The impact of weather on economic growth and its production factors

Martin Henseler[*] Ingmar Schumacher[†]

April 2019

Forthcoming in the journal *Climatic Change*

[*]Partnership for Economic Policy (PEP), Nairobi, Kenya, Thünen Institute of Rural Studies, Bundesallee 64, D-38116 Braunschweig, Germany, and EDEHN - Equipe d'Economie Le Havre Normandie, Universite du Havre, 25 Rue Philippe Lebon, F-76600 Le Havre, France

[†]IPAG Business School, 184 boulevard Saint-Germain, 75006 Paris, France. Tel.: +352 621264575. E-mail: ingmar.schumacher@ipag.fr.

We thank Marshall Burke, Michael Oppenheimer and Gary Yohe for comments on a previous version, as well as three anonymous referees and the editor for their valuable suggestions that helped improve the article.

Abstract

We investigate the influence of weather on countries' GDP and their main components of production, namely total factor productivity, capital stock and employment. Our panel dataset includes annual observations on 103 countries for the period 1961-2010. We find that the main impacts of weather occur through temperature and drive the growth in GDP. Our results show that, for higher levels of temperature, the poor countries are much more strongly impacted than the rich countries. We also find that weather impacts per capita GDP growth through all its factors of production, with the largest impacts on total factor productivity. Again it is the poor countries for which these impacts are the strongest. The findings provide empirical evidence for negative impacts of temperature on economic growth and its factors of production, and furthermore point towards climate change as an important driver of international inequality.

Keywords: weather variations, economic growth, employment, capital stock, total factor productivity.
JEL classification: Q54.

1 Introduction

The evidence for human-induced climate change is now overwhelming (Pachauri et al. 2014). The recent IPCC (2018) report describes how even a 1.5°C warming over pre-industrial levels may lead to increased coastal flooding, extreme weather events or significant risks to ecosystems. There is clear evidence that climate change impacts are already occurring at more regional and locals levels (Zivin and Neidell 2014, Schlenker and Roberts 2009, Parry 2007, Dell et al. 2014, IPCC 2014, Belasen and Polachek 2008, Strobl 2011). The big question is, however, whether we can identify an impact from climatic variables also at the aggregate level. If we can show that climatic conditions have an aggregate impact, then this gives some indication that the current belief of limited aggregate impacts at low levels of warming should potentially be contested. Our objective in this article is, thus, to study whether it is possible to identify impacts from climatic conditions on GDP and its factors of production at the country level throughout the recent period.

There is already evidence for country-level impacts from climatic conditions on economic growth. Burke et al. (2015) find that temperature affects economic growth in a non-linear way. In particular, they obtain an inversely u-shaped relationship between temperature and economic growth, with a maximum at 13°C. Economic growth is significantly negatively affected for temperatures above and below this level, and this relationship is robust across many different specifications. The authors then conclude that, if no mitigation actions will be undertaken, the expected temperature increase will reduce average income levels around the world by roughly a quarter towards the end of this century. This article is a major step forward in showing that the microeconomic impacts of climate change (Zivin and Neidell 2014, Schlenker and Roberts 2009, Parry 2007, Dell et al. 2014, IPCC 2014, Belasen and Polachek 2008, Strobl 2011) can also be found at the macroeconomic level. Our intention here is to go a step further by investigating whether temperature also affects GDP's main components of production (total factor productivity, capital stock and employment), as they are the drivers of economic growth. This would allow us to understand for which components of production we need to search for climatic impacts at the macroeconomic level (Dell et al. 2012, Burke et al. 2015). Knowing which components of production are consistently impacted at the macroeconomic level would then help in identifying priorities for both researchers and policy makers in order to support design and evaluation of effective climate change policies. For example, if temperature were to predominantly affect capital, then it would make sense to direct policy towards disaster prevention and adaptation (Pielke Jr 1998, Fankhauser and Tol 2005). This would also warrant a more stringent climate policy (Dietz and Stern 2015). However, if temperature were to mostly affect total factor productivity, then subsidies towards R&D would be useful (Nordhaus 2010). If instead temperature were to reduce labor (e.g. via disease spread), then climate policy may want to concern itself mostly with health issues (Mariani et al. 2010). For example, it has been shown that undernourishment due to temperature shocks leads to lower levels of human capital and health (Jensen 2000). Clearly, knowing the precise channel through which temperature impacts GDP growth allows a better allocation of a region's limited finances to minimize potential short and long-term effects.

We undertake this study by combining Penn World Table data with the climatic data used in Burke et al. (2015). We obtain an (unbalanced) panel dataset that includes data on 103 countries for the period 1961-2010, yielding a maximum of 6,496 country-year specific observations. Our results show that temperature affects GDP growth in an inversely u-shaped way. However, in contrast to Burke et al. (2015), we find that poor countries are more strongly impacted by temperature than rich countries. Our results differ as we focus more on the very poor countries[1]. Our main focus, though, is on assessing whether there is an impact from weather conditions onto the drivers of GDP, namely the factors of production. Overall we find that all factors of production are impacted by temperature, but most strongly for poor countries.

In particular, we find clear evidence that TFP growth is negatively impacted by higher temperature levels, with increasing temperature resulting in a reduction of TFP growth from its maximum level. This result is in line with a recent article by Letta and Tol (2018),

[1] If we use a similar cutoff point as Burke et al. (2015) in order to distinguish between rich and poor then we also do not find a difference between rich and poor countries.

who also study the impact of climatic variables on TFP growth. Instead of looking at the weather variables in levels they study the change. One of their main conclusions, in line with Dell et al. (2012), is that TFP growth is linearly affected by temperature changes. While their results are not exactly comparable to ours (as we look at levels), we find some evidence for a non-linear relationship, with high temperatures inducing a strongly negative impact on TFP growth. Our result is very much in line with some of the firm-level results in e.g. Zhang et al. (2018).

When we look at the impact of temperature on the growth of capital stocks, we find that higher temperature levels tend to have a negative impact on the growth of capital. However, we show that this result is driven by the sample of poor countries. In fact, only poor countries are consistently negatively affected by higher temperature levels, while the results for the rich sample are less significant. This is in line with Fankhauser et al. (2016) who emphasize that it is difficult for poor countries to raise climate-resilient investments and that access to finance is an issue in developing countries that are more strongly impacted by climatic changes. Thus, to our knowledge, this is the first article showing that weather variables do have a significantly negative impact on the growth of capital stocks in poor countries.

Our results for employment growth are very much in line with those for the growth on capital stocks. We find that higher temperature levels have a significantly negative impact on employment growth in poor countries, while there is little evidence for an impact in rich countries. We suggest that this result arises as the poor countries tend to be more agriculturally-dependent and variations in weather or higher levels of temperature affects most strongly the agricultural sector. While there exists a growing number of articles that have linked weather conditions to employment at local or regional levels (Desbureaux and Rodella 2019, Greene 2018), to out knowledge this is the first article which thus provides evidence of a negative impact of weather on both employment and capital in poor countries at the national level.

In section 2 we first describe the data, in section 3 the methodology, in section 4 we present our results and in section 5 we derive several implications and provide further discussions. Section 6 concludes with some main take-away points.

2 The data

We use the climatic variables temperature and precipitation from the dataset in Burke et al. (2015). This spatially-disaggregated data comes from Matsuura and Willmott (2012) and Burke et al. (2015) weighted the observations by population density using Gridded Population of the World data (CIESIN n.d.), and then aggregated them to the country-year level.

For our economic data we rely on the Penn World Tables 8.1 (Feenstra et al. 2015). As the measure for economic output we use real GDP per capita at constant 2005 national prices. Economists tend to assume a production function whose factors, when combined, yields economic output. These factors of production are capital stock, TFP and employment[2]. Since all these variables are available in the Penn World Tables, for consistency reasons, this allows us to identify impacts at the level of the production components within the same dataset. We use capital stock at constant prices (rkna), which is estimated based on the Perpetual Inventory Method and includes only fixed and reproducible assets summing to gross fixed capital accumulation from the National Accounts. Also, this measure of capital stocks accounts for differences in the composition of asset over time and across countries.

TFP measures how much output a specific measure of input produces. The measure of TFP that we use is Total Factor Productivity at constant national prices (rtfpna), normalized for each country to one in 2005. It is calculated based on real GDP data at constant prices from national accounts relative to a Törnqvist quantity index of factor inputs.

The measure of employment (emp) developed in the Penn World Tables calculates the

[2]Another factor of production is human capital. However, there is no annual data on human capital, but instead it is only available at five year intervals and then gets interpolated to the annual level. Thus, this variable would not be useful for our purposes.

total number of persons engaged in productive activity. This does not only include employees and employers, but also self-employed, unpaid family workers engaged in economic activity, apprentices and military personnel.

Together with the climatic variables our dataset consists of an (unbalanced) panel dataset that includes data on 103 countries for the period 1961-2010, which yields a maximum of 6,496 country-year specific observations for the growth rate of capital, and a minimum of 4,280 country-year observations for the growth rate of TFP. To differentiate between the rich and poor sample we utilize a dummy which takes the value of one if a country's per capita income (PPP adjusted) was below the global 20^{th} percentile in 1980, and a zero otherwise.[3] Table 2 presents the main summary statistics. In Table 1 we highlight those countries in bold which belong to the sample of poor countries. This table also includes more detailed information on the equation-specific country-year sample. Table 3 shows little correlation between our three components of production at the aggregate level. We thus refrain from investigating the relationship between our dependent variables in a system of equations,[4] but instead we study the equations separately.

3 The methodology

We assume that GDP is a function of climatic variables, proxied by temperature and precipitation. However, GDP represents the final product that arises from combining capital (rkna), labor (emp) and total factor productivity (rtfpna)[5]. Though the exact combination of the three components of production is a matter of discussion among economists,

[3]We also run robustness on this cutoff point.

[4]Also, in this kind of approach a system of equations faces many problems. Firstly, issues result from the convergence due to the large amount of dummies and trend variables. Secondly, a system of equations that uses the same independent variables would yield the same empirical results as running each regression separately. Thus, in order to make a system of equations meaningful one would need to use restrictions. Suitable restrictions can only be obtained from a deep model. This is an entirely different, although viable and complementary, approach.

[5]In general, total factor productivity represents our 'measure of ignorance', and it comprises as diverse factors such as technological progress or structural changes.

they have in common that they impact GDP positively. Our hypothesis is that climatic conditions affect each of the three components of production in a similar way as GDP. In order to investigate this we run an OLS regression with both temperature and precipitation being exogenous, non-linear determinants of GDP growth. We add time and country dummies, and country-specific trends. Using i as the country index and t the time index, we then denote $y_{it} = \{\text{rkna}_{it}, \text{rtfpna}_{it}, \text{emp}_{it}\}$, T_{it} is temperature and P_{it} is precipitation, μ_i the country-level fixed effects, v_t the time fixed effects, $\theta_{i1}t + \theta_{i2}t^2$ controls for country-specific, non-linear time trends, and ϵ_{it} is the error. Thus we run the following regressions

$$\Delta \ln y_{it} = \alpha_1 T_{it} + \alpha_2 T_{it}^2 + \beta_1 P_{it} + \beta_2 P_{it}^2 + \mu_i + v_t + \theta_{i1}t + \theta_{i2}t^2 + \epsilon_{it}. \tag{1}$$

By relying on this approach, we control for country-fixed effects, for shocks common to all countries, and for non-linear country-specific trends. We allow each country to have its own level and non-linear trend in growth, with the impact of the climatic variables being identified from within-country deviations from this trend. This approach has been shown to be a superior approach to e.g. autoregressive models. This approach is in line with Burke et al. (2015), who provides a more detailed account of the robustness of this approach. The results of these regressions are presented in Figures 1a to 1d and Table 4.

Based on the discussions in e.g. Parry (2007), we also investigate whether or not poorer countries tend to be impacted stronger by climatic variations. By introducing a dummy variable we control for heterogeneous impacts among rich and poor countries. We then interact this dummy with the climatic variables to understand whether or not the non-linear impact of the climatic variables is different between rich and poor countries. Since our preferred threshold (the 20^{th} percentile) is chosen arbitrarily, we study how different levels of this threshold (10%, 20%, 30% and 50%) impact the results. We present the results for the 20^{th} percentile cutoff in Figures 2a to 2d and Table 5.

