The impact of temperature on production factors

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Abstract

In a recent econometric study Burke et al. (2015) find that temperature affects economic growth non-linearly. We extend their analysis by investigating the influence of temperature on the main components of production, namely total factor productivity, capital stock and employment. Our panel dataset includes observations on 103 countries for the period 1961-2010. We confirm Burke et al. (2015) assumption that the main impacts of temperature arise in total factor productivity, which is significantly negatively affected for high levels of temperature. Neither capital nor employment seem to be affected by temperature. However, we find that temperature impacts rich and poor differently, with the poor being significantly more strongly impacted for higher temperature levels. These results hold across all components of production. We find these results to be robust across different cutoff points dividing the rich and poor samples, continue to hold if we use temperature anomaly instead of temperature, and also apply for further robustness exercises. The findings provide empirical evidence for negative impacts of temperature on poor countries and support the political and scientific discussions of mitigation policies and climate change impacts.

Keywords: temperature, economic growth, employment, capital stock, total factor productivity.

JEL classification: Q54.

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We thank Marshall Burke for comments on a previous version.

1 Introduction

In a recent econometric study, the authors Marshall Burke, Solomon Hsiang and Edward Miguel (2015) find that temperature affects economic growth non-linearly. 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, Field et al. 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 help design and evaluate effective climate change policies.

In our approach we agree with the method and results in Burke et al. (2015) and thus build upon their approach. Burke et al. (2015) assume that the identified effect of temperature on GDP growth results from TFP alone. However, their assumption requires additional research due to two main reasons. First, their assumption requires empirical proof to be considered as scientifically valid. Second, the focus on TFP and the exclusion of the other components of GDP might be too restrictive to detect the temperature's full influence on production. Thus, complementary to Burke et al. (2015) we assume that all components of output (TFP, capital and employment) are potentially affected by temperature and we search for empirical evidence. Furthermore, understanding whether there is an impact from temperature on all components of output will contribute to reconciling the literature's microeconomic results with their macroeconomic ones. We undertake this study by combining Penn World Table data with the 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 confirm the assumption in Burke et al. (2015) that at the aggregate level the main effects of temperature are on TFP growth. More specifically, we find that temperature affects the growth rate of TFP in an inversely u-shaped relationship, with a maximum at roughly 9°C. Increasing temperature results in a reduction of TFP growth from its maximum level. We find little evidence that this relationship is driven by the rich countries in our sample but instead conclude that this relationship between temperature and TFP growth only holds for the poor countries. Our econometric results indicate that both the growth of capital stock and employment growth do not seem to be affected by temperature at the aggregate level. However, when differentiating between the rich and the poor countries, we find that the poor countries are negatively affected by larger temperatures, while the richer countries tend to be unaffected.

In section 2 we first describe the methodology in Burke et al. (2015) and how we extend theirs. In section 3 we describe our results and in section 4 we conclude with implications and further discussions.

2 The empirical approach

2.1 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. Burke et al. (2015) used per capita Gross Domestic Product (GDP) from the

World Bank World Development Indicators. This dataset contains neither information on capital stocks nor TFP. Burke et al. (2015) showed the robustness of their results to using economic output (real GDP at constant 2005 national prices) from the Penn World Tables.

The Penn World Tables 8.1 (Feenstra et al. 2015) contain, besides the data on GDP, also estimates of capital stock and TFP. Thus, for consistency reasons, we are able to identify impacts at the level of the production components within the same dataset.

In our empirical study we thus rely on the Penn World tables for capital stock at constant prices (rkna), TFP at constant national prices (rtfpna), as well as employment (emp). 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 rkna, and a minimum of 4,280 country-year observations for the growth rate of rtfpna. 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$^{\text{th}}$ percentile in 1980, and a zero otherwise.[1] 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,[2] but instead we study the equations separately.

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

[2] 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.

2.2 The methodology

Burke et al. (2015) show a non-linear relationship between country-specific deviations from weather trends and growth trends, while controlling for shocks which are common to all countries. Their basic assumption is 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)[3]. Though the exact combination of the three components of production is a matter of discussion among economists, they have in common that they impact GDP positively. Burke et al. (2015) assume that the impact of climatic conditions mainly arises through TFP. We suggest that a large body of microeconomic evidence points also to significant impacts on the other components of production (Zivin and Neidell 2014, Dell et al. 2009, Albouy 2016). Furthermore, simply assuming that TFP is the main driver behind the relationship between temperature and GDP is insufficient for scientific validity. This assumption requires empirical validation. Hence, our hypothesis is that climatic conditions affect each of the three components of production in a similar way as GDP.

