita can overcome this, and provide evidence on whether the negative impact of temperature shocks on the growth rate of TFP gets smaller or disappears as countries grow richer.

As Column (1) in Table 9 shows, this is the case. The interaction with GDP per capita is positive and significant at the 1% level: solving the first derivative with respect to ΔTemp, and re-transforming the natural logarithm of GDP in dollars, suggests that the marginal effect of a 1°C annual increase becomes zero when income is approximately $34,400 per person per year for countries classified as "hot"[15], approximately $14,900 per person per year for countries not classified as "hot"[16], and approximately $25,600 per person per year for the sample as a whole[17] (see Figures 3, 4 and 5 for a graphical representation of the marginal effects, at different GDP per capita levels, for the three cases). This indicates that, even though the estimates are inevitably imprecise, and the GDP level where the marginal effect of ΔTemp turns zero depends on the initial temperature level, development always means reduced vulnerability and, ultimately, immunity from the impact of temperature shocks on TFP growth rate.

The second alternative specification includes an interaction between temperature changes and a measure of institutional quality, Polity2 ('Polity IV Project', 2014). We added this interaction because it could be the case that negative impacts come not through being a poor country, but through poor institutions, i.e. through low institutional quality. In the context of the well-known debate on the determinants of long-run development (Acemoglu, Jonson & Robinson, 2000; Diamond, 1999; Easterly & Levine, 2003; Gallup, Sachs, & Mellinger, 1999), the institution hypothesis is one of the two main currents (the other being the geography hypothesis). Institutions are considered by many (Acemoglu, Johnson & Robinson, 2000; Acemoglu, Johnson & Robinson, 2001; Easterly and Levine, 2003; Rodrik, Subramanian & Trebbi, 2004) as the fundamental cause of economic growth in the long-run. This specification thus constitutes a way of testing once again the relationship between climate, institutions and development.

We use Polity2 as a measure of institutions. Polity2 ranges from -10 to 10 and combines the democracy and autocracy scores from the Polity IV dataset. In order to investigate whether or not the impact of temperature appears also, or exclusively, through the institutional channel, we interact it with annual temperature changes and add this interaction to the baseline specification with the "poor" interaction.

Column (2) in Table 9 shows our finding is not altered: the negative impact of temperature still appears through being poor, and the coefficient for the total effect in poor countries is analogous both in significance and magnitude to the previous ones. There is some weak evidence that the interaction between temperature shocks and Polity2 has a positive effect on the TFP growth rate, but this is not

[15] In natural logarithm: 10.447 (SE = 1.234).

[16] In natural logarithm: 9.609 (SE = 0.351).

[17] In natural logarithm: 10.150 (SE = 0.283).

enough to justify a rethinking of our main conclusion.

G. Labour productivity growth as the dependent variable

We find a negative effect of weather shocks on total factor productivity growth, but only in poor countries. This is probably due to the fact that poor countries have a much larger share of their GDP in the agricultural sector, much more outdoor work and lower adaptive capacity, which suggests that one of the channels could be an impact on (outdoor) labour productivity.

Labour productivity is one of the components of total factor productivity. We use labour productivity growth in place of TFP growth as an alternative dependent variable for two reasons: first, it represents an additional and useful to check the robustness for our core findings; and second, it could provide insights on the channels through which temperature affects TFP growth and on the reasons why this is only the case for poor countries. Hence, we repeat our basic specification, replacing annual TFP growth with annual labour productivity growth, where labour productivity is defined as annual output per person employed. Data on labour productivity have been obtained by Penn World Table, PWT 8.1 (PWT 8.1, 2016), by dividing real GDP at constant national prices by the annual number of persons employed.

Table 10 shows the results for the baseline sample, Table A.10 for the alternative sample: the impact of temperature shocks on labour productivity growth is negative and significant only in poor countries, and the coefficients are remarkably consistent and very similar in magnitude and significance to those of the TFP regressions, which suggests, as discussed in further detail in Section 6, that this is indeed a key channel responsible for the temperature-TFP relationship in poor countries. This has also been shown in studies of microdata (Cachon, Gallino, & Olivares, 2012; Heal & Park, 2015; Niemelä, Hannula, Rautio, Reijula, & Railio, 2002; Sudarshan & Tewari, 2013),

H. Labour force and capital stock

Dell, Jones and Olken (2012) studied the impact of temperature variations on the growth rate of per capita income. Their results are qualitatively similar to ours: unusually hot years negatively affect growth, but only in poor countries. We investigate the growth rate of total factor productivity, and hypothesize that this explains Dell, Jones and Olken’s results. However, their result could also be explained, at least partly, by changes in the labour force or capital stock.

Table 11 shows the results for regressions of the annual growth rate of the number of persons employed[18] and the annual growth rate of real capital stock on temperature and precipitation change. Both the explanatory variables are statistically insignificant in the main specification, and only the total effect of temperature change on the growth rate of the capital stock in poor countries is positive and weakly significant at the 10% level. In other words, Dell, Jones and Olken's temperature impact on income growth is due to the effect of temperature on total factor productivity growth, perhaps dampened by an effect of temperature on capital deepening.

I. Regressions with Driscoll-Kraay standard errors

Countries are not independent from each other. In the specifications above, we do not check or correct for spatial autocorrelation. As Dell, Jones & Olken (2014) notice, in the weather-economy literature this is usually accomplished by making use of Conley (1999) standard errors which allow correlation to decay smoothly with distance. However, the use of Conley (1999) standard errors would make little sense in our sample, given that the choice of common distance cutoff points would be equally applied to countries as different in geographical size as China and Trinidad and Tobago. Hence, we opted for the use of Driscoll and Kraay (1998) standard errors, which are robust to cross-sectional / spatial and temporal dependence.

Table 12 reports the results of the baseline FE regressions for the main sample, Table A.11 for the alternative sample. The significance of the coefficients is slightly diminished in some of the specifications, but the overall picture is that our core findings are not altered when taking into account the possibility of spatial dependence between countries.

Section 6
Implications of climate change

What do these results mean for future climate change? The temperature in poor countries in the almost half century of our sample saw an increase of approximately 0.6°C, or on average 0.012 per year. This means, with a leap in terms of external validity, that annual TFP growth rate was reduced by 0.012*1.762 (cf. Table 7) = 0.021% (SE = 0.006%) per year. Extrapolating with regard to climate change[19], since the 21st century could see an additional global warming of 0.3-4.8°C relative to the period 1986-2005 (IPCC 2013), a very simple calculation shows that, if past relationships will

[18] Full data on the size of the labour force were not available in PWT 8.1.

[19] Given that the standard deviation for temperature change is 0.56 °C (cf. Table 1), interannual variability is quite large relative to the projected trend, so while this extrapolation should be interpreted with the usual caution, its implications should not be *a priori* dismissed.

continue to hold, and indeed excluding both intensification and adaptation, annual TFP growth rate could be reduced by 0.005-0.085% per year. This is an upper bound, as we estimated the short-run semi-elasticity rather than the long-run one.

In the worst case scenario of a further 4.8°C warming, annual TFP growth in poor countries would be lowered by about 0.085% during this century. This is not trivial, considering that it would be an additional dynamic effect to be added to the current impact estimates, but it is much smaller than hypothesized and simulated in recent literature. In the simulation using DICE 2010 run by Dietz and Stern (2015), and in particular in their endogenous TFP model with standard assumptions about the damage function and climate sensitivity, annual *global* TFP growth rate is reduced by about 0.20 percentage points, for the period 2005-2205 and with a temperature increase of 5.7°C above pre-industrial levels. Using our estimates and their scenario, we find a value of 1.762*(4.9/200) = 0.04%[20], roughly five times lower and, importantly, *only* for poor countries.

