ECONOMIC POLICY

Bundesministerium der Finanzen

72nd Economic Policy Panel Meeting

22-23 October 2020

Supported by the
Federal Ministry of Finance, Germany

The Link between Regional Temperature and Regional Incomes: Econometric Evidence with Sub-National Data

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The organisers would like to thank the Federal Ministry of Finance, Germany, for their support. The views expressed in this paper are those of the author(s) and not those of the supporting organization.

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August 2020

ABSTRACT

We study the link between temperature and economic development at the sub-national level, employing cross-sectional data from two distinct sources. In contrast to the existing cross-country literature on the temperature-income relationship, our setting allows for the inclusion of country fixed effects. Once accounting for country fixed effects, we do not find a statistically robust relationship between regional temperature and three different measures of regional economic development (per capita GDP, nightlights and gross cell production). We also test whether temperature is non-linearly related to regional income (with hotter regions being potentially particularly prone to adverse effects of temperature on income) but find no systematic evidence in favor of such a relationship. Finally, we examine whether the effect of temperature on economic development is especially pronounced in poorer regions (e.g., due to weaker adaptation). Again, there is no statistically robust evidence for such a link.

JEL Classification: Q54; Q56; R11

Keywords: regional temperature; regional economic development; sub-national data; non-linearity

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* We would like to thank Gustavo Torrens insightful comments and helpful discussions which significantly improved the manuscript. Two anonymous referees provided valuable comments and suggestions. Funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany´s Excellence Strategy – EXC 2052/1 – 390713894.
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I. INTRODUCTION

The roles of climate change and increasing temperatures in economic development have received renewed attention in the cross-country literature in recent years, with a number of studies tending to find a negative relationship between increasing temperatures and income (e.g., Burke et al., 2015, 2018; Dell et al., 2009, 2012; Lanzafame, 2014). Some contributions suggest a non-linear, inverted-U relationship between income and temperature, meaning that colder countries might benefit from increasing temperatures, while hotter countries tend to lose out (e.g., Burke et al., 2015, 2018; Deryugina and Hsiang, 2014; Nordhaus, 2006; Zhao et al., 2018). Moreover, some studies find that especially relatively poor countries might suffer from higher temperatures, partly due to being located in already hotter parts of the world and partly due to having fewer (financial) means available to adapt to further temperature increases (e.g., Dell et al., 2012; Moore and Diaz, 2015; Zhao et al., 2018).

Our contribution to the literature on the temperature-income relationship is three-fold. First, we correlate *sub-national data* on temperature with sub-national data on economic development (e.g., regional GDP per capita). We gather two data sets on climatic and economic indicators for a large number of sub-national units (also called *regions* in our contribution). In detail, using data from Gennaioli et al. (2014) and the *Demographic and Health Surveys* (henceforth *DHS*), we are able to analyze between 1,542 to 15,533 sub-national units in developed and developing economies from all continents. Both datasets allow us to account for the within-country heterogeneity in temperatures and incomes, an aspect that is by construction neglected when only taking a cross-country perspective.

Second, the use of regional data allows us to account for country fixed effects, thereby holding constant all factors that are specific to a country as a whole, including country-specific policies, institutions, colonial history or aspects of culture. Thus, we are able to draw conclusions on the relationship between regional temperature and regional incomes, while accounting for these potentially relevant country-specific influences.

Third, we explore the effect of temperature on three different measures for sub-national incomes: regional GDP per capita from 1950 to 2010, gross cell production within a DHS cluster as well as nightlights within a DHS cluster. Using alternative indicators of regional economic development ought to add a broad view to our empirical analysis.

Using data for 1,542 sub-national administrative regions from different continents yields no statistically robust relationship between temperature and regional GDP per capita once controlling for country-specific heterogeneity with country fixed effects.[1] By means of interaction effects, we also consider potential differences in the link between temperature and regional economic development between rich and poor regions. We find no evidence for such differences. Furthermore, we find no systematic evidence for an inverted-U relationship between regional temperature and regional incomes. Using alternative indicators of regional economic development by employing data from the DHS, we find, if anything, a positive relationship between temperature and nightlights within a DHS cluster (which becomes statistically insignificant after more covariates have been added). The relationship between temperature and gross cell production within a DHS cluster is, if anything, slightly negative, with no difference between rich and poor regions. There is again no evidence for an inverted-U relationship between temperature and nightlights nor for temperature and gross cell production. A series of extensions (e.g., by considering sub-samples and analyzing the roles of maximum temperatures, minimum temperatures, precipitation or other controls) provides support for our main finding of no straightforward impact of regional temperature on regional economic development once controlling for country specific heterogeneity with fixed effects.

The remainder of this paper is structured as follows: Section II provides theoretical considerations and a literature review. Section III describes our data sources and empirical approach. Section IV presents our results and offers interpretations. Section V concludes.

II. THEORETICAL CONSIDERATIONS AND LITERATURE REVIEW

THEORETICAL CONSIDERATIONS

Recently, there has been renewed interest in exploring the relationship between temperature and economic indicators such as per capita GDP or economic growth, which has been driven by evidence for anthropogenic climate change (e.g., Carleton and Hsiang, 2016, Dell et al., 2014). There are different pathways through which higher temperatures may be detrimental to economic development (e.g., Burke et al., 2015; Easterly and Levine, 2003; Gallup et al., 1999).

First, higher temperatures may adversely affect agricultural production, e.g., by contributing to water stress or the spread of plant pests (e.g., Schlenker and Lobell, 2010; Carter et al., 2018). Especially when economies are poor and have difficulties to adapt, such adverse effects may hurt overall economic development.

[1] We tend to find a negative link between regional temperature and regional incomes when not accounting for country specific heterogeneity.

Second, higher temperatures may adversely affect human productivity in general. For instance, with higher temperatures it becomes more exhaustive for the human body to regulate its temperature. Increased heat stress in turn could adversely affect labor performance and productivity (e.g., Burke et al., 2015). The adverse effects of heat stress may also be felt in non-agrarian sectors of the economies, e.g., negatively affecting industrial production.

Third, higher temperatures may contribute to the spread of debilitating diseases (e.g., Malaria, Dengue fever) by facilitating the spread of disease vectors (e.g., mosquitos). These diseases may adversely affect labor productivity as well as the accumulation of human capital (e.g., by contributing to school absenteeism or permanent mental or physical disability), which in turn could discourage economic development (e.g., Gallup et al., 1999; Ang et al., 2018).

Fourth, higher temperatures may have long-run effects on political and economic institutions by affecting the modes of agricultural production and the suitability of land for foreign settlers due to the incidence of specific diseases. For instance, especially debilitating diseases may have prevented the spread of inclusive institutions (e.g., sound property rights) in the past centuries and instead given rise to more extractive modes of production (e.g., the use of forced labor) and more extractive economic and political institutions. Extractive institutions (e.g., weak property rights, a weak rule of law) in turn are anticipated to discourage innovation and investment, thus leading to lower levels of economic development compared to economies that enjoy more inclusive economic and political institutions (e.g., Acemoglu et al., 2001; Nikolaev and Salahodjaev, 2017).

COUNTRY LEVEL EVIDENCE

The relationship between temperature and income is usually investigated at the country level. For instance, Dell et al. (2009) find a negative relationship between income per capita and temperature; referring to the year 2000, countries experienced a drop in income of 8.5% with every 1 °C increase in temperature. Hsiang (2010) suggests that a temporary 1 °C increase in surface temperature is associated with a contemporaneous 2.5% reduction in non-agricultural production output for 28 countries in the Caribbean and Central America. Lanzafame (2014) investigates the short- and long-term effect of weather shocks on income of 36 African countries, finding that African economies are damaged by such shocks. Employing a global sample of more than 160 countries, Burke et al. (2015, 2018) project a reduction in global income by 15-25% in 2100 if global warming continues to be unmitigated. Focusing on economic growth, Dell et al. (2012) find a negative but statistically insignificant relationship between temperature and growth on average; however, they also show that the link between temperature and growth is negative and statistically significant for poor countries (for rich countries the link is positive but not statistically significant).

Interestingly, earlier studies that aim at explaining cross-country differences in economic development tend to find little evidence for a direct effect of temperature on economic development (e.g., Acemoglu et al., 2001; Rodrik et al., 2004; Sala-I-Martin et al., 2004). Instead, these studies emphasize the role of factors such as institutions, trade and geography (e.g., access to navigable rivers and the sea) in accounting for cross-country differences in economic success.[2]

EVIDENCE AT THE SUB-NATIONAL LEVEL

By construction, cross-country studies do not investigate within-country heterogeneity regarding temperature and economic development. However, recent studies have started to analyze the income-temperature relationship using county or (geographical) grid cell level data to address this shortcoming. Nordhaus (2006) analyzes 25,572 grid cells (on a 1° latitude by 1° longitude scale) and finds a 0.9-3% decrease in economic activity (depending on the specific proxy of economic activity) linked to temperature increases. Dell et al. (2009) find that a 1 °C rise in temperature is related to a 1.2-1.9% decline in municipal incomes for 7,684 municipalities in 12 countries in the Americas; interestingly, their results also suggest that the within-country cross-sectional correlation is substantially weaker than any cross-country correlation. Zhao et al. (2018) analyze 10,597 global grid cells using data from Nordhaus (2006) and find a negative association between temperature and economic activity which is in some specifications statistically significant.[3] Focusing only on China, Li et al. (2019) consider data from 31 Chinese provinces, finding that temperature exerts both positive and negative effects on regional economic growth depending on the level of average temperatures; this points to a non-linear relationship between sub-national temperature and economic growth data. A similar result is obtained by Deryugina and Hsiang (2014) who focus on the United States. Colacito et al. (2019) suggest that a rise in the average summer temperature in the United States is

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[2] These studies still account for diverse covariates that may be correlated with temperature. For instance, if past temperature played a role for diseases, the establishment of settlements, subsequent institutional development and subsequent education, the link today between temperature and income is not necessarily exogenous but may depend on such covariates.

[3] Interestingly, some of their results show a statistically positive link between temperature and growth for rich subnational units (cells) and negative but insignificant relationships for poor subnational units (e.g., Table 3, column 1).

associated to a reduction in the annual state growth rate, while the link between average yearly temperature and economic growth is positive but statistically insignificant.

NON-LINEAR EFFECTS

The literature provides some evidence in favor of a non-linear relationship between temperature and income. Two cross-country studies by Burke et al. (2015, 2018) examine this non-linearity for more than 160 countries and find the relationship to be concave, with productivity being highest at approximately 13 °C and declining at higher temperatures. Deryugina and Hsiang (2014), Nordhaus (2006) and Zhao et al. (2018) also find evidence in favor of an inverted U-shape with a maximum at about 15, 12 and 16 °C, respectively. For Zhao et al. (2018) this inverted U-shape only holds for poor subnational units. Li et al. (2019) places the “beneficial” temperature threshold at approximately 23 °C, meaning that almost all of today’s Chinese provinces could experience positive effects from rising temperatures. On the other hand, Dell et al. (2009, 2012) and Lanzafame (2014) find little evidence that the relationship between income and temperature is non-linear.

ADAPTATION

A concern of the literature is the rate of adaptation to climate change (e.g., Moore and Diaz, 2015). Dell et al. (2009) suggest that approximately half of the negative effect of any temperature increase on income is eliminated through adaptation in the long-run. According to Dell et al. (2012), the main factor governing adaptation and thus accounting for the amount of economic damage due to rising temperatures is a country’s income level. Poorer countries are expected to see lower rates of adaptation (e.g., in terms of using better machinery to compensate for reduced crop yields) and may thus experience stronger adverse economic effects. Several studies distinguish between rich and poor countries or regions and find that the negative effect of temperature tends to be more relevant for poor areas (Dell et al., 2012; Zhao et al., 2018). Burke et al. (2015, 2018), on the other hand, find no relevant difference in the link between temperature and income in rich and poor countries, respectively.

III. DATA AND EMPIRICAL STRATEGY

DATA

We employ two distinct datasets that allow us to explore potential links between *regional* temperatures on measures of *regional* economic development. Temperature as well as GDP per capita at the regional level are drawn from Gennaioli et al. (2014), while further climate data as well as nightlights and gross cell production come from the DHS. Descriptions, descriptive statistics and data sources of the data can be found in Table 4 in the Supplementary Information.