Empirically, Burke et al. (2015) run an OLS regression with both temperature and precipitation being exogenous, non-linear determinants of GDP growth. They 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, and $\theta_{i1}t + \theta_{i2}t^2$ 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

[3] In general, total factor productivity represents our 'measure of ignorance', and it comprises as diverse factors such as technological progress or structural changes. We discuss this more deeply in the last section.

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. The appendix in Burke et al. (2015) 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 arbitrarily chosen, we study how different levels of this threshold (10%, 20%, 30% and 50%) impact the results. We present the results in Figures 2a to 2d and Table 9, and the varying threshold results in Figures 3a to 6d.

3 The results

Our results confirm the basic findings in Burke et al. (2015). Temperature impacts GDP per capita growth non-linearly in an inversely u-shaped relation (Figure 1a). While Burke et al. (2015) found the turning point at around 13°C we find a slightly lower turning point at roughly 10°C.[4] 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[5], while the rest of the difference is likely due to the difference in the

[4] 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.

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

sample. Importantly, our results from the differentiated impacts between rich and poor are qualitatively different compared to Burke et al. (2015). In particular, Burke et al. (2015) 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 (Figure 3a). However, decreasing the cutoff point increases the difference between how rich and poor countries respond to temperature (Figure 4a, 5a and 6a). 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.

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 is statistically significantly different from zero (Figure 1b). The turning point 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 (Figure 2b, 3b, 4b, 5b and 6b). 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 find evidence that temperature impacts the growth of capital stocks of the poor. We find little[6] 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 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 employment at the aggregate level (Figure 1c), with no difference between rich or poor for the cutoff point as used in Burke et al. (2015) (Figure 2c). However, for lower levels of the cutoff point we find statistically significant differences between the response of employment growth in rich and poor countries. Employment growth in poor countries is significantly stronger affected by temperature than in the rich countries.

Thus, overall we confirm the assumption in Burke et al. (2015) that mainly temperature drives GDP growth through its impact in TFP. However, this effect is clearly heterogeneous across the countries. In particular, we find that for poor countries with a GDP below the 30^{th} percentile in the world GDP distribution), higher temperature levels impact all components of GDP negatively.

3.1 Robustness

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. Te lagged residuals turn out to be statistically signifi-

[6] 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.

cantly different from zero for each regression (see the lagged residual statistics at bottom of the regression Tables 5 to 8), which indicates the presence of serial correlation. In line with Burke et al. (2015), we resort to cluster-robust standard errors in the main regressions (clustered at the country level), and in addition we use the Newey-West estimator with different lag lengths for robustness. The Newey-West estimator shows 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.

To 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 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 safely 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.

Tables 5 to 8 present a series of robustness tests related to the error term. We check the errors and drop potential outliers from the regressions (visual inspection 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 (Table 5 and 6, 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.

Our final robustness exercise uses anomalies[7] of the climatic variables instead of levels (Figures 7a to 8d). Anomalies are a better measure of deviations from long-term climatic conditions. This advantage 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 Fig 1a,b with Fig 7 a,b and Fig 2a,b with Fig 8 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 Fig 1c and Fig 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 Fig 1c and Fig 7c) and no difference between the impact on rich and poor countries (compare Fig 2c and 8c). For the impact on employment Fig 7d and 8d (the figures representing the impact of temperature anomaly) indicate a clearly convex relation for the effect on the aggregated sample (compare Fig 1d and Fig 7d) and for the both rich and poor sample (compare Fig 2d and 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 thus 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 sig-

[7] 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.

nificantly 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.

4 Implications and discussions

The growth rate of GDP tends to be best explained by the growth rate of TFP (Easterly and Levine 2001). After all it explains a large share of variations in GDP in cross-sections and across time (Acemoglu 2008) and it furthermore encompasses everything that impacts GDP but capital and labor. Our results confirm the assumption in Burke et al. (2015) that the impact of temperature on GDP growth comes from variations in TFP. In addition, we find evidence that temperature impacts all components of GDP 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. However, some further implications that should be drawn from this analysis. We now provide some microfounded arguments that support this impact on TFP, capital stock and employment, and also discuss why the impact turns out to be more important for the poor than for the rich countries.

A main issue is that we identify the main impacts of temperature on GDP growth to arise through TFP which itself is a mere residual. TFP is the unexplained part of GDP, which comprises everything else but capital and employment. So what do we know about TFP that may help us in placing these results into perspective?[8]

Temple (1999) argue that uncertainty is an important factor in explaining differences in TFP and thus in TFP growth. The more important temperature changes are the larger will be the uncertainty surrounding the impact from 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. Strategic planning will force them to spend more money on measures that reduce the future impact of increased

[8] As our results are for the short-run, we will not discuss potential long-run determinants or implications.

temperature on production (e.g. in adaptive technology). Thereby they may be unable to invest in the currently most productive technologies. Hence, higher expected temperatures combined with farmer's risk aversion can reduce current investments in more productive technologies. These reductions in investment can also reduce the demand for the development of more productive technologies (via R&D). Since, the application of more productive technologies represents an important aspect of TFP growth, the investments into adaptive technologies may thus have a negative impact on TFP. A similar explanation would apply for the relationship between temperature and investments in capital.

