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Weather, Climate and Total Factor Productivity

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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 the Penn World Table, we test this hypothesis by directly examining the nature of the relationship between annual temperature shocks and TFP growth rates in the period 1960–2006. The results show a negative relationship only exists in poor countries, where a 1 °C annual increase in temperature decreases TFP growth rates by about 1.1–1.8 percentage points, whereas the impact is indistinguishable from zero in rich countries. Extrapolating from weather to climate, the possibility of dynamic effects of climate change in poor countries increases concerns over the distributional issues of future impacts and, from a policy perspective, restates the case for complementarity between climate policy and poverty reduction.

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1 Introduction

Since the path-breaking work of Nordhaus (1991), economists have argued in favour of a modest carbon tax. A Pigou tax is justified if it is more likely than not that climate change has a net negative impact on present welfare. Although frequently challenged in favour of more stringent climate policy, estimates of the social cost of carbon have not increased over the years (Tol 2018). Three independent author teams (Moore and Diaz 2015; Dietz and Stern 2015; Moyer et al. 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 average 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 2018), but they have been criticized because they could not fully capture the potential damage by future climate change (Pindyck 2012, 2013; Stern 2013; Weitzman 2009, 2011).

Besides static impacts on welfare, there are also dynamic ones: climate change affects the growth rate of the economy (Fankhauser and 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 (2005) 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 and Diaz 2015; Dietz and Stern 2015; Moyer et al. 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 Integrated Assessment Models (IAMs), to allow climate impacts to affect TFP growth.[1] They find a much stronger case for stringent emission abatement.

Similarly, Moyer et al. (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 Social Cost of Carbon (SCC) than the IWG one.[3]

However, these works do not provide any empirical evidence for this claim and the consequent simulations (Tol 2018). 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 et al. (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 et al. 2001; Easterly and Levine 2003; Rodrik et al. 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 et al. (2016). Alsan (2014) shows that the tse–tse fly is a major factor in the underdevelopment in Sub-Saharan Africa. Andersen et al. (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 et al. (2014).

As far as climate change is concerned, though, this literature is problematic for a number of reasons. First, as emphasized by Tol (2018), 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,

[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 et al. 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 et al. 2006). See also Nordhaus (2007), Stern (2013) and Tol et al. (2006).

[4] As they explain: "panel data exploit the exogeneity of cross-time weather variation, allowing for causative identification".

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 to 2003, Dell et al. (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 et al. (2015), studying 166 countries between 1960 and 2010, find that productivity peaks at about 13 °C and declines non-linearly thereafter, without significant heterogeneity between rich and poor countries, leading them to predict impacts much larger than previously estimated. More recently, Using detailed micro-data on Chinese firm production, Zhang et al. (2018) document an inverted-U shape relationship between temperature and TFP at the firm level.

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 et al. 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 et al. (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. This conclusion is subjected to *caveats* and must be interpreted with caution. Nonetheless, it basically confirms the results of Dell et al. (2012) and rejects the conclusions of Burke et al. (2015). We also show that the assumptions of Dietz and Stern (2015), Moore and Diaz (2015) and Moyer et al. (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 TFP growth. Third, unlike other previous 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.

Fourth, we show the main reason behind the impact on TFP growth in poor countries is labour productivity, thus linking the existing macro literature with the recent micro studies on the relationship between temperature and human physiology.

The outline of the rest of this paper is as follows. Section 2 provides a theoretical background on the potential TFP-climate change relationship. Section 3 presents data and descriptive statistics. Section 4 describes the identification strategy. Section 5 presents empirical results. Section 6 investigates the potential explanations for the heterogeneity of impacts detected in Sect. 5. Section 7 discusses the implications of the results with regard to climate change. Section 8 sums up, illustrates some *caveats* and concludes.

2 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:

$$\mathrm{Y}_t = (1 - \Omega_t^{\mathrm{Y}})(1 - \Lambda_t)[\mathrm{A}_t \mathrm{N}_t^{1-\alpha} \mathrm{K}_t^{\alpha}] \tag{1}$$

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

$$\mathrm{K}_{t+1} = \mathrm{K}_t(1 - \delta) + s\mathrm{Y}_t \tag{2}$$

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[5]:

$$\Omega_t^{\mathrm{Y}} = 1 - \frac{1}{1+\pi_1 \Delta \mathrm{T}_t + \pi_2 \Delta \mathrm{T}_{\mathrm{t}}^2} \tag{3}$$

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}.

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 and Tol 2005; Moyer et al. 2014).

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

$$\mathrm{A}_{t+1} = (1-\Omega_t^{\mathrm{A}})(1 - \delta_t^{\mathrm{A}})\,\mathrm{A}_t + \alpha\,(I_t) \tag{4}$$

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.

[5] 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 a steep increase of damages at higher temperatures (Stern 2013; Weitzman 2010).

Damages are then partitioned between output and TFP:

$$\Omega_t^{\mathrm{A}} = \mathrm{f}^{\mathrm{A}} \cdot \Omega_t \tag{5}$$

$$\Omega_t^{\mathrm{Y}} = 1 - \frac{(1 - \Omega_t)}{\left(1 - \Omega_t^{\mathrm{A}}\right)} \tag{6}$$

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

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 $\mathrm{f}^{\mathrm{A}} = 0.05$ 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 et al. (2014) explore the consequences of different values of f^{A} between 1 and 100%. They show that $\mathrm{f}^{\mathrm{A}} = 0.05$ 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 et al. (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”.