First, we use a dataset collected by Gennaioli et al. (2014) that contains economic as well as geographic variables for 1,542 regions (mainly administrative units such as states and provinces) in 83 countries. As for the *GDP per capita data* at the *sub-national level*, Gennaioli et al. (2014) collect data from national/regional statistical offices between 1950 and 2010. The sample covers more than 90% of the world's GDP and includes a large number of countries and regions from Asia, South America, Oceania, North America and Europe. African regions are under-represented in this dataset. The dataset includes a variable measuring regional temperature, originally obtained from the WorldClim database. This variable indicates average temperatures per region between 1950-2000. This operationalization allows us to directly follow Dell et al. (2009) who also use temperature data averaged over the 1950-2000 period.

Second, we employ a dataset comprised of DHS data. The DHS program primarily collects representative household survey data in the field of demographics and health in more than 90 countries; to date there are approximately 400 surveys available. The program is implemented by *ICF International* and is mainly funded by the *United States Agency for International Development*, which allows DHS to conduct national surveys at least every five years with an average sample size of between 5,000 to 30,000 respondents (see ICF International (2019) for more information). DHS covers a large number of African countries, which constitutes a valuable complement to the Gennaioli et al. (2014) dataset. DHS survey data contains a variety of climatic information which are obtained from the *Geographic Information System*. For instance, we have available temperature, precipitation, frost days, wet days, etc. available. This information is available for small geographical units called *clusters*.[4] We employ two separate cross-sectional samples for 2005 with 31 surveys and 14,130 cluster-level observations and for 2015 with 37 surveys and 15,533 cluster-level observations.[5]

[4] Clusters are a representative selection of *Enumeration Areas*, a statistical unit for population census; see ICF International (2012) for the selection process of *Enumeration Areas*, clusters and households by DHS.

[5] To get a high number of observations we included surveys that were conducted three years before or after 2005 and 2015, respectively. There was always only one survey per country.

GDP data does not exist on the level of DHS clusters; therefore, we use two alternative variables to capture average income of a cluster: *nightlights*, which is the average nighttime luminosity of the area (composite cloud-free radiance values) available for 2015, and *gross cell production* (GCP), which is the average Purchasing Power Parity (PPP) in 2005 US dollars for the 2 km (urban) or 10 km (rural) buffers surrounding the DHS survey cluster (see the DHS Sampling Manual at ICF International (2012) for further information). In particular, nightlights are commonly used in the literature as a proxy for sub-national economic growth and income (e.g., Alsan, 2015; Chen and Nordhaus, 2011; Henderson et al., 2012; Kulkarni et al., 2011).

EMPIRICAL STRATEGY

Using the data from Gennaioli et al. (2014) and DHS (2005, 2015), we examine whether warmer regions (clusters) tend to be less or more wealthy than their colder counterparts within the same country. This investigation may allow to draw potential insights regarding adaptation to hotter temperatures: if comparatively warmer sub-national regions within a country are equally rich than colder regions, adaptation to hot or cold temperatures might be possible within reasonable time frames.

Our empirical strategy follows a simple regression approach common in the literature. Using Gennaioli et al. (2014) data, our first equation to estimate regional GDP per capita in region *r* of country *i* at time *t* is specified as follows:

$$\ln\left(\frac{GDP}{cap}\right)_{r,i,t} = \beta(Temperature)_{r,i} + \omega_i + \lambda_t + \epsilon_{r,i,t} \tag{1}$$

where ω_i and λ_t are country- and time-fixed effects and $\epsilon_{r,i,t}$ is an error term. We cluster standard errors at the country level. Country fixed effects account for any country-specific and time-invariant unobservables such us colonial history, national culture or institutions, etc. They can be employed because we analyze *regional* temperature and *regional* incomes. Time fixed effects capture contemporary global phenomena.

Most recent studies of the temperature-income relationship employ fixed effects strategies, while the use of further control variables is rare (e.g., Burke et al., 2015, 2018; Deryugina and Hsiang, 2014; Li et al., 2019).[6] In particular, the recent literature does not take account of changes in property rights, democracy, macroeconomic variables, trade patterns,

[6] There are a few exceptions: Dell et al. (2009) use a set of geographic variables such as distance to coast; Hsiang (2010) controls for cyclone activities; Zhao et al. (2018) uses a set of economic and geographic controls such as population growth or precipitation; and Nordhaus (2006) uses mean distance from coast, mean elevation, and absolute value of latitude.

diverse social and demographic variables, education, etc. over time. We follow these examples for our main results and proceed to run parsimonious models that do not include further controls in the baseline estimations. It might be argued that such a strategy gives any potential relationship between regional temperature and income a comparatively high chance to emerge. If, for example, higher temperatures are linked to the spread of disease and thereby also contribute to worse institutions or lower levels of education, not accounting for the disease environment, institutions or education overemphasizes the link between temperature and income, i.e. while present regional temperature is external to present regional income it is not necessarily exogenous. Indeed, older studies that account for additional covariates usually found no effects of temperature or related variables on GDP per capita or growth in cross-country regressions (e.g., Acemoglu et al., 2001; Rodrik et al., 2004; Sala-I-Martin et al., 2004). For reasons of completeness, we include several control variables to our baseline regressions but relegate this analysis to the Supplementary Information.

Similarly to the analysis of the regional data from Gennaioli et al. (2014), we employ country fixed effects in a regression setting for the DHS data samples. Again, we cluster standard errors at the country level. We explore the dependent variables nightlights and gross cell production of region *r* in country *i* in years 2015 and 2005:

$$\ln{(nightlights)}_{r,i,2015} = \beta(Temperature)_{r,i,2015} + \omega_i + \epsilon_{r,i,2015} \quad (2)$$

$$\ln{(gross\ cell\ production)}_{r,i,2005} = \beta(Temperature)_{r,i,2005} + \omega_i + \epsilon_{r,i,2005} \quad (3)$$

Following our theoretical considerations, we expect the temperature-income relationship to be negative in models (1) to (3), i.e., we expect hotter regions to be less wealthy. As highlighted in the literature review, however, the evidence is slightly mixed and we expect that, in particular, the inclusion of country fixed effects to capture relevant heterogeneity may substantially weaken any potential link between regional temperatures and incomes (e.g., Dell et al., 2009).

The literature suggests that we should account for heterogenous effects between rich and poor countries and potential non-linearities. As additions to the simple parsimonious models in (1) to (3), we thus extend these models accordingly in some specifications. First, to explore regional heterogeneity, we estimate additional models that include an interaction term with the dummy variable *Poor* that equals one if a region's income is below the average of the full sample and zero otherwise (see also Dell et al., 2012; Zhao et al., 2018 for similar approaches). We hypothesize that a potential negative link between temperature on incomes is stronger in relatively poorer regions due to weaker adaptation. Second, we consider non-linearities in the temperature-income relationship, i.e. potential negative correlations between higher temperatures and incomes may be particularly pronounced in hotter regions. We add a quadratic term of temperature to allow for such non-linear effects thereby following Burke et al. (2015; 2018), Deryugina and Hsiang (2014) and Nordhaus (2006).

IV. THE LINK BETWEEN REGIONAL TEMPERATURE AND REGIONAL INCOMES

SIMPLE CORRELATIONS

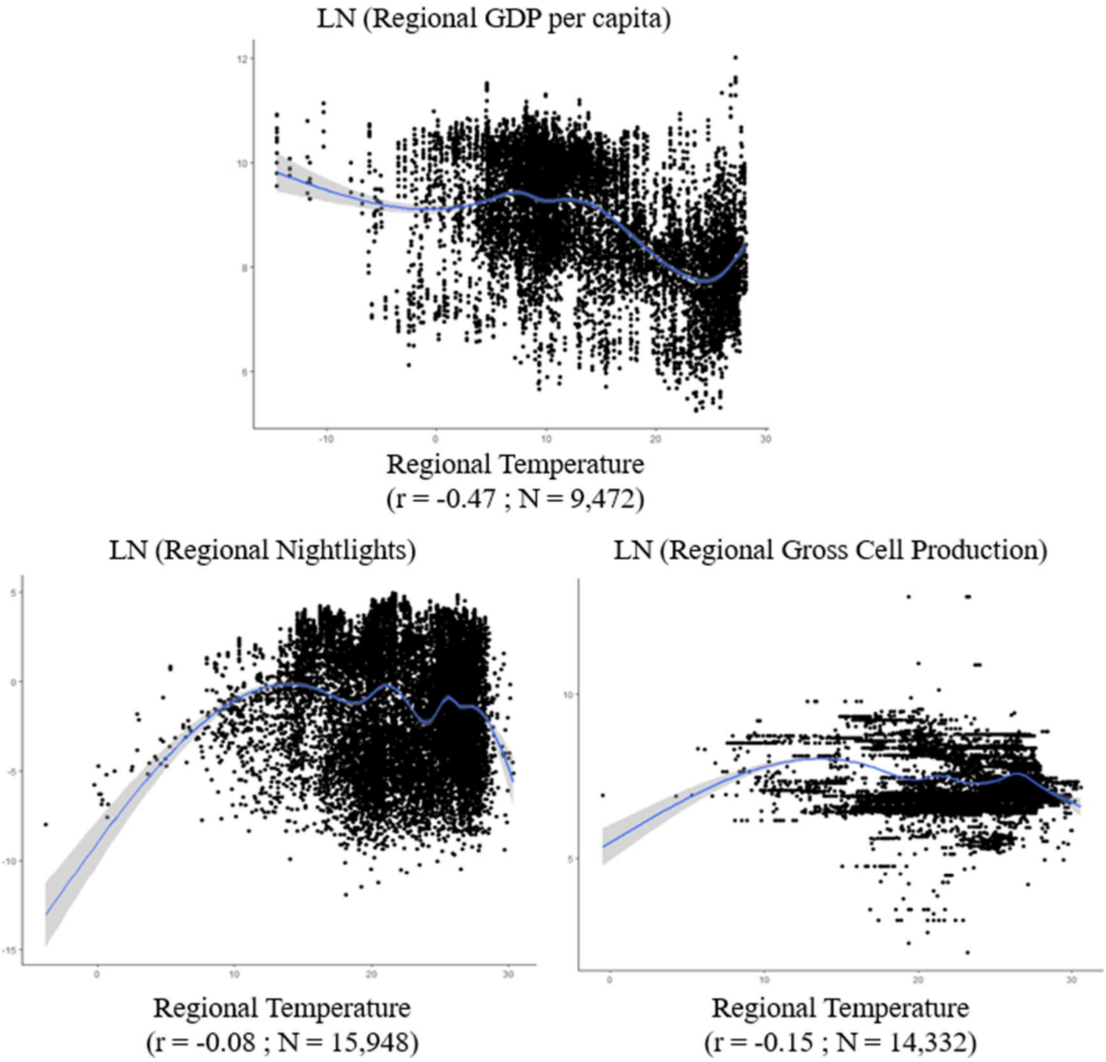
Figure 1 shows the relationship between regional temperature and our three dependent variables: regional GDP per capita, regional nightlights and regional gross cell production.

The relationships tend to be negative and the Pearson correlation coefficients lie between -0.08 (for nightlights) and -0.47 (for GDP per capita). Thus, simple correlations point to a negative relationship between regional temperature and incomes, i.e., hotter regions tend to be less wealthy. This is broadly consistent with insights from the existing cross-country literature (e.g., Burke et al., 2015, 2018; Dell et al., 2009, 2012).

Figure 1 also highlights that there is substantial variation in temperature and each of the regional development measures. Indeed, the richest region in our dataset (Abu Dhabi in the United Arab Emirates) is also among the hottest, with an average temperature of 27.3°C. Moreover, some exceptionally cold regions such as the Yukon Territory in Canada are among the richest regions in the world.[7] The large heterogeneity within countries emphasizes the relevance of our analysis as an extension to the existing cross-country literature.

[7] We eliminate such potential outliers from the analysis in further explorations in the Supplementary Material. We also consider the effect of extremely low/high temperatures on regional economic development as part of our sensitivity checks.

