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Center for Research in Economics, Management and the Arts

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

Working Paper No. 2020-01

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

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ABSTRACT

We study the effect of temperature on economic development on the sub-national level, employing cross-sectional data for up to 15,533 sub-national units from two distinct sources. In contrast to the existing cross-country literature on the temperature-income relationship, our setting allows us to exploit sub-national heterogeneity through the inclusion of country fixed effects and mitigate omitted variable bias. We find no negative relationship between regional temperature and four different measures of economic development (per capita GDP, growth of per capita GDP, nightlights and gross cell production). We also test whether temperature is non-linearly related to income (with hotter regions being potentially particularly prone to adverse effects of temperature on income) but find no 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), but find no robust evidence for this proposition. In sum, our findings suggest that adaptation to temperature differences could be feasible and relevant.

JEL-Classification: Q54; Q56; R11

Keywords: Regional temperature; regional income; sub-national data; non-linearity

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I. INTRODUCTION

The role of climate change and related temperature increases for economic development has received renewed attention in the cross-country literature in recent years (e.g., Burke et al., 2015, 2018; Dell et al., 2009, 2012; Lanzafame, 2014). Numerous studies find significant negative effects of higher temperature on income. Furthermore, some contributions to the literature suggest a non-linear, inverted-U relationship between income and temperature, meaning that colder countries (with average yearly temperatures of up to 13-16 degrees) might benefit from increasing temperatures, while hotter countries tend to lose (e.g., Burke et al., 2015, 2018; Deryugina and Hsiang, 2014; Nordhaus, 2006; Zhao et al., 2018). Finally, relatively poorer countries could suffer more from higher temperatures, partly due to being located in hotter parts of the world and partly due to fewer (financial) means to adapt to temperature alterations (e.g., Dell et al., 2012; Moore and Diaz, 2015; Zhao et al., 2018).

Our contribution to the recent literature on the temperature-income relationship is three-fold. First, we correlate *sub-national data* on temperature with sub-national data on economic variables (e.g., regional GDP per capita). We gathered two data sets on climatic and economic indicators for a large number of world-wide regions. Depending on the variables in use, we are able to include between 1,542 to 15,533 sub-national units, which cover mainly developed (data from Gennaioli et al. (2014) from 1950 to 2010) as well as developing countries (data from *Demographic and Health Surveys* (DHS) with data on cells for 2005 and 2015) 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.¹

Second, the use of regional data allows us to account for country fixed effects, thereby holding constant everything that is specific to a country such as country-specific policies, institutions, colonial history or aspects of culture. Thereby, we are able to draw conclusions on the relationship between regional temperature and regional income while accounting for relevant other influences. In particular, the relationship between temperatures and incomes could be affected by adaptation possibilities which, in turn, might be driven by country-specific effects that we account for.

¹ For example, in Russia we have a spread of 5,000 miles in distance, of 24 degrees in average temperature (between Republic of Sakha and Krasnodar Region) and of 47,265 USD in per capita income (between Republic of Ingushetia and Tyumen Region) according to our data.

Third, we explore the effect of temperature on four different measures for sub-national income: regional GDP per capita, growth of GDP per capita from 1950 to 2010, *gross cell production* within a DHS cluster, as well as *nightlights* within a DHS cluster.

While countries are the most common units for analyzing the link between temperatures and economic development (e.g., Burke et al., 2015, 2018; Dell et al., 2009, 2012), some literature has explored within country variation. Nordhaus (2006) relies on the G-Econ database employing proxies of economic activity² for all large countries measured at a 1° latitude by 1° longitude scale. Other literature focuses on the link between temperature for regions but is mainly limited to the United States (see e.g., Colacito et al., 2019; Dell et al., 2009; Deryugina and Hsiang, 2014) and recently China (see Li et al., 2019). In contrast to them, our analysis is global. Most closely related to us is Zhao et al. (2018) who consider grid cells and data across different continents but rely again on the G-Econ database developed by Nordhaus (2006). Instead of grid cells, we employ meaningful subnational administrative regions and typical economic indicators such as regional GDP per capita as reported by the national statistical offices and we employ data based on surveys from the DHS.³ Thereby, our regional setting is directly comparable to the cross-country literature which focusses on national GDP per capita.

Using data for 1,542 subnational administrative regions from different continents (data gathered by Gennaioli et al. (2014)) yields no systematic relationship between temperature and regional GDP per capita as well as between temperature and GDP growth.⁴ There is also no systematic difference in the effect of temperature on regional economic development between rich and poor regions. Furthermore, we find no systematic evidence for any inverted-U relationship between regional temperature and income as well as growth. Employing data from the *Demographic and Health Surveys*, we find, if anything, a positive (though usually statistically insignificant) relationship between temperature and *nightlights* within a DHS cluster. 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 and sensitivity checks (e.g.

² Nordhaus (2006) data covers 25,572 terrestrial grid cells and includes several measures of economic activity such as proxies for income by industry, employment by industry, urban and rural population or employment.

³ Moreover, we employ DHS data to analyze enumeration areas, called clusters, and explore the commonly used proxies for economic activity such as *gross cell production* and *nightlights*.

⁴ Potential effect sizes are small and comparatively precisely estimated, which may point to the absence of any (generalized) adverse effects of regional temperature.

including maximum and minimum temperatures) support our interpretations as our results continue to yield zero effects of temperatures on different regional income measures.

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

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 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):

1. Higher temperatures adversely affect agricultural production, e.g., by contributing to water stress or the spread of plant pests. Especially when economies are poor and dependent on agriculture, such adverse effects may hurt overall economic development.

2. Higher temperatures may 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 will adversely affect labor performance and productivity. The adverse effects of heat stress may also be felt in non-agrarian sectors of the economies.

3. Higher temperatures may also contribute to the spread of debilitating diseases (e.g., Malaria, Dengue fever) by facilitating the spread of disease vectors (e.g., mosquitos). These diseases will adversely affect the accumulation of human capital (e.g., by contributing to school absenteeism or permanent mental or physical disability), which in turn will discourage economic development.

4. Higher temperatures may also have long-run effects on political and economic institutions by affecting the modes of agricultural production (e.g., family vs. plantation farming) 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) by discouraging European settlements in many parts of

the world 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.

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; countries in the year 2000 experience a drop in income of 8.5% with every degree increase in temperature. Hsiang (2010) comes to a similar conclusion, finding that a temporary one degree 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. For 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. 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. Schlenker and Lobell (2010) report a negative association between temperature and agricultural output in Sub-Saharan African countries.

EVIDENCE AT THE SUB-NATIONAL LEVEL

By construction, cross-country studies cannot systematically investigate the within-country heterogeneity regarding temperature and economic development. Some recent studies have started to re-analyze the income-temperature relationship by using county or (geographical) grid cell level data. 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) due to temperature rises. Dell et al. (2009) find that a one degree rise in temperature is related to a 1.2-1.9% decline in municipal income for 7,684 municipalities in 12 countries in the Americas. Zhao et al. (2018) analyze 10,597 global grid cells using data from Nordhaus (2006) and find a weak negative association between temperature and economic activity. Focusing only on China, Li et al. (2019) consider data from 31 Chinese provinces, finding that temperature exerts both positive and negative effects on economic growth depending on the level of average temperature. A similar result is obtained

by Deryugina and Hsiang (2014) who focus on the United States. Finally, Colacito et al. (2019) suggest that a rise in the average summer temperature in the United States leads to a reduction in the annual state growth rate of 0.15 to 0.25 percentage points.