3 Data and Descriptive Statistics

3.1 Data

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

3.1.1 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 $\mathrm{RTFP}^{\mathrm{NA}}$ data,[6] where $\mathrm{RFTP}^{\mathrm{NA}}$ stands for “Real Total Factor Productivity from National Accounts data”. $\mathrm{RTFP}^{\mathrm{NA}}$ is a country-specific index of TFP which, in the benchmark year, 2005, takes value 1 for all countries. $\mathrm{RTFP}^{\mathrm{NA}}$ can be used to study within-country productivity growth over time. In our specifications, we use the natural logarithm of the $\mathrm{RTFP}^{\mathrm{NA}}$ index. This means that the 2005 benchmark value is 0 for all countries in the logarithmic specification. We calculate annual $\mathrm{RTFP}^{\mathrm{NA}}$ growth rates by first-differencing, and check for stationarity.[7] Henceforth, from now on, “TFP growth rate” it is intended as the annual growth rate of the natural logarithm of the $\mathrm{RTFP}^{\mathrm{NA}}$ index as taken from PWT 8.1.

These pre-estimated TFP growth data are 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 et al. 2013). This is a standard process in TFP estimation as a residual of a combination of labour and capital. TFP obviously depends on the estimate of the other components. As any measure of TFP, these PWT data are not immune from concerns about measurement error; this issue will be addressed below. For further information on the $\mathrm{RTFP}^{\mathrm{NA}}$ index and data, see Web Appendix (1).

[6] 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.

[7] For the panel unit root tests for annual TFP growth, temperature change and precipitation change, see Web Appendix (2), Tables A.1–A.6.

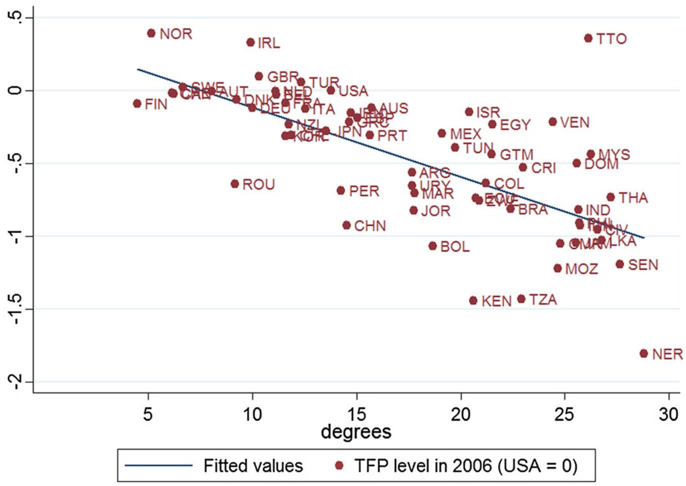

Fig. 1 TFP levels and average temperatures in 2006

3.1.2 Temperature and Precipitation Data

These data are taken from the *Terrestrial Air Temperature and Precipitation: 1900–2006 Monthly Time Series* (Matsuura and Willmott 2007), from the University of Delaware (UDEL), as aggregated to the country-year level by (Dell et al. 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.

3.1.3 GDP Data

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

3.2 Descriptive Statistics

The main dataset is composed of 60 countries[8] 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 and 3 °C. Finally, precipitation exhibits even greater variability.

[8] The choice of the countries has been made on the basis of data availability. For the list of countries, see Web Appendix (4).

Table 1 Descriptive statistics

	Mean	Var	SD	Min	Max	Obs
TFP growth rate	0.481	15.485	3.935	− 56.055	26.759	2760
ΔTemp	0.012	0.318	0.564	− 2.952	2.442	2760
ΔPre	− 0.014	5.942	2.438	− 35.398	37.640	2760
GDP_percap	8.480	1.022	1.011	6.084	10.353	2820

TFP growth rate is the annual percentage change and expressed in natural logarithm
Temperature change is annual and expressed in °C
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

4 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.[9] Our identification strategy is straightforward and follows Dell et al. (2012). The baseline specification of our model is the following:

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

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 et al. (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 et al. (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.

One may be worried that rainfall is the only observed control variable in our specification. However, since many traditional control variables are themselves affected by climate, adding more time-varying observables which are endogenous to the weather variation could actually be counterproductive and partially offset part of the true weather effect. This is the so-called over-controlling problem (Dell et al. 2014) or ‘bad control’ (Burke et al. 2015), a well-known issue in climate literature, which calls for caution and recommends to include only plausibly exogenous covariates.

As for the other elements in the equation, μ_i are country fixed effects, θ_{rt} are region × time fixed effects, where this interaction allows for differentiated trends in different regions, as suggested by Dell et al. (2014), in order to isolate idiosyncratic local shocks.[10] Finally, ε_{it} are error terms adjusted for clustering at the country level.

Reverse causality is a minor worry. Confounding variables, instead, could be a cause of concern. 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. For instance, weather variations could lead to short-term reallocation of workers across industries or sectors, or short-term unemployment, that could be imperfectly measured by annual data on the labour force. The measurement problem is more likely to occur

[9] For the appropriateness of the FE approach compared to a random effects (RE) specification, see Web Appendix (2), Table A.7.