Similarly, Moyer, Woolley, Matteson, Glotter and Weisbach (2014) alter the growth path of TFP in DICE, allowing for a reduction in the annual *global* growth rate by more than 0.20%, over a 300-year period and under a predicted temperature increase of 5.9°C above pre-industrial. Under these conditions, we would predict an annual decrease by 0.03%, but again *only* for poor countries.

In Moore and Diaz (2015), who endogenize TFP in a two-region (rich and poor) version of DICE 2013R, using parameters calibrated on the empirical findings of Dell, Jones & Olken (2012), the decrease in annual TFP growth rate in poor countries is approximately 0.52%, over the period 2015-2105, with a temperature increase over the century of about 3°C. Conversely, our derived calculations for this simulation point to a reduction in the annual growth rate of TFP in poor countries by about 0.06%, almost an order of magnitude lower that their projection.

Unlike the papers above, we stress that once a certain income per capita threshold is reached, these negative impacts would disappear altogether. Our estimates point to an upper threshold of $34,400 income per capita (for hot countries), a value which, according to global projections, will be largely surpassed during this century.

These results further increase concerns over distributional issues of future impacts. As Tol (2015) shows, it is widely accepted that poor countries will be the ones who will suffer the most from climate

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[20] In the DICE model, temperature in 2005 is already 0.83 °C above pre-industrial.

change impacts. This work confirms and reinforces this view. Additionally, as explained in Inklaar and Timmer (2013), Keller (2004), Griffith, Redding, and Van Reenen (2004), TFP growth as a determinant of long-run economic growth is more important in poor countries than in rich ones.

Finally, given that, as noted by Gillingham et al. (2015): "uncertainty in the growth of productivity (or output per capita) is known to be a critical parameter in determining all elements of climate change", all this calls for complementarity between climate policy and poverty reduction (Schelling, 1992).

Section 7
Discussion and conclusion

We test the recently advanced hypothesis that climate change harms TFP growth by looking at the past relationship between TFP growth rates and temperature shocks. We find a negative relationship only in poor countries. The relationship is robust to alternative samples, alternative data, alternative specifications, and to spatial autocorrelation. There is some evidence that temperature shocks may have a negative effect in hot countries too. The estimated temperature effect on TFP growth probably explains the effect on economic growth found in previous papers, and is probably explained by temperature effects on labour productivity. While statistically significant, our upper bound estimate suggest that climate change would reduce TFP growth by less than 0.1%.

The findings of this paper confirm the results of Dell, Jones and Olken (2012), who also found a statistically significant but modestly sized relationship between temperature levels and economic growth only in poor countries, and that showed using lags and long differences a persistence of weather impacts in the medium run which is likely to mean the presence of growth effects other, or rather, than level output effects. Our results contradict the conclusions of Burke, Miguel and Hsiang (2015), who found large impacts of temperature on productivity.

Using the first differences of TFP and temperature levels, this work not only alleviates the issue of non-stationarity in panel analysis which may tend to produce spurious results, but also directly addresses the issue of potential long-run growth effects, since its main dependent variable is notably one of the main drivers of long-run economic growth (Solow, 1956). In this different perspective, an impact on annual TFP growth is already, *per se* a long-term impact. There is no need to use first differences, since in this scenario temperature shocks affects economic activity not through Equation (1), but directly through Equation (4).

However, a number of limits and *caveats* for this work also need to be made clear. First: data quality. TFP data represent the so-called *Solow residual*, and in fact this is the way they are calculated in PWT 8.1 (Feenstra, Inklaar, & Timmer, 2013 & 2015; Inklaar & Timmer, 2013). Therefore the estimates are potentially affected by measurement error and a whole host of errors in the specification and the estimation of the production function used to derive TFP. Weather data as well notably suffer from measurement error and different data quality in different countries. However, the issue of measurement error is alleviated here since the results appear to be robust to sample choices, to different specifications of key explanatory variables, and to different weather data with different aggregation methods.

Second, as already mentioned in the introduction, external validity with respect to future climate change. Again, weather variations are *not* climate variations: the first are random shorter-run temporal variations, the second are averages over several decades (Dell, Jones & Olken, 2014). In other words climate, as emphasized by Auffhammer, Hsiang, Schlenker and Sobel (2013), is a long average of weather at a given location. It is thus key to always keep in mind that a 1°C shock in a given year and place is not equivalent to a permanent 1°C global increase, and that projections like the simple extrapolation with regard to global warming we performed above typically suffer from this drawback. In other words, we estimated the short-run semi-elasticity, whereas we need to know the long-run semi-elasticity.

Third, future climate change, especially if pronounced as it is projected in some extreme emission scenarios (IPCC, 2013) may well entail consequences and effects which lie outside historical experience. Substantial sea level rise, a thermohaline circulation slowdown, the release of methane from melting permafrost are all potential intensifying effects which are indeed not captured by this analysis, based on a period in which there was only limited climatic variability and limited warming.

Fourth, every forecast or projection based on this study implies the assumption that past historical relationship will continue to hold in the future. As argued in Dell, Jones and Olken (2014) and Tol (2015), this could indeed not be the case, either due to intensification of negative impacts or to adaptation through development in the long run.

Fifth, total factor productivity is an aggregate measure, and changes in total factor productivity are due to a variety of changes in underlying economic phenomena. With our data it is impossible to open this black box, but future research should attempt this using micro-data and natural experiments.

The central finding of this work is that TFP growth rates of poor countries are affected by temperature shocks in recent past. Once again, poverty means vulnerability. However, this causal relationship between temperature, poverty and productivity growth is subjected to *caveats* and should be interpreted with caution. What this analysis suggests is the fact that weather shocks affect economic growth through the TFP channel only when coupled with poverty, not that climate change will harm future economic growth by affecting technological progress, as hypothesized in literature. Hence, given the preeminent importance of TFP growth for long-run development, and under the assumption that weather impacts have at least some external validity with regard to climate change, the main conclusions that stem from this paper are an increase of concerns over the inequality of future impacts, a policy guideline which considers poverty reduction as a crucial and paramount element of climate policy and, at the research level, a call for further studies on the potential dynamic effects of future climate change.

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Table 1

Descriptive Statistics

	Mean	Var	sd	Min	Max	Obs
TFP growth rate	0.481	15.49	3.935	-56.05	26.76	2760
△Temp	0.0121	0.318	0.564	-2.952	2.442	2760
△Pre	-0.0142	5.942	2.438	-35.40	37.64	2760
GDP_percap	8.480	1.022	1.011	6.084	10.35	2820

TFP growth rate is the annual percentage change and expressed in natural logarithm.
Temperature change is annual and expressed in degree Celsius.
Precipitation change is annual and expressed in units of 100 mm per year.
GDP per capita is in natural logarithm of 1990 international Geary - Khamis dollars.