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 degrees and strongly declining at higher temperatures. This is in line with Deryugina and Hsiang (2014), Nordhaus (2006) and Zhao et al. (2018) who find evidence in favor of an inverted U-shape with a maximum at about 15, 12 and 16 degrees, respectively. Li et al. (2019) places the “beneficial” temperature threshold at 23.37 degrees, meaning that almost all Chinese provinces could experience positive effects from rising temperatures. Schlenker and Lobell (2010) also find a strong non-linear relationship between temperatures and corn, soybean, and cotton yields. On the other hand, Dell et al. (2009, 2012) and Lanzafame (2014) find little or no evidence that the relationship between income and temperature is non-linear.

ADAPTATION

A concern of the existing literature is the rate of adaptation to climate change. This rate has to be considered when estimating the potentially negative consequences of temperature increases (e.g., Moore and Diaz, 2015). Indeed, Dell et al. (2009) suggest that approximately half of the negative effect of 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. Here, 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. Indeed, 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 difference in the effect of temperature on income in rich and poor countries, respectively.

III. DATA AND EMPIRICAL STRATEGY

DATA

We employ two distinct datasets that allow us to estimate the link between *regional* temperatures on measures of *regional* economic development. Temperature as well as GDP per capita at the regional level and regional growth of GDP per capita from 1950 to 2010 are drawn from Gennaioli et al. (2014), while further climate data as well as *gross cell production* and *nightlights* come from the *Demographic and Health Surveys* (DHS). Further descriptions, descriptive statistics and data sources of all our data can be found in Table A.1 and A.2 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 around the world. As for the GDP per capita and GDP per capita growth 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 due to data constraints; they represent about 4% of all regions in the dataset. In total, we have approximately 9,500 data points available when using the Gennaioli et al. (2014) dataset.

The dataset includes a variable measuring regional temperature, obtained from the WorldClim database. This variable indicates the average temperature per region between 1950 and 2000. Thereby, we follow Dell et al. (2009) who also use temperature data that is averaged over the 1950-2000 period.⁵ Consequently, our analysis explores whether relatively warmer regions are more or less wealthy than relatively colder regions, controlling for country fixed effects and other characteristics. We start exploring the full panel dataset and then construct seven cross-sections for the years 1950, 1960, 1970, 1980, 1990, 2000 and 2010 to compare the effects of different temperature levels on regional GDP over time. This allows us to draw potential insights regarding adaptation to hotter temperatures: if comparatively warmer sub-national regions within a country are equally rich as medium or colder regions, adaptation to hotter or colder temperatures might be possible within reasonable time frames.

Second, we also 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

⁵ Cross-country studies have usually yearly or five-yearly average temperature data available (e.g., Burke et al., 2015, 2018). Grid cell approaches explore a shorter time horizon (e.g., Nordhaus, 2006; Zhao et al., 2018).

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 supplement to the Gennaioli et al. (2014) dataset. DHS survey data contains a variety of geographic information which are obtained from the *Geographic Information System* (GIS). In particular, we have temperature, precipitation, frost days, wet days, etc. available. This information is available for small geographical units called clusters.⁶

GDP data does not exist on the cluster-level; 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 DHS Sampling Manual at ICF International (2012)). We thus have available 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.⁷

EMPIRICAL STRATEGY

Our cross-sectional databases from Gennaioli et al. (2014) and DHS (2005, 2015) allow us to examine whether warmer regions (clusters) tend to be less or more wealthy than their colder counterparts. Our empirical strategy follows a 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:

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

where ω_i and λ_t are country- and time-fixed effects and $\epsilon_{r,i,t}$ is an error term. Country fixed effects account for any country-specific and time-invariant unobservables such as colonial history, national institutions etc. They can be employed because we analyze *regional*

⁶ 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).

⁷ 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.

temperature and *regional* income. Time fixed effects capture contemporary global phenomena. As our regional temperature variable is time invariant, this setting does not capture changes in regional GDP per capita over time. To analyze how regional temperature affects regional GDP per capita at different time periods (decades) we also estimate a sequence of seemingly unrelated regressions in sensitivity tests below, among other tests.

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).⁸ We follow these examples for our main results and proceed to run parsimonious models that do not include further economic, demographic or political controls. It might be argued that such a strategy gives temperature a comparatively high chance to emerge as an explanatory factor for income. Indeed, older literature that took account of additional covariates found no effects of temperature or related variables on GDP per capita or growth (e.g., Acemoglu et al., 2001; Rodrik et al., 2004; Sala-I-Martin et al., 2004). In an attempt to further explore such matters too, we include several regional and national control variables to our baseline regressions and discover that the effect of temperature is rather sensitive towards their inclusion (Table A.7 in the Supplementary Information).

In a second model, we replace regional per capita GDP by the per capita GDP growth rate between the first and the last available regional GDP entry recorded. Our panel data turns into a cross-section with the following estimation equation:

$$GDPgrowth_{r,i} = \beta(Temperature)_{r,i} + \omega_i + \epsilon_{r,i,t} \quad (2)$$

Similarly, we employ country fixed effects in a regression setting for the DHS data samples. We predict *nightlights* and *gross cell production* of region r in country i in year 2015 and 2005 by employing the following equations:

$$nightlights_{r,i,2015} = \beta(Temperature)_{r,i,2015} + \omega_i + \epsilon_{r,i,2015} \quad (3)$$

$$gross\ cell\ production_{r,i,2005} = \beta(Temperature)_{r,i,2005} + \omega_i + \epsilon_{r,i,2005} \quad (4)$$

Following the literature (e.g., Burke et al., 2015, 2018; Dell et al., 2009, 2012; Lanzafame, 2014), we expect the temperature-income relationship to be negative in models (1) to (4), i.e., we expect hotter regions to be less wealthy.

⁸ 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.

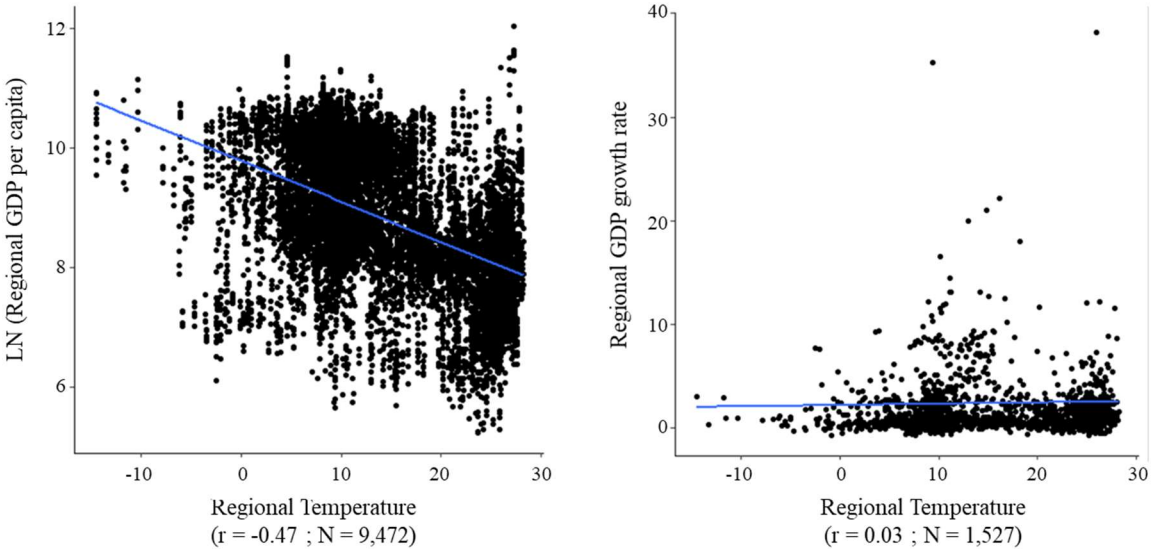
To account for adaptation effects and further exploit regional heterogeneity, we estimate additional models that include an interaction term with the dummy variable *Poor* that equals 1 if a region's income is below the average of the full sample and 0 otherwise (see also Dell et al., 2012; Zhao et al., 2018 for similar approaches). According to the literature, we hypothesize that the potential negative effect of temperature on income (β_2) is stronger in relatively poorer regions due to weaker adaptation.