In the empirical literature it is widely presumed that capital intensity is a strong determinant of TFP (Isaksson 2007). As a result, investments in capital should foster TFP growth. Thus, significant changes in temperature led to two impacts on TFP: an impact from temperature directly on TFP and an indirect one from temperature on capital stock which then impacts TFP. In general we would expect a negative impact from higher temperatures on TFP growth. However, there is an additional theoretical link via capital that may potentially reverse this relationship. Foster et al. (2001) discuss how TFP may be increased as a result of re-allocations of economic activity from producers with low productivity to those with high productivity. Their argument rests on the theory of creative destruction in the line of Schumpeter (1934). Creative destruction represents a mediating factor in the impact from temperature on TFP. While at the aggregate level we tend to find a negative impact from temperature changes on TFP and capital, creative destruction may actually lead to a negative relationship between capital and TFP. Our macroeconomic data does not allow to assess this channel, which requires a more microeconometric, firm-level oriented approach.

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.

We found that the poor sample is mostly affected by high temperature, which has significant implications for the climate change discussion. 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 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 TFP and capital growth 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 TFP differences and TFP growth rates for the evolution of inequality over time.

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5 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.

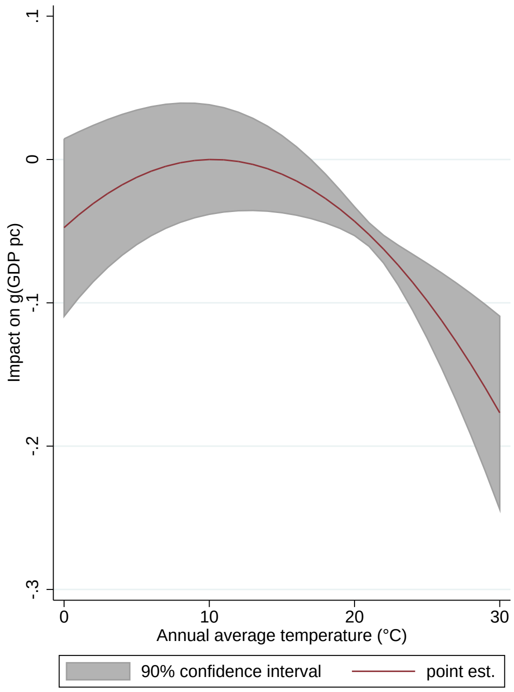
Table 2: Summary statistics

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

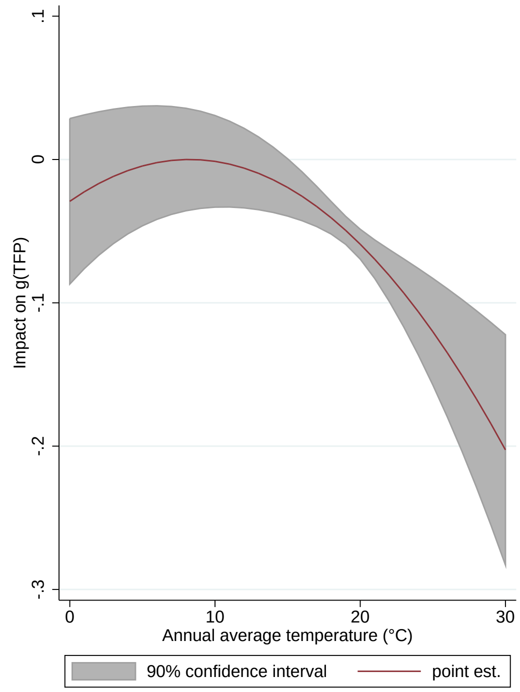
Table 3: Correlation table

	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)

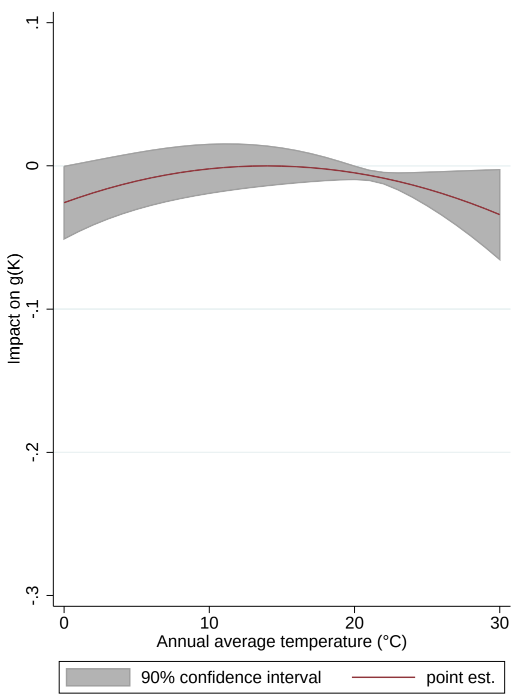
Numbers in brackets indicate the significance level of the correlation. The sample is based on $g(rtfpna)$, but there are no changes if one considers the full samples for $g(rkna)$ and $g(emp)$.