Table 2

Relationship between annual TFP growth rates and temperature changes

Dependent variable: annual TFP growth rate	(1)	(2)	(3)	(4)	(5)	(6)
△Temp	-0.485**	-0.029	0.057	0.098	0.008	0.051
	(0.216)	(0.136)	(0.143)	(0.123)	(0.134)	(0.120)
△Pre	-0.033	-0.042*	-0.047**	-0.048**	-0.049**	-0.051**
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Poor x △Temp		-1.493***	-1.195**		-1.315***	
		(0.404)	(0.468)		(0.437)	
Hot x △Temp			-0.684	-0.612		
			(0.452)	(0.429)		
Poor_2 x △Temp				-1.425***		-1.513***
				(0.420)		(0.410)
Hot_2 x △Temp					-1.048**	-0.979**
					(0.484)	(0.481)
_cons	1.416***	1.338***	1.280***	1.271***	1.284***	1.273***
	(0.327)	(0.331)	(0.322)	(0.324)	(0.318)	(0.319)
N	2760	2760	2760	2760	2760	2760
R^2	0.208	0.215	0.216	0.217	0.216	0.218
adj. R^2	0.121	0.128	0.129	0.131	0.130	0.131
AIC	14749.211	14727.177	14725.510	14720.275	14723.930	14718.702
Total effect in poor countries		-1.523***	-1.139**	-1.327***	-1.307***	-1.462***
		(0.406)	(0.515)	(0.456)	(0.453)	(0.420)
Total effect in hot countries			-0.627	-0.515	-1.040**	-0.928*
			(0.402)	(0.388)	(0.473)	(0.477)

Notes:

All specifications include country FE and Region x Time FE.
Poor is a dummy with value 1 for countries with below median GDP per capita in 1960.
Hot is a dummy with value 1 for countries with above median average temperature in the 1960s.
Poor_2 is a dummy with value 1 for countries with below median GDP per capita.
Hot_2 is a dummy with value 1 for countries with average temperature in the 1960s above the 75%.
Temperature change is annual and expressed in degree Celsius.
Precipitation change is annual and expressed in units of 100 mm per year.
Standard errors are in parentheses and are clustered at the country level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3

Descriptive Statistics – Sample B

	Mean	Var	Sd	Min	Max	Obs
TFP growth rate	0.0475	18.07	4.251	-57.82	37.10	2448
∆Temp	0.0220	0.327	0.572	-2.952	2.442	2448
∆Pre	-0.0198	5.890	2.427	-35.40	37.64	2448
GDP_percap	8.619	0.945	0.972	6.084	10.67	2516

TFP growth rate is the annual percentage change and expressed in natural logarithm.
Temperature change is annual and expressed in degree Celsius.
Precipitation change is annual and expressed in units of 100 mm per year.
GDP per capita is in natural logarithm of 1990 international Geary - Khamis dollars.

Table 4

Relationship between annual TFP growth rates and temperature changes – Sample B

Dependent variable: Annual TFP growth rate	(1)	(2)	(3)	(4)	(5)	(6)
ΔTemp	-0.345*	0.053	0.087	0.071	0.077	0.075
	(0.193)	(0.111)	(0.114)	(0.112)	(0.113)	(0.113)
ΔPre	-0.033	-0.041**	-0.043**	-0.046**	-0.043**	-0.046**
	(0.020)	(0.018)	(0.018)	(0.018)	(0.019)	(0.019)
Poor x ΔTemp		-1.200***	-1.125***		-1.198***	
		(0.318)	(0.328)		(0.318)	
Hot x ΔTemp			-0.230	-0.093		
			(0.334)	(0.323)		
Poor_2 x ΔTemp				-1.308***		-1.337***
				(0.314)		(0.314)
Hot_2 x ΔTemp					-0.244	-0.196
					(0.316)	(0.319)
_cons	1.362***	1.295***	1.282***	1.283***	1.290***	1.284***
	(0.307)	(0.304)	(0.302)	(0.303)	(0.302)	(0.303)
N	2448	2448	2448	2448	2448	2448
R^2	0.198	0.202	0.202	0.203	0.202	0.203
adj. R^2	0.121	0.126	0.126	0.127	0.126	0.127
Total effect in poor countries		-1.147***	-1.037***	-1.237***	-1.121***	-1.262***
		(0.351)	(0.370)	(0.354)	(0.355)	(0.354)
Total effect in hot countries			-0.143	-0.022	-0.166	-0.120
			(0.318)	(0.314)	(0.309)	(0.313)

Notes:

All specifications include country FE and Region x Time FE.
Poor is a dummy with value 1 for countries with below median GDP per capita in 1970.
Hot is a dummy with value 1 for countries with above median average temperature in the 1970s.
Poor_2 is a dummy with value 1 for countries with below median GDP per capita.
Hot_2 is a dummy with value 1 for countries with above median average temperature.
Temperature change is annual and expressed in degree Celsius.
Precipitation change is annual and expressed in units of 100 mm per year.
Standard errors are in parentheses and are clustered at the country level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5

Relationship between annual TFP growth rates and temperature changes – CRU Data

Dependent variable: Annual TFP growth rates	(1)	(2)	(3)	(4)	(5)	(6)
∆Temp	-0.288	0.100	0.145	0.136	0.104	0.124
	(0.198)	(0.108)	(0.114)	(0.111)	(0.113)	(0.108)
∆Pre	-0.034	-0.043	-0.046	-0.046	-0.043	-0.045
	(0.034)	(0.034)	(0.033)	(0.033)	(0.034)	(0.034)
Poor x ∆Temp		-1.411***	-1.297***		-1.400***	
		(0.396)	(0.435)		(0.428)	
Hot x ∆Temp			-0.337	-0.113		
			(0.383)	(0.402)		
Poor_2 X ∆Temp				-1.553***		-1.599***
				(0.446)		(0.416)
Hot_2 x ∆Temp					-0.076	-0.015
					(0.406)	(0.404)
_cons	1.409***	1.352***	1.333***	1.331***	1.350***	1.337***
	(0.329)	(0.330)	(0.334)	(0.335)	(0.328)	(0.330)
N	2760	2760	2760	2760	2760	2760
R^2	0.206	0.212	0.212	0.213	0.212	0.213
adj. R^2	0.119	0.125	0.125	0.126	0.125	0.126
Total effect in poor countries		-1.311***	-1.152**	-1.416***	-1.296***	-1.475***
		(0.401)	(0.470)	(0.478)	(0.449)	(0.434)
Total effect in hot countries			-0.192	0.023	0.028	0.109
			(0.343)	(0.371)	(0.381)	(0.385)

Notes:

All specifications include country FE and Region x Time FE.
Poor is a dummy with value 1 for countries with below median GDP per capita in 1960.
Hot is a dummy with value 1 for countries with above median average temperature in the 1960s.
Poor_2 is a dummy with value 1 for countries with below median GDP per capita.
Hot_2 is a dummy with value 1 for countries with above median average temperature.
Temperature change is annual and expressed in degree Celsius.
Precipitation change is annual and expressed in units of 100 mm per year.
Standard errors are in parentheses and are clustered at the country level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6

Relationship between annual TFP growth rates and temperature changes in rich countries

Dependent variable: Annual TFP growth rate	(1)	(2)	(3)	(4)	(5)	(6)
△Temp	-1.523***	-1.139**	-1.667***	-1.327***	-1.307***	-1.462***
	(0.406)	(0.515)	(0.369)	(0.456)	(0.453)	(0.420)
△Pre	-0.042*	-0.047**	-0.045*	-0.048**	-0.049**	-0.051**
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Rich x △Temp	1.493***	1.195**			1.315***	
	(0.404)	(0.468)			(0.437)	
Hot x △Temp		-0.684		-0.612		
		(0.452)		(0.429)		
Rich_2 x △Temp			1.683***	1.425***		1.513***
			(0.375)	(0.420)		(0.410)
Hot_2 x △Temp					-1.048**	-0.979**
					(0.484)	(0.481)
_cons	1.338***	1.280***	1.323***	1.271***	1.284***	1.273***
	(0.331)	(0.322)	(0.333)	(0.324)	(0.318)	(0.319)
N	2760	2760	2760	2760	2760	2760
R^2	0.215	0.216	0.216	0.217	0.216	0.218
adj. R^2	0.128	0.129	0.130	0.131	0.130	0.131
Total effect in rich countries	-0.029	0.057	0.016	0.098	0.008	0.051
	(0.136)	(0.143)	(0.125)	(0.123)	(0.134)	(0.120)