Finally, to consider potential non-linearities in the temperature-income relationship (where the adverse effect of higher temperatures may be particularly pronounced in hotter regions), we add a squared temperature to all our models. Here, we follow Burke et al. (2015, 2018), Deryugina and Hsiang (2014) and Nordhaus (2006).

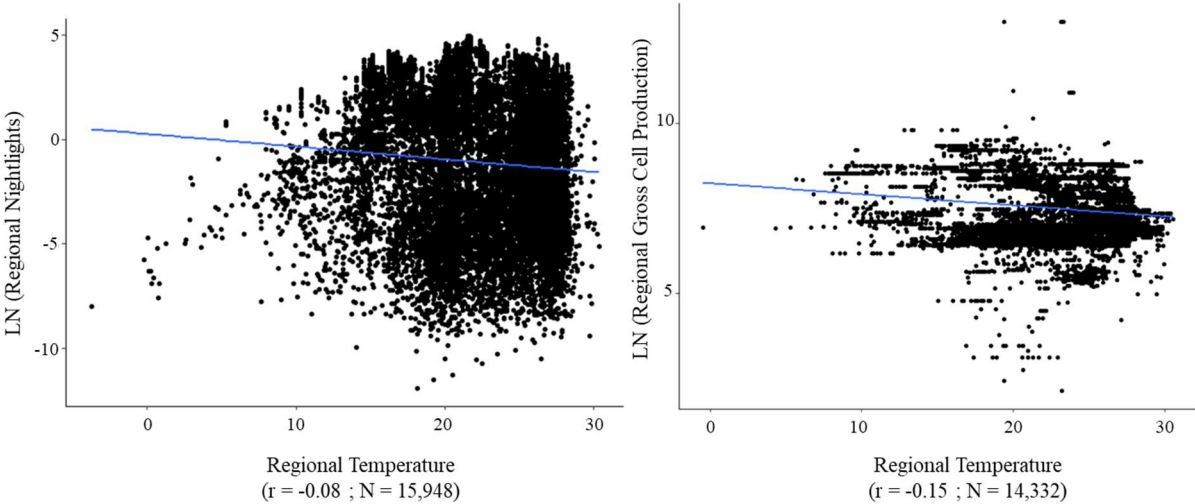
IV. THE LINK BETWEEN REGIONAL TEMPERATURE AND REGIONAL INCOME *CORRELATIONS*

Figure 1 shows the relationship between temperature and our four dependent variables: regional log GDP per capita, regional GDP per capita growth rate, regional log *nightlights* and regional log *gross cell production*.

Figure 1: The link between regional income and regional temperature



Note: Scatterplots summarize all available GPD p.c. observations and growth rates per region between 1950 and 2010 in Gennaioli et al. (2014).



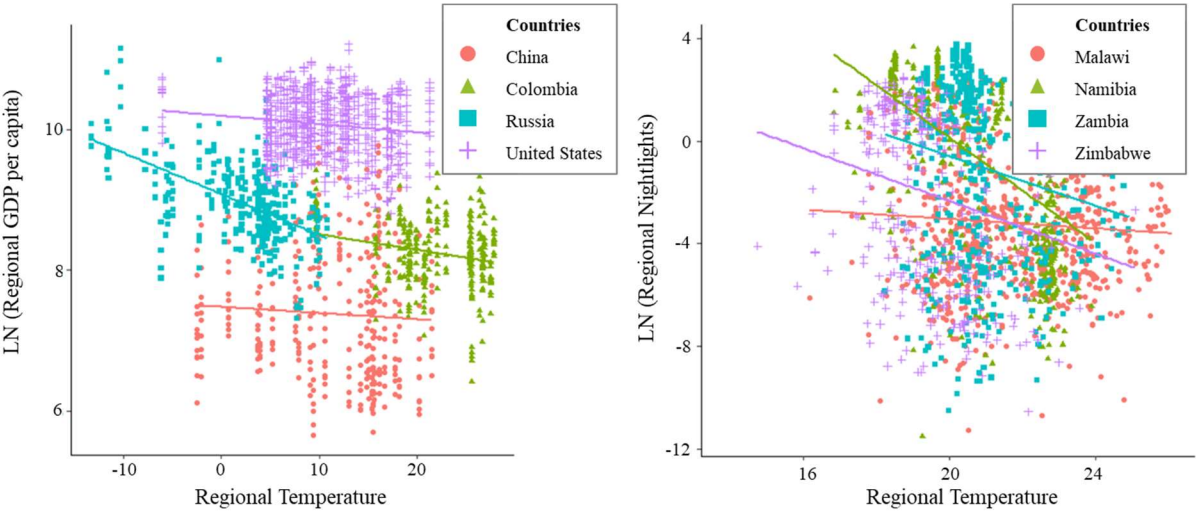
Note: Scatterplots summarize all available Nightlights observations in 2015 and Gross Cell Production observations in 2005 from DHS.

Except for regional growth rates (where correlation is close to zero), we observe a negative relationship between temperature and income, i.e., hotter regions tend to be less wealthy. This is consistent with insights from the existing cross-country literature (e.g., Burke et al., 2015, 2018; Dell et al., 2009, 2012). However, Figure 1 highlights that there is substantial variation in temperature and each of the regional outcome 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 Tyumen region in Russia or the Yukon Territory in Canada are among the richest regions in the world. Similarly, some regions seem to have exceptionally high growth rates or very low nightlight

intensity. As a sensitivity test, we eliminate such potential outliers⁹ from the analysis (results are relegated to Supplementary Information in Table A.6). In any event, heterogeneity within countries matters substantially and alongside country specific characteristics.

The large heterogeneity within countries highlights the relevance of our analysis as an important extension to the existing cross-country literature. Figure 2 emphasizes this heterogeneity in selected countries for (the log of) regional *GDP per capita* (China, Colombia, Russia and United States) and (the log of) *nightlights* (Malawi, Namibia, Zambia, Zimbabwe).¹⁰ In all cases we observe a substantial spread of income and temperature, given that all countries are of considerable size and therefore cover various climatic zones and, potentially, exhibit different levels of economic development between regions. Take Russia for instance: West and East are separated by more than 5,000 miles. Average yearly regional temperature ranges from -13 degrees (Republic of Sakha) to +11 degrees (Krasnodar Region), whereas per capita income ranges from 2,025 USD (Republic of Ingushetia) to 49,290 USD (Tyumen region).

Figure 2: Heterogeneity within countries and links between regional income/*nightlights* and temperature for selected countries



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

In sum, 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 only, the cross-country literature cannot account for this considerable spread, meaning that an adverse relationship between temperature and income at the country level may be due to this rather high level of

⁹ Outliers are selected by plotting distribution curves and eliminating isolated regions that represent very high values of our four dependent variables.