[10] For the list of regions, see Web Appendix (5).

in low-income countries. As temperature shocks impact TFP only in low-income countries, this possible measurement problem would not be innocuous.[11] However, 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 precisely 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.

5 Baseline Results

Table 2 reports the results for the baseline specification of Eq. (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[12]—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 × ΔTemp 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.[13] 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

[11] See, e.g., Colmer (2017) on the link between weather changes and labour reallocation across sectors.

[12] The cut-off point for GDP per capita is approximately 2684.33 international Geary–Khamis dollars (1990 benchmark year).

[13] 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 entire empirical analysis and its results should therefore be interpreted with caution and are no further discussed here.

Table 2 Relationship between annual TFP growth rates and temperature changes

Dependent variable: annual TFP growth rate	(1)	(2)	(3)	(4)	(5)	(6)
ΔTemp	− 0.485**	− 0.029	0.057	0.098	0.008	0.051
	(0.216)	(0.136)	(0.143)	(0.123)	(0.134)	(0.120)
ΔPre	− 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 × ΔTemp		− 1.493***	− 1.195**		− 1.315***	
		(0.404)	(0.468)		(0.437)	
Hot × ΔTemp			− 0.684	− 0.612		
			(0.452)	(0.429)		
Poor_2 × ΔTemp				− 1.425***		− 1.513***
				(0.420)		(0.410)
Hot_2 × ΔTemp					− 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)

All specifications include country FE and Region × 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 °C. 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. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

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, where median GDP per capita is now calculated over the whole 1960—2006 period and not just in 1960 as above.[14] The "poor" interaction is again strongly significant, with the coefficient of Poor_2 × ΔTemp 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.

[14] In this case the cut-off point for GDP per capita is approximately 4417.1 international Geary–Khamis dollars (1990 benchmark year).

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 terms of policy guidelines on climate change, we conduct a variety of sensitivity tests to ensure the robustness of our results. In particular, the following robustness checks are performed: the repetition of the baseline specification for a different dataset, comprising 68 countries and covering the period 1970–2006; 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; a different classification between poor and rich countries; regressions on changes in the number of persons employed and capital stock; the use of Driscoll and Kraay (1998) standard errors in place of clustered standard errors for the baseline analysis in both samples; an investigation of persistence of temperature effects through the inclusion of lags in the regressions; five different sensitivity tests to check for robustness with respect to climatic data and functional forms of the weather variables. These robustness checks are presented and discussed in the online appendix.[15] Our key finding, i.e. the pattern of heterogeneity of impacts between rich and poor countries, is never contradicted.

6 Heterogeneity in the Impacts of Temperature Shocks

Having established robustness of our results, we now move to a more in-depth analysis of the heterogeneity of impacts.

Such heterogeneous pattern could be due to intrinsic differences, between rich and poor countries, in climate, levels of development, quality of institutions and composition of TFP. Below we discuss and test for each of these factors.

6.1 Differences in Climate and Non-linearity of Temperature Impacts

One might object that the reason for the heterogeneity in the impacts of temperature shocks between is that we fail to account for non-linearity of temperature effects, i.e. the exogenous difference in climatic conditions between rich and poor countries. Indeed, this is what Burke et al. (2015) results suggest: "with most poor countries on the downward slope of the response function [between the temperature level and the GDP growth rate] but rich countries distributed almost symmetrically around the optimum, a linear regression for the effect of temperature would recover a steep negative in poor countries but ambiguous (and closer to zero) slope for rich countries".[16]

To take this relevant possibility into account, we perform two separate tests. In Table 3 we present a different specification in which we include the square of annual temperature change as an additional independent variable in the regressions, and we also interact it with the "poor" and "hot" dummies like we do for annual temperature change in the main

[15] See Web Appendix (3).

[16] Supplementary Information, page 20.

specification. As Columns (1)–(6) show, the square of annual temperature change is almost always insignificant, even in poor countries. The total weather impacts are slightly bigger.

In Table 4 we opt for a different specification to capture potential non-linearity. First, we follow the test recommended by Bigano et al. (2006) and Burke et al. (2015): in Column (1) we include only an interaction between annual temperature change and average temperature. ΔTemp has a positive and strongly significant impact but the interaction with average temperature is negative and strongly significant. This suggests that the impact of hot weather is positive in cool countries and negative in warm countries. However, when we also include an interaction between temperature change and average GDP per capita in Column (2), the picture is different: now temperature shocks have a *negative* and significant impact, while the interaction with GDP per capita is positive and significant. While the interaction with average temperature is still negative and significant (although almost halved in magnitude), the sign change of the coefficient of temperature shocks reveals that the temperature response is being driven by average income, rather than by average temperature. The significant, negative interaction with average temperature suggests that hotter countries suffer from bigger impacts, but because of the high correlation between heat and wealth it is difficult to separate the two effects.

Finally, in Columns (3) and (4) we explore in further detail the possibility of differential responses due to heat and affluence. In Column (3) we interact temperature shocks with dummies capturing average temperature quartiles, i.e. we group countries in 4 categories: cold, mild, warm and hot. This specification with temperature bins is relatively non-parametric and can further shed light on potential non-linearity. The results in Column (3) confirm the presence of non-linear dynamics: the impact of temperature shocks is positive and significant for cold countries and negative and significant for mild, warm and hot countries.