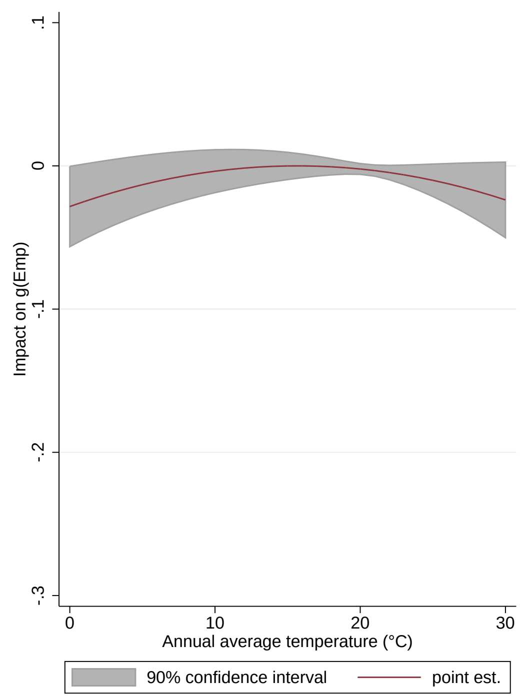
(a) g(GDPpc)



(b) g(rtfpna)

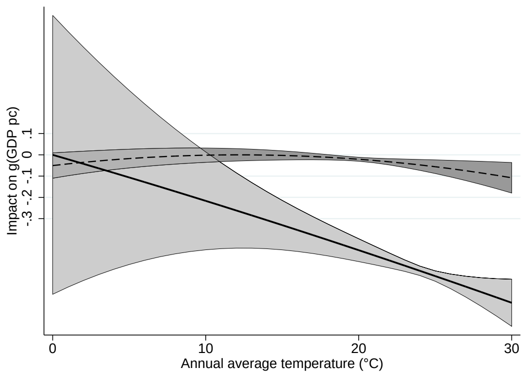


(c) g(rkna)

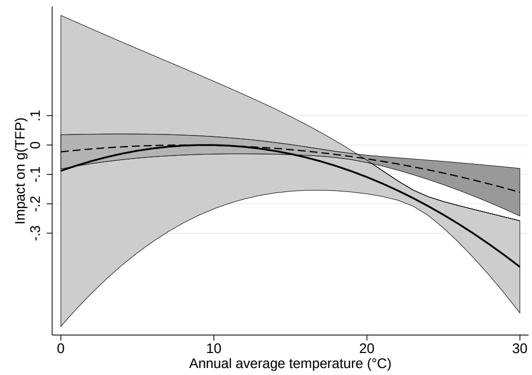


(d) g(emp)

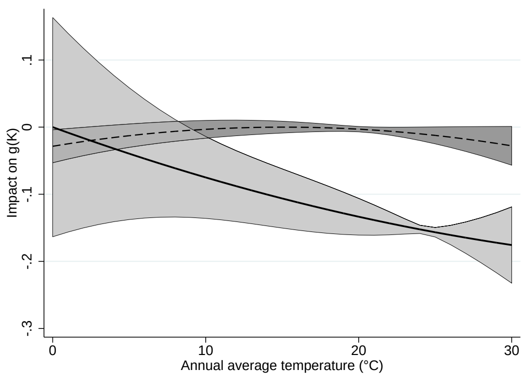
Figure 1: Impacts of temperature on the growth rates of components of production
Gray region is 90% confidence interval, results are relative to optimum level



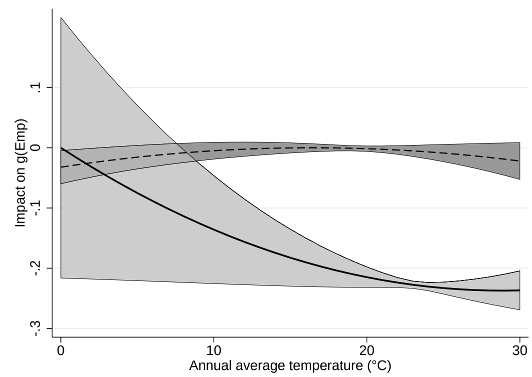
(a) g(GDPpc)



(b) g(TFP)



(c) g(K)



(d) g(E)

Figure 2: Impacts of temperature on the growth rates of components of production in rich and poor countries - cutoff is 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.