Notes:

All specifications include country FE and Region x Time FE.
Rich is a dummy with value 1 for countries with above median GDP per capita in 1960.
Hot is a dummy with value 1 for countries with above median average temperature in the 1960s.
Rich_2 is a dummy with value 1 for countries with above median GDP per capita.
Hot_2 is a dummy with value 1 for countries with above median average temperature.
Temperature change is annual and expressed in degree Celsius.
Precipitation change is annual and expressed in units of 100 mm per year.
Standard errors are in parentheses and are clustered at the country level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7

Annual TFP growth rates and temperature changes in poor countries

	Annual TFP growth rate
∆Temp	-1.762***
	(0.459)
∆Pre	-0.067
	(0.044)
_cons	1.745***
	(0.378)
N	1380
R^2	0.226
adj. R^2	0.073

Notes
The specification includes country FE and Region x Time FE.
Temperature change is annual and expressed in degree Celsius.
Precipitation change is annual and expressed in units of 100 mm per year.
Standard errors are in parentheses and are clustered at the country level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8

Specification with a double interaction term

Dependent variable: annual TFP growth rate	(1)	(2)
∆Temp	0.126	0.066
	(0.131)	(0.122)
∆Pre	-0.047**	-0.051**
	(0.023)	(0.024)
Poor x ∆Temp	-1.576**	
	(0.765)	
Hot x ∆Temp	-1.170***	
	(0.252)	
Poor x Hot x ∆Temp	0.919	
	(0.896)	
Poor_2 x ∆Temp		-1.570***
		(0.455)
Hot_2 x ∆Temp		-1.412***
		(0.427)
Poor_2 x Hot_2 x ∆Temp		0.571
		(0.814)
_cons	1.274***	1.258***
	(0.316)	(0.320)
N	2760	2760
R^2	0.216	0.218
adj. R^2	0.129	0.131
AIC	14723.706	14718.412
Total effect in hot and poor countries	-1.701***	-2.344***
	(0.449)	(0.515)

Notes:
All specifications include country FE and Region x Time FE.
Poor is a dummy with value 1 for countries with below median GDP per capita in 1960.
Hot is a dummy with value 1 for countries with above median average temperature in the 1960s.
Poor_2 is a dummy with value 1 for countries with below median GDP per capita.
Hot_2 is a dummy with value 1 for countries with above median average temperature.
Temperature change is annual and expressed in degree Celsius.
Precipitation change is annual and expressed is in units of 100 mm per year.
Standard errors are in parentheses and are clustered at the country level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9

Specifications with GDP per capita and Polity2

Dependent variable: annual TFP growth rate	(1)	(2)
ΔTemp	-5.065**	-0.518
	(1.921)	(0.318)
ΔPre	-0.046**	-0.050**
	(0.022)	(0.022)
Poor x ΔTemp		-0.823**
		(0.328)
Polity2 x ΔTemp		0.062*
		(0.032)
Polity2		-0.012
		(0.034)
GDP_percap	-0.216	
	(0.689)	
GDP x ΔTemp	0.532***	
	(0.195)	
Hot x ΔTemp	-0.675	
	(0.454)	
_cons	3.158	1.441***
	(6.143)	(0.404)
N	2760	2705
R^2	0.214	0.224
adj. R^2	0.127	0.136
Total effect in poor countries		-1.342***
		(0.336)

Notes
All specifications include country FE and Region x Time FE.
Poor is a dummy with value 1 for countries with below median GDP per capita in 1960.
Hot is a dummy with value 1 for countries with above median average temperature in the 1960s.
Temperature change is annual and expressed in degree Celsius.
Precipitation change is annual and expressed in units of 100 mm per year.
Standard errors are in parentheses and are clustered at the country level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10

Relationship between annual labour productivity growth rates and temperature changes

Dependent Variable: Annual labour productivity growth	(1)	(2)	(3)	(4)	(5)	(6)
ΔTemp	-0.543**	-0.068	0.037	0.095	-0.027	0.037
	(0.227)	(0.159)	(0.164)	(0.131)	(0.155)	(0.131)
ΔPre	-0.037	-0.047*	-0.052**	-0.054**	-0.054**	-0.056**
	(0.025)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Poor x ΔTemp		-1.559***	-1.197**		-1.366***	
		(0.412)	(0.481)		(0.448)	
Hot x ΔTemp			-0.831*	-0.717		
			(0.466)	(0.434)		
Poor_2 x ΔTemp				-1.522***		-1.644***
				(0.421)		(0.411)
Hot_2 x ΔTemp					-1.133**	-1.036**
					(0.503)	(0.498)
_cons	2.535***	2.454***	2.383***	2.374***	2.395***	2.381***
	(0.515)	(0.518)	(0.511)	(0.514)	(0.507)	(0.508)
N	2760	2760	2760	2760	2760	2760
R^2	0.211	0.218	0.219	0.221	0.219	0.221
adj. R^2	0.125	0.132	0.133	0.135	0.133	0.135
AIC	15259.399	15239.634	15237.136	15230.769	15236.537	15229.933
Total effect in poor countries		-1.627***	-1.160**	-1.427***	-1.394***	-1.607***
		(0.405)	(0.526)	(0.455)	(0.457)	(0.414)
Total effect in hot countries			-0.794*	-0.621	-1.161**	-0.999*
			(0.416)	(0.395)	(0.501)	(0.503)

Notes:

All specifications include country FE and Region x Time FE.
Poor is a dummy with value 1 for countries with below median GDP per capita in 1960.
Hot is a dummy with value 1 for countries with above median average temperature in the 1960s.
Poor_2 is a dummy with value 1 for countries with below median GDP per capita.
Hot_2 is a dummy with value 1 for countries with above median average temperature.
Temperature change is annual and expressed in degree Celsius.
Precipitation change is annual and expressed is in units of 100 mm per year.
Standard errors are in parentheses and are clustered at the country level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11

Regressions with number of persons employed and capital stock as dependent variables

	(1) Growth rate in the number of persons employed	(2) Growth rate in the number of persons employed	(3) Capital stock growth rate	(4) Capital stock growth rate
△Temp	0.068	0.016	3.610	0.663
	(0.079)	(0.096)	(2.335)	(0.560)
Poor x △Temp		0.172		9.661*
		(0.152)		(5.465)
△Pre	0.004	0.005	-0.174	-0.114
	(0.014)	(0.014)	(0.322)	(0.338)
_cons	2.533***	2.542***	4.106	4.608
	(0.439)	(0.437)	(4.347)	(4.338)
N	2760	2760	2760	2760
R^2	0.171	0.172	0.129	0.132
adj. R^2	0.080	0.081	0.034	0.037
AIC	10968.569	10969.314	27815.168	27808.350
Total effect in poor countries		0.188		10.323*
		(0.126)		(5.866)

Notes:
All specifications include country FE and Region x Time FE.
Poor is a dummy with value 1 for countries with below median GDP per capita in 1960.
Temperature change is annual and expressed in degree Celsius.
Precipitation change is annual and expressed is in units of 100 mm per year.
Standard errors are in parentheses and are clustered at the country level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12