However, when we add the respective interactions with average GDP per capita (Column (4)), the signs of the coefficients for temperature shocks are negative for all the groups, and significant only for mild and hot countries, whereas the interaction with average GDP per capita is always positive, and weakly significant for mild and hot countries. The qualitative insight is that there is no differential response due to heat, and that the relationship between TFP growth and temperature shocks is mediated by income.

On the whole, these tests suggest that there is no evidence of meaningful non-linear effects of temperature shocks, and that a linear function is the best approximation of the TFP-temperature relationship for this dataset, in line with Dell et al. (2012). We also confirm their finding that countries at different levels of development respond differently to weather shocks. Therefore, heterogenous climates in rich and poor countries do not account for the heterogenous impacts.

6.2 Differences in Development and/or Institutions

Are poor countries vulnerable to temperature shocks because of the existence of a development and/or institutional gap compared to rich countries?

To answer this question, 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 50 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 50 years. Interacting annual temperature changes with GDP per capita can over-

Table 3 Checking for non-linearity of temperature impacts—square of temperature change

Dependent variable: annual TFP growth rate	(1)	(2)	(3)	(4)	(5)	(6)
ΔTemp	– 0.490**	– 0.037	0.050	0.092	0.001	0.045
	(0.215)	(0.134)	(0.140)	(0.120)	(0.132)	(0.117)
$(\Delta\text{Temp})^2$	– 0.110	– 0.143*	– 0.151*	– 0.135**	– 0.151*	– 0.131*
	(0.101)	(0.077)	(0.076)	(0.067)	(0.076)	(0.066)
ΔPre	– 0.033	– 0.042*	– 0.046**	– 0.048**	– 0.049**	– 0.051**
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Poor × ΔTemp		– 1.484***	– 1.181**		– 1.306***	
		(0.403)	(0.451)		(0.434)	
Poor × $(\Delta\text{Temp})^2$		0.182	0.207		0.175	
		(0.343)	(0.323)		(0.340)	
Hot × ΔTemp			– 0.694	– 0.611		
			(0.447)	(0.425)		
Hot × $(\Delta\text{Temp})^2$			0.017	0.090		
			(0.430)	(0.440)		
Poor_2 × ΔTemp				– 1.421***		– 1.507***
				(0.407)		(0.407)
Poor_2 × $(\Delta\text{Temp})^2$				0.094		0.088
				(0.346)		(0.353)
Hot_2 × ΔTemp					– 1.051**	– 0.980**
					(0.479)	(0.473)
Hot_2 × $(\Delta\text{Temp})^2$					0.081	0.127
					(0.621)	(0.629)
_cons	1.439***	1.355***	1.294***	1.284***	1.298***	1.287***
	(0.324)	(0.325)	(0.307)	(0.307)	(0.307)	(0.307)
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	0.128	0.130	0.129	0.130
AIC	14750.611	14728.335	14724.544	14719.561	14722.997	14717.998
Total effect in poor countries		– 1.523***	– 1.132**	– 1.332***	– 1.307***	– 1.464***
		(0.406)	(0.497)	(0.443)	(0.452)	(0.420)
Total effect in hot countries			– 0.648	– 0.522	– 1.048**	– 0.929**
			(0.400)	(0.387)	(0.465)	(0.464)

All specifications include country FE and Region × 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 °C. 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 4 Checking for non-linearity of temperature impacts—temperature bins

Dependent variable: annual TFP growth rate	(1)	(2)	(4)	(5)
ΔTemp	0.884*** (0.177)	– 5.113** (2.464)		
Avg. temp. × ΔTemp	– 0.110*** (0.018)	– 0.059** (0.022)		
ΔPre	– 0.051** (0.023)	– 0.049** (0.023)	– 0.051** (0.023)	– 0.051** (0.023)
Avg. GDP per capita × ΔTemp		0.601** (0.245)		
Cold × ΔTemp			0.028** (0.012)	– 0.198 (0.234)
Mild × ΔTemp			– 0.060** (0.029)	– 0.614** (0.293)
Warm × ΔTemp			– 0.062*** (0.022)	– 0.229 (0.210)
Hot × ΔTemp			– 0.082*** (0.016)	– 0.233** (0.089)
Cold × ΔTemp × Avg. GDP per capita				0.024 (0.025)
Mild × ΔTemp				0.063* (0.032)
Warm × ΔTemp				0.021 (0.024)
Hot × ΔTemp				0.019* (0.011)
_cons	1.258*** (0.314)	1.248*** (0.322)	1.237*** (0.312)	1.236*** (0.331)
N	2760	2760	2760	2760
R^2	0.215	0.217	0.216	0.218
Adj. R^2	0.129	0.131	0.129	0.130
AIC	14723.915	14719.631	14723.828	14716.536

All specifications include country FE and Region × Time FE. Avg. Temp. is country average temperature. Avg. GDP per capita is country average GDP per capita. Cold, Mild, Warm and Hot are dummies capturing average temperature quartiles