¹⁰ Note that Gennaioli et al. (2014) and DHS (2015) have a different regional focus (developed vs. developing countries).

aggregation. Meanwhile, our regional approach allows us to investigate any potentially highly 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 on regional per capita income (specifications (1)-(4)) and its growth rate between the first and the last available GDP p.c. data point available (specifications (5)-(8)). We now always account for country heterogeneity by including country fixed effects, which capture all national characteristics that could influence the relationship between temperature and income. Time fixed effects can only be applied when regional income shows variation over time (specifications (1)-(4)). In specifications on growth (columns (5)-(8)), meanwhile, we just have one observation per region.

In the parsimonious specification (1), the coefficient for the relationship between temperature and log regional GDP p.c. is negative, close to zero (with a point estimate of -0.004) and statistically insignificant at conventional levels. Thus, accounting for country specific heterogeneity, there is no systematic link between regional temperature and regional income. Given that the coefficient estimate is small and the standard error estimate is not unreasonably large, the specification tends to provide evidence of absence of any link between regional temperature and regional incomes.¹¹ Put differently, regions within a country are not systematically wealthier or poorer only because they are colder or hotter. In specification (5) we investigate the link between regional temperature and regional growth when controlling for country fixed effects. Here, we again observe no clear relationship between the two variables. We also note that the addition of regional temperature to the model does not improve the overall fit of the model, i.e., when estimating a pure fixed effects model without any controls the R^2 is 0.86 when regional GDP is the dependent variable and 0.62 when growth is the dependent variable. Including regional temperature increases R^2 by 0.0002 and 0.0019, respectively. This

¹¹ Also note that our setting gives regional temperature a high chance to emerge as an explanatory factor for income differences as we do not include any covariates in our main regressions (similar to the recent cross-country literature). Nevertheless, we provide an initial attempt to include regional and national control variables that are available and that we believe to be relevant for predicting income. In fact, they add between 0.01 and 0.1 to R^2 in regressions with per capita GDP and per capita GDP growth and between 0.05 and 0.2 in regressions with *nightlights*, whereas regressions with *GCP* lose about 0.1 in explanatory power (Table A.7).

is suggestive that regional temperature tends to have a comparatively small explanatory power for GDP and growth.

In a second step, we include a dummy variable called *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 effect of temperature on GDP per capita or growth is more relevant in poorer regions. The variable *Poor* itself must have a significantly negative coefficient when explaining regional GDP per capita. A positive coefficient in the growth regressions would be consistent with conditional convergence. We observe a significant drop in regional GDP per capita by 61% and a statistically insignificant increase in growth if the region is poor. Temperature continues to have no effect on regional income, independent of whether the region is considered poor or rich (specification (2)). The interaction term is positive and statistically significant in specification (6) i.e., growth tends to be higher in poorer and warmer regions when differentiating between poor and rich regions.

Potential effects of temperature on income might be non-linear, following an inverted U-shape. For instance, Burke et al. (2018) and Zhao et al. (2018) find that economic growth is concave in temperature, meaning that cooler regions might actually benefit from a rise in temperature (e.g., as agricultural productivity improves), while already warmer regions lose. In contrast to this literature, specification (3) tends to show a U-shape when employing regional data, suggesting that the negative effect of temperature on income is reversed when the average annual temperature exceeds 13°. Interpreting these results, we must keep in mind that regions from Gennaioli et al. (2014) in general are relatively cool with an average annual temperature of about 14 degrees; for instance, many African regions, which may have driven previous results due to their dependence on agriculture, are not included in this sample (however they are included in the DHS samples below). Moreover, there are numerous hot regions in the sample which, at the same time, have high incomes.

A large strand of the literature 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). We include years of education in our regression and interact it with temperature, too. This allows us to explore whether temperature has weaker effects on income in relatively well-educated regions; potentially, assuming that education is more positively correlated with adaptation, this allows regions with high education levels to maintain their income levels. However, while years of education have a strong and statistically

significant effect on regional GDP per capita (with every additional year of schooling raising GDP p.c. by 24% (specification (4)), we find that its effect is independent of temperature. Again, for regional growth we find no effect of temperature (specification (8)).

The results of Table 1 show that the findings of past literature (see e.g., Burke et al., 2015, 2018; Dell et al., 2009, 2012; or Lanzafame, 2014) are not that robust when transferred to the regional level. Controlling for country specific heterogeneity, there is no support for the view that warmer regions are systematically poorer than colder regions. The estimated coefficients of temperature are close to zero, while being comparatively precisely estimated, indicating that there is no effect of regional temperature on regional income and growth. Moreover, poorer regions do not seem to suffer more from hotter temperatures than richer regions. It is important to note that heterogeneity within countries, i.e., among regions within a country, is substantial regarding temperature and income. This suggests that there is no systematic link between warmer temperatures and incomes, with national institutions, national policy or other national factors potentially helping regions to adapt.

Table 1: Baseline regressions for the effect of temperature on regional income and growth when accounting for country and partly time fixed effects

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ln GDP region	Ln GDP region	Ln GDP region	Ln GDP region	Growth	Growth	Growth	Growth
temperature	-0.004 (0.007)	0.007 (0.009)	-0.025** (0.012)	0.012 (0.013)	0.040 (0.027)	-0.016 (0.027)	0.022 (0.042)	0.069 (0.052)
Poor		-0.612*** (0.114)				0.211 (0.371)		
temperature x Poor		-0.013 (0.009)				0.065** (0.030)		
temperature²			0.001* (0.001)				0.001 (0.002)	
Years of Education				0.238*** (0.038)				-0.072 (0.128)
temperature x Years of Education				-0.002 (0.002)				-0.004 (0.005)
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	NO	NO	NO	NO
Observations	9,472	9,472	9,472	7,504	1,527	1,527	1,527	1,505
R2	0.858	0.884	0.86	0.893	0.626	0.631	0.626	0.627
Residual Std. Error	0.438 (df=9344)	0.396 (df=9342)	0.436 (df=9343)	0.379 (df=7381)	1.714 (df=1444)	1.704 (df=1442)	1.715 (df=1443)	1.722 (df=1422)
F Statistic	445.6***	553.3***	447.3***	506.9***	29.49***	29.38***	29.14***	29.15***

Note: The regressions estimate the effect of temperature on logarithmized regional GDP p.c. and regional growth in regressions with the dummy variable Poor (1 if regional GDP is below sample average; 0 otherwise) and its interaction with temperature, Years of education its interaction with temperature, as well as temperature squared. Regressions are run with the Gennaioli et al. (2014) dataset with country and partly 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.

In a similar manner, we run the model as outlined above employing our two DHS samples. The unit of observations are DHS clusters. We use the logarithm of *nightlights* and *gross cell production* (GCP) as dependent variables. Here, we are dealing with cross-sectional data, as our variables *nightlights* and *gross cell production* are only available for 2015 and 2005, respectively. We again account for country fixed effects. Results of estimation equations (3) and (4) are presented in Table 2. The results suggest a positive relationship between the cluster temperature and *nightlights* within a cluster, i.e., with every increase in temperature we observe an increase in *nightlights* by 18% to 40%. In relatively poor regions, this positive effect is somewhat less pronounced (specification (2)). 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 insignificant.

The relationship of temperature with *gross cell production* is ambiguous. If anything, temperature seems to have a small but negative effect on *gross cell production*, i.e., results suggest that higher temperatures in a cluster tend to reduce *gross cell production* in 2005 by approximately 3%. This only holds in the presence of the dummy variable *Poor*, which is the only other significant variable in our model (specification (5)).