4 The results

Our main results are that temperature impacts GDP per capita growth non-linearly in an inversely u-shaped relation (Figure 1a). These results are thus in line with Burke et al. (2015). A slight difference is that while Burke et al. (2015) found the turning point at around 13°C we find a slightly lower turning point at roughly 10°C.[6] Furthermore, we cannot confirm that at low temperature levels the impact on per capita GDP growth is statistically significantly different from zero. A part of this difference can be explained by the usage of the actual growth rate instead of the log-differences[7], while the rest of the difference is likely due to the difference in the sample. Importantly, our results from the differentiated impacts between rich and poor are qualitatively different compared to Burke et al. (2015). In particular, they concluded that rich countries are less affected by temperature, but they do not find that the response from the rich sample is different from the poor one. Burke et al. (2015) differentiate the rich and poor countries at a cut-off point at the median of world GDP distribution in 1980, while we separate the samples with a cut-off point at 20^{th} percentile (and run robustness on this cutoff point). Using the same cutoff point between rich and poor as Burke et al. (2015) (median of world GDP distribution in 1980) confirms their result (see online Appendix). However, decreasing the cutoff point increases the difference between how rich and poor countries respond to temperature. Hence, the somewhat arbitrary cutoff point (median GDP level) used in Burke et al. (2015) seems to mask the differences between rich and poor as there are still too many rich in the poor sample. We, therefore, conclude that GDP growth in (sufficiently) poor countries tends to be negatively affected at high temperature levels.

At the aggregate level we find little evidence of a negative impact on TFP for low temperatures. For higher temperatures we confirm a strong impact on TFP growth which

[6]The quantitative differences in the results might be caused by different datasets used. Burke et al. (2015) used data from the World Development Indicators and from the Penn World Tables as robustness. Our results do not fully correspond to theirs from the Penn World Tables as they used a previous version of this dataset.

[7]Using log-differences as Burke et al. (2015) instead of the actual growth rate increases the turning point to 11°C.

is statistically significantly different from zero (Figure 1b). This result is similar to Letta and Tol (2018), who instead of looking at the impact of temperature levels, study changes in temperature. We find a turning point which is with roughly 9°C slightly lower than that for GDP growth. The negative effects of higher temperature levels are stronger in the poor countries than in the rich countries for cutoff points below the 30^{th} percentile (see Figure 2b and online Appendix). For cutoffs below the 20^{th} percentile the confidence intervals for the poor sample are very large at low temperature levels, resulting from few observations. However, the overall shape is comparable to the poor country sample with larger cutoff percentiles and thus more observations. Thus, our results indicate that poor countries with a GDP less than the 30^{th} percentile have a stronger impact on TFP growth. This result can be interpreted as the poor countries being less capable to protect their production against the influence of increasing temperature (e.g. implementing adaptation policies or applying adaptive technologies).

We find only weak evidence for the hypothesis that temperature impacts the growth of capital stocks at the aggregate level (Figure 1b). Nevertheless, when splitting the sample into poor and rich we conclude that higher temperature impacts the growth of capital stocks of the poor. We find little[8] impact from temperature on the capital stock of the rich countries (Figure 2b). Thus, it seems that the poor countries are less able to accumulate capital stocks at elevated temperatures, which is likely due to the fact that a larger share of their production comes from agriculture. Higher levels of temperature diminish agricultural physical and monetary yields which causes lower savings and thus less capital accumulation. In addition, our results suggest that the rich sample still has a concave relationship between capital growth and temperature, but for the poor sample this seems more linear, or even a marginally convex. The heterogeneous impact of temperature on capital stocks between the rich and poor samples is then more in line with the earlier work by Dell et al. (2012) and gets masked if one only looks at the full sample.

There is only weak evidence for an effect of temperature on the growth rate of employ-

[8] We are cautious to interpret the seemingly negative relationship between temperature and the growth of capital stock for very low levels of temperature levels, since this finding results from few observations.

ment at the aggregate level (Figure 1c). However, if we distinguish between the effects on rich and poor countries then we find statistically significant differences between the response of employment growth. Employment growth in poor countries is significantly stronger affected by temperature than in the rich countries.

Thus, overall we find that mainly temperature drives GDP growth with a clearly heterogeneous effect across countries. In particular, poor countries with a GDP below the 30^{th} percentile in the world GDP distribution tend to negatively impacted at high temperature levels across all factors of production, while for rich countries only TFP growth is negatively impacted at elevated temperatures.

4.1 Robustness

We undertook a variety of robustness test, all the results of which are available in the online Appendix. To test for serial correlation we obtain the residuals from each regression and run regressions with the residuals as the dependent variable. Its lags and all previous regressors serve as independent variables. The lagged residuals turn out to be statistically significantly different from zero for each regression (see the lagged residual statistics at bottom of the regression Supplementary Tables 1 to 4), which indicates the presence of serial correlation. The cluster-robust standard errors that we used in the main regressions (clustered at the country level) should take care of this problem. In addition, we use the Newey-West estimator with different lag lengths for robustness. The results in Supplementary Tables 1-4 with the Newey-West estimator show that our OLS results are robust to considering autocorrelation of various lengths (1 and 2 lags). In fact, the standard errors tend to be even smaller if we use two lags.

One important question is whether or not temperature shocks produce temporary or persistent effects on GDP growth. In Supplementary Table 5 and 6 in the online Appendix we introduce one and two annual lags of the weather variables. We do not find these lags to be statistically significantly different from zero[9]. However, the signs of these lags tend

[9]The only exception being a marginally significant temperature lag at t-2, while the t-1 lag is not

to be the opposite from the contemporaneous impact of the respective variable, indicating a slight dampening effect over time. Our results are thus in line with Dell et al. (2012) who found that lags of temperature are not important determinants of economic growth, suggesting that the cumulative impacts of temperature is similar to its contemporaneous impact.

Sometimes the use of a dummy in order to separate impacts masks the difference between two groups. Thus, instead of relying on a dummy to separate the marginal impact of temperature between rich and poor countries we also split the sample into rich and poor countries and then run the regressions separately (Supplementary Figures 7 and 8 in the online Appendix). We find no significant difference to our results with the dummy.

An additional robustness exercise that we undertook is the Fisher randomization test (Edgington and Onghena 2007). The idea is that, in case the errors were not normally distributed, the t-statistic would yield a biased result. One way to relax this assumption on the normality of errors is then to randomize the variable of interest (in our case temperature) over the years within each cluster (i.e. country). The results in this case should be spurious. If we thus randomly allocate temperature, re-run the regressions, and do this many times, we should obtain approximately a normal distribution of the t-statistics of temperature, which contains mostly spurious results. Our t-statistic from the main regression should then be in tails of the resulting distribution if the results are not to be spurious. We used 5000 draws with replacement for our Fisher randomization test. The results (Supplementary Figures 8 and 9 in the online Appendix) show that our t-statistics fall within the tails of the distribution, thus indicating that the results are not spurious.

To furthermore avoid spurious results we check for a potential cointegration relationship between the dependent variables and our climatic variables by running several unit root tests on our climatic variables. If we find that the climatic variables do not have a unit root then we do not need to investigate a potential cointegration relationship. For

significant.

the panel data unit root tests we resort to the Dickey-Fuller, Philipps-Perron and the Im-Pesaran-Shin tests. The H0 assumes that all panels are non-stationary, the H1 assumes that at least one panel is stationary. We run these tests with various lag lengths, demeaned series, time trends, etc. In all cases we can say that it is highly unlikely that our climatic variables are non-stationary (p-values less than 0.0001). Thus we do not need to search for a cointegration relationship between the dependent variables and our climatic variables.

We check the errors and drop potential outliers from the regressions based on visual inspection, which yields the criterion $|e_{it}| < .2$. Dropping these larger residuals reduces the sample by 26 observations which are spread across all countries. The tests indicate that the results for GDP and TFP are not fully robust. For these variables the impact of temperature seems to flatten out, with only high levels of temperature have a negative impact that is statistically significantly different from zero (Supplementary Table 1 and 4, regressions 4). We also run the regressions for capital and employment at the sample of TFP. While the signs of the overall impact of temperature on capital and employment remain unchanged, we lose some statistical significance. Nevertheless, the overall shape and significance levels of the non-linear impact from temperature on these dependent variables remains.

As an additional robustness exercise we use anomalies[10] of the climatic variables instead of levels (Supplementary Figures 5 and 6 in the online Appendix). Anomalies are a better measure of deviations from long-term climatic conditions which avoids potential scale effects (Barrios et al. 2010). Furthermore, the standard deviation corrects for historic variations and takes into account that some countries naturally possess a larger variability in their climatic variables. Overall, the shape of the figures representing the impact of temperature on GDP and TFP is similar for absolute temperature levels and anomalies and for the impact on aggregated and disaggregated samples (compare Figures 1a,b with

[10] Anomalies are calculated as $x^a_{it} = (x_{it} - \bar{x}_i)/sd(x)_i$, where x^a_{it} is the anomaly of the climatic variable x in country i at time t, x_{it} is the country-time specific observation, $\bar{x}_i$ is the country-specific average of x_{it} over the time horizon, and $sd(x)_i$ is the country-specific standard deviation of the variable during the sample.

Supplementary Figures 5 a,b and Figures 2a,b with Supplementary Figures 6 a,b). However, the figures presenting the impact of temperature on capital growth and employment differ for the absolute temperature levels and the temperature anomalies. In contrast to Figures 1c and Figures 2c (the figures displaying the impact of average temperature on capital growth) the figures representing the impact of temperature anomalies indicate only weak evidence for the effect on the aggregated sample (compare Figure 1c and Supplementary Figure 6c) and no difference between the impact on rich and poor countries (compare Figure 2c and Supplementary Figure 6c). For the impact on employment Supplementary Figures 5d and 6d (the figures representing the impact of temperature anomaly) indicate a clearly convex relation for the effect on the aggregated sample (compare Figure 1d and Supplementary Figures 6d) and for the both rich and poor sample (compare Figure 2d and Supplementary Figure 8d). Thus, the climate variable of temperature anomaly seems to provide clearer evidence than the influence of absolute temperatures. The likely reason is that deviations from long-term trends more strongly affect the agricultural sector, and hence agriculturally-dependent countries. Thus those countries whose employment is mainly in the agricultural sector are then driving our results for employment growth. In contrast, temperature anomalies do not help us in identifying an impact on the growth of capital, which could mean that within-country variations in the level of temperature are more important for capital stock growth than normalized deviations from long-term trends. For example, many of the poor countries became significantly warmer during the past years which should be associated with a stronger decline in their agricultural production and thus savings. As a consequence, we would expect this decline in savings to diminish the growth of capital.

5 Implications and discussions

One of our main results in this article is that GDP per capita growth is negatively affected by temperature, and this result is mainly driven by the group of poor countries in the world. This stands in contrast to the result in Burke et al. (2015), who find no statistically significant difference in the impact of temperature between the rich and poor countries. As suggested above, the difference in results derives from the fact that we look more closely at the very poor countries (those below the 20^{th} percentile in the world income distribution). This implies that, if our efforts to curb carbon emissions remain limited, then the expected increase in temperature is likely to widen the gap between the rich and poor countries. This widening gap may lead to important impacts on future migration flows (Marchiori et al. 2017), on conflicts (Withagen 2014), and raises important policy questions about inequality (Roberts 2001). One relevant result in the literature is that efforts to curb emissions should be much larger if the poor regions suffer disproportionately more than the rich (Dennig et al. 2015). The empirical results that we present here do point in this direction.

In a first-best world we obviously know that the most efficient climate policy would be taxes or quotas. In this case, it is clearly not (that) important which factors of production are impacted by temperature changes, as the market will fully internalize the climate externality. However, we do not live in a first-best world and efficient carbon pricing is unlikely, at least in the near future. Hence the market is not going to fully internalize the climate externality and thus there are going to be unpriced damages. It is in this case that a policy maker would find it informative where the damages are likely to occur in order to be able to adapt to, or prevent, further impacts.

In order to understand where these impacts from temperature on per capita GDP growth come from, we look at the factors of production that drive GDP growth, namely TFP, capital stocks and employment. We find evidence that temperature impacts all components of GDP, but does so predominantly only in the poor countries. Our results then suggest that the attention of climate policy should be extended to TFP, capital stocks and employment in poor countries.[11] We now provide some microfounded arguments that support this impact on TFP, capital stock and employment, and also discuss why the impacts turn out to be more important for the poor than for the rich countries.