Standard errors are in parentheses and are clustered at the country level. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

come 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 5 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",[17] approximately $14,900 per person per year for countries not classified as "hot",[18] and approximately $25,600 per person per year for the sample as a whole[19] (see Figs. 2, 3 and 4 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,

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

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

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

Table 5 Specifications with GDP per capita and Polity 2

Dependent variable: annual TFP growth rate	(1)	(2)
ΔTemp	– 5.065** (1.921)	– 0.518 (0.318)
ΔPre	– 0.046** (0.022)	– 0.050** (0.022)
Poor × ΔTemp		– 0.823** (0.328)
Polity 2 × ΔTemp		0.062* (0.032)
Polity 2		– 0.012 (0.034)
GDP_percap	– 0.216 (0.689)	
GDP × ΔTemp	0.532*** (0.195)	
Hot × ΔTemp	– 0.675 (0.454)	
_cons	3.158 (6.143)	1.441*** (0.404)
N	2760	2705
R^2	0.214	0.224
Adj. R^2	0.127	0.136
AIC	14355.504	6698.196
Total effect in poor countries		– 1.342*** (0.336)

All specifications include country FE and Region × 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 °C. 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

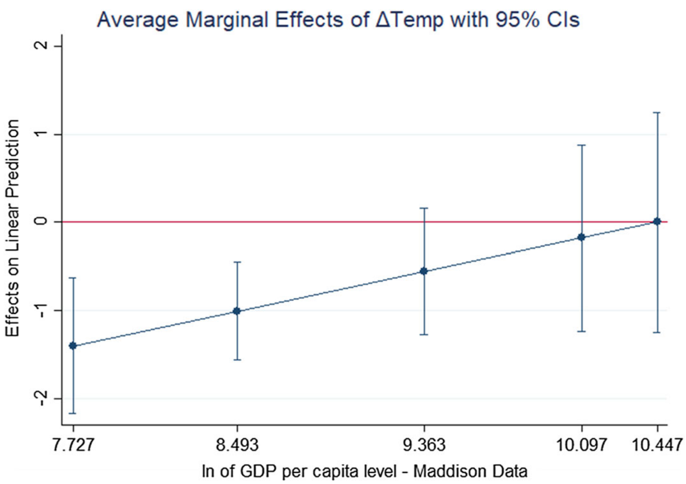

Fig. 2 Marginal effect of ΔTemp at different GDP per capita levels—hot = 1

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, Polity 2 (‘Polity IV Project’ 2014). We added this interaction because it could be the case that negative impacts come not through being a poor

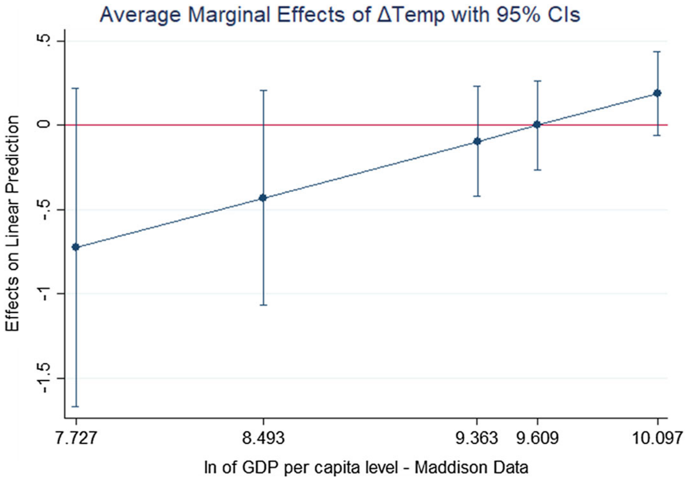

Fig. 3 Marginal effect of ΔTemp at different GDP per capita levels—hot = 0

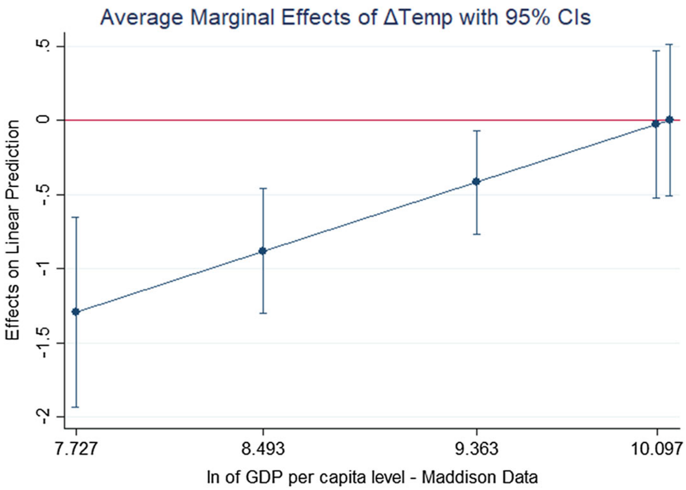

Fig. 4 Marginal effect of ΔTemp at different GDP per capita levels—whole sample

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 et al. 2001; Diamond 1999; Easterly and Levine 2003; Gallup et al. 1999), the institution hypothesis is one of the two main currents (the other being the geography hypothesis). Institutions are considered by many (Acemoglu et al. 2001; Easterly and Levine 2003; Rodrik et al. 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 Polity 2 as a measure of institutions. Polity 2 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 5 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 Polity 2 has a positive effect on the TFP growth rate, but this is not enough to justify a rethinking of our main conclusion.