Baseline specification with Driscoll-Kraay standard errors

Dependent variable: annual TFP growth rate	(1)	(2)	(3)	(4)	(5)	(6)
∆Temp	-0.485**	-0.029	0.057	0.098	0.008	0.051
	(0.200)	(0.130)	(0.164)	(0.164)	(0.134)	(0.142)
∆Pre	-0.033	-0.042*	-0.047*	-0.048*	-0.049*	-0.051*
	(0.026)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Poor x ∆Temp		-1.493***	-1.195**		-1.315***	
		(0.432)	(0.566)		(0.448)	
Hot x ∆Temp			-0.684	-0.612		
			(0.487)	(0.470)		
Poor_2 x ∆Temp				-1.425**		-1.513***
				(0.565)		(0.443)
Hot_2 x ∆Temp					-1.048**	-0.979**
					(0.457)	(0.431)
_cons	0.184	0.402*	0.429**	0.480**	0.470**	0.519**
	(0.166)	(0.212)	(0.200)	(0.204)	(0.204)	(0.208)
N	2760	2760	2760	2760	2760	2760
Within R^2	0.208	0.215	0.216	0.217	0.216	0.218
Total effect in poor countries		-1.523***	-1.139*	-1.327**	-1.307***	-1.462***
		(0.462)	(0.660)	(0.644)	(0.487)	(0.472)
Total effect in hot countries			-0.627	-0.515	-1.040**	-0.928**
			(0.383)	(0.390)	(0.412)	(0.383)

Notes:

All specifications include country FE and Region x Time FE.
Poor is a dummy with value 1 for countries with below median GDP per capita in 1960.
Hot is a dummy with value 1 for countries with above median average temperature in the 1960s.
Poor_2 is a dummy with value 1 for countries with below median GDP per capita.
Hot_2 is a dummy with value 1 for countries with above median average temperature.
Temperature change is annual and expressed in degree Celsius.
Precipitation change is annual and expressed is in units of 100 mm per year.
Driscoll-Kraay standard errors are in parentheses, and allow up to two lags of autocorrelation.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1