[11] How precisely climate policy then should address the various impacts is more a microeconomic question that a macroeconomic study such as ours cannot answer.

One of our results is that temperature affects TFP growth negatively across the whole sample in an inversely u-shaped way, with the poor countries nevertheless being more strongly impacted than the rich countries. This result is also in line with the one in Letta and Tol (2018), who study the same sample as we do but look at the impact of temperature changes instead of the level. In contrast to us, Letta and Tol (2018) do not find an important non-linear relationship between temperature and TFP growth. Interestingly, in a microeconometric study on data from half a million Chinese manufacturing plants over the years 1998-2007, Zhang et al. (2018) find an inverted u-shaped relationship between temperature and TFP. This thus confirms our finding of an inverted u-shaped relationship also at the firm level.

There is evidence that temperature shocks are a key driver of adverse impacts on productivity in the agricultural sector. Letta et al. (2018) show that consumption growth in poor households in Tanzania is negatively impacted by temperature shocks, the transmission channel being the impact from temperature on total factor productivity in the agriculture sector. The impact of climate change on agricultural yields and productivity is furthermore well-documented in the vast literature of the IPCC (Pachauri et al. 2014). We will, therefore not discuss this channel more deeply here but simply acknowledge that our more aggregated results show that poor countries, which are known to be predominantly agriculturally-dependent, see significant impacts on total factor productivity for higher temperature levels.

If we look at historic data, then we observe that the growth rate of GDP tends to be best explained by the growth rate of TFP (Easterly and Levine 2001). This is the case as TFP explains most of the differences in GDP across countries and over time (Acemoglu 2008). The reason for this is that it encompasses everything that impacts GDP but capital and labor, such as institutions or productivity. In addition, Temple (1999) argues that uncertainty is an important factor in explaining differences in TFP and thus in TFP growth. The IPCC report has shown that further climatic changes will also lead to more weather (both temperature and precipitation) extremes (pp. 7ff Pachauri et al. 2014). This increase in weather extremes will therefore drive up uncertainty surrounding the impact from climatic changes, and thus higher temperature, on production. Hence investors (or farmers), faced with a larger uncertainty, may not always take the most profitable option when choosing 'their right mix of production factors, may reduce necessary investments, and receive less capital, all of which potentially harms productivity growth. A similar explanation would apply for the relationship between temperature and investments in capital.

Empirical results in the literature explain why temperature may have little effect on employment (Foster et al. 2001). Employment tends to be very mobile and this makes wages very responsive to the demand side conditions. Thus, whenever the marginal product of labor changes, for example due to reductions in TFP from worsened climatic conditions, then the wage rates will adjust quickly. Thus, the demand for labor will remain approximately constant. However, this should only be the case if, for example, the demand for labor in a large enough urban sector can compensate for the reduction in employment in the rural sector. This is unlikely to be the case for poor agriculturally-dependent countries. Thus our results show a stronger impact of temperature variations on the agriculturally-dependent poor sample. One article that supports this channel with a microeconomic analysis is Desbureaux and Rodella (2019). The authors, using monthly labour force surveys from 78 cities in Latin America, find that droughts decrease the probability of being employed, employment duration, as well as income, with the main impacts in the informal sector. The reason for the main impacts being in the informal sector is that the regions investigated in Desbureaux and Rodella (2019) have strong social laws that protect workers in the formal sector, which therefore do not see (significant) reductions in income and employment. This could also be the reason for which we see such a strong impact in our poor sample, but little impact of temperature in our rich sample.

Another reason why we see a limited impact from temperature on production factors in rich countries is that richer countries tend to have better property rights and access to credit compared to poor countries. Hisali et al. (2011) used the 2005/06 Uganda national household survey in order to identify adaptation strategies. The authors found that factors that reduce adaptation capabilities to droughts as e.g. a result of higher temperatures reduces, among others, access to credit and the security of land tenure. This should thus bear a direct impact on the ability of poor households to save, on the employment opportunities, but also on the ability to invest. With lower access to credit it is clear that poor countries will see lower investments not only in capital stocks but also in productivity-enhancing technology that may furthermore shelter them from the adverse impacts of climate change (Di Falco et al. 2011, Villavicencio et al. 2013).

6 Conclusions

In this article we investigate if weather conditions proxied by temperature and precipitation affect GDP growth as well as its factors of production, namely total factor productivity, capital stocks and employment. We use a large panel dataset of 103 countries over the period 1961-2010, yielding a maximum of 6,496 country-year specific observations.

We find that GDP per capita growth is affected negatively by higher temperatures, and that this result is mostly driven by the poor countries in our dataset. This result is slightly different compared to those in Burke et al. (2015), who also investigate the impact of weather variables on the growth of GDP per capita, but who do not find a statistically significantly different impact between the rich and poor countries as they use a cutoff (median of the world income distribution) that masks this difference by including too many sufficiently rich countries in the group of the poor countries.

Our more detailed analysis shows that the factors of production in the poor countries are statistically significantly stronger impacted by higher temperature levels than those in the rich countries. Our results for TFP are in line with Letta and Tol (2018), who use a somewhat different setup compared to ours, as well as the firm-level results in Zhang et al. (2018), while our results for capital stocks and employment growth are novel.

As Dell et al. (2009) show, temperature can explain 23% of cross-country income differences. We have shown that these differences are likely to arise in the poor countries, which are subject to larger temperatures and thus have lower TFP, employment and capital growth rates. These growth differences obviously accentuate cross-country income differences over time. Even larger population growth in the poor regions is unlikely to compensate for these shortfalls. If already a quarter of cross-country income differences can be explained by temperature, then increasing climatic changes coupled with stronger impacts on all factors of production in the poor countries will increase these income differences during the future years. Thus, our results indicate that policy makers and researchers have to pay additional attention to the role of climate change onto the factors of production in poor countries for the evolution of inequality over time.

An important open question is in how far these climate impacts are going to change over the course of the next century. As Tol (2018) has recently argued, the poor countries are going to be the ones who suffer the most from climate change. Furthermore, as we have seen, per capita GDP growth and the growth of the factors of production tend to be mostly impacted in poor countries. During the next years, we do however expect most of these poor countries to grow. The question then is as to what will change during the growth path in order for them to avoid the negative impacts from climate change. One likely factor would be that they will be less agriculturally-dependent and thus be less affected by weather changes. Another factor would be that they would have the money to adapt their economy and needs better to the climatic changes. Future research should, therefore, more deeply assess as to what is the precise difference between the rich and the poor that makes the poor so much more prone to impacts from climate change.

References

Acemoglu, Daron, *Introduction to modern economic growth*, Princeton University Press, 2008.

Barrios, Salvador, Luisito Bertinelli, and Eric Strobl, "Trends in rainfall and economic growth in Africa: A neglected cause of the African growth tragedy," *The Review of Economics and Statistics*, 2010, *92* (2), 350–366.

Belasen, Ariel R and Solomon W Polachek, "How hurricanes affect wages and employment in local labor markets," *The American Economic Review*, 2008, *98* (2), 49–53.

Burke, Marshall, Solomon M Hsiang, and Edward Miguel, "Global non-linear effect of temperature on economic production," *Nature*, 2015.

CIESIN, I., "Gridded population of the world, Version 3."

Dell, M, B Jones, and B Olken, "Temperature and Income: Reconciling New Cross-Sectional and Panel Estimates," *American Economic Review Papers and Proceedings*, 2009, *99* (2), 198–204.

Dell, Melissa, Benjamin F Jones, and Benjamin A Olken, "Temperature shocks and economic growth: Evidence from the last half century," *American Economic Journal: Macroeconomics*, 2012, *4* (3), 66–95.

___, ___, and ___, "What do we learn from the weather? The new climate–economy literature," *Journal of Economic Literature*, 2014, *52* (3), 740–798.

Dennig, Francis, Mark B Budolfson, Marc Fleurbaey, Asher Siebert, and Robert H Socolow, "Inequality, climate impacts on the future poor, and carbon prices," *Proceedings of the National Academy of Sciences*, 2015, *112* (52), 15827–15832.

Desbureaux, Sebastien and Aude-Sophie Rodella, "Drought in the city: The economic impact of water scarcity in Latin American metropolitan areas.," *World Development*, 2019, *114*, 13 – 27.

Dietz, Simon and Nicholas Stern, "Endogenous growth, convexity of damage and climate risk: how Nordhaus' framework supports deep cuts in carbon emissions," *The Economic Journal*, 2015, *125* (583), 574–620.

Easterly, William and Ross Levine, "It's Not Factor Accumulation: Stylized Facts and Growth Models," *The World Bank Economic Review*, 2001, *15* (2), 177–219.

Edgington, Eugene and Patrick Onghena, *Randomization tests*, Chapman and Hall/CRC, 2007.

Falco, Salvatore Di, Marcella Veronesi, and Mahmud Yesuf, "Does Adaptation to Climate Change Provide Food Security? A Micro-Perspective from Ethiopia," *American Journal of Agricultural Economics*, 2011, *93* (3), 829–846.

Fankhauser, Sam, Aditi Sahni, Annie Savvas, and John Ward, "Where are the gaps in climate finance?," *Climate and Development*, 2016, *8* (3), 203–206.

Fankhauser, Samuel and Richard SJ Tol, "On climate change and economic growth," *Resource and Energy Economics*, 2005, *27* (1), 1–17.

Feenstra, Robert C, Robert Inklaar, and Marcel P Timmer, "The next generation of the Penn World Table," *The American Economic Review*, 2015, *105* (10), 3150–3182.

Foster, Lucia, John C Haltiwanger, and Cornell John Krizan, "Aggregate productivity growth: lessons from microeconomic evidence," in "New developments in productivity analysis," University of Chicago Press, 2001, pp. 303–372.

Greene, Christina, "Broadening understandings of drought ‚Äì The climate vulnerability of farmworkers and rural communities in California (USA)," *Environmental Science & Policy*, 2018, *89*, 283 – 291.

Hisali, Eria, Patrick Birungi, and Faisal Buyinza, "Adaptation to climate change in Uganda: Evidence from micro level data," *Global Environmental Change*, 2011, *21* (4), 1245 – 1261.

IPCC, *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, IPCC, Geneva, Switzerland, 151 pp, 2014.

——, "Special Report on Global Warming of 1.5°C," 2018.

Jensen, Robert, "Agricultural volatility and investments in children," *American Economic Review*, 2000, *90* (2), 399–404.

Jr, Roger A Pielke, "Rethinking the role of adaptation in climate policy," *Global environmental change*, 1998, *8* (2), 159–170.

Letta, Marco and Richard S. J. Tol, "Weather, Climate and Total Factor Productivity," *Environmental and Resource Economics*, Jun 2018.

——, Pierluigi Montalbano, and Richard S.J. Tol, "Temperature shocks, short-term growth and poverty thresholds: Evidence from rural Tanzania," *World Development*, 2018, *112*, 13 – 32.

Marchiori, Luca, Jean-François Maystadt, and Ingmar Schumacher, "Is environmentally induced income variability a driver of human migration?," *Migration and Development*, 2017, *6* (1), 33–59.

Mariani, Fabio, Agustin Pérez-Barahona, and Natacha Raffin, "Life expectancy and the environment," *Journal of Economic Dynamics and Control*, 2010, *34* (4), 798–815.

Matsuura, K. and C. J. Willmott, "Terrestrial air temperature and precipitation: Monthly and annual time series (1900 - 2010) v 3.01," 2012.

Nordhaus, William D, "Modeling induced innovation in climate-change policy," in "Technological change and the environment," Routledge, 2010, pp. 188–215.

Pachauri, Rajendra K, Myles R Allen, Vicente R Barros, John Broome, Wolfgang Cramer, Renate Christ, John A Church, Leon Clarke, Qin Dahe, Purnamita Dasgupta et al., *Climate change 2014: synthesis report. Contribution of Working Groups I, II and III to the fifth assessment report of the Intergovernmental Panel on Climate Change*, IPCC, 2014.

Parry, Martin L, *Climate change 2007-impacts, adaptation and vulnerability: Working group II contribution to the fourth assessment report of the IPCC*, Vol. 4, Cambridge University Press, 2007.