6.3 Differences in the Composition of TFP

We find a negative effect of weather shocks on total factor productivity growth, but only in poor countries. Results from the previous section suggest the reason for this pattern is the development, rather than institutional, gap between rich and poor countries. Such gap must also entail heterogeneity in the composition of TFP which makes TFP growth vulnerable to temperature shocks 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 6 shows the results for the baseline sample:[20] 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 Sect. 7, 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 et al. 2012; Heal and Park 2015; Niemelä et al. 2002; Sudarshan and Tewari 2013).

In sum, the pattern of heterogeneity in impacts is due to the differences in levels of development—including institutional quality, access to markets, capital and technology, health care and education—and in the composition of total factor productivity, which make poor countries more vulnerable to temperature shocks compared to rich ones.

7 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 °C per year. There were positive and negative shocks to the annual temperature but the positive shocks were, on average, 0.012 °C larger. This means that, on average, negative shocks to the annual TFP growth rate were 0.012 °C/year * 1.523 (cf. Table 2, Column (2)) = 0.018% (SE = 0.005%) per year larger than positive shocks.

[20] Cf. Table A.24 in Web Appendix (3) for the alternative sample.

Table 6 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** (0.227)	− 0.068 (0.159)	0.037 (0.164)	0.095 (0.131)	− 0.027 (0.155)	0.037 (0.131)
ΔPre	− 0.037 (0.025)	− 0.047* (0.024)	− 0.052** (0.024)	− 0.054** (0.024)	− 0.054** (0.024)	− 0.056** (0.024)
Poor × ΔTemp		− 1.559*** (0.412)	− 1.197** (0.481)		− 1.366*** (0.448)	
Hot × ΔTemp			− 0.831* (0.466)	− 0.717 (0.434)		
Poor_2 × ΔTemp				− 1.522*** (0.421)		− 1.644*** (0.411)
Hot_2 × ΔTemp					− 1.133** (0.503)	− 1.036** (0.498)
_cons	2.535*** (0.515)	2.454*** (0.518)	2.383*** (0.511)	2.374*** (0.514)	2.395*** (0.507)	2.381*** (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*** (0.405)	− 1.160** (0.526)	− 1.427*** (0.455)	− 1.394*** (0.457)	− 1.607*** (0.414)
Total effect in hot countries			− 0.794* (0.416)	− 0.621 (0.395)	− 1.161** (0.501)	− 0.999* (0.503)

All specifications include country FE and Region × 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 °C. 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. *$p<0.10$, **$p<0.05$, ***$p<0.01$

The 21st century could see an additional global warming of 0.3–4.8 °C[21] (IPCC 2013). To make projections on the impacts of future climate change, we incorporated in our main dataset data on country-specific warming in the future period 2071–2095 compared to the reference period 1980–2004. These data represent the average projected warming for Representative Concentration Pathway (RCP) 8.5 (the business-as-usual scenario) for each country across all global climate models included in the Coupled Model Intercomparison Project, Phase 5 (CMIP5), upon which the IPCC's Fifth Assessment Report was based.[22]

[21] Given that the standard deviation for annual 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.

[22] The data (for both temperature and precipitation change) were downloaded from: http://regclim.coas.oregonstate.edu/visualization/gccv/cmip5-global-climate-changeviewer/index.html.

These projections were used in conjunction with the benchmark estimates from Column (2) in Table 2 to predict the impact of future warming on TFP growth. Average warming by the end of the century for countries in our sample is 3.912 °C, and there is no heterogeneity in warming between rich and poor countries.

The results predict that, by the year 2095, climate change will entail a decrease of approximately 3 percentage points in TFP growth, on average, compared to a scenario without climate change. However, this aggregate prediction hides a sharp heterogeneity: TFP growth in poor countries will suffer from a reduction of 5.96%, compared to a decrease of only 0.11% in rich countries. If past relationships will continue to hold, and excluding both intensification and adaptation, annual TFP growth rate in poor countries could be reduced by about 0.06% per year. Over almost a 100 years, total factor productivity in poor countries would be 5.30% below where it would be without climate change. This is an upper bound, as we estimated the short-run semi-elasticity rather than the long-run one. This extrapolation is not immune to concerns about external validity.

In the worst case scenario, annual TFP growth in poor countries would be lowered by about 0.06% 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 1.523*(4.9/200) = 0.04%,[23] roughly five times lower and, importantly, *only* for poor countries.

Similarly, Moyer et al. (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 and 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 0.05%, an order of magnitude lower than 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 (2018) shows, it is widely accepted that poor countries will be the ones who will suffer the most from climate change impacts. This work confirms and reinforces this view, by detecting dynamic effects from temperature shocks, and their persistence over time, only in poor countries. Additionally, as explained in Inklaar and Timmer (2013), Keller (2004), Griffith et al. (2004), TFP growth as a determinant of long-run economic growth is more important in poor countries than in rich ones.

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

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).

8 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 et al. (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 et al. (2015), who found large aggregate 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 Eq. (1), but directly through Eq. (4).

Conversely, Dell et al. (2012) could not explicitly show the presence of growth effects.