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: 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

Table 6: 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

Table 7: 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

Table 8: 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

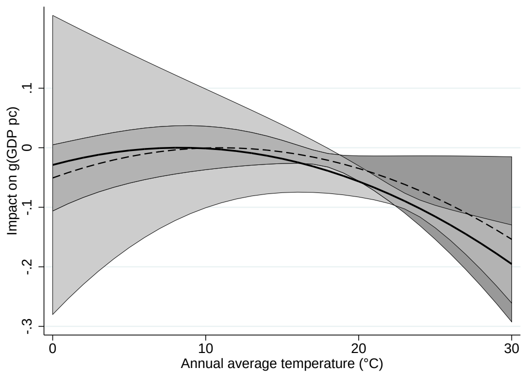
Table 9: Main table, poor versus rich impacts (cutoff 20%)

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

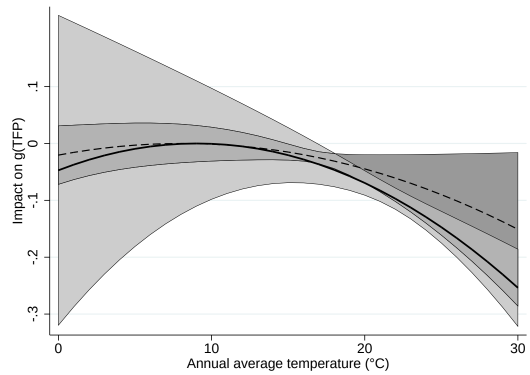
Robust standard errors in parentheses

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

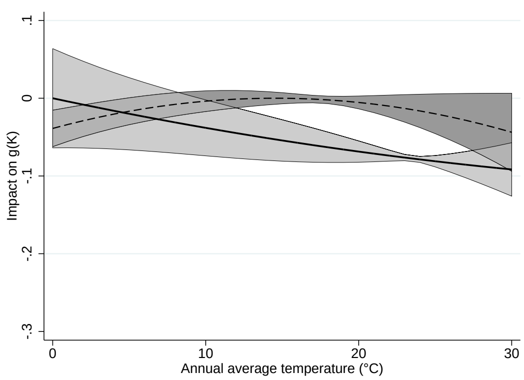
Errors are robust standard errors and clustered at country level. All regressions are run with time dummies, country dummies, country-time dummies



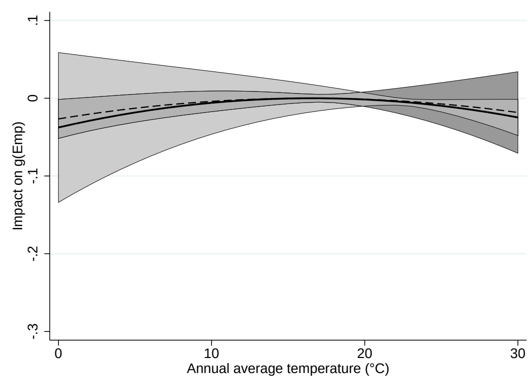
(a) g(GDPpc)



(b) g(rtfpna)



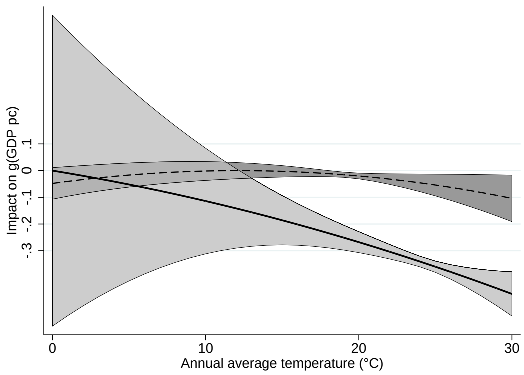
(c) g(rkna)



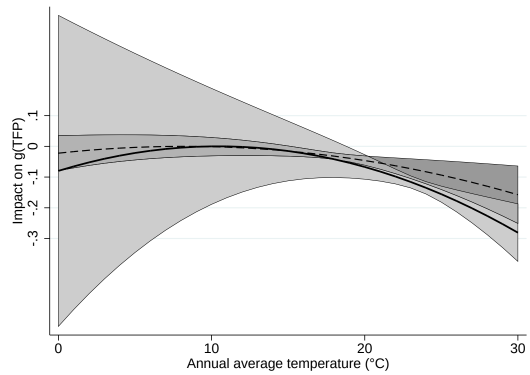
(d) g(emp)

Figure 3: Impacts of temperature on the growth rates of components of production - cutoff 50^{th} percentile

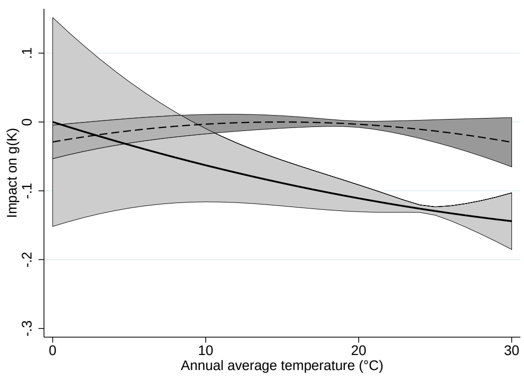
The Light gray shaded region indicates the 90% confidence interval for poor sample, darker grey the corresponding one for the rich sample, dashed line is average response from rich sample, thick black line the average response from poor sample, results are relative to optimum level.