Roberts, J. Timmons, "Global Inequality and Climate Change," *Society & Natural Resources*, 2001, *14* (6), 501–509.

Schlenker, Wolfram and Michael J Roberts, "Nonlinear temperature effects indicate severe damages to US crop yields under climate change," *Proceedings of the National Academy of sciences*, 2009, *106* (37), 15594–15598.

Strobl, Eric, "The economic growth impact of hurricanes: evidence from US coastal counties," *Review of Economics and Statistics*, 2011, *93* (2), 575–589.

Temple, Jonathan, "The New Growth Evidence," *Journal of Economic Literature*, 1999, *37* (1), 112–156.

Tol, Richard SJ, "The Economic Impacts of Climate Change," *Review of Environmental Economics and Policy*, 2018, *12* (1), 4–25.

Villavicencio, Xavier, Bruce A. McCarl, Ximing Wu, and Wallace E. Huffman, "Climate change influences on agricultural research productivity," *Climatic Change*, Aug 2013, *119* (3), 815–824.

Withagen, Cees, "The climate change, migration and conflict nexus," *Environment and development economics*, 2014, *19* (3), 324–327.

Zhang, Peng, Olivier Deschenes, Kyle Meng, and Junjie Zhang, "Temperature effects on productivity and factor reallocation: Evidence from a half million chinese manufacturing plants," *Journal of Environmental Economics and Management*, 2018, *88*, 1 – 17.

Zivin, Joshua Graff and Matthew Neidell, "Temperature and the allocation of time: Implications for climate change," *Journal of Labor Economics*, 2014, *32* (1), 1–26.

7 Appendix

Table 1: Overview of country-year observations

Country code	g(rkna)	g(emp)	g(tfpna)	Country code	g(rkna)	g(emp)	g(tfpna)
ARG, AUS, AUT, BEL, BOL, BRA, CAN, CHE, CHL, **CHN**, CRI, CYP, DEU, DNK, DOM, ECU, EGY, ESP, FIN, FRA, GBR, GRC, GTM, IND, IRL, IRN, ISL, ISR, ITA, JAM, JOR, JPN, KEN, KOR, LUX, MAR, MEX, MYS, NDL, NOR, NZL, PER, PHL, PRT, SWE, THA, TTO, TUR, URY, USA, VEN, ZAF, ZWE	50	50	50	BLZ, VCT	40	30	n.a.
BEN, MUS	50	30	30	HUN, SAU	40	40	40
BFA, **BGD**, COL, **ETH**, GHA, LKA, **MWI**, NGA, PAK, **UGA**, ZMB	50	50	n.a.	OMN, SDN	40	40	n.a.
GIN	50	30	n.a.	AGO, ALB, **KHM**, **VNM**	39	39	n.a.
HND, PRY	50	40	40	BGR, IRQ, KWT, POL, QAT	39	39	39
PAN	50	41	41	BRN, BTN, DJI, LBN, STP	39	30	n.a.
SLV	50	35	n.a.	**LAO**, MNG, SWZ	39	30	30
BDI, BWA,**CAF**, FJI, GAB, MTR, NAM, **RWA**, **SLE**, **TGO**	49	30	30	SUR	39	37	n.a.
CIV,CMR, IDN, **MOZ**, **NER**, SEN, TUN, **TZA**	49	49	49	GEO, TKM, UZB, YEM	20	20	n.a.
COG	49	30	50	KGZ, LVA, MDA, RUS, SVK, TJK, UKR	20	20	20
COM, **CPV**, **GMB**, GNB, **GNQ**, **LSO**, **NPL**, **TCD**	49	30	n.a.	ARM, CZE, EST, HRV, KAZ, LTU, SRB, SVN	19	19	19
MDG, **MLI**, SYR	49	49	n.a.	AZE, **BIH**, BLR, MKD	19	19	n.a.
LBR	46	30	n.a.	LKA	n.a.	n.a.	50
BHS	40	37	n.a.				
Total					6,496	5,923	4,280

Countries for the 20% cutoff point in our poor sample are in bold.

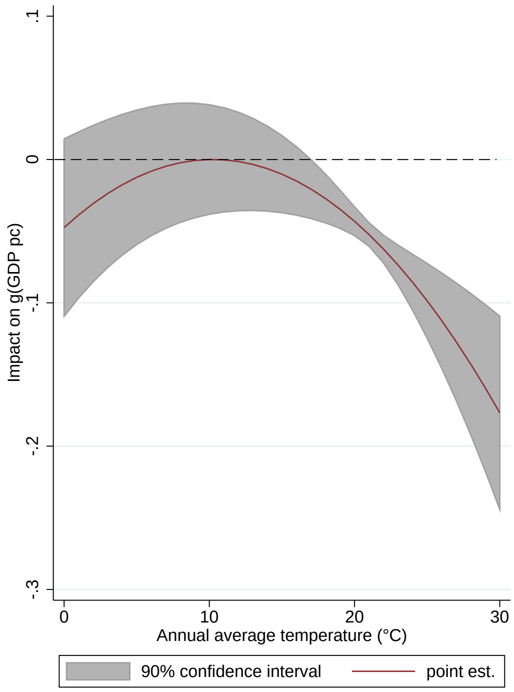
Table 2: Summary statistics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
g(GDPpc)	0.022	0.064	-0.671	0.926	7380
g(rkna)	0.043	0.038	-0.048	0.883	7380
g(rtfpna)	0.004	0.051	-0.661	0.526	4756
g(emp)	0.022	0.029	-0.213	0.338	6641
temperature	19.075	7.378	-6.49	29.61	7351
precipitation	1155.945	741.547	5.38	4877.74	7351
temp. anomaly	0	0.988	-3.094	3.7	6496
precip. anomaly	0	0.988	-4.139	4.748	6496
interact	0.212	0.409	0	1	8611

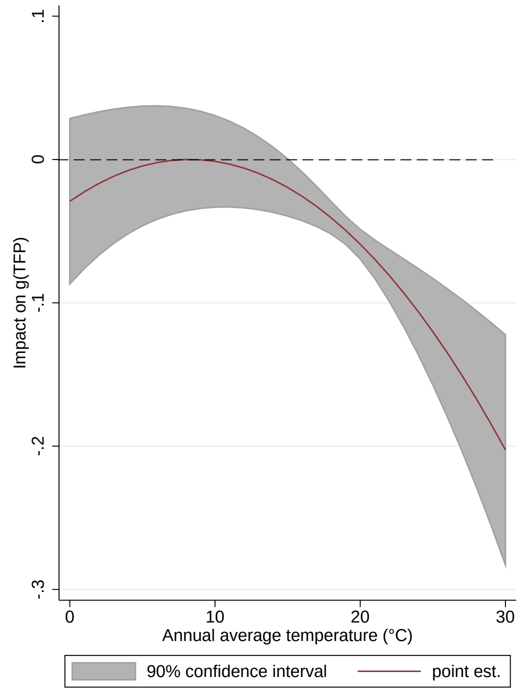
Table 3: Correlation table

	g(GDP)	g(rtfpna)	g(rkna)
g(rtfpna)	0.9028		
	(0.0000)		
g(rkna)	0.3201	-0.0033	
	(0.0000)	(0.8305)	
g(emp)	0.2245	-0.0901	0.1767
	(0.0000)	(0.0000)	(0.0000)

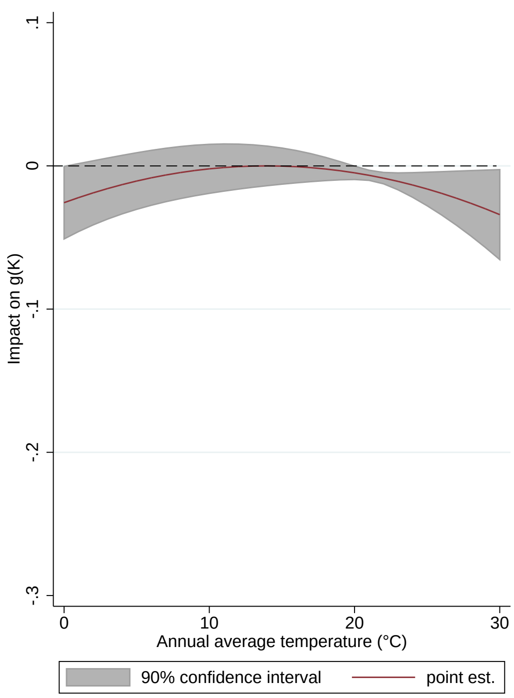
Numbers in brackets indicate the significance level (p-value) of the correlation. The sample is based on $g(rtfpna)$, but there are no changes if one considers the full samples for $g(rkna)$ and $g(emp)$.



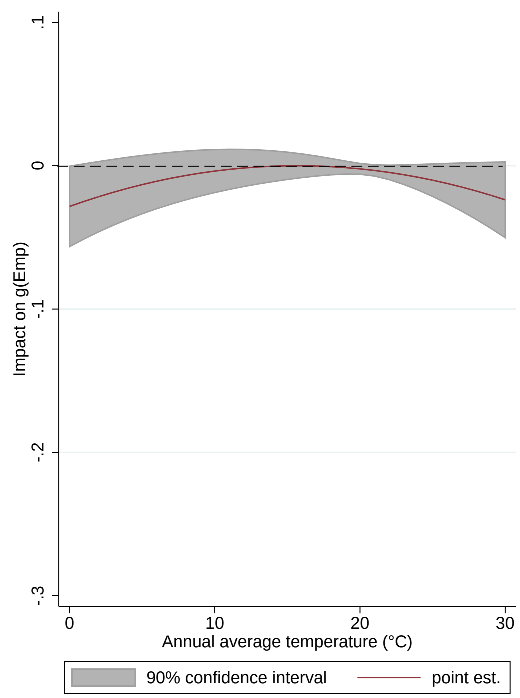
(a) g(GDPpc)



(b) g(rtfpna)



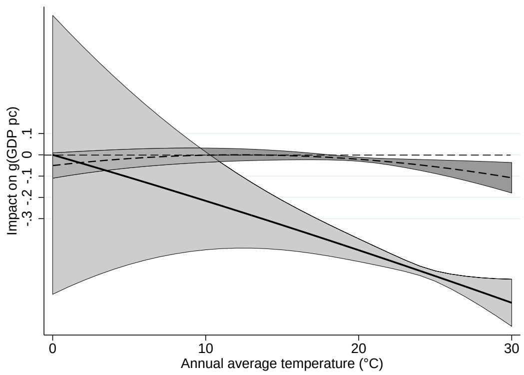
(c) g(rkna)



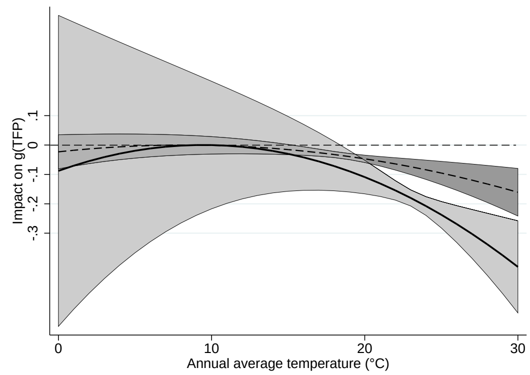
(d) g(emp)

Figure 1: Impacts of temperature on the growth rates of components of production in the full sample.

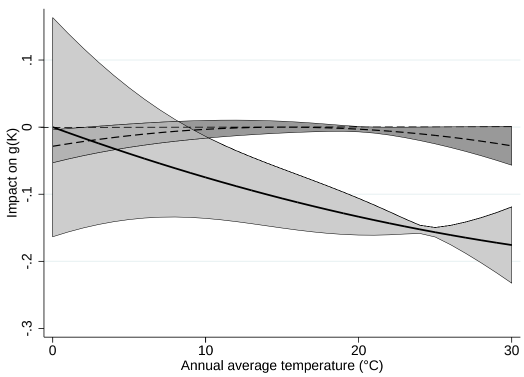
Gray region is 90% confidence interval, results are relative to optimum level.