Interestingly, we also detect empirical evidence for persistence of impacts in poor countries, where the negative impacts of temperature shocks on TFP growth are not absorbed in the short run and cumulate over time.

However, a number of limits and *caveats* for this work also need to be made clear. First: sample size and data quality. Both our samples only include less than 70 countries (60 and 68, respectively). Although together they account for a large share of world GDP and population, sample size is indeed reduced. As for 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 et al. 2013, 2015; Inklaar and 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. Unfortunately, to the best of our knowledge there is no availability of other TFP datasets at the country level covering such a long timespan. Weather data as well notably suffer from measurement error and different data quality in different countries. However, the issue of measurement error is at least partially 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 et al. 2014). In other words climate, as emphasized by Auffhammer et al. (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 only 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.

Such an intensification of impacts may well change the picture we depicted, both quantitatively and qualitatively.

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 et al. (2014) and Tol (2018), 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. Particularly, our analysis should be repeated with TFP data by country, year, and industry—data which are, to the best of our knowledge, not yet available.

Sixth, estimates of TFP may be biased by adaptation to climate change. If a country diverts investment from productive capital to defensive capital (e.g., seawalls), then this would register as a drop in total factor productivity. Defensive investment may be more likely after hot weather. Since temperature is autocorrelated, this would bias our estimates. There are no international data on defensive investment, let alone defensive investment to protect against weather shocks and climate change. We therefore cannot estimate the size of this bias. We suspect, however, that this bias is small as few countries have invested heavily in adaptive capacity.

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.

References

Acemoglu D, Johnson S, Robinson JA (2001) The colonial origins of comparative development: an empirical investigation. Am Econ Rev 91(5):1369–1401

Alsan M (2014) The effect of the tsetse fly on African development. Am Econ Rev 105(1):382–410

Andersen TB, Dalgaard C-J, Selaya P (2016) Climate and the emergence of global income differences. Rev Econ Stud 83:1334–1363

Anthoff D, Tol RS, Yohe GW (2009) Risk aversion, time preference, and the social cost of carbon. Environ Res Lett 4(2):024002

Auffhammer M, Hsiang SM, Schlenker W, Sobel A (2013) Using weather data and climate model output in economic analyses of climate change. Rev Environ Econ Policy 7:181–198

Balk, D et al (2004) Center for International Earth Science Information Network (CIESIN), Columbia University; International Food Policy Research Institute (IFPRI), the World Bank Centro Internacional de Agricultura Tropical (CIAT), 2004. Global Rural-Urban Mapping Project (GRUMP), Palisades, NY: CIESIN, Columbia University. http://sedac.ciesin.columbia.edu/gp

Bansal R, Ochoa M (2011) Temperature, aggregate risk, and expected return*s*. NBER Working Paper No. 17575

Bigano A, Hamilton JM, Tol RSJ (2006) The impact of climate on holiday destination choice. Clim Change 76(3–4):389–406

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

Cachon G, Gallino S, Olivares M (2012) Severe weather and automobile assembly productivity. Columbia Business School Research Paper, (12/37)

Colmer J (2017). Weather, labour reallocation, and industrial production: evidence from India. Unpublished Manuscript

Conley TG (1999) GMM estimation with cross sectional dependence. J Econom 92(1):1–45

CRU (2016) Climatic Research Unit, University of East Anglia. Retrieved 9 July 2016 from http://www.cru.uea.ac.uk/data

Dell M, Jones BF, Olken BA (2012) Temperature shocks and economic growth: evidence from the last half century. Am Econ J Macroecon 4(3):66–95

Dell M, Jones BF, Olken BA (2014) What do we learn from the weather? The new climate–economy literature. J Econ Lit 52(3):740–798

Diamond J (1999) Guns, germs, and steel: the fates of human societies. WW Norton & Company, New York

Dietz S, Stern N (2015) Endogenous growth, convexity of damage and climate risk: how Nordhaus' framework supports deep cuts in carbon emissions. Econ J 125(583):574–620

Driscoll JC, Kraay AC (1998) Consistent covariance matrix estimation with spatially dependent panel data. Rev Econ Stat 80(4):549–560

Easterly W, Levine R (2003) Tropics, germs, and crops: how endowments influence economic development. J Monet Econ 50(1):3–39

Fankhauser S, Tol RS (2005) On climate change and economic growth. Resour Energy Econ 27(1):1–17

Feenstra RC, Inklaar R, Timmer M (2013) PWT 8.0—a user guide. Groningen Growth and Development Centre, University of Groningen

Feenstra RC, Inklaar R, Timmer MP (2015) The next generation of the Penn World Table. Am Econ Rev 105(10):3150–3182

Gallup JL, Sachs JD, Mellinger AD (1999) Geography and economic development. Int Reg Sci Rev 22(2):179–232

Gillingham K, Nordhaus WD, Anthoff D, Blanford G, Bosetti V, Christensen P, McJeon H, Reilly J, Sztorc P (2015). Modeling uncertainty in climate change: a multi-model comparison. NBER Working Paper No. 21637

Griffith R, Redding S, Van Reenen J (2004) Mapping the two faces of R&D: productivity growth in a panel of OECD industries. Rev Econ Stat 86(4):883–895