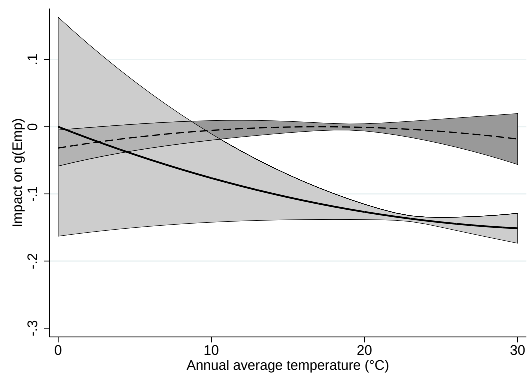
(a) g(GDPpc)



(b) g(rtfpna)



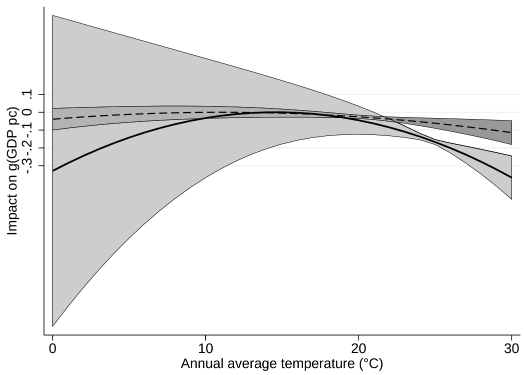
(c) g(rkna)



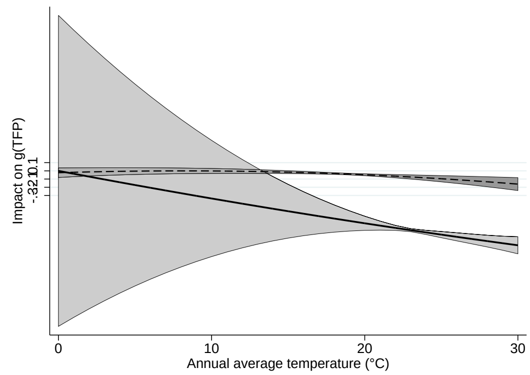
(d) g(emp)

Figure 4: Impacts of temperature on the growth rates of components of production - cutoff 30^{th} percentile

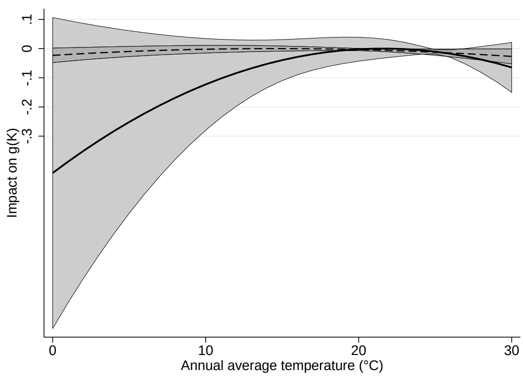
The Light gray shaded region indicates the 90% confidence interval for poor sample, darker grey the corresponding one for the rich sample, dashed line is average response from rich sample, thick black line the average response from poor sample, results are relative to optimum level.



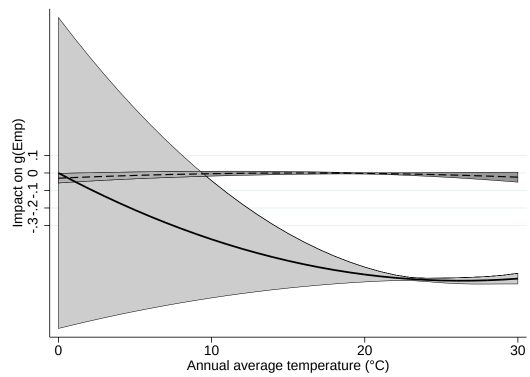
(a) g(GDPpc)



(b) g(rtfpna)