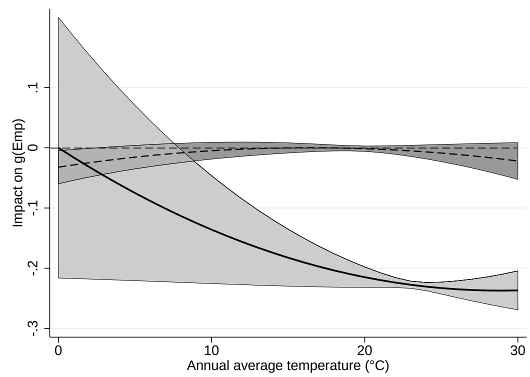
(a) g(GDPpc)



(b) g(TFP)



(c) g(K)



(d) g(E)

Figure 2: Impacts of temperature on the growth rates of the components of production, separated into rich and poor countries - cutoff is 20^{th} percentile.

The Light gray shaded region indicates the 90% confidence interval for the poor sample, the darker grey region the corresponding one for the rich sample, the dashed line is the average response from the rich sample, the thick black line the average response from the poor sample, results are relative to the optimum level.

Table 4: Main regression results

VARIABLES	(1) g(GDPpc)	(2) g(rkna)	(3) g(rtfpna)	(4) g(emp)
temperature	0.00928**	0.00368*	0.00707*	0.00362**
	(0.00418)	(0.00191)	(0.00406)	(0.00166)
temperature^2	-0.000453***	-0.000132*	-0.000428***	-0.000116**
	(0.000155)	(7.38e-05)	(0.000156)	(5.63e-05)
precipitation	1.70e-05	-2.17e-06	6.32e-06	-6.55e-06*
	(1.05e-05)	(4.02e-06)	(8.80e-06)	(3.84e-06)
precipitation^2	-3.45e-09	8.32e-10	-2.05e-10	3.70e-10
	(2.77e-09)	(1.14e-09)	(2.56e-09)	(1.11e-09)
+ the other controls (see text)				
Observations	6,496	6,496	4,280	5,923
R-squared	0.255	0.570	0.252	0.380

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Errors are robust standard errors and clustered at country level. All regressions are run with time dummies, country dummies, country-time dummies

Table 5: Main table, poor versus rich impacts (cutoff 20%)

VARIABLES	(1) g(GDP pc)	(2) g(K)	(3) g(TFP)	(4) g(Emp)
temperature	0.00828**	0.00378**	0.00560	0.00393**
	(0.00387)	(0.00171)	(0.00391)	(0.00173)
temperature*poor	-0.0209	-0.00831	0.0186	-0.0164*
	(0.0351)	(0.0106)	(0.0276)	(0.00976)
temperature^2	-0.000340**	-0.000125**	-0.000339**	-0.000119**
	(0.000144)	(6.20e-05)	(0.000147)	(6.03e-05)
temperature^2*poor	-7.71e-05	8.20e-05	-0.000984	0.000285
	(0.000796)	(0.000290)	(0.000667)	(0.000189)
precipitation	4.37e-06	-5.40e-06	-1.33e-06	-7.17e-06*
	(1.10e-05)	(4.36e-06)	(9.00e-06)	(4.15e-06)
precipitation*poor	7.08e-05**	6.03e-06	0.000185***	2.78e-06
	(3.16e-05)	(1.05e-05)	(5.52e-05)	(8.32e-06)
precipitation^2	-4.03e-10	1.01e-09	2.38e-09	5.31e-10
	(2.92e-09)	(1.18e-09)	(2.24e-09)	(1.17e-09)
precipitation^2*poor	-1.75e-08*	5.30e-10	-6.13e-08***	-2.18e-09
	(9.25e-09)	(3.47e-09)	(1.33e-08)	(2.92e-09)
+ the other controls (see text)				
Observations	6,397	6,397	4,230	5,824
R-squared	0.261	0.570	0.259	0.383

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Errors are robust standard errors and clustered at country level. All regressions are run with time dummies, country dummies, country-time dummies

The impact of weather on production factors
ONLINE APPENDIX

Martin Henseler* Ingmar Schumacher†

April 2019

*Partnership for Economic Policy (PEP), Nairobi, Kenya, Thünen Institute of Rural Studies, Bundesallee 64, D-38116 Braunschweig, Germany, and EDEHN - Equipe d'Economie Le Havre Normandie, Universite du Havre, 25 Rue Philippe Lebon, F-76600 Le Havre, France

†IPAG Business School, 184 boulevard Saint-Germain, 75006 Paris, France. Tel.: +352 621264575. E-mail: ingmar.schumacher@ipag.fr.

Supplementary Table 1: Robustness results for g(GDPpc)

Dependent variable: g(GDPpc)				
	(1)	(2)	(3)	(4)
VARIABLES	OLS	Newey lag(1)	Newey lag(2)	OLS (censored)
temperature	0.00928**	0.00928***	0.00928***	0.00454
	(0.00418)	(0.00327)	(0.00330)	(0.00311)
temperature^2	-0.000453***	-0.000453***	-0.000453***	-0.000254**
	(0.000155)	(0.000132)	(0.000130)	(0.000106)
precipitation	1.70e-05	1.70e-05*	1.70e-05*	1.37e-05
	(1.05e-05)	(9.74e-06)	(9.72e-06)	(8.63e-06)
precipitation^2	-3.45e-09	-3.45e-09	-3.45e-09	-2.09e-09
	(2.77e-09)	(2.39e-09)	(2.39e-09)	(2.09e-09)
+ the other controls (see text)				
Observations	6,496	6,496	6,496	6,431
R-squared	0.255			0.347
lagged resid coeff	0.101			
lagged resid p-val	0.0129			

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Errors are robust standard errors and clustered at country level. All regressions are run with time dummies, country dummies, country-time dummies

Supplementary Table 2: Robustness results for g(rtfpna)

Dependent variable: g(rtfpna)				
	(1)	(2)	(3)	(4)
VARIABLES	OLS	Newey lag(1)	Newey lag(2)	OLS (censored)
temperature	0.00707*	0.00707**	0.00707**	0.00355
	(0.00406)	(0.00331)	(0.00334)	(0.00339)
temperature^2	-0.000428***	-0.000428***	-0.000428***	-0.000260**
	(0.000156)	(0.000159)	(0.000154)	(0.000119)
precipitation	6.32e-06	6.32e-06	6.32e-06	9.44e-06
	(8.80e-06)	(9.83e-06)	(9.61e-06)	(8.61e-06)
precipitation^2	-2.05e-10	-2.05e-10	-2.05e-10	-2.88e-10
	(2.56e-09)	(2.35e-09)	(2.30e-09)	(2.17e-09)
+ the other controls (see text)				
Observations	4,280	4,280	4,280	4,254
R-squared	0.252			0.330
lagged resid coeff	0.0537			
lagged resid p-val	0.0159			

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Errors are robust standard errors and clustered at country level. All regressions are run with time dummies, country dummies, country-time dummies

Supplementary Table 3: Robustness results for g(rkna)

Dependent variable: g(rkna)				
	(1)	(2)	(3)	(4)
VARIABLES	OLS	Newey lag(1)	Newey lag(2)	OLS (censored)
temperature	0.00368*	0.00368**	0.00368**	0.00349**
	(0.00191)	(0.00150)	(0.00153)	(0.00156)
temperature^2	-0.000132*	-0.000132**	-0.000132**	-0.000123*
	(7.38e-05)	(5.42e-05)	(5.55e-05)	(6.42e-05)
precipitation	-2.17e-06	-2.17e-06	-2.17e-06	-1.47e-06
	(4.02e-06)	(3.90e-06)	(3.87e-06)	(3.82e-06)
precipitation^2	8.32e-10	8.32e-10	8.32e-10	2.55e-10
	(1.14e-09)	(9.70e-10)	(9.66e-10)	(9.89e-10)
+ the other controls (see text)				
Observations	6,496	6,496	6,496	6,487
R-squared	0.570			0.641
lagged resid coeff	0.642			
lagged resid p-val	0.00986			

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Errors are robust standard errors and clustered at country level. All regressions are run with time dummies, country dummies, country-time dummies

Supplementary Table 4: Robustness results for g(emp)

Dependent variable: g(emp)				
	(1)	(2)	(3)	(4)
VARIABLES	OLS	Newey lag(1)	Newey lag(2)	OLS (censored)
temperature	0.00362**	0.00362**	0.00362**	0.00325**
	(0.00166)	(0.00157)	(0.00162)	(0.00162)
temperature^2	-0.000116**	-0.000116**	-0.000116**	-9.59e-05*
	(5.63e-05)	(5.71e-05)	(5.84e-05)	(5.49e-05)
precipitation	-6.55e-06*	-6.55e-06	-6.55e-06	-6.52e-06*
	(3.84e-06)	(4.41e-06)	(4.36e-06)	(3.88e-06)
precipitation^2	3.70e-10	3.70e-10	3.70e-10	4.46e-10
	(1.11e-09)	(1.22e-09)	(1.21e-09)	(1.12e-09)
+ the other controls (see text)				
Observations	5,923	5,923	5,923	5,920
R-squared	0.380			0.390
lagged resid coeff	0.235			
lagged resid p-val	0.0135			

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Errors are robust standard errors and clustered at country level. All regressions are run with time dummies, country dummies, country-time dummies

Supplementary Table 5: Robustness results: one lag in climate variables

VARIABLES	(1) g(GDP pc)	(2) g(K)	(3) g(TFP)	(4) g(Emp)
temperature_t	0.00991**	0.00373**	0.00705*	0.00382**
	(0.00407)	(0.00175)	(0.00390)	(0.00156)
temperature_{t-1}	-0.00306	-0.00127	-0.000104	-0.00174
	(0.00461)	(0.00183)	(0.00439)	(0.00161)
$\text{temperature}_t{}^2$	-0.000482***	-0.000118*	-0.000444***	-0.000113**
	(0.000147)	(6.61e-05)	(0.000150)	(5.26e-05)
$\text{temperature}^2_{t-1}$	0.000140	-3.68e-05	0.000116	2.57e-06
	(0.000159)	(5.89e-05)	(0.000185)	(6.75e-05)
precipitation_t	1.62e-05	-1.75e-06	4.18e-06	-6.35e-06*
	(1.06e-05)	(3.81e-06)	(8.90e-06)	(3.70e-06)
$\text{precipitation}_{t-1}$	-1.42e-06	1.25e-06	1.82e-05*	8.25e-07
	(1.14e-05)	(4.24e-06)	(1.08e-05)	(5.21e-06)
precipitation^2_t	-3.19e-09	7.89e-10	0	3.80e-10
	(2.79e-09)	(1.06e-09)	(2.61e-09)	(1.06e-09)
$\text{precipitation}^2_{t-1}$	-1.09e-09	-1.26e-10	-3.52e-09	-3.31e-10
	(2.88e-09)	(1.14e-09)	(2.39e-09)	(1.26e-09)
Constant	0.0254	0.0310	-0.0321	0.0380
	(0.0579)	(0.0294)	(0.0469)	(0.0304)
Observations	6,496	6,496	4,280	5,923
R-squared	0.256	0.570	0.253	0.381