Table 2: Baseline regressions for the effect of temperature on *nightlights* in 2015 and *gross cell production* in 2005 when accounting for country fixed effects

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
	Ln_nightlights	Ln_nightlights	Ln_nightlights	Ln_GCP	Ln_GCP	Ln_GCP
temperature	0.181*** (0.067)	0.203*** (0.059)	0.397** (0.191)	-0.012 (0.011)	-0.026** (0.012)	0.054 (0.063)
Poor		-2.370** (0.977)			-1.428*** (0.358)	
temperature x Poor		-0.084** (0.04)			0.018 (0.013)	
temperature²			-0.005 (0.005)			-0.002 (0.001)
Country FE	YES	YES	YES	YES	YES	YES
Time FE	NO	NO	NO	NO	NO	NO
Observations	15,533	15,533	15,533	14,130	14,130	14,130
R2	0.381	0.579	0.382	0.84	0.891	0.84
Residual Std. Error	2.627 (df=15495)	2.165 (df=15493)	2.625 (df=15494)	0.379 (df=14098)	0.312 (df=14096)	0.378 (df=14097)
F Statistic	257.3***	546.6***	251.5***	2382***	3493***	2318***

Note: The regressions estimate the effect of temperature 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 temperature, as well as temperature squared. Nightlights (gross cell production) regressions are run with DHS data for the year 2015 (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.

EXTENTIONS AND SENSITIVITY TESTS

In the following, we present three empirical extensions, aiming at refining our previous estimations.

First, we reconsider our subnational administrative data and create seven year-subsamples, i.e., one cross-section for every first year of a new decade (1950, 1960, 1970, 1980, 1990, 2000, 2010). We proceed with our three main specifications (as seen in Tables 1 and 2) for every year-subsample. The results for the seven cross-sections (Table A.3 in the Supplementary Information) confirm the ambiguous effect of regional temperature on regional GDP per capita. While we observe a negative and statistically significant relationship between temperature and log GDP per capita in a few cases, this effect is sensitive to alterations in specifications in all year-subsamples. For all specifications, the effect of regional temperature on regional GDP per capita is small, as shown by the coefficient estimates ranging between 0.004 to 0.033; that is, regions within a country that are one degree warmer than the average region of the country tend to have a 0.4% to 3.3% smaller GDP. When interacted with *Poor*, we only find significantly negative coefficients in subsamples for 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 medicine, agriculture etc.) that decoupled temperature effects from income. As in Table 1, there does not

seem to be a clear non-linear relationship between regional temperature and regional GDP per capita.

To refine our results from Table 2, we employ the DHS data and account for a popular critique of using average temperature, namely that temperature averages neglect potentially large variation in temperature between months or even days (e.g., Barreca, 2012; Deschênes and Greenstone, 2007; Ranson, 2014; Schlenker and Lobell, 2010). DHS enables us to calculate 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. Results are presented in Table A.4 in the Supplementary Information. We find a statistically significantly negative impact of strong fluctuations, accounting for a reduction in *nightlights* by 16% with every additional degree between minimum and maximum temperature in rich regions. Interestingly, this effect is almost cancelled out if we are dealing with poor regions (positive coefficient of 0.13). We find no robust relationship between temperature fluctuations and *gross cell production* as shown in columns (3) and (4) of Table A.4.

Finally, we exploit our two DHS cross-sections for the difference of summer and winter temperatures, expressed by temperature measured in December and July. As DHS data contains mostly countries from the southern hemisphere, we summarize December temperature to be summer time and July temperatures to be winter time. As in Table 2, the results in Table A.5 show that *nightlights* are positively correlated with warmer temperatures in December, indicated by statistically significantly positive coefficients between 0.23 and 0.35. The effect in poorer regions is approximately 50% smaller. Effects of winter time temperatures are less clear, as temperature exerts a much smaller, but still positive, effect on *nightlights* (0.15 in column (4) or 0.12 when interacted with *Poor* (column (5))). Interestingly, being relatively poor (in terms of *nightlights*) in July is more than thrice as harmful than being poor in December, which is potentially due to the fact that fewer sunlight hours in winter (around July) have to be compensated with electricity, which is often unstable or unaffordable in developing regions (see Adeoye and Spataru, 2019; Jiang et al., 2020 for different season-dependent electricity demands in developing countries). This, in return, might explain the stronger negative effect of *Poor* on *gross cell production* (columns (8) and (11)). Whereas temperature in December seems to have no effect on GCP, we observe a negative relationship between temperature in July and GCP of around 0.02 to 0.03. As in all our previous results, we find no support that the relationship between temperature and income (independent of which proxy is used) is non-linear.

DISCUSSION AND CAVEATS

With this research effort, we aim at contributing to the discussion on whether hotter climate is related to lower income. We explore specifically whether hotter regions have a lower income compared to colder regions, independent of any country-specific circumstances such as institutions. Previous empirical and theoretical contributions have argued that hot temperature may have a *direct* impact on human productivity, labor morale and productivity or on 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 might be characterized by lower per capita incomes. However, our results for several thousand sub-national administrative units and DHS clusters suggest that there is no systematic effect of regional temperature on regional income. Indeed, anecdotal evidence suggests that some of the richest regions in the world are among the hottest and among the coldest in the world (e.g., regions in the United Arab Emirates or Canada). We also find little evidence that poorer regions experience more income losses from hotter temperatures.

Interpreting our findings, we must highlight two caveats regarding our data. First, when focusing on subnational administrative units (data from Gennaioli et al. (2014)), we employ average temperature data for a time period of fifty years, while sub-national per capita GDP is available for several years in this time period. Thus, we do not analyze income changes due to changes in yearly temperature. DHS on the other hand, provides us with two cross-sections for the years 2005 and 2015. Empirically, this leaves us unable to include region fixed effects or country-time fixed effects, where the latter would allow us to account for anything that is unique for a specific nation and time period. Thus, we cannot explore how changes in temperature affect changes in GDP per capita for a specific region, i.e., we do not know whether a region in the United Arab Emirates becoming even hotter would experience a decrease in GDP per capita. Put differently, due to the cross-sectional character of the DHS data, we are restricted to exploring differences between regions rather than differences over time. Therefore, we caution to draw any direct conclusion regarding the effects of (future) anthropogenic climate change.¹² At the same time, the world regions provide numerous examples that hot temperatures can go along with high incomes similarly as cold temperatures may go along with high incomes too.

¹² Of course, we also worry that there might be a bias against researchers who find no evidence that hotter temperatures decrease GDP per capita.

Second, due to their unavailability on the regional level, we are not able to add many potentially time-variant control variables that may explain regional income. Precipitation, extreme weather events such as cyclone activity, population specifics, regional institutions, regional ethno-linguistic diversity, redistribution, etc. are only a few examples from past literature. Similar to the cross-country literature, potential omitted variable bias cannot be fully ruled out even if we include country fixed effects, i.e. while regional temperature is certainly external to a region's GDP, it does not need to be exogenous.

VI. CONCLUSIONS

This paper explores the impact of temperature on income for a large number of sub-national regions and clusters. We use data on 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 temperature, 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 additional data from the *Demographic and Health Surveys*. This sub-national focus allows us to account for country fixed effects and therefore control for any factors that are country specific but relevant to regional growth (e.g., national institutions and policies).