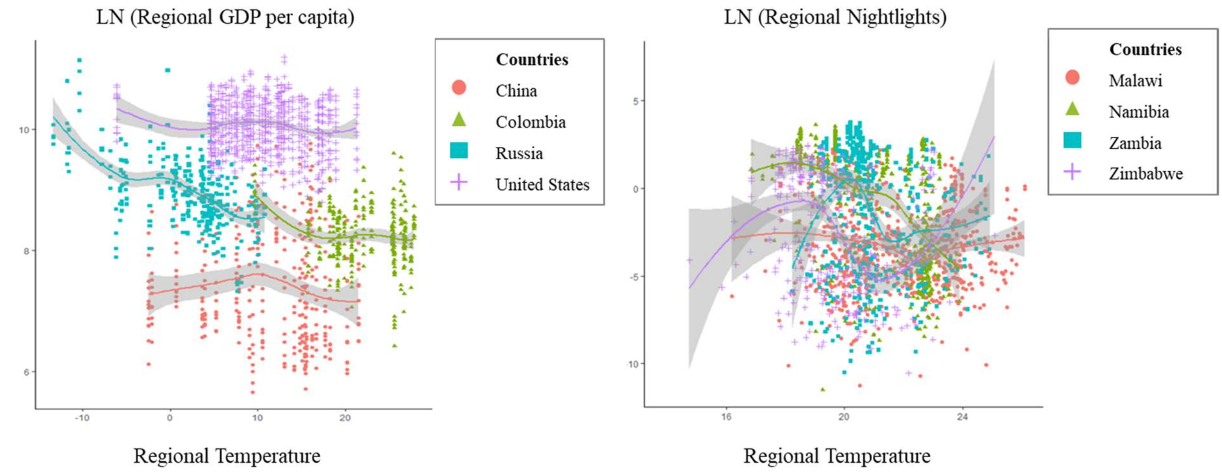
Figure 1: *The link between regional economic development and regional temperature*



Note: Scatterplots summarize all available GDP p.c. observations per region between 1950 and 2010 in Gennaioli et al. (2014) and all available Nightlights and Gross Cell Production observations per cluster in DHS (2015) and DHS (2005). The drawn line reports a non-linear smoothed means.

Figure 2 shows the heterogeneity in selected countries for regional GDP per capita (China, Colombia, Russia and the United States) and nightlights (Malawi, Namibia, Zambia and Zimbabwe). We observe a substantial intra-country variation both in economic development and temperature; for instance, all considered countries are of considerable size and therefore cover various climatic zones. Take Russia as an example: West and East are separated by more than 5,000 miles. Average yearly regional temperatures range from -13°C (Republic of Sakha) to +11°C (Krasnodar).

__Figure 2:__ Heterogeneity within countries and links between regional incomes/nightlights and temperature for selected countries



Note: Scatterplots summarize all available GDP p.c. observations (1950-2010) and Nightlights observations (2015) per region/cluster for selected countries.

Thus, regions or clusters within a country can be relatively hot or cold and relatively poor or rich. The variation is substantial. By using national averages of temperature and income, the cross-country literature cannot account for this considerable sub-national spread. Meanwhile, our approach allows us to investigate relevant within country heterogeneity, while also being able to account for country specific characteristics with country fixed effects. Thereby, it naturally extends and complements the existing literature.

MAIN ECONOMETRIC RESULTS

Table 1 shows the relationship between regional temperature and regional per capita incomes. Results of specification (1) report the association between the two variables without fixed effects (see Figure 1), whereas in specifications (2) to (4) we control for country and time fixed effects, which capture country- and time-specific characteristics that could influence the relationship between temperature and income.

In the parsimonious specification (1) without fixed effects, we find that a one-unit (1°C) increase in regional temperature is associated to a reduction in regional GDP p.c. by 0.067 log units. This is broadly consistent in terms of magnitude with previous research efforts such as Dell et al. (2009). Temperature explains about 22% of the variation of regional GDP per capita.

As soon as we introduce country and time fixed effects in specification (2), the coefficient associated with temperature moves close to zero with point estimate of -0.004. It is now statistically insignificant at conventional levels. Thus, accounting for country and time specific heterogeneity, there is no statistically robust link between regional temperature and regional incomes.[8] Given that the coefficient estimate for temperature is small and the standard error estimate is not unreasonably large, the specification tends to provide some evidence of the absence of any link between regional temperature and regional incomes.

Once controlling for country specific heterogeneity with fixed effects, regions within a country are not systematically wealthier or poorer because they are colder or hotter. Moreover, the addition of regional temperature only marginally improves the overall fit of the model ($R^2 = 0.8564$) compared to a pure fixed effects only model without temperature ($R^2 = 0.8563$). This suggests that regional temperature tends to have a comparatively small explanatory power for regional GDP once fixed effects are accounted for. Given institutions, culture and other potential country specific effects that are reflected in the fixed effects, our results may point to adaptation possibilities to higher temperatures at the regional level, i.e. initially colder regions may copy coping strategies from hotter regions.

Table 1: *Baseline regressions for the effect of temperature on regional incomes when accounting for country and time fixed effects*

Dependent Variable →	(1) Ln_GDP_region	(2) Ln_GDP_region	(3) Ln_GDP_region	(4) Ln_GDP_region
Temperature	-0.067*** (0.011)	-0.004 (0.007)	0.007 (0.009)	-0.025** (0.012)
Poor			-0.613*** (0.114)	
Temperature x Poor			-0.013 (0.009)	
Temperature²				0.001* (0.001)
Country FE	NO	YES	YES	YES
Time FE	NO	YES	YES	YES
Observations	9,472	9,472	9,472	9,472
R^2	0.221	0.856	0.883	0.858

Note: The regressions estimate the effect of temperature on logarithmized regional GDP p.c. in regressions with the dummy variable Poor (1 if regional GDP per capita is below sample average; 0 otherwise) and its interaction with temperature, as well as temperature squared. Regressions are run with the Gennaioli et al. (2014) dataset without and with country and time fixed effects. Robust clustered standard error estimates (country-level) are presented below the coefficients. Significance levels are indicated by *p<0.1; **p<0.05; ***p<0.01.

8 Dell et al. (2009) also experience a substantial decrease of the effect of temperature on sub-national economic development when introducing fixed effects. However, in their setting the link remains statistically significant. This is likely due to the sample of 12 countries on which they focus; our country coverage is much larger.

To further investigate the relevance of heterogeneity, we run a simple regression with regional income as a dependent variable and regional temperature as the single independent variable *for each country separately*. As shown in Table 5 in the Supplementary Information, the coefficients associated with temperature are often statistically insignificant; they can be both positive and negative. We plot their distribution in Figure 3. This analysis raises confidence in our interpretation that there is no straightforward relationship between regional temperatures and economic development once fixed effects are accounted for.

Still, the literature suggests that there may be some heterogeneity between the rich and the poor. In specification (3) of Table 1, we include a dummy variable *Poor* for whether a region is below the sample average of regional GDP per capita (dummy equals 1) or above (dummy equals 0). We then interact this dummy variable with temperature to explore whether the link between temperature and GDP per capita is more relevant in poorer regions. By construction, the variable *Poor* itself must have a significantly negative coefficient when explaining regional GDP per capita. The coefficient of the interaction term is negative but statistically insignificant. The coefficient of temperature itself is positive but also statistically insignificant.[9] Higher temperature does not seem to be related to regional incomes, independent of whether the region is considered poor or rich.

One explanation for a statistically insignificant link between regional temperature and income might be that the relationship between the two variables is non-linear. For instance, Burke et al. (2018) and Zhao et al. (2018) suggest that the relationship may follow an inverted-U shape in relation to temperature, meaning that cooler regions might benefit from a rise in temperature (e.g., as agricultural productivity improves), while already warmer regions lose out. We follow this inspiration and introduce a quadratic term in specification (4) of Table 1. The findings tend to show, if anything, a U-shape when employing regional data. Interpreting these results, we note that regions from Gennaioli et al. (2014) in general are relatively cool with an average annual temperature of about 14 °C; African countries, which may have driven previous results in the cross-country literature due to their dependence on agriculture, are not included in this sample. To further consider non-linearities, we estimate Generalized Additive Model with country fixed effects and plot our findings from this semi-parametric non-linear model using cubic regression splines in Figure 4 in the Supplementary Appendix. The figure

[9] Positive and statistically significant links for temperature and growth at the subnational level are shown for example by Zhao et al. (2018), p. 540, Table 3, column 1.

suggests that there is no clear non-linear pattern, which corresponds to our result that temperature and regional economic development do not follow an obvious (inverted) U-shape.

Finally, it might be argued that our setting gives regional temperature a high chance to emerge as a factor explaining income differences as we do not include any other covariates in our model; that is, omitting potentially relevant controls may bias our estimates. In the Supplementary Information (Table 6), we provide additional estimates that include a set of potentially relevant controls (e.g., regional levels of education, Malaria ecology, regional geography etc.). Including these controls, however, does not affect our main interpretations.

In sum, our results speak to past research efforts studying differences in economic development between countries: these studies rarely found that temperature played a substantial role (e.g., Acemoglu et al., 2001; Rodrik et al., 2004; Sala-I-Martin et al., 2004). Indeed, our estimated coefficients of temperature are close to zero when accounting for fixed effects. Their inclusion constitutes the major reason for the discrepancy of our results to previous evidence as cross-sectional analyses may conflate generally higher temperature with other characteristics (see also Dell et al., 2014, p. 753). This suggests that national factors such as institutions, policies, culture, etc., which tend to be very similar across regions within the same country, matter more strongly to regional economic development than inter-regional differences in temperature. At the same time, relevant factors that are determined at the country level may also facilitate adaptation to higher or lower temperatures within countries and thus further ameliorate the effect of temperature on income. Finally, migration from particularly cold or hot regions to moderate temperature regions can be more easily achieved within rather than between countries. This straightforward re-allocation of human (and physical) capital within a country is another potential pathway through which the potentially ill effects of temperature on regional economic development might be plausibly accommodated.

As alternative indicators of regional economic development, we use the logarithms of nightlights and gross cell production as dependent variables. As outlined above, these variables are drawn from the DHS. The unit of observations are DHS clusters. Our variables nightlights and gross cell production (GCP) are available for 2015 and 2005, respectively. Our results are presented in Table 2 and Table 3.

Table 2: *Baseline regressions for the effect of temperature on nightlights in 2015 when accounting for country fixed effects*

Dependent Variable →	(1) Ln_nightlights	(2) Ln_nightlights	(3) Ln_nightlights	(4) Ln_nightlights
Temperature	-0.060	0.181***	0.203***	0.397**
	(0.059)	(0.067)	(0.059)	(0.191)
Poor			-2.370**	
			(0.977)	
Temperature x Poor			-0.084**	
			(0.040)	
Temperature²				-0.005
				(0.005)
Country FE	NO	YES	YES	YES
Observations	15,533	15,533	15,533	15,533
Adj. R^2	0.006	0.379	0.578	0.380

Note: The regressions estimate the effect of temperature on logarithmized regional *nightlights* in regressions with the dummy variable Poor (1 if regional *nightlights* is below sample average; 0 otherwise) and its interaction with temperature, as well as temperature squared. Regressions are run with DHS data for the year 2015 with country fixed effects. Robust clustered standard error estimates (country-level) are presented below the coefficients. Significance levels are indicated by *p<0.1; **p<0.05; ***p<0.01.

Without country fixed effects (specification 1) temperature and nightlights are negatively correlated. The results with country fixed effects of specifications (2) to (4) suggest, if anything, a positive relationship between the cluster temperature and nightlights within a cluster.[10] In relatively poor regions, this positive effect is somewhat less pronounced (specification 3). We also find that the relationship between temperature and nightlights does not follow a non-linear pattern as the coefficient for the squared term of temperature is statistically insignificant. A potential explanation for the positive relationship between temperature and nightlights might be that people tend to shift economic activity towards the evening or night in hotter regions.[11] If this is the case, it would be consistent with our insignificant findings regarding regional incomes as this could be seen as an adaptation strategy. However, working at night may still have negative welfare effects if people would prefer to work during the day; at the same time, working at night may also adversely affect human health.