Robust standard errors in parentheses

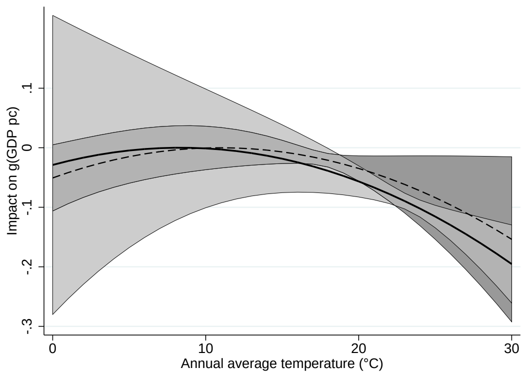
*** p<0.01, ** p<0.05, * p<0.1

Supplementary Table 6: Robustness results: two lags in climate variables

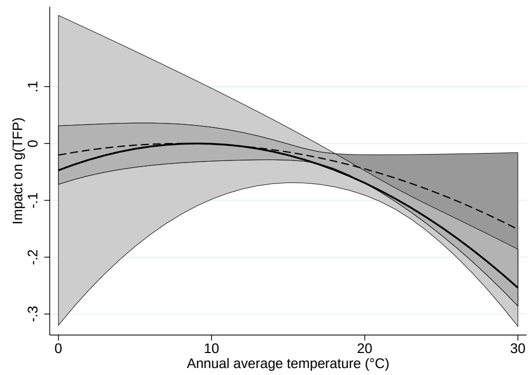
	(1)	(2)	(3)	(4)
VARIABLES	g(GDP pc)	g(K)	g(TFP)	g(Emp)
temperature_t	0.00830**	0.00301*	0.00585	0.00326**
	(0.00397)	(0.00179)	(0.00362)	(0.00165)
temperature_{t-1}	-0.00200	-0.00205	0.00217	-0.00212
	(0.00414)	(0.00185)	(0.00418)	(0.00158)
temperature_{t-2}	-0.00569	0.000565	-0.00300	-0.00261
	(0.00390)	(0.00161)	(0.00315)	(0.00195)
temperature^2_t	-0.000451***	-0.000107	-0.000392***	-0.000102*
	(0.000144)	(6.89e-05)	(0.000140)	(5.55e-05)
$\text{temperature}^2_{t-1}$	9.88e-05	-7.54e-06	3.55e-05	1.83e-05
	(0.000156)	(5.50e-05)	(0.000192)	(6.69e-05)
$\text{temperature}^2_{t-2}$	0.000196*	-3.86e-05	0.000191	2.60e-05
	(0.000117)	(5.70e-05)	(0.000116)	(6.86e-05)
precipitation_t	2.07e-05*	-2.22e-06	1.04e-05	-6.22e-06
	(1.09e-05)	(3.88e-06)	(9.11e-06)	(3.81e-06)
$\text{precipitation}_{t-1}$	-1.27e-06	1.73e-06	1.59e-05	1.56e-06
	(1.18e-05)	(4.08e-06)	(1.11e-05)	(5.17e-06)
$\text{precipitation}_{t-2}$	-1.15e-05	-5.19e-06	5.84e-06	-2.97e-06
	(1.02e-05)	(4.28e-06)	(1.13e-05)	(5.05e-06)
precipitation^2_t	-4.03e-09	9.02e-10	-1.14e-09	3.35e-10
	(2.90e-09)	(1.08e-09)	(2.68e-09)	(1.07e-09)
$\text{precipitation}^2_{t-1}$	-1.36e-09	-1.59e-10	-3.26e-09	-6.06e-10
	(2.99e-09)	(1.06e-09)	(2.55e-09)	(1.21e-09)
$\text{precipitation}^2_{t-2}$	3.90e-09	1.19e-09	-1.17e-09	1.84e-09
	(2.54e-09)	(1.13e-09)	(2.99e-09)	(1.60e-09)
Constant	0.0843	0.0385	-0.0496	0.107***
	(0.0819)	(0.0366)	(0.0588)	(0.0400)
Observations	6,363	6,363	4,203	5,824
R-squared	0.251	0.572	0.241	0.382

Robust standard errors in parentheses

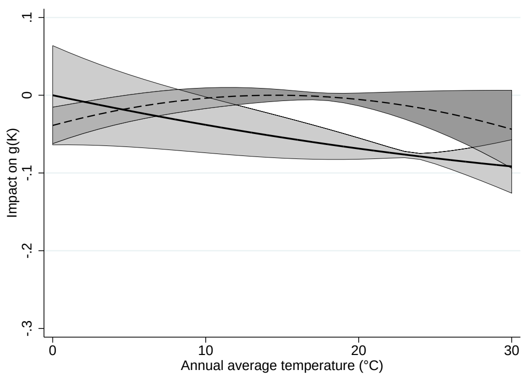
*** p<0.01, ** p<0.05, * p<0.1



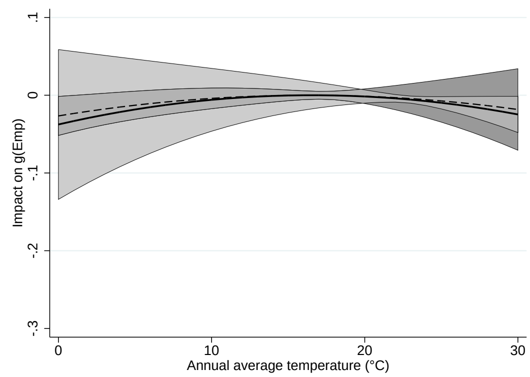
(a) g(GDPpc)



(b) g(rtfpna)



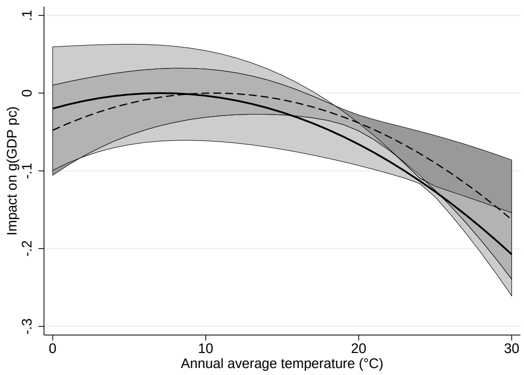
(c) g(rkna)



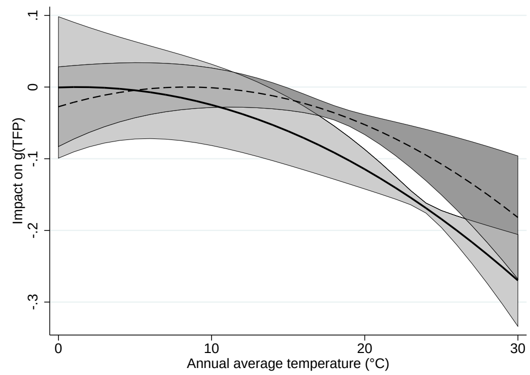
(d) g(emp)

Supplementary Figure 1: Impacts of temperature on the growth rates of components of production - cutoff 50^{th} percentile

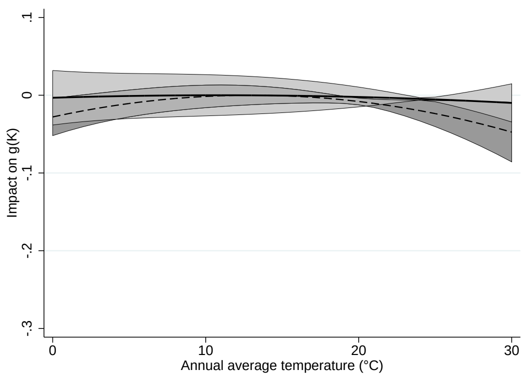
The Light gray shaded region indicates the 90% confidence interval for poor sample, darker grey the corresponding one for the rich sample, dashed line is average response from rich sample, thick black line the average response from poor sample, results are relative to optimum level.



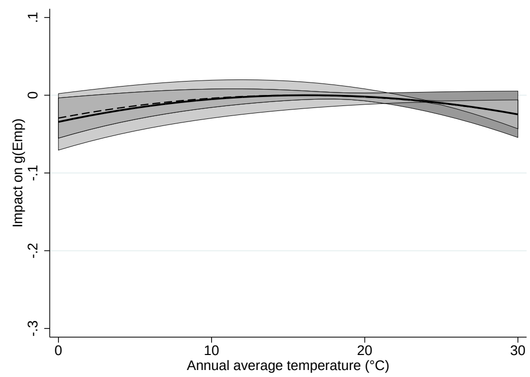
(a) g(GDPpc)



(b) g(rtfpna)



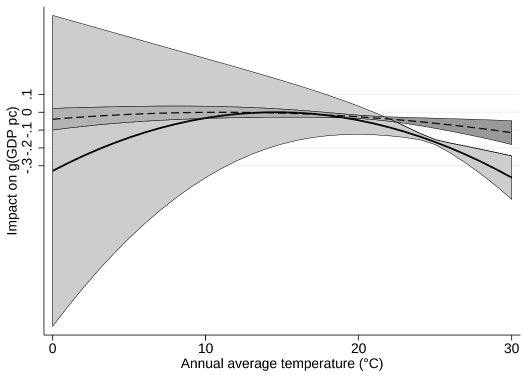
(c) g(rkna)



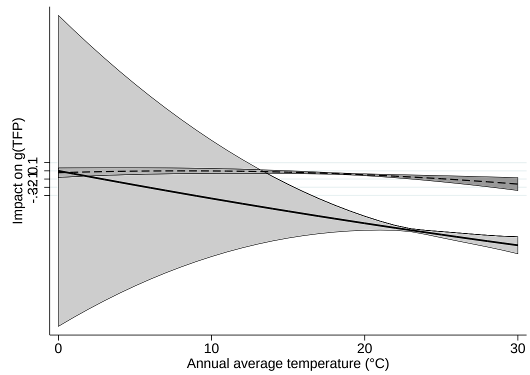
(d) g(emp)

Supplementary Figure 2: Impacts of temperature on the growth rates of components of production - cutoff 30^{th} percentile

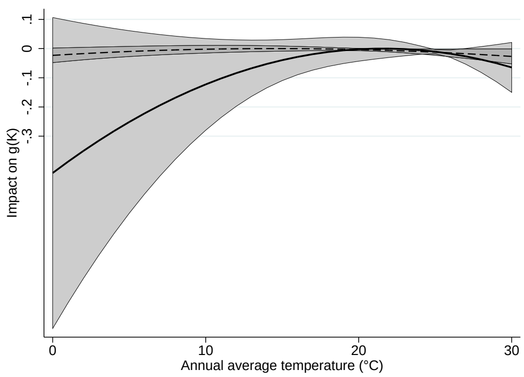
The Light gray shaded region indicates the 90% confidence interval for poor sample, darker grey the corresponding one for the rich sample, dashed line is average response from rich sample, thick black line the average response from poor sample, results are relative to optimum level.



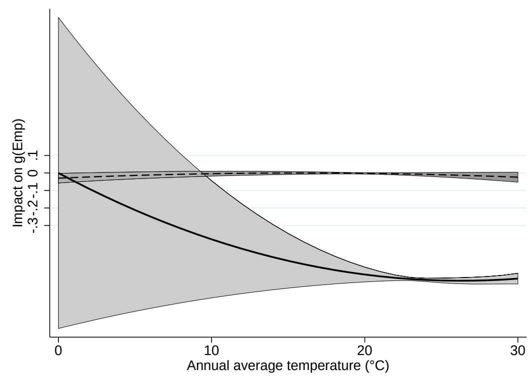
(a) g(GDPpc)



(b) g(rtfpna)



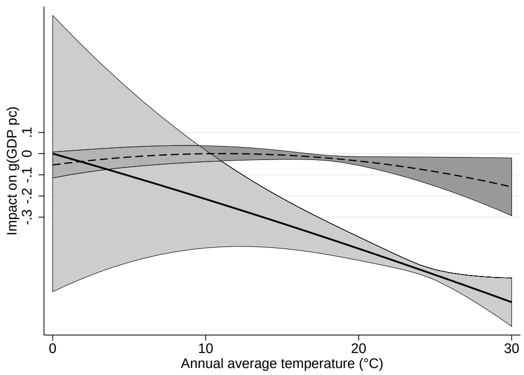
(c) g(rkna)



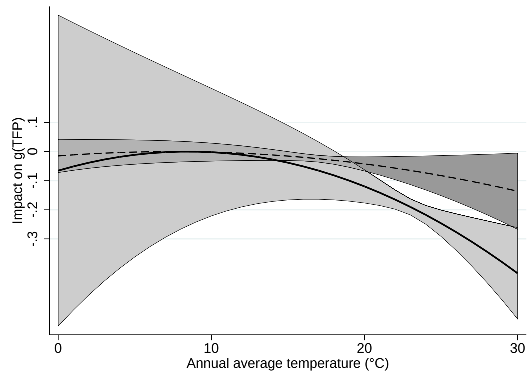
(d) g(emp)

Supplementary Figure 3: Impacts of temperature on the growth rates of components of production - cutoff 10^{th} percentile

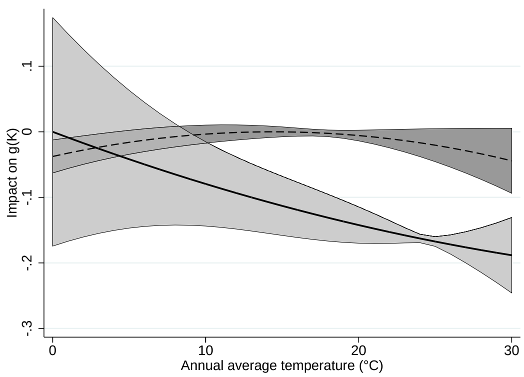
The Light gray shaded region indicates the 90% confidence interval for poor sample, darker grey the corresponding one for the rich sample, dashed line is average response from rich sample, thick black line the average response from poor sample, results are relative to optimum level.