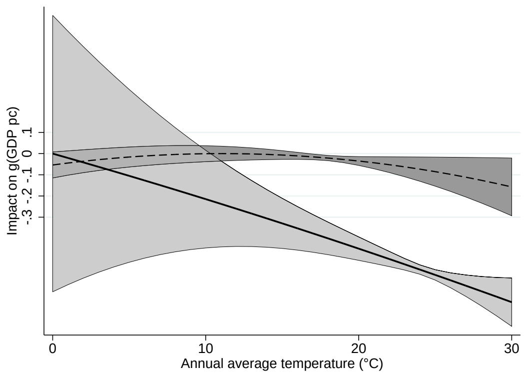
(c) g(rkna)



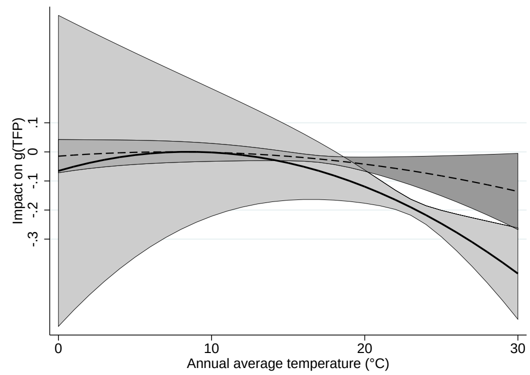
(d) g(emp)

Figure 5: Impacts of temperature on the growth rates of components of production - cutoff 10^{th} percentile

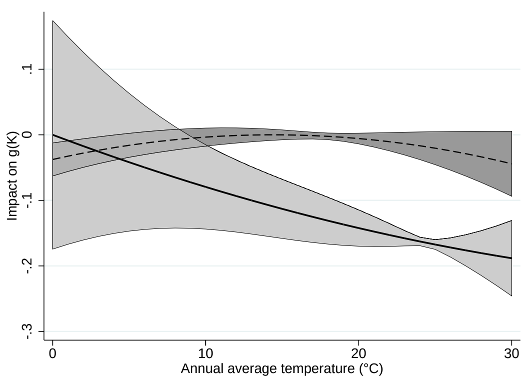
The Light gray shaded region indicates the 90% confidence interval for poor sample, darker grey the corresponding one for the rich sample, dashed line is average response from rich sample, thick black line the average response from poor sample, results are relative to optimum level.



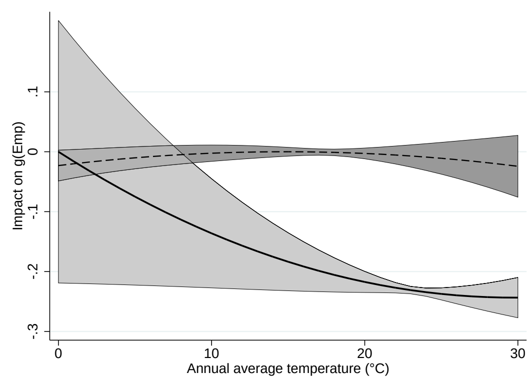
(a) g(GDPpc)



(b) g(rtfpna)



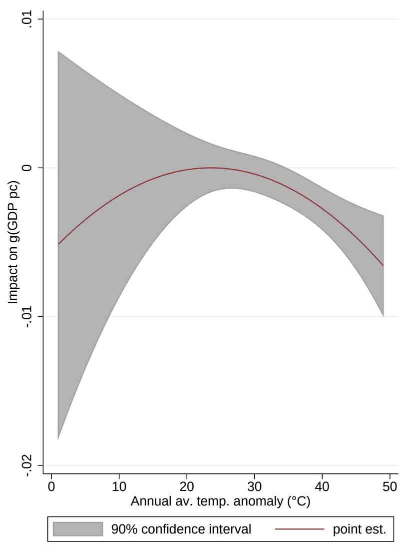
(c) g(rkna)



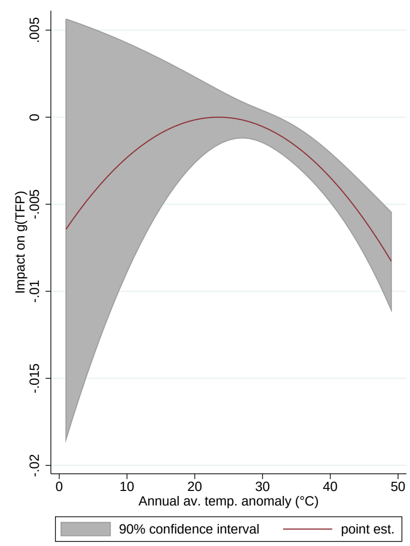
(d) g(emp)

Figure 6: Impacts of temperature on the growth rates of components of production - cutoff 10^{th} percentile and excluding 10^{th} to 50^{th} percentile