[10] It is noteworthy that any statistical significance of the positive relationship between temperature and nightlights vanishes once if we also control for other potential determinants of nightlights such as latitude or Malaria ecology (see Table 7 in the Supplementary Information). This finding is rather in line with our previous result that there is no statistically robust link between regional temperature and economic development, proxied with nightlights.

[11] We thank a referee for suggesting this explanation.

Table 3: *Baseline regressions for the effect of temperature on gross cell production in 2005 when accounting for country fixed effects*

Dependent Variable →	(1) Ln_GCP	(2) Ln_GCP	(3) Ln_GCP	(4) Ln_GCP
Temperature	-0.032	-0.012	-0.026**	0.054
	(0.036)	(0.011)	(0.012)	(0.063)
Poor			-1.428***	
			(0.358)	
Temperature x Poor			0.018	
			(0.013)	
Temperature²				-0.002
				(0.001)
Country FE	NO	YES	YES	YES
Time FE	NO	NO	NO	NO
Observations	14,130	14,130	14,130	14,130
Adj. R^2	0.022	0.839	0.891	0.840

Note: The regressions estimate the effect of temperature on logarithmized regional gross cell production in regressions with the dummy variable Poor (1 if regional gross cell production is below sample average; 0 otherwise) and its interaction with temperature, as well as temperature squared. Regressions are run with DHS data for the year 2005 with country fixed effects. Robust clustered standard error estimates (country-level) are presented below the coefficients. Significance levels are indicated by *p<0.1; **p<0.05; ***p<0.01.

Finally, we explore the relationship of temperature and gross cell production in 2005 in Table 3. Again, the simple correlation without controlling for fixed effects suggests a negative association (specification 1). Once country fixed effects are introduced in specification (2), there is no statistically robust relationship between temperature and gross cell production. There is also no evidence of a temperature effect that is only relevant to relatively poor regions (specification 3). Rather, the baseline coefficient for temperature is negative and statistically significant, suggesting that for this sample of relatively poor countries, the comparatively rich clusters might have faced disadvantages of higher temperatures. Again, any statistically significant link between temperature and gross cell production disappears once we control for additional covariates, as shown in Table 8 in the Supplementary Information.

EXTENSIONS AND FURTHER ROBUSTNESS CHECKS

Our results do not suggest a statistically robust link (linear or not) between temperature and different measures of economic development at the regional level once country specific heterogeneity is accounted for. Point estimations of the association between temperature and different income measures are usually close to zero.

While we provide little evidence of a *general* relationship between regional temperature and development, it is still possible that this relationship may be relevant to specific settings.[12] Indeed, as climate change is happening, we need to explore diverse settings to provide information where adverse economic effects could occur. Below, we briefly discuss a variety of empirical extensions to reflect the role of temperature in regional economic development in various settings. We report our estimates in the Supplementary Information for completeness.

First, we reconsider our sub-national administrative data from Gennaioli et al. (2014) and explore seven subsamples for each decade, i.e., we explore a cross-section for every first year of a new decade (1950, 1960, 1970, 1980, 1990, 2000, 2010). The results for the seven cross-sections are reported in Table 9. They show a statistically significant and negative relationship between temperature and regional GDP for the years 1950 and 1960. We might conclude that poorer regions had more difficulties to cope with higher temperatures before 1970 but thereafter found adaption methods (such as improvements in agriculture, etc.) that mitigated temperature effects on income. Taking the results of the most recent period in the set (i.e. 2010), we find a quantitatively small but statistically insignificant negative relationship in specification (19) of Table 9. There is no systematic evidence for an inverted-U relationship between regional temperature and regional GDP per capita.

We employ the DHS data and account for a popular critique of using average temperature, namely that temperature averages neglect variation in temperature between months or even days (e.g., Barreca, 2012; Deschênes and Greenstone, 2007; Ranson, 2014; Schlenker and Lobell, 2010). The DHS enables us to investigate the difference between the lowest and highest monthly temperature per year and regress it on the logarithm of nightlights in 2015 and gross cell production in 2005. Moreover, we also explore temperatures in July and December separately. As DHS data contains mostly countries from the southern hemisphere, we consider December temperatures to be the summer and July temperatures to be the winter temperatures.[13] Using these alternative climate variables, no clear and robust pattern emerges. The results for nightlights in Table 10 suggest that there is no average effect of temperature difference but that there may be some heterogeneity between richer and poorer regions and Summer and Winter temperatures. For gross cell production in Table 11, we find a negative

[12] For instance, Colacito et al. (2019) shows a negative relationship between temperature and growth for summer temperatures (but not for average yearly temperature); Dell et al. (2012) find a negative relationship for poor countries (but not for rich countries); There are relevant differences regarding the optimum temperature for studies investigating inverted-U relationships such as Deryugina and Hsiang (2014), Nordhaus (2006), Zhao et al. (2018) or Li et al. (2019).

[13] In poorer countries, fewer sunlight hours in winter (around July) may have to be compensated with electricity, which may be unstable or difficult to afford in developing regions (see Adeoye and Spataru, 2019; Jiang et al., 2020 for different season-dependent electricity demands in developing countries).

relationship with temperatures in July. Future research may explore the relevance of seasonal temperatures or temperature differences at the regional level.

In Table 12 we explore an array of subsets from our original data for our three indicators for sub-national economic activity in a generally parsimonious setting. We address potentially distorting effects due to outliers, exclude regions facing armed conflict, exclude regions with extreme temperatures, explore temperature weighted by the log of population, explore different continents separately, explore regions with different income levels separately and take account of education[14]. The interpretation of the results would broadly correspond to the interpretations given above.

In Table 13 we replace regional per capita GDP by the per capita GDP growth rate between the first and the last available regional GDP entry recorded to explore any potential link between temperature changes and growth rates. Again, we do not observe robust links between temperature changes and growth rates.

Finally, Table 14 constitutes an additional attempt to account for the influence of precipitation which is available in the DHS data only. As soon as we introduce country fixed effects the link between precipitation and nightlights as well as gross cell production becomes insignificant. This broadly corresponds to the literature which suggests that the effect of climate conditions on development will emerge – if anything – through temperature, while the role of precipitation is less certain (Dell et al., 2014, p.753).

DISCUSSION AND CAVEATS

Some empirical and theoretical contributions have argued that hot temperature may have a *direct* impact on economic activity by adversely affecting, e.g., human productivity, labor morale, agricultural production or the spread of diseases; hot temperatures may furthermore have an *indirect* impact on development by contributing to the emergence of extractive institutions (e.g., Easterly and Levine, 2003; Gallup et al., 1999). Consequently, hotter regions within a country might be characterized by lower per capita incomes. Our results for several thousand sub-national administrative units and DHS clusters suggest that there is no systematic effect of regional temperature on regional incomes. Anecdotal evidence suggests that some of

[14] We build on the large literature that points to the role of education in economic development, with higher levels of education being conducive to economic progress (e.g., Barro, 1991; Bowles, 1972; Mincer, 1974) and potentially fostering adaptation to higher temperatures.

the richest regions in the world are among both the hottest and coldest in the world (e.g., regions in the United Arab Emirates or Canada).

Interpreting our findings, we would like to discuss potential caveats which might be addressed by future research: First, we analyze levels of economic development and do not analyze income changes due to changes in yearly temperature as we employ average temperature data for a time period of fifty years (similar to Dell et al. (2009)) or investigate sub-national units for a given year. Empirically, this leaves us unable to include region fixed effects or country-time fixed effects, where the latter would allow us to account for unique nation-time specific trends. Thus, we cannot explore how changes in temperature affect changes in economic development. Therefore, we caution to draw any direct conclusion regarding the economic effects of (future) anthropogenic climate change. At the same time, there exist numerous examples at the regional level that hot temperatures can go hand in hand with high incomes. It might be possible to learn from these regions in terms of coping with high and/or increasing temperatures.

Second, due to their unavailability on the regional level, we are not able to add many time-variant or time-invariant regional controls. Extreme weather-related events such as cyclone activity, regional population dynamics, regional ethno-linguistic diversity, regional redistribution, etc. are only a few examples of variables that may also matter to regional economic development. Similar to the cross-country literature, potential omitted variable bias thus cannot be fully ruled out even if we include country fixed effects. Moreover, migration between regions within a country tends to be easier than migration between countries. Temperature could be correlated with migration and migration could be related to economic activity per capita which would then be a potential confounding factor in our analysis.[15]

Third, caution must be exercised when dealing with temperature datasets that aggregate data for regions or over time, as weather station data may be interpolated or modeled rather than directly measured, or found to be misaligned with original measurements because of rounding or conversion errors (see e.g., Nese, 1994; Rhines et al., 2015). This, however, affects data from cross-country datasets as well as regional datasets.[16]

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[15] Beine and Parsons (2015) do not find direct effects of long-run climatic factors on international migration employing data from 1960 to 2000.

[16] Climate observations often underlie measurement biases due to undesired instrument exposures, which can account for measurement errors of up to 3.6 °C (e.g., Mahmood et al., 2006).

V. CONCLUSIONS

This paper explores the relationship of temperature and income for a large number of sub-national regions and clusters. We use data on regional temperature, GDP per capita and GDP per capita growth for 1,542 administrative regions in 83 countries for the years 1950 to 2010 from Gennaioli et al. (2014). Moreover, we employ data on regional temperature and nightlights for 15,533 sub-national clusters for the year 2015 in 37 countries and gross cell production for 14,130 sub-national clusters for the year 2005 in 31 countries, using data from DHS.

We observe a negative and statistically significant relationship between regional temperature and regional GDP per capita when we do not account for country fixed effects. By contrast, we do not find a consistent and robust link between regional temperature and regional economic development once accounting for country fixed effects. We also do not find that there are systematic differences in the role of temperature in regional incomes between rich and poor regions when accounting for country fixed effect. We tend to find a positive relationship between temperature and nightlights that is slightly weaker for poor regions. However, this relationship becomes statistically insignificant once more covariates are added. Similarly, there is no statistically robust relationship between temperature and gross cell production. Finally, regardless of which regional economic development proxy is employed, we find no systematic support across our different samples and measures for an inverted-U relationship between temperature and development at the regional level.

Compared to the cross-country literature on the temperature-income relationship, our approach using sub-national data allows us to account for a heterogeneity within a country. We are able to add to the discussion on the non-linearity assumption of the temperature-income relationship as well as to the discussion whether poor regions suffer more strongly from hot temperatures due to a failure of sufficiently adapting to them. Currently, the missing time variation of the temperature variable at the regional and the cluster level does not allow us to draw conclusions on how changes in temperatures are related to changes in economic activity. Ideally, we would want to analyze regional temperature for every year from 1950 onwards, so that we can employ region fixed effects. This would allow for an even more stringent testing of the temperature-development relationship compared to our present approach. The analysis of other important climatic indicators on the sub-national level (such as the number of hot days, floods, cyclone activity, etc.) would constitute another interesting avenue for future research. We think that more research is required in this domain to establish clear-cut results to offer reasonable policy advice. We hope that our paper can inspire such analyses at the regional level.