TFP levels and average temperatures in 2006

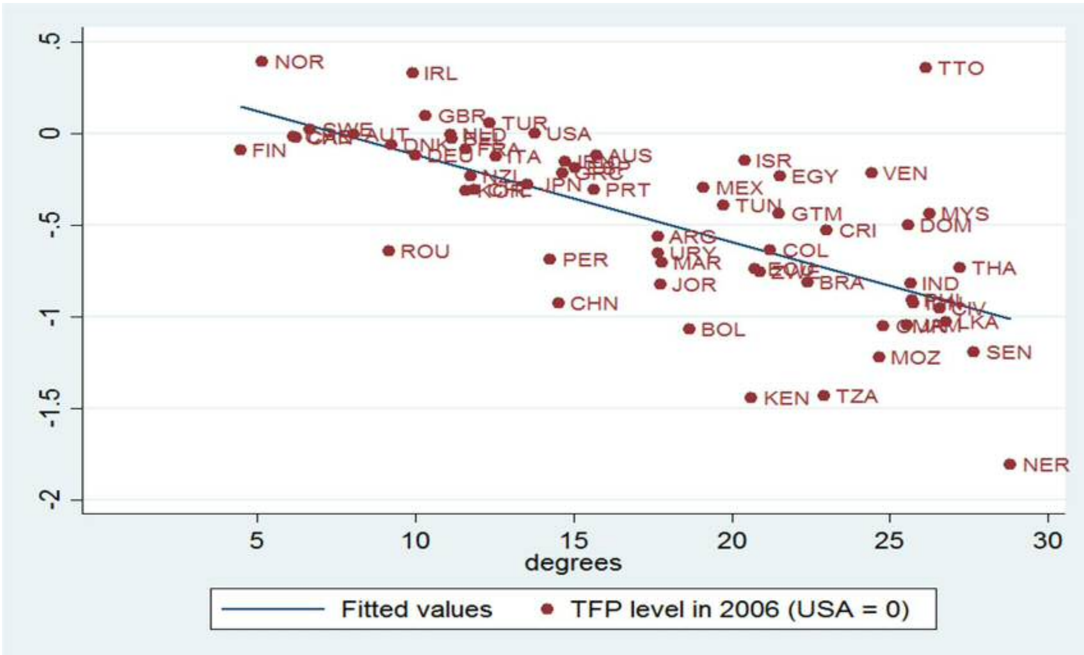


Figure 2

TFP growth rates and temperature shocks in poor countries

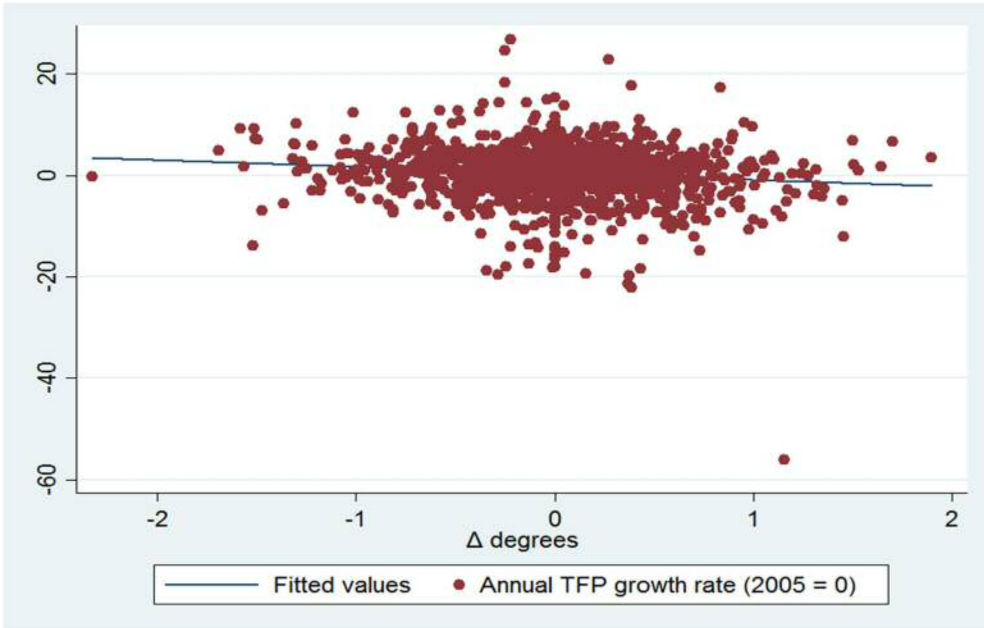


Figure 3

Marginal effect of ΔTemp at different GDP per capita levels – hot = 1

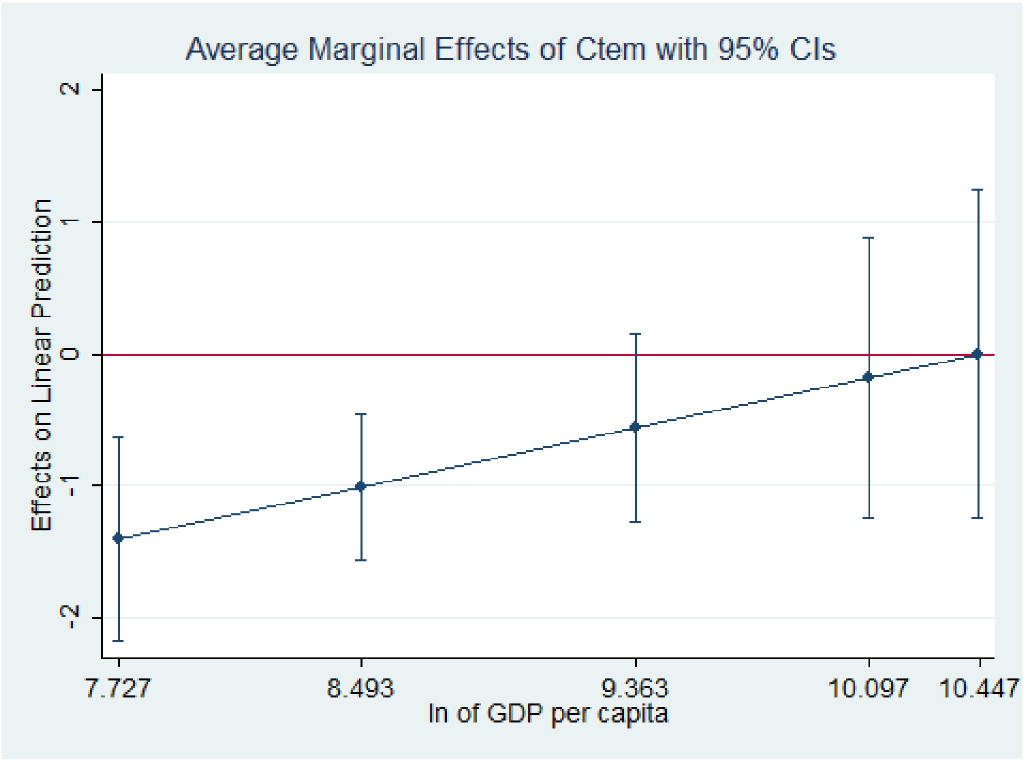


Figure 4

Marginal effect of ΔTemp at different GDP per capita levels – hot = 0

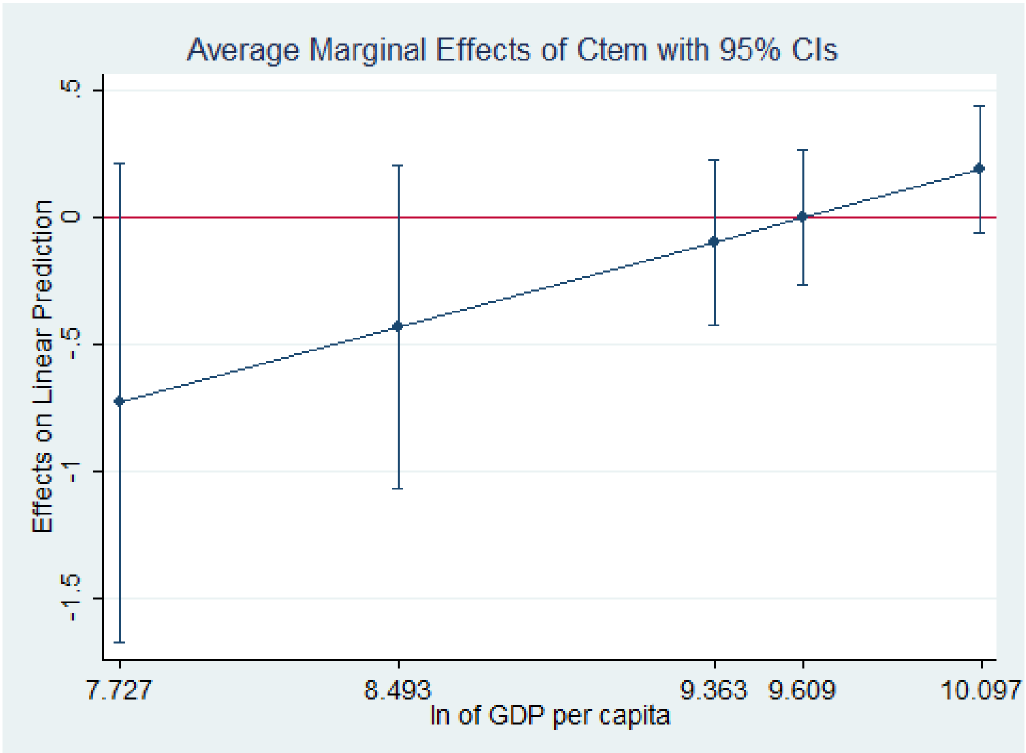
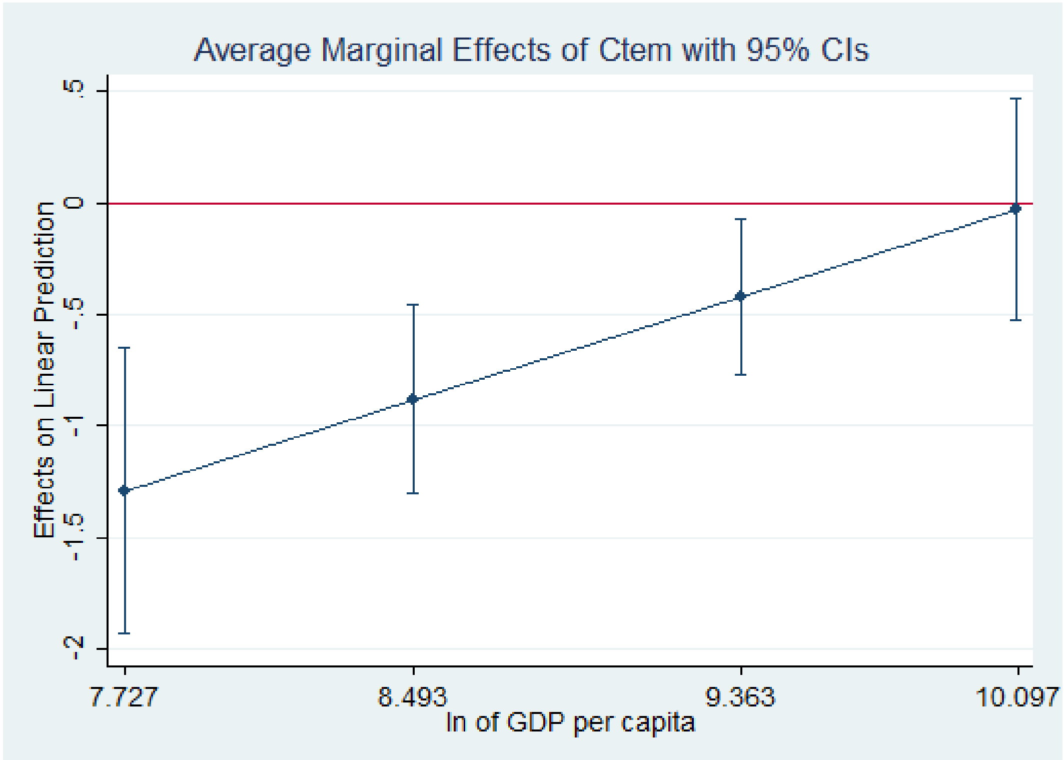


Figure 5

Marginal effect of ΔTemp at different GDP per capita levels

– whole sample



Appendices

(1) Construction of the RTFP^{NA} Index in PWT 8.1

Since version 8.0, the Penn World Tables include data on TFP at the country level (Feenstra, Inklaar & Timmer, 2013). In particular, there are two measures of TFP in PWT 8.1. The first one is CTFP, where the prefix C stays for "current year": this is a measure of TFP levels of countries in a given year compared to the US, whose TFP levels are 1 in each year. It is thus a measure of relative TFP levels which allows for comparisons among countries (Feenstra, Inklaar & Timmer, 2015), and can be seen as an index of technological catch-up or as the distance from the technological frontier (represented by the US).