We are unable to identify a consistent and robust link between regional temperature and regional incomes. We observe, if anything, a quantitatively negligible negative relationship between regional temperature and regional GDP per capita. This relationship is sensitive to different specifications. We also do not find that there are systematic differences in the role of temperature in regional income between rich and poor regions. We find a relatively stable *positive* relationship between temperature and nightlights that is slightly weakened for poor regions. The relationship between temperature and growth or gross cell production is ambiguous. Regardless of which regional income proxy is employed, we find no support for a non-linear relationship between temperature and income 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 also 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 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 is a caveat of our approach. 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 relationship than with country fixed effects. Until then, we caution to remain critical towards transferring the negative effect of temperature on income found in the cross-country literature to the regional level. We think that far more research is required in this domain to establish clear-cut results and offer policy conclusions.

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VII. SUPPLEMENTARY INFORMATION

Table A.1: Descriptive statistics (main variables)

Variable (dependent variable in respective sample)	Description	Median	Mean	Std. Dev.	Min	Max	Observations	Source
Ln GDP region	Logarithm of the gross domestic product per capita in a region (in constant 2005 PPP US\$).	0.02	0.03	0.04	-0.35	0.45	7,945	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	Gennaioli et. al (2014)
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	DHS (2015)
Ln Gross Cell Production (GCP)	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	DHS (2005)
temperature (Ln_GDP_region)	Temperature (Celsius) averaged for the period 1950 to 2000 within the subnational region.	12.60	14.18	8.06	-14.49	28.19	9,472	Gennaioli et. al (2014)
temperature (Growth)	Temperature (Celsius) averaged for the period 1950 to 2000 within the subnational region.	12.18	14.19	8.22	-14.49	28.19	1,527	Gennaioli et. al (2014)
temperature (Ln_nightlights)	The average yearly temperature (in degree celsius) 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	DHS (2015)
temperature (Ln_GCP)	The average yearly temperature (in degree celsius) within the 2 km (urban) or 10 km (rural) buffer surrounding the DHS survey cluster location.	23.64	22.79	4.26	-0.50	30.55	14,594	DHS (2005)
Poor (Ln_GDP_region)	Dummy variable equals 1 if region is below sample average regarding per capita GDP. 0 otherwise.	1.00	0.63	0.48	0	1	9,472	DHS, Gennaioli (2014)
Poor (Growth)	Dummy variable equals 1 if region is below sample average regarding per capita GDP. 0 otherwise.	1.00	0.87	0.34	0	1	1,527	DHS, Gennaioli (2014)

Table A.1 continued: Descriptive statistics (main variables)

Variable (dependent variable in respective sample)	Description	Median	Mean	Std. Dev.	Min	Max	Observations	Source
Poor (Ln_nightlights)	Dummy variable equals 1 if region is below sample average regarding nightlights. 0 otherwise.	1.00	0.78	0.41	0	1	19,036	DHS (2015)
Poor (Ln_GCP)	Dummy variable equals 1 if region is below sample average regarding gross cell production. 0 otherwise.	1.00	0.66	0.47	0	1	14,332	DHS (2005)
Years of education (Ln_GDP_region)	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	Gennaioli et. al (2014)
Years of education (Growth)	Average years of schooling from primary school onwards for the population aged 15 years or older in a region.	6.90	7.01	2.95	0.99	12.95	1,505	Gennaioli et. al (2014)
Diff Max Min (Ln_nightlights)	The difference between the average annual maximum and minimum temperature (in degree celsius) 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	DHS (2015)
Diff Max Min (Ln_GCP)	The difference between the average annual maximum and minimum temperature (in degree celsius) within the 2 km (urban) or 10 km (rural) buffer surrounding the DHS survey cluster location.	5.39	7.35	5.23	0.55	21.41	14,594	DHS (2005)
Temperature December (Ln_nightlights)	The average monthly temperature in December (in degree celsius) 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	DHS (2015)
Temperature December (Ln_GCP)	The average monthly temperature in December (in degree celsius) within the 2 km (urban) or 10 km (rural) buffer surrounding the DHS survey cluster location.	23.06	21.00	5.55	-6.22	29.70	14,594	DHS (2005)

Table A.1 continued: Descriptive statistics (main variables)

Variable (dependent variable in respective sample)	Description	Median	Mean	Std. Dev.	Min	Max	Observations	Source
Temperature July (Ln_nightlights)	The average monthly temperature in July (in degree celsius) 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	DHS (2015)
Temperature July (Ln_GCP)	The average monthly temperature in July (in degree celsius) within the 2 km (urban) or 10 km (rural) buffer surrounding the DHS survey cluster location.	24.86	23.24	5.42	1.76	35.66	14,594	DHS (2005)
Precipitation (Ln_nightlights)	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	DHS (2015)
Precipitation (Ln_GCP)	The average precipitation measured within the 2 km (urban) or 10 km (rural) buffer surrounding the DHS survey cluster (in milimeters) in 2005.	84.96	92.79	63.01	0.08	288.50	13,733	DHS (2005)

Table A.2: Descriptive statistics (control variables)

Variable (dependent variable in respective sample)	Description	Median	Mean	Std. Dev.	Min	Max	Obs	Source
Landlockedcountry (Ln_GDP_region)	Dummy variable that is equal to 1 if the country is landlocked, 0 otherwise.	0	0.10	0.30	0	1	9,472	
Landlockedcountry (Growth)		0	0.13	0.34	0	1	1,527	
Landlockedregion (Ln_GDP_region)	Dummy variable that is equal to 1 if the region is landlocked, 0 otherwise.	1	0.54	0.50	0	1	9,472	
Landlockedregion (Growth)		1	0.60	0.49	0	1	1,527	
dist_gg (Ln_GDP_region)	The ratio of 1 over 1 plus the region's average distance to the nearest coastline in thousands of kilometres. Higher values for this variable indicate that a region is closer to the coast, smaller values indicate larger average distances to the coast. Gennaioli et al. (2014) create an equal distance projection of the Collins-Bartholomew World Digital Map and a map of the coastlines. With these two maps Gennaioli et al. (2014a) create a raster with the distance to the nearest coastline of each cell in a given region. In order to obtain the average distance to the nearest coastline, the authors sum the distance to the nearest coastline of all cells within each region and divide that sum by the number of cells in the region.	29,424	179,507	323,358	0	2,099,284	9,487	
dist_gg (Growth)		55,018	202,807	348,378	0	2,099,284	1,527	
km_length_coast (Ln_GDP_region)	Length of coast in km.	0	462	3,801	0	103,225	9,487	
km_length_coast (Growth)		0	346	2,944	0	103,225	1,527	
nbr (Ln_GDP_region)	Dummy variable that is equal to 1 if the region has a border to another region in a neighboring country, 0 otherwise.	0	0.43	0.50	0	1	9,487	
nbr (Growth)		0	0.47	0.50	0	1.00	1,527	
nbr_nr (Ln_GDP_region)	Number of borders to other countries incl. A region's own country border.	1	1.59	0.87	0	8.00	9,472	
nbr_nr (Growth)		1	1.63	0.85	0	8.00	1,527	
Latitude (Ln_GDP_region)	Latitude of the centroid of each region calculated in ArcGIS.	37.47	33.50	16.47	0.02	69.95	9,472	
Latitude (Growth)		38.17	34.02	16.83	0.02	69.95	1,527	
Area_sqkm (Ln_GDP_region)	Area in square kilometers.	14,448	85,603	273,708	28	3,920,299	9,472	
Area_sqkm (Growth)		11,031	64,796	228,508	28	3,920,299	1,527	
Malaria_ecology (Ln_GDP_region)	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	28.68	9,472	
Malaria_ecology (Growth)		0.01	1.20	3.12	0	28.68	1,527	