VI. LITERATURE

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VII. SUPPLEMENTARY INFORMATION

Figure 3: *Histogram of temperature coefficients from* Table 5

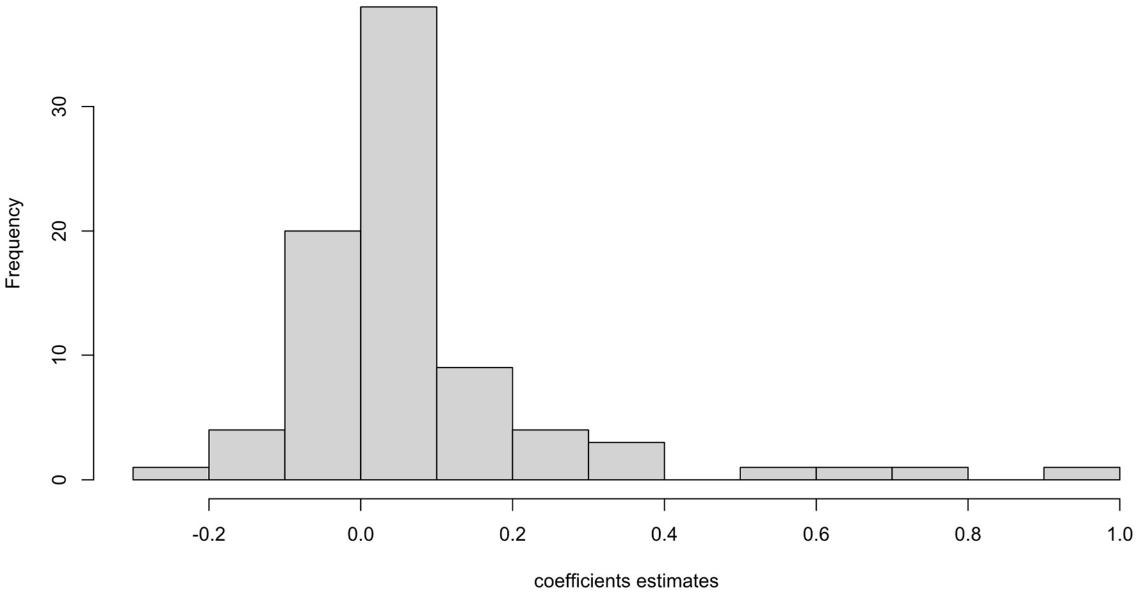

Figure 4: *Generalized Additive Model with Country and Time Fixed Effects with temperature as a non-linear model using cubic regression splines*

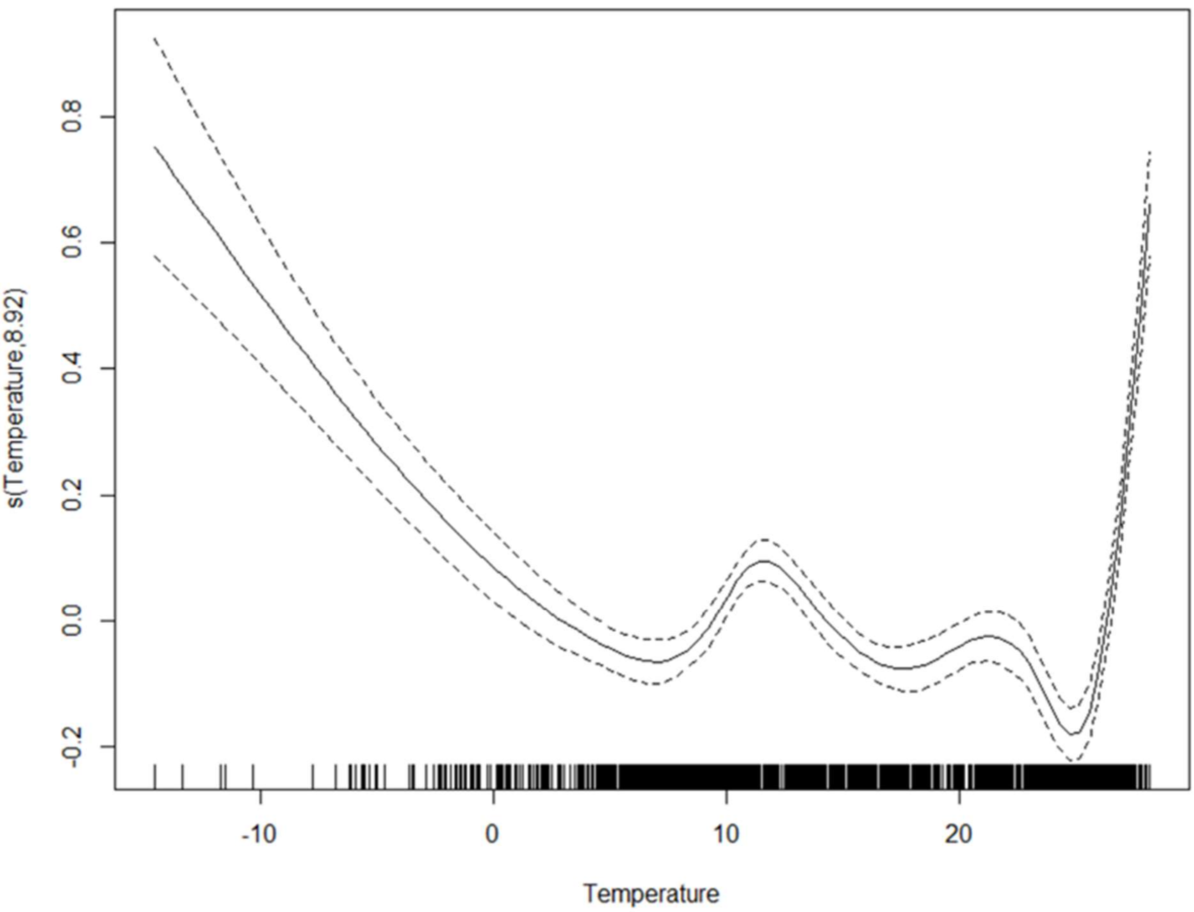

Table 4: *Descriptive statistics*

Variable	Description	Median	Mean	Std. Dev.	Min	Max	Obs
Variables used in regressions with Ln(GDP_region) (Source: Gennaioli et al. (2014))							
Ln(GDP_region)	Logarithm of the gross domestic product per capita in a region (in constant 2005 PPP US$).	8.83	8.82	1.16	5.24	12.02	9,472
Temperature	Temperature (Celsius) averaged for the period 1950 to 2000 within the sub-national region.	12.60	14.18	8.06	-14.49	28.19	9,472
Poor	Dummy variable equals 1 if region is below sample average regarding per capita GDP; 0 otherwise.	1.00	0.63	0.48	0.00	1.00	9,472
Years of education	Average years of schooling from primary school onwards for the population aged 15 years or older in a region.	7.41	7.21	3.25	0.39	13.76	7,504
Landlocked country	Dummy variable that is equal to 1 if the country is landlocked; 0 otherwise.	0.00	0.10	0.30	0	1	9,472
Landlocked region	Dummy variable that is equal to 1 if the region is landlocked; 0 otherwise.	1.00	0.54	0.50	0	1	9,472
nbr	Dummy variable that is equal to 1 if the region has a border to another region in a neighboring country; 0 otherwise.	0.00	0.43	0.50	0.00	1.00	9,487
nbr_nr	Number of borders to other countries incl. A region's own country border.	1.00	1.59	0.87	0.00	8.00	9,487
Latitude	Latitude of the centroid of each region calculated in ArcGIS.	37.47	33.50	16.47	0.02	69.95	9,472
Ln(Area_sqkm)	Logarithm of the area in square kilometers.	9.58	9.75	1.76	3.34	15.18	9,472

Malaria_ecology	The "malaria ecology" index of Kiszewski et al. (2004) measures the risk of being infected by Malaria. The index variable ranges from 0 to 39 with higher values indicating a higher risk and thus less Malaria stability. The index takes into account both climatic factors and the dominant vector species to give an overall measure of the component of malaria variation that is exogenous to human intervention. The index is calculated for grid squares of one half degree longitude by one half degree latitude. Regional averages are calculated via ArcGIS.	0.01	1.09	2.72	0.00	28.68	9,472
Ln(Cum_Oil_Gas_ Prod)	(Logarithmized) cumulative oil, gas and liquid natural gas production from the time production began to 2000. Oil and liquid natural gas were collected in millions of barrels. Gas was collected in billions of cubic feet and divided by 6 to convert to millions of barrels of oil equivalents.	0.00	0.00	0.01	0.00	0.12	9,472
Ln(Pop_density)	Logarithm of the population density which is measured as people per square kilometres in a region.	4.12	4.02	1.74	-4.65	10.06	9,472
Capital is in Region	Dummy variable that is equal to 1 if the region contains a national capital city; 0 otherwise.	0.00	0.05	0.22	0.00	1.00	9,467
Ln(GDP_country)	Logarithm of the gross domestic product per capita in a country (in constant 2005 PPP US$).	9.00	9.00	1.05	5.90	11.56	9,472
	Variables used in regressions with Growth (Source: Gennaioli et al. (2014))						
Growth	Growth of gross domestic product per capita in a region (in constant 2005 PPP US$) between the first and the last available year.	0.89	1.79	2.73	-0.73	38.12	1,527
Temperature	see description of variables used in regressions with Ln(GDP_region).	12.18	14.19	8.22	-14.49	28.19	1,527
Poor	see description of variables used in regressions with Ln(GDP_region).	1.00	0.87	0.34	0	1	1,527

Years of education	see description of variables used in regressions with Ln(GDP_region).	6.90	7.01	2.95	0.99	12.95	1,505
Landlocked country	see description of variables used in regressions with Ln(GDP_region).	0.00	0.13	0.34	0	1	1,527
Landlocked region	see description of variables used in regressions with Ln(GDP_region).	1.00	0.60	0.49	0	1	1,527
nbr	see description of variables used in regressions with Ln(GDP_region).	0.00	0.47	0.50	0	1	1,527
nbr_nr	see description of variables used in regressions with Ln(GDP_region).	1.00	1.63	0.85	0.00	8.00	1,527
Latitude	see description of variables used in regressions with Ln(GDP_region).	38.17	34.02	16.83	0.02	69.95	1,527
Ln(Area_sqkm)	see description of variables used in regressions with Ln(GDP_region).	9.31	9.50	1.68	3.34	15.18	1,527
Malaria_ecology	see description of variables used in regressions with Ln(GDP_region).	0.01	1.20	3.12	0.00	28.68	1,527
Ln(Cum_Oil_Gas_Prod)	see description of variables used in regressions with Ln(GDP_region).	0.00	0.00	0.01	0.00	0.12	1,527
Ln(Pop_density)	see description of variables used in regressions with Ln(GDP_region).	4.15	4.07	1.70	-4.03	9.73	1,527
Capital is in Region	see description of variables used in regressions with Ln(GDP_region).	0.00	0.05	0.23	0.00	1.00	1,527
Ln(GDP_country)	see description of variables used in regressions with Ln(GDP_region).	8.86	8.85	0.96	6.26	11.14	1,527
Variables used in regressions with Ln(Nightlights_Composite) (Source: DHS (2015))							
Ln(Nightlights_ Composite)	Logarithm of the average nighttime luminosity of the area (Composite cloud-free radiance values) within the 2 km (urban) or 10 km (rural) buffer surrounding the DHS survey cluster location in 2015.	-0.78	-1.02	3.34	-11.92	4.94	15,948

temperature	The average yearly temperature (in °C) within the 2 km (urban) or 10 km (rural) buffer surrounding the DHS survey cluster location.	23.19	22.52	4.36	-3.77	30.38	18,604
Poor	Dummy variable equals 1 if region is below sample average regarding *nightlights*; 0 otherwise.	1.00	0.78	0.41	0	1	19,036
Diff Max Min	The difference between the average annual maximum and minimum temperature (in °C) within the 2 km (urban) or 10 km (rural) buffer surrounding the DHS survey cluster location.	5.42	7.62	5.76	0.56	29.24	18,604
Temperature December	The average monthly temperature in December (in °C) within the 2 km (urban) or 10 km (rural) buffer surrounding the DHS survey cluster location.	22.83	20.85	6.21	-13.66	29.68	18,604
Temperature July	The average monthly temperature in July (in °C) within the 2 km (urban) or 10 km (rural) buffer surrounding the DHS survey cluster location.	24.57	22.96	5.16	2.03	34.52	18,604
Precipitation	The average precipitation measured within the 2 km (urban) or 10 km (rural) buffer surrounding the DHS survey cluster (in milimeters) in 2015.	87.11	89.13	59.99	0.17	368.69	17,289
Latitude	Latitude	8.27	7.49	17.99	-30.59	42.43	19,051
Ln(pop)	The logarithm of the count of individuals living within the 2 km (urban) or 10 km (rural) buffer surrounding the DHS survey cluster in 2015 (number of people).	10.50	10.37	1.77	-3.63	15.60	18,247
Aridity	The dataset represents the average yearly precipitation divided by average yearly potential evapotranspiration in 2015, an aridity index defined by the United Nations Environmental Programme (UNEP). Index between 0 (most arid) and 300 (most wet).	23.37	24.88	18.12	0.02	136.13	17,289