The other, and the one used in this study is RTFP^{NA}. This index is calculated using the growth rate of real GDP from national accounts data, in conjunction with the growth rates of capital stock at constant national prices and of the labour force (Feenstra, Inklaar & Timmer, 2013). This is a standard process in TFP estimation since, as a residual representing a combination of labour and capital productivity, TFP is obviously dependent on the estimates of the other components. As discussed above, RTFP^{NA} is normalized to 1 in 2005 for all countries, and since we use natural logarithms in our specification, the normalized value for 2005 is 0.

More specifically, Inklaar and Timmer (2013) describe how the productivity measurement starts from the following general production function:

$$Y = Af(K, L) = AK^{\alpha}(Ehc^{1-\alpha}) \tag{A.1}$$

where, in the second equality, labour input is defined as the product of the number of workers in the economy *E* times their average human capital *hc* and α is the output elasticity of capital.

A second-order approximation to the production function *f* is represented by the Törnqvist quantity index of factor inputs Q^T, which can be used to compare inputs between *t-1* and *t* for a given country as follows:

$$\ln Q_{t,t-1}^{T} = \frac{1}{2}(\alpha_t + \alpha_{t-1})\ln\frac{K_t}{K_{t-1}} + \left[1 - \frac{1}{2}(\alpha_t + \alpha_{t-1})\right]\ln\frac{L_t}{L_{t-1}} \tag{A.2}$$

In order to implement this equation, they make the assumption that the output elasticity of capital is approximated by the country's share of GDP that is not earned by labour. They assume a common labour share neither across countries nor over time, i.e., the input index in equation (A.2) is the more flexible Törnqvist index rather than the more common Cobb-Douglas function.

Finally, growth of productivity over time is given by:

$$RTFP_{t,t-1}^{NA} = \frac{RGDP_t^{NA}}{RGDP_{t-1}^{NA}} / Q_{t,t-1}^{T} \qquad \text{(A.3)}$$

where $RGDP^{NA}$ stands for real GDP at constant national prices.

For further information with regard to the construction of the $RTFP^{NA}$ index, see Feenstra, Inklaar and Timmer (2013), Feenstra, Inklaar and Timmer (2015) and Inklaar and Timmer (2013).

(2) Statistical tests

A. Panel unit root tests

In order to check that our main variables are stationary, we performed panel unit root tests for annual TFP growth, annual temperature change and annual precipitation change. In particular, we used two unit root tests which are both[21] fit when N > T, as it is the case in our sample: the Im, Pesaran, and Shin (2003) test and the Harris and Tzavalis (1999) test. The results, reported in Tables A.1-A.6, confirm that the tested variables are indeed stationary.

Table A.1

Im-Pesaran-Shin unit-root test for annual TFP growth

Ho: All panels contain unit roots	Number of panels = 60
Ha: Some panels are stationary	Number of periods = 46
AR parameter: Panel-specific	Asymptotics: T,N →Infinity sequentially
Panel means: Included	
Time trend: Included	Cross-sectional means removed
ADF regressions: No lags included	

	Statistic	p-value	Fixed-N exact critical values 1%	5%	10%
t-bar	-5.8532		-2.360	-2.310	-2.280
t-tilde-bar	-4.3796				
Z-t-tilde-bar	-27.9582	0.0000			

[21] The Im-Pesaran-Shit (2003) test is fit when N > T if a time trend is included.

Table A.2

Im-Pesaran-Shin unit-root test for ∆Temp

Ho: All panels contain unit roots	Number of panels = 60
Ha: Some panels are stationary	Number of periods = 46
AR parameter: Panel-specific	Asymptotics: T,N→Infinity sequentially
Panel means: Included	
Time trend: Included	Cross-sectional means removed
ADF regressions: No lags included	

	Statistic	p-value	Fixed-N exact critical values 1%	5%	10%
t-bar	-9.7663		-2.360	-2.310	-2.280
t-tilde-bar	-5.4829				
Z-t-tilde-bar	-38.5654	0.0000			

Table A.3

Im-Pesaran-Shin unit-root test for ∆Pre

Ho: All panels contain unit roots	Number of panels = 60
Ha: Some panels are stationary	Number of periods = 46
AR parameter: Panel-specific	Asymptotics: T,N →Infinity sequentially
Panel means: Included	
Time trend: Included	Cross-sectional means removed
ADF regressions: No lags included	

	Statistic	p-value	Fixed-N exact critical values 1%	5%	10%
t-bar	-10.2704		-2.360	-2.310	-2.280
t-tilde-bar	-5.5661				
Z-t-tilde-bar	-39.3644	0.0000			

Table A.4

Harris-Tzavalis unit-root test for annual TFP growth

Ho: Panels contain unit roots	Number of panels = 60
Ha: Panels are stationary	Number of periods = 46
AR parameter: Common	Asymptotics: N → Infinity,
Panel means: Included	T fixed
Time trend: Included	Cross-sectional means removed

	Statistic	z	p-value
rho	0.1823	-50.3642	0.0000

Table A.5

Harris-Tzavalis unit-root test for ∆Temp

Ho: Panels contain unit roots	Number of panels = 60
Ha: Panels are stationary	Number of periods = 46
AR parameter: Common	Asymptotics: N → Infinity, T fixed
Panel means: Included	
Time trend: Included	Cross-sectional means removed

	Statistic	z	p-value
rho	-0.3900	-93.9377	0.0000

Table A.6

Harris-Tzavalis unit-root test for ∆Pre

Ho: Panels contain unit roots	Number of panels = 60
Ha: Panels are stationary	Number of periods = 46
AR parameter: Common	Asymptotics: N → Infinity,
Panel means: Included	T fixed
Time trend: Included	Cross-sectional means removed

	Statistic	z	p-value
rho	-0.4215	-96.3329	0.0000

B. FE vs RE

To test the appropriateness of a fixed effects - panel approach rather than a random effects (RE) specification, we performed a test using the approach suggested by Mundlak (1978). The traditional Hausman test, in fact, is not recommended when time fixed effects are included in the regressions, and is based on the assumption of homoskedasticity, which is very unlikely to hold in our sample. The Mundlak test, in contrast, allows for heteroskedastic errors and serial intracorrelation.

Essentially, we performed a RE regression including panel-level means of our time-varying variables – in the specification we used, temperature change, precipitation change and the interaction between and the poor dummy – and then tested for the joint significance of the coefficients for the means time varying variables. The results, reported in Table A.7, are strongly in favour of a FE approach.

Table A.7

Mundlak test – Random Effects GLS regression with added panel-level means

Dependent variable: Annual TFP growth rate	(1)
∆Temp	-0.029
	(0.136)
Poor x ∆Temp	-1.493***
	(0.405)
∆Pre	-0.042*
	(0.023)
Mean_∆Temp	-3.160
	(6.413)
Mean_ Poor x ∆Temp	29.436***
	(10.984)
Mean_∆Pre	2.456**
	(1.138)
_cons	2.575***
	(0.723)
N	2760
R^2	0.226

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Test on the joint significance of the panel-level means for the time varying variables:

(1) Mean_∆Temp = 0
(2) Mean_∆Pre = 0
(3) Mean_ Poor x ∆Temp

chi2(3) = 9.40
Prob > chi2 = 0.0245

(3) Additional results

Table A.8

CRU Weather Data – Descriptive Statistics

	Mean	Var	sd	Min	Max	Obs
ΔTemp_2	0.0147	0.303	0.550	-3	2.700	2760
ΔPre_2	0.00164	4.877	2.208	-16.36	16.61	2760

Temperature change is annual and expressed in degree Celsius.
Precipitation change is annual and expressed in units of 100 mm per year.