Gennaioli et al. (2014)

Table A.2 continued: Descriptive statistics (control variables)

Variable (dependent variable in respective sample)	Description	Median	Mean	Std. Dev.	Min	Max	Obs	Source
Ln_Cum_Oil_Gas_Prod (Ln_GDP_region)	(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	0	0.01	0	0.12	9,472	Gennaioli et al. (2014)
Ln_Cum_Oil_Gas_Prod (Growth)		0	0	0.01	0	0.12	1,527	
Ln_Pop_density (Ln_GDP_region)	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	9,467	
Ln_Pop_density (Growth)		4.15	4.07	1.70	-4.03	9.73	1,527	
CapitalisinRegion (Ln_GDP_region)	Dummy variable that is equal to 1 if the region contains a national capital city, 0 otherwise.	0	0.05	0.22	0	1.00	9,472	
CapitalisinRegion (Growth)		0	0.05	0.23	0	1.00	1,527	
Ln_GDP_country (Ln_GDP_region)	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	
Ln_GDP_country (Growth)		8.86	8.85	0.96	6.26	11.14	1,527	
Latitude (Ln_nightlights)	Latitude	8.27	7.49	17.99	-30.59	42.43	19,051	
Latitude (Ln_GCP)		10.94	8.80	17.17	-30.53	42.43	14,910	
All_Population_Count (Ln_nightlights)	The count of individuals living within the 2 km (urban) or 10 km (rural) buffer surrounding the DHS survey cluster in 2015/2005 (number of people).	36,260	105,362	225,056	0.03	5,947,797	18,247	DHS (2015) / DHS (2005)
All_Population_Count (Ln_GCP)		29,883	89,975	190,116	1.95	5,205,736	14,451	
Aridity (Ln_nightlights)	The dataset represents the average yearly precipitation divided by average yearly potential evapotranspiration in 2015/2005, an aridity index defined by the United Nations Environmental Programme (UNEP). Index between 0 (most arid) and 300 (most wet).	24.25	25.56	18.61	0.02	136.13	17,289	
Aridity (Ln_GCP)		22.46	26.28	19.32	0.01	103.05	13,733	
drought_episodes (Ln_nightlights)	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	5.00	5.43	2.68	1	10.00	13,205	
drought_episodes (Ln_GCP)		5.00	5.03	2.90	1	10.00	10,250	
Enhanced_Vegetation_Index (Ln_nightlights)	The average vegetation index value within the 2 km (urban) or 10 km (rural) buffer surrounding the DHS survey cluster in 2015/2005. Vegetation index value between 0 (least vegetation) and 10000 (Most vegetation).	3,043	2,966	1,086	7.00	6,093	18,683	
Enhanced_Vegetation_Index (Ln_GCP)		2,982	2,991	1,124	39.00	6,246	14,642	
Frost_Days (Ln_nightlights)	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 2015/2005. 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	0.73	2.33	0	28.69	17,289	
Frost_Days (Ln_GCP)		0	0.53	1.72	0	26.81	13,733	

Table A.2 continued: Descriptive statistics (control variables)

Variable (dependent variable in respective sample)	Description	Median	Mean	Std. Dev.	Min	Max	Obs	Source
global_human_footprint (Ln_nightlights)	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	100	18,971	DHS (2015) / DHS (2005)
global_human_footprint (Ln_GCP)		38.51	44.60	19.63	0	100	14,878	
growing_season_length (Ln_nightlights)	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 - 149 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	16	18,465	
growing_season_length (Ln_GCP)		9.00	8.42	3.80	1	16	14,470	
Irrigation (Ln_nightlights)	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	100	18,604	
Irrigation (Ln_GCP)		0.12	9.29	19.84	0	100	14,594	
ITN_Coverage (Ln_nightlights)	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 2015/2005.	0.62	0.60	0.23	0	1	10,202	
ITN_Coverage (Ln_GCP)		0.01	0.08	0.10	0	0.42	7,666	
Malaria_Incidence (Ln_nightlights)	(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 2015/2005.	0.17	0.20	0.15	0	0.71	10,202	
Malaria_Incidence (Ln_GCP)		0.30	0.31	0.19	0	0.75	7,666	
Malaria_Prevalence (Ln_nightlights)	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 2015/2005.	0.11	0.17	0.15	0	0.81	10,202	
Malaria_Prevalence (Ln_GCP)		0.25	0.29	0.22	0	0.97	7,666	
PET (Ln_nightlights)	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 2015/2005.	3.77	3.84	0.77	1.93	7.33	17,289	
PET (Ln_GCP)		3.82	3.92	0.83	2.21	7.65	13,733	

Table A.2 continued: Descriptive statistics (control variables)

Variable (dependent variable in respective sample)	Description	Median	Mean	Std. Dev.	Min	Max	Obs	Source
proximity_to_national_borders (Ln_nightlights)	The geodesic distance (meters) to the nearest international borders in 2014.	30,870	60,730	76,116	3.42	594,383	19,052	DHS (2015) / DHS (2005)
proximity_to_national_borders (Ln_GCP)		35,808	65,852	75,878	1.17	551,786	14,911	
Proximity_to_Protected_Areas (Ln_nightlights)	The 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.	49,560	64,738	59,398	0	634,071	19,052	
Proximity_to_Protected_Areas (Ln_GCP)		44,801	60,165	55,590	0	455,946	14,911	
proximity_to_water (Ln_nightlights)	The 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.	41,398	82,153	103,324	0	696,903	19,052	
proximity_to_water (Ln_GCP)		41,509	80,076	97,399	0	698,653	14,911	
Rainfall (Ln_nightlights)	The average annual rainfall (in millimeters) within the 2 km (urban) or 10 km (rural) buffer surrounding the DHS survey cluster location in 2015/2005.	1,004	1,064	723	0	5,574	18,805	
Rainfall (Ln_GCP)		1,045	1,159	812	0	4,875	14,673	
Slope (Ln_nightlights)	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	23.13	19,004	
Slope (Ln_GCP)		0.83	1.77	2.23	0	22.80	14,881	
Wet_Days (Ln_nightlights)	The average number of days receiving rainfall within the 2 km (urban) or 10 km (rural) buffer surrounding the DHS survey cluster location in 2015/2005.	8.29	8.32	4.32	0	23.67	17,289	
Wet_Days (Ln_GCP)		8.55	8.84	4.62	0	22.42	13,733	

Table A.3: Baseline regressions for the effect of temperature on regional income 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*** (0.011)	0.009 (0.016)	-0.031 (0.02)	-0.021*** (0.007)	-0.004*** (0.0004)	-0.01 (0.016)	-0.013 (0.009)	-0.003 (0.007)	-0.011 (0.011)	-0.005 (0.009)
Poor		0.092 (0.196)			-0.11 (0.12)			-0.443*** (0.129)		
temperature x Poor		-0.044** (0.02)			-0.018* (0.009)			-0.011 (0.013)		
temperature²			0.00001 (0.001)			-0.0004 (0.001)			-0.0001 (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
R2	0.782	0.803	0.782	0.839	0.844	0.839	0.873	0.881	0.873	0.889
Residual Std. Error	0.406 (df=200)	0.388 (df=198)	0.407 (df=199)	0.397 (df=270)	0.392 (df=268)	0.397 (df=269)	0.408 (df=296)	0.396 (df=294)	0.409 (df=295)	0.401 (df=509)
F Statistic	136.9***	132.3***	129.9***	135.5***	138***	131***	172.1***	178.4***	167.2***	261.3***