drought_episodes	The average number of drought episodes (categorized between 1 (low) and 10 (high)) for the areas within the 2 km (urban) or 10 km (rural) buffer surrounding the DHS survey cluster location based on 1980-2000 precipitation data.	5.00	5.43	2.68	1.00	10.00	13,205
Enhanced_ Vegetation_Index	The average vegetation index value within the 2 km (urban) or 10 km (rural) buffer surrounding the DHS survey cluster in 2015. Vegetation index value between 0 (least vegetation) and 10000 (Most vegetation).	3,043.00	2,965.72	1,085.59	7.00	6,093.00	18,683
Frost_Days	The average number of days in which the minimum temperatures of the location surrounding the DHS survey cluster within 2 km (urban) or 10 km (rural) buffers met the criteria to be categorized as a "frosty" day in 2015. Frost days is a synthetic measurement that is based off of the minimum temperature. The full formula to calculate the number of days can be found in the cited Harris et al. (2014) or in New, Hulme, and Jones (2000).	0.00	0.73	2.33	0.00	28.69	17,289
global_human_ footprint	The average of an index between 0 (extremely rural) and 100 (extremely urban) for the location within the 2 km (urban) or 10 km (rural) buffer surrounding the DHS survey cluster based on 1995-2004 data. It is created from nine global data layers covering human population pressure (population density), human land use and infrastructure (built-up areas, nighttime lights, land use/land cover), and human access (coastlines, roads, railroads, navigable rivers).	36.79	43.15	20.11	0.00	100.00	18,971

growing_season_ length	The length of the growing season in days (reported in one of 16 categories) for the area within the 2 km (urban) or 10 km (rural) buffer surrounding the DHS survey cluster location based on data collected between 1961 and 1991. 1: 0 days; 2: 1 - 29 days; 3: 30 - 59 days; 4: 60 - 89 days; 5: 90 - 119 days; 6: 120 - 149 days; 7: 150 - 179 days; 8: 180 - 209 days; 9: 210 - 239 days; 10: 240 - 269 days; 11: 270 - 299 days; 12: 300 - 329 days; 13: 330 - 364 days; 14: < 365 days; 15: 365 days; 16: > 365 days.	9.00	8.27	3.57	1.00	16.00	18,465
Irrigation	The average proportion of the area within the 2 km (urban) or 10 km (rural) buffer surrounding the DHS survey cluster location equipped for irrigation in 2005.	0.10	9.40	20.26	0.00	100.00	18,604
ITN_Coverage	The average number of people within the 2 km (urban) or 10 km (rural) buffer surrounding the DHS survey cluster location who slept under an insecticide treated net the night before they were surveyed in 2015.	0.62	0.60	0.23	0.00	1.00	10,202
Malaria_Incidence	(Rate!)The average number of people per year who show clinical symptoms of plasmodium falciparum malaria within the 2 km (urban) or 10 km (rural) buffer surrounding the DHS survey cluster location in 2015.	0.17	0.20	0.15	0.00	0.71	10,202
Malaria_ Prevalence	The average parasite rate of plasmodium falciparum (PfPR) in children between the ages of 2 and 10 years old within the 2 km (urban) or 10 km (rural) buffer surrounding the DHS survey cluster location in 2015.	0.11	0.17	0.15	0.00	0.81	10,202
PET	The average annual potential evapotranspiration (PET) (millimeters per year) within the 2 km (urban) or 10 km (rural) buffer surrounding the DHS survey cluster location in 2015.	3.77	3.84	0.77	1.93	7.33	17,289
Ln(proximity_to_ national_borders)	The logarithmized geodesic distance (meters) to the nearest international borders in 2014.	10.34	10.11	1.59	1.23	13.30	19,052

Ln(Proximity_to_ Protected_Areas)	The logarithmized geodesic distance (meters) to the nearest protected area as defined by the United Nations Environment World Conservation Monitoring Centre in 2017. Examples of protected places include national parks, national forests, and national seashores. The dataset includes both aquatic and terrestrial protected areas.	10.82	10.61	1.15	1.89	13.36	18,876
Ln(proximity_to_ water)	The logarithmized geodesic distance (meters) to either a lake or the coastline in 2017. For this extraction we used only the lakes dataset (L2) at full resolution and the shoreline dataset (L1), also at full resolution, in the GSHHG database. The datasets used were based on the World Vector Shorelines, CIA World Data Bank II, and Atlas of the Cryosphere.	10.64	10.30	1.80	0.05	13.45	18,923
Rainfall	The average annual rainfall (in millimeters) within the 2 km (urban) or 10 km (rural) buffer surrounding the DHS survey cluster location in 2015.	1,003.75	1,063.54	723.33	0.00	5,574.00	18,805
Slope	Slope (in degrees) is a measurement of how rough the terrain around a DHS cluster is in 1996. The United States Geological Survey GTOPO30 digital elevation model was processed into slope by using the slope tool in ArcMap 10.5.0.	0.85	1.81	2.35	0.00	23.13	19,004
Wet_Days	The average number of days receiving rainfall within the 2 km (urban) or 10 km (rural) buffer surrounding the DHS survey cluster location in 2015.	8.29	8.32	4.32	0.00	23.67	17,289
Variables used in regressions with Ln(Gross_Cell_Production)) (Source: DHS (2005))							
Ln(Gross_Cell_ Production)	Logarithm of the average Purchasing Power Parity (PPP) in 2005 US dollars for the 2 km (urban) or 10 km (rural) buffers surrounding the DHS survey cluster.	7.30	7.49	0.94	2.13	12.98	14,332

temperature	see description of variables used in regressions with Ln(Nightlights_Composite) with data from 2005.	23.64	22.79	4.26	-0.50	30.55	14,594
Poor	see description of variables used in regressions with Ln(Nightlights_Composite) with data from 2005.	1.00	0.66	0.47	0	1	14,332
Diff Max Min	see description of variables used in regressions with Ln(Nightlights_Composite) with data from 2005.	5.39	7.35	5.23	0.55	21.41	14,594
Temperature December	see description of variables used in regressions with Ln(Nightlights_Composite) with data from 2005.	23.06	21.00	5.55	-6.22	29.70	14,594
Temperature July	see description of variables used in regressions with Ln(Nightlights_Composite) with data from 2005.	24.86	23.24	5.42	1.76	35.66	14,594
Precipitation	see description of variables used in regressions with Ln(Nightlights_Composite) with data from 2005.	84.96	92.79	63.01	0.08	288.50	13,733
Latitude	see description of variables used in regressions with Ln(Nightlights_Composite) with data from 2005.	10.94	8.80	17.17	-30.53	42.43	14,910
Ln(pop)	see description of variables used in regressions with Ln(Nightlights_Composite) with data from 2005.	10.31	10.20	1.76	0.67	15.47	14,451
Aridity	see description of variables used in regressions with Ln(Nightlights_Composite) with data from 2005.	22.46	25.98	18.94	0.01	103.05	13,733
drought_episodes	see description of variables used in regressions with Ln(Nightlights_Composite) with data from 2005.	5.00	5.03	2.90	1.00	10.00	10,250
Enhanced_ Vegetation_Index	see description of variables used in regressions with Ln(Nightlights_Composite) with data from 2005.	2,982.00	2,990.85	1,124.38	39.00	6,246.00	14,642
Frost_Days	see description of variables used in regressions with Ln(Nightlights_Composite) with data from 2005.	0.00	0.53	1.72	0.00	26.81	13,733
global_human_ footprint	see description of variables used in regressions with Ln(Nightlights_Composite) with data from 2005.	38.51	44.60	19.63	0.00	100.00	14,878
growing_season_ length	see description of variables used in regressions with Ln(Nightlights_Composite) with data from 2005.	9.00	8.42	3.80	1.00	16.00	14,470

Irrigation	see description of variables used in regressions with Ln(Nightlights_Composite) with data from 2005.	0.12	9.29	19.84	0.00	100.00	14,594
ITN_Coverage	see description of variables used in regressions with Ln(Nightlights_Composite) with data from 2005.	0.01	0.08	0.10	0.00	0.42	7,666
Malaria_Incidence	see description of variables used in regressions with Ln(Nightlights_Composite) with data from 2005.	0.30	0.31	0.19	0.00	0.75	7,666
Malaria_ Prevalence	see description of variables used in regressions with Ln(Nightlights_Composite) with data from 2005.	0.25	0.29	0.22	0.00	0.97	7,666
PET	see description of variables used in regressions with Ln(Nightlights_Composite) with data from 2005.	3.82	3.92	0.83	2.21	7.65	13,733
Ln(proximity_to_ national_borders)	see description of variables used in regressions with Ln(Nightlights_Composite) with data from 2005.	10.49	10.23	1.62	0.15	13.22	14,911
Ln(Proximity_to_ Protected_Areas)	see description of variables used in regressions with Ln(Nightlights_Composite) with data from 2005.	10.73	10.49	1.21	2.90	13.03	14,766
Ln(proximity_to_ water)	see description of variables used in regressions with Ln(Nightlights_Composite) with data from 2005.	10.65	10.33	1.75	0.09	13.46	14,788
Rainfall	see description of variables used in regressions with Ln(Nightlights_Composite) with data from 2005.	1,045.00	1,159.44	811.64	0.00	4,875.00	14,673
Slope	see description of variables used in regressions with Ln(Nightlights_Composite) with data from 2005.	0.83	1.77	2.23	0.00	22.80	14,881
Wet_Days	see description of variables used in regressions with Ln(Nightlights_Composite) with data from 2005.	8.55	8.84	4.62	0.00	22.42	13,733

Table 5: *The link between regional temperature and income within countries*

Country	Coefficient of variable temperature	SE	P-value	Sig.
Albania	0.0597	0.0412	0.148	
Argentina	-0.0657	0.0095	0.000	***
Australia	0.0058	0.0137	0.673	
Austria	-0.0118	0.0226	0.602	
Bangladesh	0.0974	0.1568	0.535	
Belgium	0.1473	0.1057	0.163	
Benin	0.5138	1.4672	0.726	
Bolivia	0.0107	0.0107	0.317	
Bosnia and Herzegovina	-0.0847	0.0799	0.289	
Brazil	-0.1399	0.0126	0.000	***
Bulgaria	-0.0090	0.0355	0.800	
Canada	-0.0329	0.0091	0.000	***
Chile	-0.0204	0.0229	0.372	
China	-0.0088	0.0047	0.059	*
Colombia	-0.0220	0.0071	0.002	***
Croatia	0.0371	0.0430	0.389	
Czech Republic	0.2192	0.1157	0.058	*
Denmark	0.7093	0.3031	0.019	**
Ecuador	0.0663	0.0137	0.000	***
Egypt, Arab Rep.	-0.0541	0.0456	0.236	
El Salvador	-0.1050	0.0947	0.268	
Estonia	0.1518	0.1944	0.435	
Finland	0.0685	0.0456	0.133	
France	-0.0303	0.0357	0.396	
Germany, East	0.0150	0.2332	0.949	
Germany, West	0.0821	0.1478	0.579	
Greece	0.0317	0.0350	0.366	
Guatemala	0.0555	0.0188	0.003	***
Honduras	0.0257	0.0304	0.398	
Hungary	0.0609	0.1207	0.614	
India	0.0080	0.0058	0.169	
Indonesia	0.2506	0.0454	0.000	***
Iran, Islamic Rep.	0.0470	0.0142	0.001	***
Ireland	0.2245	0.2108	0.287	
Italy	-0.0534	0.0120	0.000	***
Japan	0.0067	0.0097	0.490	
Jordan	-0.0055	0.0873	0.950	
Kazakhstan	-0.0092	0.0193	0.635	
Kenya	-0.0300	0.0469	0.522	
Korea, Rep.	-0.0411	0.0446	0.358	
Kyrgyz Republic	0.0486	0.0343	0.156	