Hallegatte S (2005) The long time scales of the climate–economy feedback and the climatic cost of growth. Environ Model Assess 10(4):277–289

Harris RD, Tzavalis E (1999) Inference for unit roots in dynamic panels where the time dimension is fixed. J Econom 91(2):201–226

Heal G, Park J (2015) Goldilocks economies? Temperature stress and the direct impacts of climate change. NBER Working Paper No. 21119

Hope C (2006) The marginal impact of CO_2 from PAGE2002: an integrated assessment model incorporating the IPCC's five reasons for concern. Integr Assess 6(1):19–56

Hsiang SM, Jina AS (2014) The causal effect of environmental catastrophe on long-run economic growth: Evidence from 6700 cyclones. NBER Working Paper No. 20352

Huntington E (1922) Civilization and climate. Yale University Press, New Haven

Im KS, Pesaran MH, Shin Y (2003) Testing for unit roots in heterogeneous panels. J Econom 115(1):53–74

Inklaar R, Timmer M (2013) Capital, labor and TFP in PWT8.0. University of Groningen (Unpublished)

Keller W (2004) International technology diffusion. J Econ Lit 42(3):752–782

Lemoine D, Kapnick S (2015) A top-down approach to projecting market impacts of climate change. Nat Clim Change 6(5):514–519

Maddison Project (2016). Retrieved 9 July 2016 from http://www.ggdc.net/maddison/maddison-project/home.html

Matsuura K, Willmott C (2007) Terrestrial air temperature and precipitation: 1900–2006. Gridded monthly time series. Version 1.01. University of Delaware. http://climate.geog.udel.edu/~climate/

Moore FC, Diaz DB (2015) Temperature impacts on economic growth warrant stringent mitigation policy. Nat Clim Change 5(2):127–131

Moyer EJ, Woolley MD, Glotter M, Weisbach DA (2014) Climate impacts on economic growth as drivers of uncertainty in the social cost of carbon. J Legal Stud 43(2):401–425

Mundlak Y (1978) On the pooling of time series and cross section data. Econom J Econom Soc 46:69–85

Niemelä R, Hannula M, Rautio S, Reijula K, Railio J (2002) The effect of air temperature on labour productivity in call centres—a case study. Energy Build 34(8):759–764

Nordhaus WD (1991) To slow or not to slow: the economics of the greenhouse effect. Econ J 101(407):920–937

Nordhaus WD (2007) A review of the Stern review on the economics of climate change. J Econ Lit 45(3):686–702

Nordhaus WD (2008). A question of balance: economic modeling of global warming. Yale University Press, New Haven. Retrieved, 1(10), 2011

Olsson O, Hibbs DA (2005) Biogeography and long-run economic development. Eur Econ Rev 49(4):909–938

Pindyck RS (2012) Uncertain outcomes and climate change policy. J Environ Econ Manag 63(3):289–303

Pindyck RS (2013) Climate change policy: What do the models tell us? J Econ Lit 51(3):860–872

Polity IV Project (2014) Retrieved 9 July 2016 from http://www.systemicpeace.org/polity/polity4.htm

PWT 8.1 (2016) | PWT Releases | University of Groningen. Retrieved 9 July 2016 from http://www.rug.nl/research/ggdc/data/pwt/pwt-8.1

Rodrik D, Subramanian A, Trebbi F (2004) Institutions rule: the primacy of institutions over geography and integration in economic development. J Econ Growth 9(2):131–165

Schelling TC (1992) Some economics of global warming. Am Econ Rev 82(1):1–14

Solow RM (1956) A contribution to the theory of economic growth. Q J Econ 70:65–94

Stern N (2013) The structure of economic modeling of the potential impacts of climate change: grafting gross underestimation of risk onto already narrow science models. J Econ Lit 51(3):838–859

Stern NH, Peters S, Bakhshi V, Bowen A, Cameron C, Catovsky S et al (2006) Stern review: the economics of climate change, vol 30. Cambridge University Press, Cambridge

Stocker TF, Qin D, Plattner GK, Tignor M, Allen SK, Boschung J, Nauels A, Xia Y, Bex V, Midgley PM (2013) IPCC, 2013: climate change 2013: the physical science basis. Contribution of working group I to the fifth assessment report of the intergovernmental panel on climate change. Cambridge Univ. Press, Cambridge, New York

Sudarshan A, Tewari M (2013) The economic impacts of temperature on industrial productivity: evidence from indian manufacturing. ICRIER Working Paper No. 278

Tol RSJ (2018) Economic impacts of climate change. Rev Environ Econ Policy 12(1):4–25

Tol RS, Yohe GW et al (2006) A review of the Stern Review. World Econ Henley Thames 7(4):233

Weitzman ML (2009) On modeling and interpreting the economics of catastrophic climate change. Rev Econ Stat 91(1):1–19

Weitzman ML (2010) What is the‘damages function’ for global warming—And what difference might it make? Clim Change Econ 1(01):57–69

Weitzman ML (2011) Fat-tailed uncertainty in the economics of catastrophic climate change. Rev Environ Econ Policy 5(2):275–292

Zhang P, Deschenes O, Meng K, Zhang J (2018) Temperature effects on productivity and factor reallocation: evidence from a half million chinese manufacturing plants. J Environ Econ Manag 88(2018):1–17