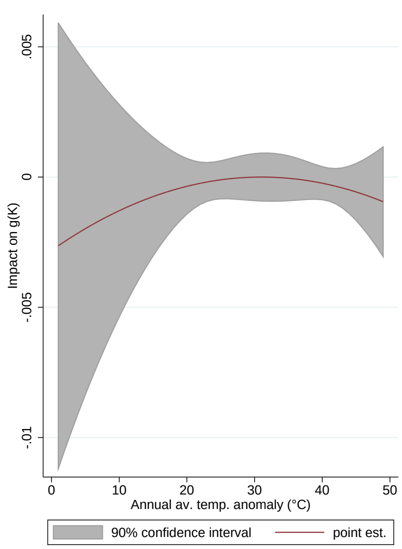
The Light gray shaded region indicates the 90% confidence interval for poor sample, darker grey the corresponding one for the rich sample, dashed line is average response from rich sample, thick black line the average response from poor sample, results are relative to optimum level.



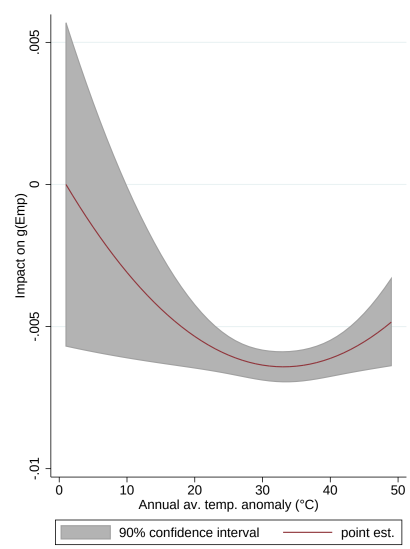
(a) g(GDPpc)



(b) g(rtfpna)



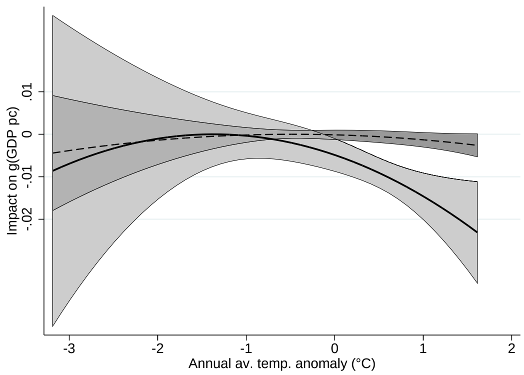
(c) g(rkna)



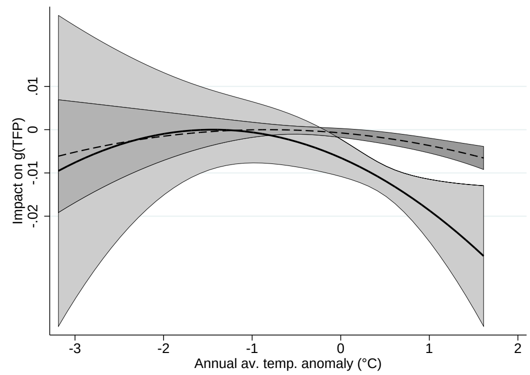
(d) g(emp)

Figure 7: Impacts of temperature anomaly on the growth rates of components of production

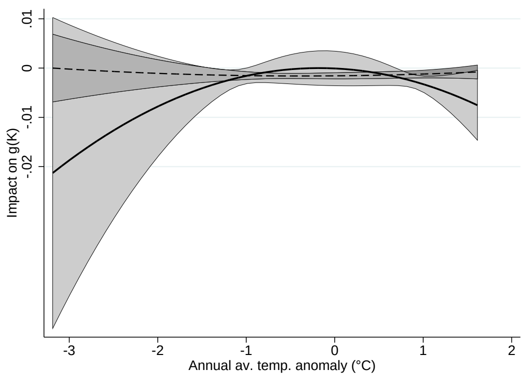
The Light gray shaded region indicates the 90% confidence interval for poor sample, darker grey the corresponding one for the rich sample, dashed line is average response from rich sample, thick black line the average response from poor sample, results are relative to optimum level.



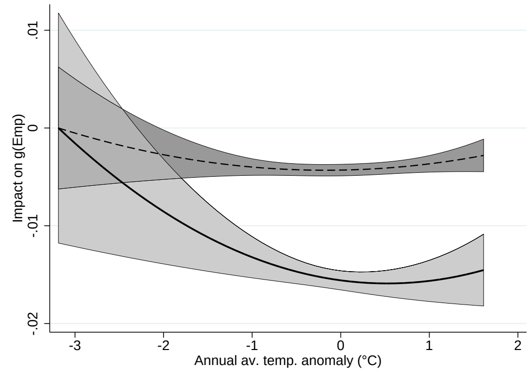
(a) g(GDPpc)



(b) g(rtfpna)



(c) g(rkna)



(d) g(emp)

Figure 8: 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.