Latvia	0.3650	0.1147	0.001	***
Lesotho	0.0289	0.0745	0.698	
Lithuania	-0.1974	0.3259	0.545	
Macedonia	0.1532	0.0672	0.023	**
Malaysia	0.2192	0.0750	0.003	***
Mexico	0.0019	0.0091	0.833	
Mongolia	0.0140	0.0206	0.497	
Morocco	0.0898	0.1040	0.388	
Mozambique	-0.2843	0.1165	0.015	**
Nepal	0.0608	0.0643	0.345	
Netherlands	0.0112	0.1577	0.943	
Nicaragua	0.0574	0.0791	0.468	
Nigeria	0.6979	0.7581	0.357	
Norway	0.0157	0.0230	0.494	
Pakistan	0.0237	0.0182	0.193	
Panama	0.1115	0.0747	0.136	
Paraguay	0.1255	0.0689	0.069	*
Peru	0.0165	0.0066	0.012	**
Philippines	0.3351	0.0925	0.000	***
Poland	0.1249	0.1209	0.302	
Portugal	0.0743	0.0597	0.213	
Romania	0.0039	0.0260	0.882	
Russian Federation	-0.0583	0.0058	0.000	***
Serbia	0.1480	0.0712	0.038	**
Slovak Republic	0.1555	0.0694	0.025	**
Slovenia	0.0111	0.0506	0.826	
South Africa	0.1504	0.0830	0.070	*
Spain	-0.0337	0.0126	0.008	***
Sri Lanka	-0.0077	0.0588	0.895	
Sweden	-0.0052	0.0200	0.796	
Switzerland	0.0427	0.0138	0.002	***
Tanzania	0.0184	0.0266	0.491	
Thailand	0.3003	0.0224	0.000	***
Turkey	0.0825	0.0099	0.000	***
Ukraine	0.0669	0.0579	0.248	
United Arab Emirates	0.9500	0.1512	0.000	***
United Kingdom	0.0744	0.0775	0.337	
United States	-0.0118	0.0042	0.005	***
Uruguay	-0.1555	0.0903	0.085	*
Uzbekistan	0.0593	0.0507	0.242	
Venezuela	0.0318	0.0207	0.124	
Vietnam	0.0941	0.0174	0.000	***

Note: Each row presents the coefficients of a simple regression with regional income as a dependent variable and regional temperature as the single independent variable. The regional data are from Gainnaioli et al. (2014).

Table 6: *Baseline regressions for the effect of temperature on regional incomes with control variables when accounting for country and time fixed effects*

Dependent Variable →	(1) Ln_GDP_region	(2) Ln_GDP_region	(3) Ln_GDP_region
Temperature	0.006	0.014*	-0.004
	(0.008)	(0.008)	(0.014)
Poor		-0.487***	
		(0.091)	
temperature x Poor		-0.011*	
		(0.007)	
Temperature²			0.0004
			(0.0004)
Control variables (see descriptive statistics)	Yes	Yes	Yes
Country FE	YES	YES	YES
Time FE	YES	YES	YES
Observations	7500	7500	7500
R^2	0.903	0.917	0.903

Note: The regressions estimate the effect of temperature on logarithmized regional GDP p.c. in regressions with the dummy variable Poor (1 if regional GDP p.c. is below sample average; 0 otherwise) and its interaction with temperature, temperature squared, as well as with a large number of control variables. Regressions are run with the Gennaioli et al. (2014) dataset with country and time fixed effects. Robust clustered standard error estimates (country-level) are presented below the coefficients. Significance levels are indicated by *p<0.1; **p<0.05; ***p<0.01.

Table 7: *Baseline regressions for the effect of temperature on regional nightlights with control variables when accounting for country fixed effects*

Dependent Variable →	(1) Ln_nightlights	(2) Ln_nightlights	(3) Ln_nightlights
Temperature	0.036	0.023	0.52
	(0.051)	(0.077)	(0.358)
Poor		-1.436	
		(1.929)	
temperature x Poor		0.013	
		(0.071)	
Temperature²			-0.011
			(0.008)
Latitude	-0.036	-0.032	-0.031
	(0.035)	(0.034)	(0.036)
Ln(pop_count)	0.043	0.02	0.043
	(0.051)	(0.052)	(0.052)
Aridity	-0.007	-0.005	-0.005
	(0.02)	(0.02)	(0.019)
drought_episodes	0.054	0.046	0.056
	(0.036)	(0.038)	(0.035)
Enhanced_Vegetation_Index	-0.0003**	-0.0002*	-0.0003**
	(0.0001)	(0.0001)	(0.0001)
Frost_Days	0.252	0.279	0.442
	(1.008)	(0.979)	(1.023)
global_human_footprint	0.140***	0.131***	0.140***
	(0.006)	(0.009)	(0.006)
growing_season_length	0.046	0.044	0.053
	(0.077)	(0.076)	(0.078)
Irrigation	0.059***	0.058***	0.059***
	(0.013)	(0.012)	(0.013)
ITN_Coverage	0.403	0.689	0.456
	(0.579)	(0.635)	(0.559)
Malaria_Incidence	-7.203*	-6.936*	-7.242*
	(4.335)	(4.126)	(4.354)
Malaria_Prevalence	2.978	2.906	2.831
	(3.549)	(3.496)	(3.536)
PET	-0.047	0.021	-0.026
	(0.453)	(0.449)	(0.455)
Ln(proximity_to_national_ borders)	-0.024	-0.021	-0.028
	(0.043)	(0.045)	(0.045)
Ln(Proximity_to_Protected_Areas)	-0.009	0.002	-0.017
	(0.079)	(0.078)	(0.074)
Ln(proximity_to_water)	0.079	0.071	0.072
	(0.055)	(0.053)	(0.054)
Rainfall	0.0005*	0.0004	0.001**

	(0.0003)	(0.0003)	(0.0002)
Slope	-0.065	-0.066	-0.065
	(0.055)	(0.051)	(0.054)
Wet_Days	0.033	0.039	0.017
	(0.076)	(0.076)	(0.074)
Country FE	YES	YES	YES
Time FE	NO	NO	NO
Observations	5,193	5,193	5,193
R^2	0.609	0.616	0.61

Note: The regressions estimate the effect of temperature on logarithmized regional nightlights in regressions with the dummy variable Poor (1 if regional nightlights is below sample average; 0 otherwise) and its interaction with temperature, temperature squared, as well as with a large number of control variables. Regressions are run with the DHS 2015 dataset with country fixed effects. Robust clustered standard error estimates (country-level) are presented below the coefficients. Significance levels are indicated by *p<0.1; **p<0.05; ***p<0.01.

Table 8: *Baseline regressions for the effect of temperature on regional gross cell production with control variables when accounting for country fixed effects*

Dependent Variable →	(1) Ln_*GCP*	(2) Ln_*GCP*	(3) Ln_*GCP*
Temperature	-0.012 (0.013)	-0.064 (0.047)	0.044 (0.05)
Poor		-2.308* (1.397)	
temperature x Poor		0.061 (0.05)	
Temperature²			-0.001 (0.001)
Latitude	-0.033* (0.017)	-0.021 (0.013)	-0.032* (0.017)
Ln(pop_count)	-0.006 (0.011)	-0.001 (0.007)	-0.006 (0.011)
Aridity	-0.003 (0.01)	-0.004 (0.01)	-0.003 (0.01)
drought_episodes	-0.011 (0.01)	-0.008 (0.009)	-0.011 (0.01)
Enhanced_Vegetation_Index	0.00001 (0.00003)	0.00004 (0.00003)	0.00001 (0.00003)
Frost_Days	0.245 (0.217)	0.207 (0.162)	0.266 (0.229)
global_human_footprint	0.002* (0.001)	0.002* (0.001)	0.002* (0.001)
growing_season_length	-0.027 (0.032)	-0.023 (0.03)	-0.027 (0.032)
Irrigation	0.002 (0.001)	0.001 (0.002)	0.002 (0.001)
ITN_Coverage	-0.578** (0.292)	-0.594* (0.322)	-0.590** (0.283)
Malaria_Incidence	-0.092 (0.584)	-0.01 (0.553)	-0.101 (0.582)
Malaria_Prevalence	-0.036 (0.504)	-0.102 (0.483)	-0.041 (0.504)
PET	-0.063 (0.07)	-0.063 (0.066)	-0.059 (0.068)
Ln(proximity_to_national_ borders)	0.009 (0.017)	-0.002 (0.019)	0.008 (0.018)
Ln(Proximity_to_Protected_Areas)	-0.024 (0.017)	-0.012 (0.014)	-0.025 (0.017)
Ln(proximity_to_water)	-0.014 (0.018)	-0.012 (0.016)	-0.015 (0.017)
Rainfall	0.0002	0.0001	0.0002

	(0.0001)	(0.0001)	(0.0001)
Slope	-0.018	-0.013	-0.018
	(0.017)	(0.013)	(0.017)
Wet_Days	-0.013	-0.001	-0.014
	(0.018)	(0.019)	(0.019)
Country FE	YES	YES	YES
Time FE	NO	NO	NO
Observations	5,128	5,128	5,128
R^2	0.762	0.802	0.763

Note: The regressions estimate the effect of temperature on logarithmized regional *gross cell production* in regressions with the dummy variable Poor (1 if regional *gross cell production* is below sample average; 0 otherwise) and its interaction with temperature, temperature squared, as well as with a large number of control variables. Regressions are run with the DHS 2005 dataset with country fixed effects. Robust clustered standard error estimates (country-level) are presented below the coefficients. Significance levels are indicated by *p<0.1; **p<0.05; ***p<0.01.

Table 9: *Baseline regressions for the effect of temperature on regional incomes when accounting for country fixed effects for seven year-subsamples*

Dependent Variable →	(1) Ln_GDP_ region 1950	(2) Ln_GDP_ region 1950	(3) Ln_GDP_ region 1950	(4) Ln_GDP_ region 1960	(5) Ln_GDP_ region 1960	(6) Ln_GDP_ region 1960	(7) Ln_GDP_ region 1970	(8) Ln_GDP_ region 1970	(9) Ln_GDP_ region 1970	(10) Ln_GDP_ region 1980
Temperature	-0.030***	0.009	-0.031	-0.021***	-0.004***	-0.01	-0.013	-0.003	-0.011	-0.005
	(0.011)	(0.016)	(0.02)	(0.007)	(0.0004)	(0.016)	(0.009)	(0.007)	(0.011)	(0.009)
Poor		0.092			-0.11			-0.443***		
		(0.196)			(0.12)			(0.129)		
Temperature x Poor		-0.044**			-0.018*			-0.011		
		(0.02)			(0.009)			(0.013)		
$Temperature^2$			0.00001			-0.0004			-0.0001	
			(0.001)			(0.001)			(0.001)	
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Observations	210	210	210	285	285	285	316	316	316	537
R^2	0.782	0.803	0.782	0.839	0.844	0.839	0.873	0.881	0.873	0.889

Dependent Variable →	(11) Ln_GDP_ region 1980	(12) Ln_GDP_ region 1980	(13) Ln_GDP_ region 1990	(14) Ln_GDP_ region 1990	(15) Ln_GDP_ region 1990	(16) Ln_GDP_ region 2000	(17) Ln_GDP_ region 2000	(18) Ln_GDP_ region 2000	(19) Ln_GDP_ region 2010	(20) Ln_GDP_ region 2010	(21) Ln_GDP_ region 2010
Temperature	-0.012**	-0.01	0.01	0.008	-0.009	-0.006	0.003	-0.033**	-0.007	0.003	-0.033**
	(0.005)	(0.016)	(0.009)	(0.011)	(0.015)	(0.012)	(0.011)	(0.016)	(0.012)	(0.009)	(0.014)
Poor	-1.160***			-1.149***			-0.913***			-0.711***	
	(0.262)			(0.427)			(0.112)			(0.09)	
Temperature x Poor	0.015			0.003			-0.008			-0.012	
	(0.012)			(0.015)			(0.012)			(0.008)	
Temperature²		0.0002			0.001			0.001**			0.001**
		(0.001)			(0.001)			(0.001)			(0.001)
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Observations	537	537	844	844	844	1,209	1,209	1,209	1,051	1,051	1,051
R^2	0.906	0.889	0.902	0.912	0.903	0.88	0.916	0.883	0.833	0.893	0.837

Note: The regressions estimate the effect of temperature on logarithmized regional GDP p.c. in regressions with the dummy variable Poor (1 if regional GDP p.c. is below sample average; 0 otherwise) and its interaction with temperature, as well as temperature squared. Regressions are run with Gennaioli et al. (2014) data subsamples for the years 1950, 1960, 1970, 1980, 1990, 2000, 2010 with country fixed effects. Robust clustered standard error estimates (country-level) are presented below the coefficients. Significance levels are indicated by *p<0.1; **p<0.05; ***p<0.01.