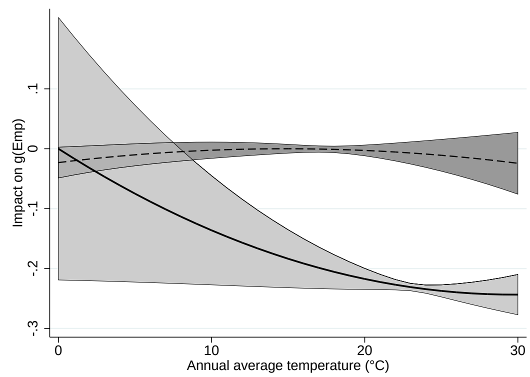
(a) g(GDPpc)



(b) g(rtfpna)



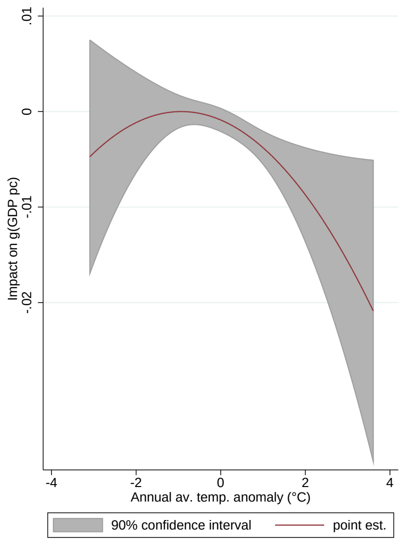
(c) g(rkna)



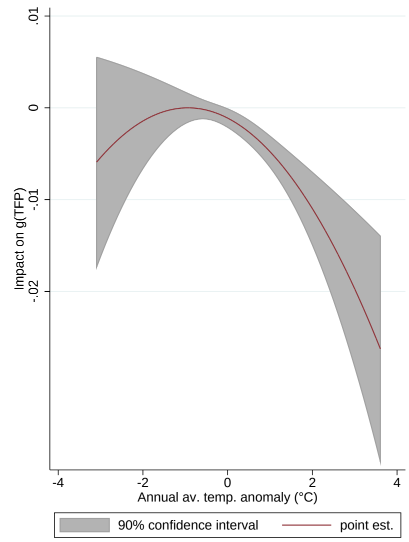
(d) g(emp)

Supplementary Figure 4: Impacts of temperature on the growth rates of components of production - cutoff 10^{th} percentile and excluding 10^{th} to 50^{th} percentile

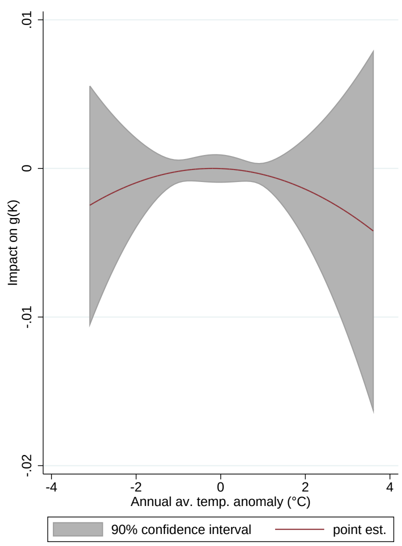
The Light gray shaded region indicates the 90% confidence interval for poor sample, darker grey the corresponding one for the rich sample, dashed line is average response from rich sample, thick black line the average response from poor sample, results are relative to optimum level.



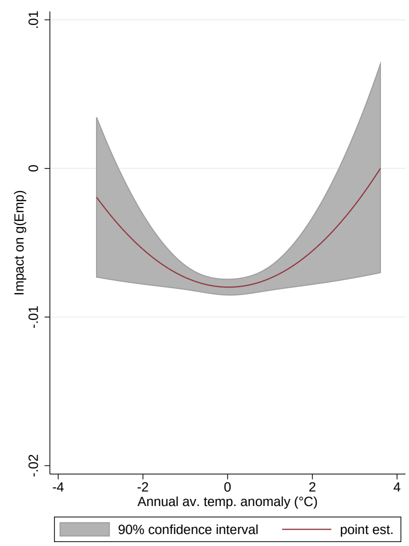
(a) g(GDPpc)



(b) g(rtfpna)



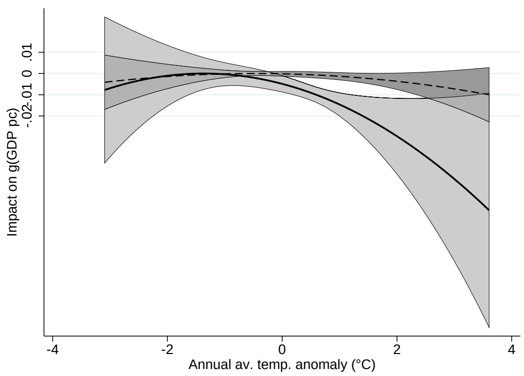
(c) g(rkna)



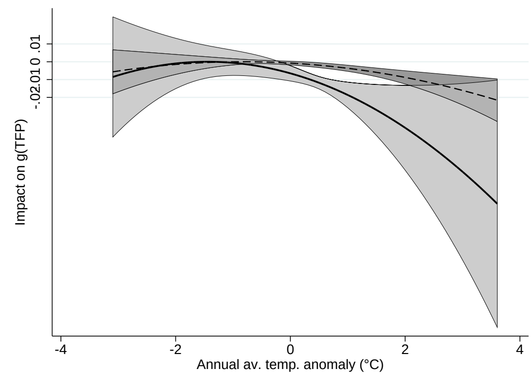
(d) g(emp)

Supplementary Figure 5: Impacts of temperature anomaly on the growth rates of components of production

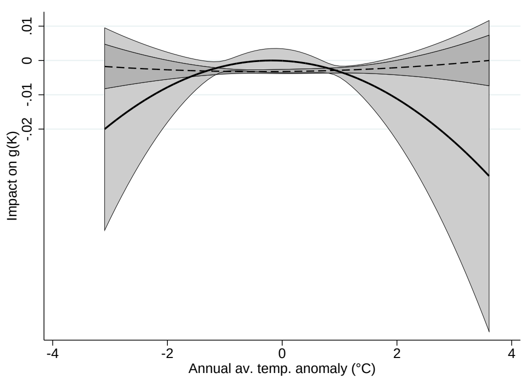
The gray shaded region indicates the 90% confidence interval for full sample, the thick black line the average response, results are relative to optimum level.



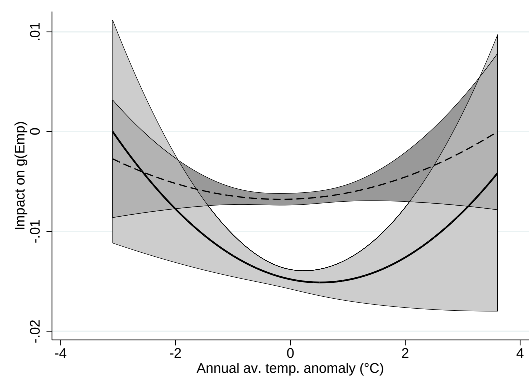
(a) g(GDPpc)



(b) g(rtfpna)



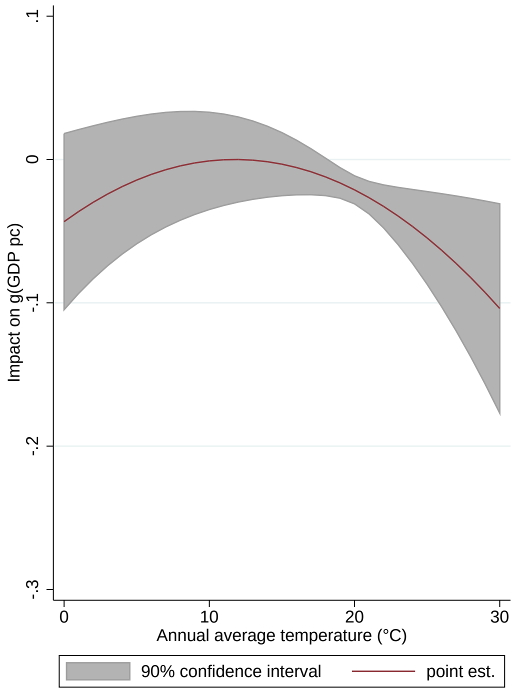
(c) g(rkna)



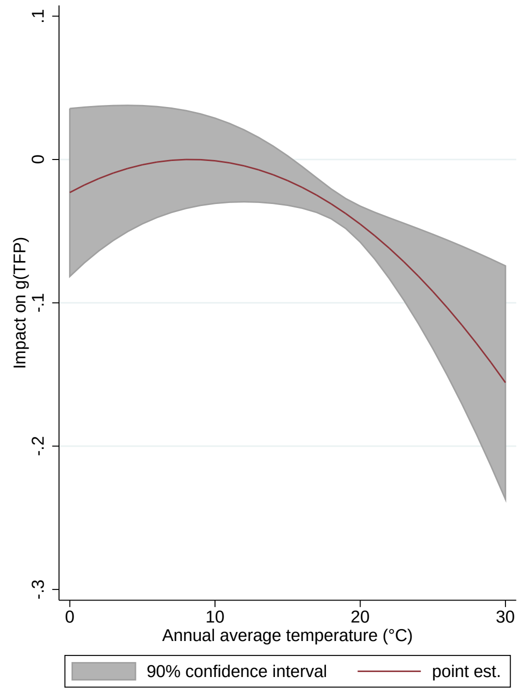
(d) g(emp)

Supplementary Figure 6: Impacts of temperature anomaly on the growth rates of components of production - cutoff 20^{th} percentile

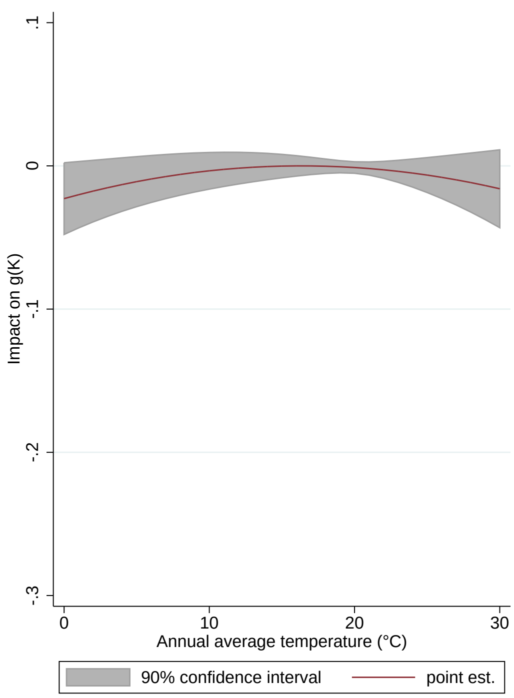
The Light gray shaded region indicates the 90% confidence interval for poor sample, darker grey the corresponding one for the rich sample, dashed line is average response from rich sample, thick black line the average response from poor sample, results are relative to optimum level.