Table A.9

Relationship between annual TFP growth rates and temperature changes -

Sample B & CRU Data

Dependent variable: Annual TFP growth rate	(1)	(2)	(3)	(4)	(5)	(6)
∆Temp_2	-0.155	0.141	0.139	0.118	0.112	0.104
	(0.158)	(0.101)	(0.106)	(0.105)	(0.103)	(0.104)
∆Pre_2	-0.043	-0.053^{*}	-0.052^{*}	-0.053^{*}	-0.050^{*}	-0.051^{*}
	(0.029)	(0.027)	(0.028)	(0.027)	(0.028)	(0.028)
Poor x ∆Temp_2		-1.001^{***}	-1.005^{***}		-1.010^{***}	
		(0.279)	(0.279)		(0.278)	
Hot x ∆Temp_2			0.014	0.109		
			(0.321)	(0.315)		
Poor_2 x ∆Temp_2				-1.126^{***}		-1.108^{***}
				(0.273)		(0.278)
Hot_2 x ∆Temp_2					0.322	0.368
					(0.312)	(0.311)
_cons	1.344^{***}	1.310^{***}	1.310^{***}	1.313^{***}	1.311^{***}	1.310^{***}
	(0.304)	(0.304)	(0.305)	(0.305)	(0.305)	(0.306)
N	2448	2448	2448	2448	2448	2448
R^2	0.197	0.200	0.200	0.200	0.200	0.200
adj. R^2	0.121	0.123	0.123	0.124	0.123	0.124
Total effect in poor countries		-0.860^{***}	-0.866^{***}	-1.007^{***}	-0.898^{***}	-1.004^{***}
		(0.301)	(0.306)	(0.300)	(0.304)	(0.307)
Total effect in hot countries			0.153	0.228	0.434	0.472
			(0.302)	(0.299)	(0.305)	(0.304)

Notes:

All specifications include country FE and Region x Time FE.
Poor is a dummy with value 1 for countries with below median GDP per capita in 1970.
Hot is a dummy with value 1 for countries with above median average temperature in the 1970s.
Poor_2 is a dummy with value 1 for countries with below median GDP per capita.
Hot_2 is a dummy with value 1 for countries with above median average temperature.
Temperature change is annual and expressed in degree Celsius.
Precipitation change is annual and expressed in units of 100 mm per year.
Standard errors are in parentheses and are clustered at the country level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.10

Relationship between annual labour productivity growth rates and temperature changes – Sample B

Dependent variable: annual labour productivity growth rate	(1)	(2)	(3)	(4)	(5)	(6)
ΔTemp	-0.382*	0.115	0.106	0.064	0.104	0.076
	(0.215)	(0.133)	(0.134)	(0.135)	(0.131)	(0.136)
ΔPre	-0.042*	-0.053**	-0.053***	-0.055***	-0.052**	-0.055**
	(0.021)	(0.020)	(0.020)	(0.020)	(0.021)	(0.021)
Poor x ΔTemp		-1.498***	-1.519***		-1.499***	
		(0.377)	(0.409)		(0.377)	
Hot x ΔTemp			0.064	0.195		
			(0.429)	(0.417)		
Poor_2 x ΔTemp				-1.655***		-1.588***
				(0.403)		(0.380)
Hot_2 x ΔTemp					0.117	0.173
					(0.398)	(0.398)
_cons	2.512***	2.428***	2.431***	2.434***	2.430***	2.427***
	(0.480)	(0.475)	(0.475)	(0.477)	(0.474)	(0.476)
N	2448	2448	2448	2448	2448	2448
R^2	0.181	0.186	0.186	0.187	0.186	0.187
adj. R^2	0.103	0.109	0.109	0.109	0.109	0.109
AIC	14034.284	14018.674	14020.654	14018.717	14020.617	14018.779
Total effect in poor countries		-1.383***	-1.413***	-1.591***	-1.396***	-1.512***
		(0.399)	(0.444)	(0.425)	(0.408)	(0.407)
Total effect in hot countries			0.169	0.259	0.221	0.249
			(0.414)	(0.415)	(0.403)	(0.406)

Notes:

All specifications include country FE and Region x Time FE.
Poor is a dummy with value 1 for countries with below median GDP per capita in 1970.
Hot is a dummy with value 1 for countries with above median average temperature in the 1970s.
Poor_2 is a dummy with value 1 for countries with below median GDP per capita.
Hot_2 is a dummy with value 1 for countries with above median average temperature.
Temperature change is annual and expressed in degree Celsius.
Precipitation change is annual and expressed is in units of 100 mm per year.
Standard errors are in parentheses and are clustered at the country level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.11

Baseline specification with Driscoll-Kraay standard errors – Sample B

Dependent variable: annual TFP growth rate	(1)	(2)	(3)	(4)	(5)	(6)
ΔTemp	-0.345***	0.053	0.087	0.071	0.077	0.075
	(0.128)	(0.172)	(0.150)	(0.138)	(0.154)	(0.141)
ΔPre	-0.033	-0.041*	-0.043**	-0.046**	-0.043**	-0.046**
	(0.020)	(0.022)	(0.021)	(0.021)	(0.020)	(0.022)
Poor x ΔTemp		-1.200***	-1.125**		-1.198***	
		(0.354)	(0.479)		(0.360)	
Hot x ΔTemp			-0.230	-0.093		
			(0.522)	(0.564)		
Poor_2 x ΔTemp				-1.308**		-1.337***
				(0.568)		(0.392)
Hot_2 x ΔTemp					-0.244	-0.196
					(0.724)	(0.710)
_cons	-0.543***	0.158	0.127	0.747***	-0.037	0.796***
	(0.084)	(0.120)	(0.135)	(0.137)	(0.064)	(0.115)
N	2448	2448	2448	2448	2448	2448
Within R^2	0.198	0.202	0.202	0.203	0.202	0.203
Total effect in poor countries		-1.147***	-1.037**	-1.237**	-1.121***	-1.262***
		(0.281)	(0.451)	(0.546)	(0.335)	(0.401)
Total effect in hot countries			-0.143	-0.022	-0.166	-0.120
			(0.552)	(0.589)	(0.825)	(0.765)

Notes:

All specifications include country FE and Region x Time FE.
Poor is a dummy with value 1 for countries with below median GDP per capita in 1970.
Hot is a dummy with value 1 for countries with above median average temperature in the 1970s.
Poor_2 is a dummy with value 1 for countries with below median GDP per capita.
Hot_2 is a dummy with value 1 for countries with above median average temperature.
Temperature change is annual and expressed in degree Celsius.
Precipitation change is annual and expressed is in units of 100 mm per year.
Driscoll-Kraay standard errors are in parentheses, and allow up to two lags of autocorrelation.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(4) List of countries in the sample

Main Dataset:

Argentina

Australia

Austria

Belgium

Bolivia

Brazil

Cameroon

Canada

Chile

China

Colombia

Costa Rica

Denmark

Dominican Republic

Ecuador

Egypt

Finland

France

Germany

Greece

Guatemala

India

Indonesia

Iran

Ireland

Israel

Italy

Ivory Coast

Jamaica

Japan

Jordan

Kenya

Malaysia

Mexico

Morocco

Mozambique

Netherlands

New Zealand

Niger

Norway

Peru

Philippines

Portugal

Romania

Senegal

South Korea

Spain

Sri Lanka

Sweden

Switzerland

Tanzania

Thailand

Trinidad & Tobago

Tunisia

Turkey

United Kingdom

United States

Uruguay

Venezuela

Zimbabwe

Countries added in Sample B

Bulgaria

Hungary

Kuwait

Panama

Paraguay

Poland

Qatar

Saudi Arabia

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