Table 10: *Baseline regressions for the effect of temperature fluctuations and temperature in December and July on nightlights in 2015 when accounting for country fixed effects*

Dependent Variable →	(1) Ln_night-lights	(2) Ln_night-lights	(3) Ln_night-lights	(4) Ln_night-lights	(5) Ln_night-lights	(6) Ln_night-lights	(7) Ln_night-lights	(8) Ln_night-lights
Diff_min_max_temp	-0.122	-0.163**						
	(0.087)	(0.066)						
dec_temperature			0.231***	0.253***	0.346***			
			(0.071)	(0.049)	(0.082)			
jul_temperature						0.152***	0.02	0.045
						(0.056)	(0.044)	(0.352)
Poor		-5.489***		-2.114***			-7.194***	
		(0.349)		(0.597)			(0.742)	
Diff_min_max_temp x Poor		0.132***						
		(0.039)						
dec_temperature x Poor				-0.106***				
				(0.024)				
jul_temperature x Poor							0.123***	
							(0.036)	
dec_temperature²					-0.003			
					(0.003)			
jul_temperature²								0.002
								(0.008)
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	15,533	15,533	15,533	15,533	15,533	15,533	15,533	15,533
R^2	0.371	0.58	0.387	0.586	0.388	0.378	0.581	0.378

Note: The regressions estimate the effect of the difference between the highest and the lowest temperature (measured in a year) on logarithmized regional *nightlights* and of the July and December temperature on logarithmized regional *nightlights* in regressions with the dummy variable Poor (1 if regional *nightlights* is below sample average; 0 otherwise) and its interaction with temperature, as well as July and December temperature squared. Regressions are run with DHS data for the year 2015 with country fixed effects. Robust clustered standard error estimates (country-level) are presented below the coefficients. Significance levels are indicated by *p<0.1; **p<0.05; ***p<0.01.

Table 11: *Baseline regressions for the effect of temperature fluctuations and temperature in December and July on gross cell production in 2005 when accounting for country fixed effects*

Dependent Variable →	(1) Ln_*GCP*	(2) Ln_*GCP*	(3) Ln_*GCP*	(4) Ln_*GCP*	(5) Ln_*GCP*	(6) Ln_*GCP*	(7) Ln_*GCP*	(8) Ln_*GCP*
Diff_min_max_temp	-0.020	-0.033						
	(0.02)	(0.03)						
dec_temperature			0.004	-0.001	0.072			
			(0.013)	(0.02)	(0.046)			
jul_temperature						-0.019**	-0.027***	-0.036
						(0.009)	(0.01)	(0.044)
Poor		-1.212***		-1.021*			-1.375***	
		(0.179)		(0.619)			(0.285)	
Diff_min_max_temp x Poor		0.024						
		(0.03)						
dec_temperature x Poor				-0.0001				
				(0.025)				
jul_temperature x Poor							0.016	
							(0.013)	
dec_temperature^2					-0.002			
					(0.001)			
jul_temperature^2								0.0004
								(0.001)
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	14,130	14,130	14,130	14,130	14,130	14,130	14,130	14,130
R^2	0.84	0.891	0.839	0.89	0.841	0.841	0.892	0.841

Note: The regressions estimate the effect of the difference between the highest and the lowest temperature (measured in a year) on logarithmized regional *gross cell production* and of the July and December temperature on logarithmized regional *gross cell production* in regressions with the dummy variable Poor (1 if regional *nightlights* (*gross cell production*) is below sample average; 0 otherwise) and its interaction with temperature, as well as July and December temperature squared. Regressions are run with DHS data for the year 2005 with country fixed effects. Robust clustered standard error estimates (country-level) are presented below the coefficients. Significance levels are indicated by *p<0.1; **p<0.05; ***p<0.01.

Table 12: *Robustness tests for the effect of temperature on regional incomes, nightlights and gross cell production*

	Test	Description	Variable	Results for Temperature
(1)	Regions with extreme incomes (proxies for income)	We conduct baseline regressions with country fixed effects (and time fixed effects in regressions with Ln_GDP_region) but exclude regions that exert GDP p.c./*nightlights*/*GCP* rates beyond +- 2 standard deviations from the sample mean.	Ln_GDP_region	*-0.005 (0.006)* N = 9,017
			Ln_*nightlights*	*0.165*** (0.053)* N = 14,562
			Ln_*GCP*	*-0.014 (0.009)* N = 13,642
(2)	Countries with armed conflicts	We conduct baseline regressions with country fixed effects (and time fixed effects in regressions with Ln_GDP_region) but exclude countries with an armed conflict in a given year. Data for conflicts are only available until 2008, which is why we were unable to conduct this test for Ln_*nightlights* (DHS 2015).	Ln_GDP_region	*-0.005 (0.006)* N = 7,858
			Ln_*GCP*	*-0.017 (0.014)* N = 12,245
(3)	Hottest and coldest regions	We conduct baseline regressions with country fixed effects (and time fixed effects in regressions with Ln_GDP_region) but exclude the hottest and the coldest region of every country.	Ln_GDP_region	*-0.005 (0.009)* N = 8,499
			Ln_*nightlights*	*0.168*** (0.063)* N = 14,345
			Ln_*GCP*	*-0.010 (0.011)* N = 12,963
(4)	Regions with extreme temperatures	We conduct baseline regressions with country fixed effects (and time fixed effects in regressions with Ln_GDP_region) but exclude regions that exert temperatures beyond +- 2 standard deviations from the sample mean.	Ln_GDP_region	*0.001 (0.008)* N = 9,142
			Ln_*nightlights*	*0.169*** (0.084)* N = 14,863
			Ln_*GCP*	*-0.012 (0.013)* N = 13,458

(5)	Weighted temperatures	We conduct baseline regressions with country fixed effects (and time fixed effects in regressions with Ln_GDP_region) but weight temperature with the logarithm of population (Ln_GDP_region) and population density (Ln_*nightlights* and Ln_*GCP*).	Ln_GDP_region	*0.003*** (0.001)* N = 9,472
			Ln_*nightlights*	*0.021*** (0.003)* N = 14,809
			Ln_*GCP*	*-0.0002 (0.001)* N = 13,693
(6)	African regions	We conduct baseline regressions with country fixed effects (and time fixed effects in regressions with Ln_GDP_region) for a subsample of regions in Africa.	Ln_GDP_region	*0.001 (0.019)* N = 361
			Ln_*nightlights*	*0.070 (0.077)* N = 10,315
			Ln_*GCP*	*-0.025** (0.012)* N = 9,221
(7)	Asian regions	We conduct baseline regressions with country fixed effects (and time fixed effects in regressions with Ln_GDP_region) for a subsample of regions in Asia.	Ln_GDP_region	*0.019 (0.014)* N = 2,983
			Ln_*nightlights*	*0.329*** (0.090)* N = 3,652
			Ln_*GCP*	*-0.002 (0.027)* N = 2,844
(8)	European regions	We conduct baseline regressions with country fixed effects (and time fixed effects in regressions with Ln_GDP_region) for a subsample of regions in Europe.	Ln_GDP_region	*-0.029* (0.016)* N = 3,359
			Ln_*nightlights*	*0.413 (Inf. 000)* N = 686
			Ln_*GCP*	*0.083 (Inf. 000)* N = 431
(9)	Low-Income countries	We conduct baseline regressions with country fixed effects (and time fixed effects in regressions with Ln_GDP_region) for a subsample of regions in low-income countries.	Ln_GDP_region	*0.012 (0.018)* N = 208
			Ln_*nightlights*	*0.183** (0.087)* N = 6,336
			Ln_*GCP*	*-0.009 (0.007)* N = 5,613

(10)	Lower- and Upper-Middle-Income countries	We conduct baseline regressions with country fixed effects (and time fixed effects in regressions with Ln_GDP_region) for a subsample of regions in lower- and upper-middle-income countries.	Ln_GDP_region Ln_*nightlights* Ln_*GCP*	*-0.002 (0.011)* N = 5,036 *0.179* (0.108)* N = 9,197 *-0.016 (0.023)* N = 8,517
(11)	Education	We conduct baseline regressions with country and time fixed effects with years of education and the interaction term between temperature and years of education as additional covariates. Whereas years of education is positive and highly significant (0.244*** (0.038)), both temperature and the interaction term remain insignificant and do not exert any effect on Ln_GDP_region.	Ln_GDP_region	*0.013 (0.013)* *Temperature* *-0.002 (0.002)* *Interaction Temperature and Education* N = 7,504

Note: The regressions estimate the effect of temperature on logarithmized regional GDP p.c., *nightlights* and *gross cell production* for a number of robustness checks including country fixed effects and robust clustered standard error estimates on the country-level; The number of observations is listed below the respective coefficient (Clustered Std. Error). Significance levels are indicated by *p<0.1; **p<0.05; ***p<0.01.

Table 13: *Baseline regressions and robustness tests for the effect of temperature on regional GDP p.c. growth when accounting for country fixed effects*

Dependent Variable →	(1) Growth	(2) Growth	(3) Growth	(4) Growth	(5) Growth	(6) Growth	(7) Growth	(8) Growth
temperature	0.013 (0.008)	0.040 (0.027)	-0.016 (0.027)	0.022 (0.042)	0.002 (0.02)	0.032 (0.024)	0.045 (0.034)	0.048* (0.028)
Poor			0.211 (0.371)					
temperature x Poor			0.065** (0.03)					
temperature²				0.001 (0.002)				
Country FE	NO	YES	YES	YES	YES	YES	YES	YES
Time FE	NO	NO	NO	NO	NO	NO	NO	NO
Controls	NO	NO	NO	NO	YES	NO	NO	NO
Observations	1,527	1,527	1,527	1,527	901	1,462	1,363	1,477
R^2	0.001	0.626	0.631	0.626	0.682	0.806	0.630	0.633

Note: The regressions estimate the effect of temperature on regional GDP p.c. growth in regressions without country fixed effects (1), with country fixed effects (2), with the dummy variable Poor (1 if regional GDP per capita is below sample average; 0 otherwise) and its interaction with temperature (3), with temperature squared (4), with a large number of control variables (see Table 6) (5), without regions that exert growth rates beyond +- 2 standard deviations from the sample mean (6), without the hottest and the coldest region of a country (7), and without regions that exert temperature values beyond +- 2 standard deviations from the sample mean (8). Regressions are run with the Gennaioli et al. (2014) dataset. Robust clustered standard error estimates (country-level) are presented below the coefficients. Significance levels are indicated by *p<0.1; **p<0.05; ***p<0.01.

Table 14: *Baseline regressions for the effect of precipitation on nightlights in 2015 and gross cell production in 2005 when accounting for country fixed effects*

Dependent Variable →	(1) Ln_night-lights	(2) Ln_night-lights	(1) Ln_*GCP*	(2) Ln_*GCP*
Precipitation	-0.017***	-0.004	-0.002***	-0.0004
	(0.0004)	(0.003)	(0.0001)	(0.001)
Poor				
Precipitation x Poor				
Precipitation²				
Country FE	NO	YES	NO	YES
Time FE	NO	NO	NO	NO
Observations	14,313	14,313	13,296	13,296
R2	0.100	0.375	0.026	0.843

Note: The regressions estimate the effect of precipitation on logarithmized regional *nightlights* (*gross cell production*) in regressions with the dummy variable Poor (1 if regional *nightlights* (*gross cell production*) is below sample average; 0 otherwise) and its interaction with precipitation, as well as precipitation squared. Nightlights (*gross cell production*) regressions are run with DHS data for the year 2015 (2005) without and with country fixed effects. Robust clustered standard error estimates (country-level) are presented below the coefficients. Significance levels are indicated by *p<0.1; **p<0.05; ***p<0.01.