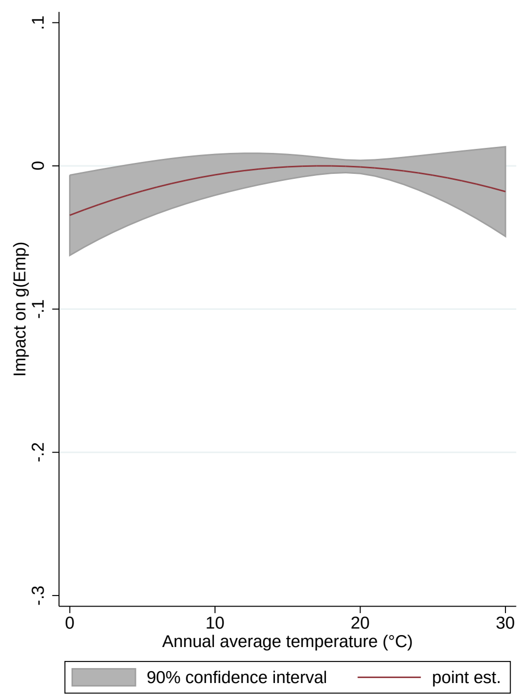
(a) g(GDPpc)



(b) g(rtfpna)



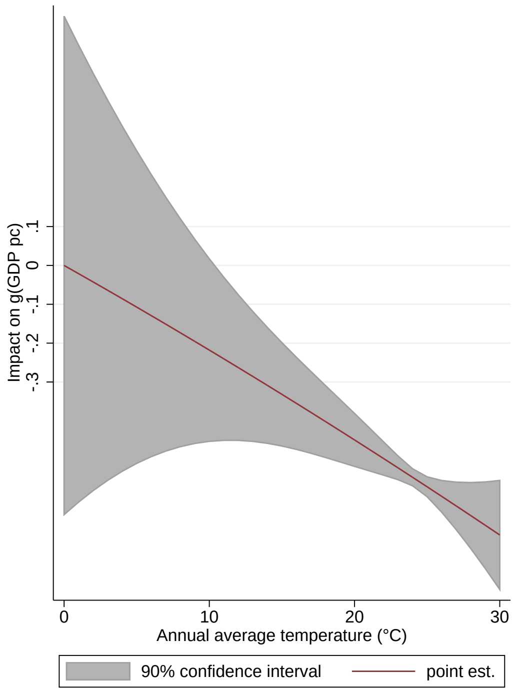
(c) g(rkna)



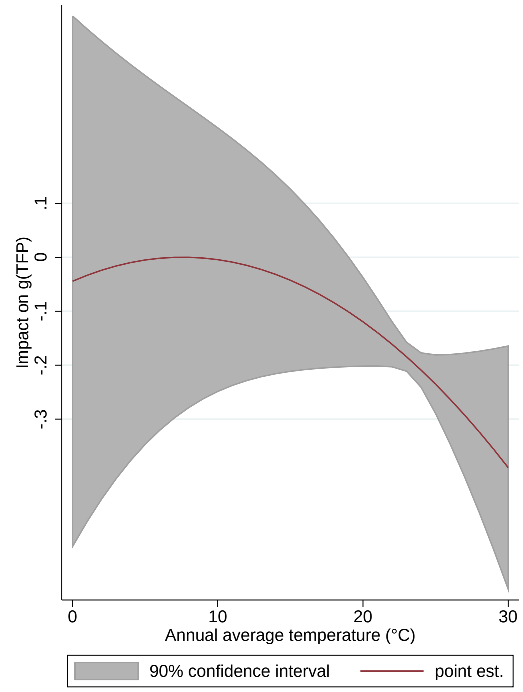
(d) g(emp)

Supplementary Figure 7: Results for high income group, cutoff is 20^{th} percentile of income distribution.

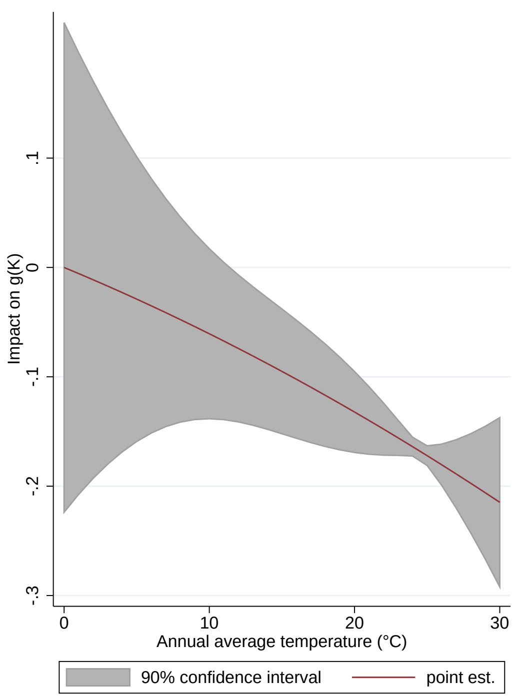
The gray shaded region indicates the 90% confidence interval for full sample, the thick black line the average response, results are relative to optimum level.



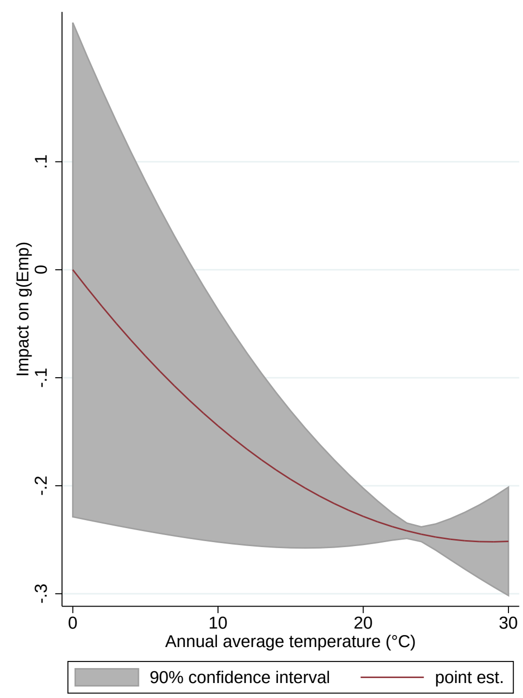
(a) g(GDPpc)



(b) g(rtfpna)



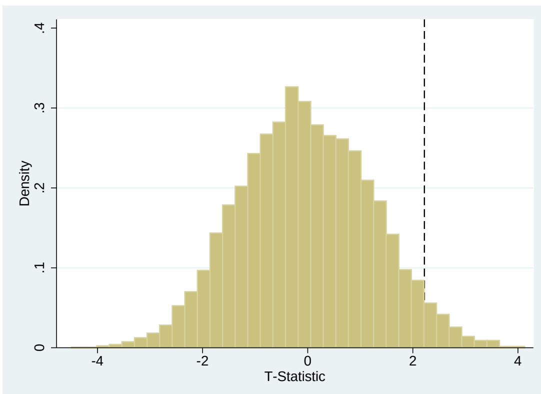
(c) g(rkna)



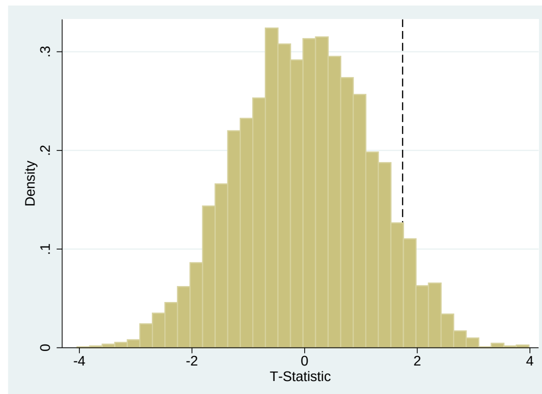
(d) g(emp)

Supplementary Figure 8: Results for low income group, cutoff is 20^{th} percentile of income distribution.

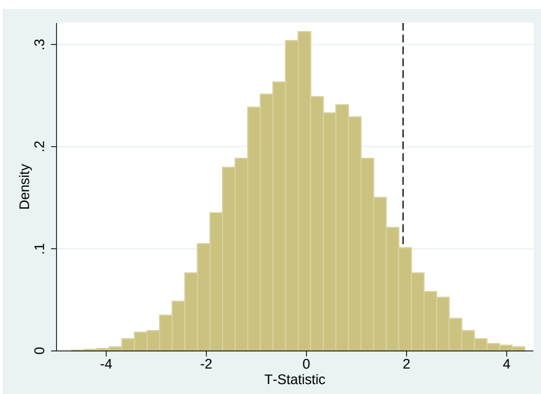
The gray shaded region indicates the 90% confidence interval for full sample, the thick black line the average response, results are relative to optimum level.



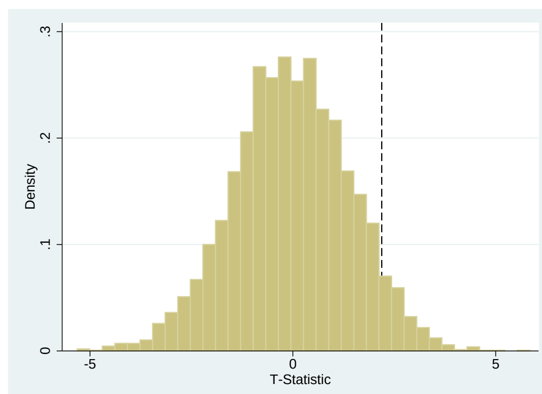
(a) g(GDPpc)



(b) g(rtfpna)

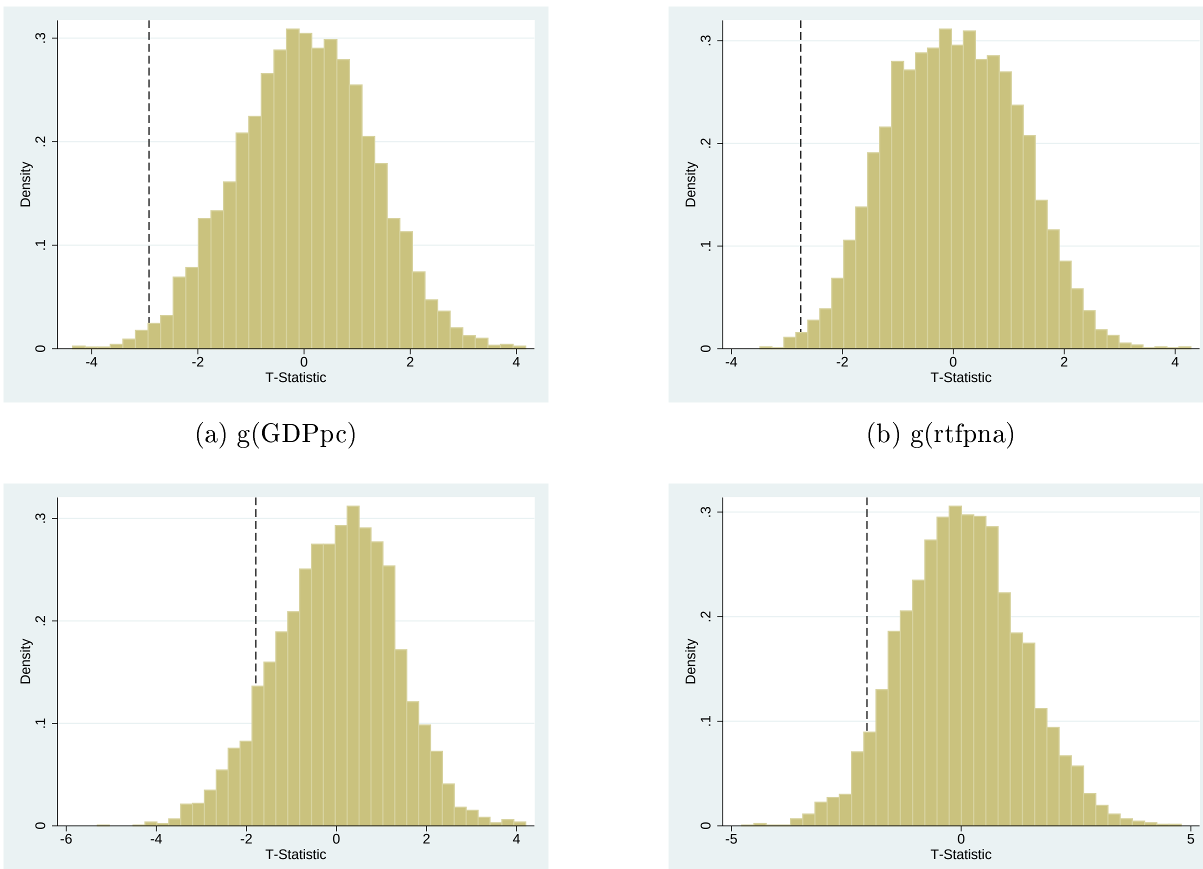


(c) g(rkna)



(d) g(emp)

Supplementary Figure 9: Fisher randomization test - Results for temperature.



(a) g(GDPpc)

(b) g(rtfpna)

(c) g(rkna)

(d) g(emp)

Supplementary Figure 10: Fisher randomization test - Results for temperature squared.