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 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 A.3 continued: Baseline regressions for the effect of temperature on regional income when accounting for country fixed effects for seven year-subsamples

	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
Dependent variable	Ln_GDP_region 1980	Ln_GDP_region 1980	Ln_GDP_region 1990	Ln_GDP_region 1990	Ln_GDP_region 1990	Ln_GDP_region 2000	Ln_GDP_region 2000	Ln_GDP_region 2000	Ln_GDP_region 2010	Ln_GDP_region 2010	Ln_GDP_region 2010
temperature	-0.012** (0.005)	-0.01 (0.016)	0.01 (0.009)	0.008 (0.011)	-0.009 (0.015)	-0.006 (0.012)	0.003 (0.011)	-0.033** (0.016)	-0.007 (0.012)	0.003 (0.009)	-0.033** (0.014)
Poor	-1.160*** (0.262)			-1.149*** (0.427)			-0.913*** (0.112)			-0.711*** (0.09)	
temperature x Poor	0.015 (0.012)			0.003 (0.015)			-0.008 (0.012)			-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
R2	0.906	0.889	0.902	0.912	0.903	0.88	0.916	0.883	0.833	0.893	0.837
Residual Std. Error	0.37 (df=507)	0.401 (df=508)	0.391 (df=802)	0.37 (df=800)	0.39 (df=801)	0.409 (df=1147)	0.342 (df=1145)	0.404 (df=1146)	0.411 (df=995)	0.329 (df=993)	0.406 (df=994)
F Statistic	273***	255.8***	205.9***	256.4***	207.5***	211.2***	302.2***	215.6***	89.96***	145.2***	91.42***

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 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 A.4: Baseline regressions for the effect of temperature fluctuations on *nightlights* and *gross cell production* in 2015 and 2005 when accounting for country fixed effects

Dependent variable	(1)	(2)	(3)	(4)
	Ln_nightlights	Ln_nightlights	Ln_GCP	Ln_GCP
Diff_min_max_temp	-0.122 (0.087)	-0.163** (0.066)	-0.020 (0.02)	-0.033 (0.03)
Poor		-5.489*** (0.349)		-1.212*** (0.179)
Diff_min_max_temp x Poor		0.132*** (0.039)		0.024 (0.03)
Country FE	YES	YES	YES	YES
Time FE	NO	NO	NO	NO
Observations	15,533	15,533	14,130	14,130
R2	0.371	0.58	0.84	0.891
Residual Std. Error	2.646 (df=15495)	2.163 (df=15493)	0.379 (df=14098)	0.312 (df=14096)
F Statistic	247.4***	549.1***	2381***	3491***

Note: The regressions estimate the effect of the difference between the highest and the lowest temperature (measured in a year) 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 temperature. Nightlights (gross cell production) regressions are run with DHS data for the year 2015 (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 A.5: Baseline regressions for the effect of temperature in December and July on *nightlights* and *gross cell production* in 2015 and 2005 when accounting for country fixed effects

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Ln nightlights	Ln nightlights	Ln nightlights	Ln nightlights	Ln nightlights	Ln nightlights	Ln GCP	Ln GCP	Ln GCP	Ln GCP	Ln GCP	Ln GCP
dec_temperature	0.231*** (0.071)	0.253*** (0.049)	0.346*** (0.082)				0.004 (0.013)	-0.001 (0.02)	0.072 (0.046)			
Poor		-2.114*** (0.597)			-7.194*** (0.742)			-1.021* (0.619)			-1.375*** (0.285)	
dec_temperature x Poor		-0.106*** (0.024)						-0.0001 (0.025)				
dec_temperature²			-0.003 (0.003)						-0.002 (0.001)			
jul_temperature				0.152*** (0.056)	0.02 (0.044)	0.045 (0.352)				-0.019** (0.009)	-0.027*** (0.01)	-0.036 (0.044)
jul_temperature x Poor					0.123*** (0.036)						0.016 (0.013)	
jul_temperature²						0.002 (0.008)						0.0004 (0.001)
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Observations	15,533	15,533	15,533	15,533	15,533	15,533	14,130	14,130	14,130	14,130	14,130	14,130
R2	0.387	0.586	0.388	0.378	0.581	0.378	0.839	0.89	0.841	0.841	0.892	0.841
Residual Std. Error	2.613 (df=15495)	2.147 (df=15493)	2.611 (df=15494)	2.632 (df=15495)	2.161 (df=15493)	2.632 (df=15494)	0.379 (df=14098)	0.314 (df=14096)	0.377 (df=14097)	0.377 (df=14098)	0.311 (df=14096)	0.377 (df=14097)
F Statistic	264.6***	563.2***	258.6***	254.6***	550.1***	248.1***	2372***	3445***	2327***	2400***	3519***	2326***

Note: The regressions estimate the effect of the July and December temperature 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 temperature, as well as July and December temperature squared. Nightlights (gross cell production) regressions are run with DHS data for the year 2015 (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 A.6: Baseline regressions for the effect of temperature on regional income, regional growth, *nightlights* and *gross cell production* when accounting for country and partly time fixed effects in subsamples without extreme outliers

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
	Ln GDP region	Ln GDP region	Ln GDP region	Growth	Growth	Growth
temperature	-0.005 (0.007)	0.006 (0.009)	-0.026** (0.012)	-0.002 (0.013)	-0.032 (0.025)	-0.001 (0.013)
Poor		-0.615*** (0.113)			0.534* (0.318)	
temperature x Poor		-0.012 (0.009)			0.031 (0.022)	
temperature²			0.001* (0.001)			-0.00003 (0.001)
Country FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	NO	NO	NO
Observations	9,436	9,436	9,436	1,495	1,495	1,495
R2	0.859	0.885	0.86	0.754	0.763	0.754
Residual Std. Error	0.435 (df=9308)	0.393 (df=9306)	0.433 (df=9307)	0.925 (df=1412)	0.908 (df=1410)	0.925 (df=1411)
F Statistic	445.3***	554.3***	447.2***	52.7***	54.0***	52.0***

Note: The regressions estimate the effect of temperature on logarithmized regional GDP p.c., regional growth, logarithmized nightlights and logarithmized gross cell production in regressions with the dummy variable Poor (1 if regional GDP/nightlights/gross cell production is below sample average; 0 otherwise) and its interaction with temperature, as well as temperature squared. Regressions are run with a subset to the Gennaioli et al. (2014), the DHS 2015 and the DHS 2005 dataset without outliers (if a region's regional GDP, growth, nightlights or gross cell production exceeds five times the sample average) with country and partly 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.

Dependent variable	(7)	(8)	(9)	(10)	(11)	(12)
	Ln nightlights	Ln nightlights	Ln nightlights	Ln GCP	Ln GCP	Ln GCP
temperature	0.167** (0.067)	0.213*** (0.064)	0.376** (0.184)	-0.013 (0.011)	-0.027** (0.011)	0.051 (0.061)
Poor		-2.081* (1.092)			-1.432*** (0.349)	
temperature x Poor		-0.089** (0.043)			0.019 (0.013)	
temperature²			-0.005 (0.005)			-0.002 (0.001)
Country FE	YES	YES	YES	YES	YES	YES
Time FE	NO	NO	NO	NO	NO	NO
Observations	14,507	14,507	14,507	14,107	14,107	14,107
R2	0.297	0.499	0.298	0.856	0.907	0.857
Residual Std. Error	2.639 (df=14469)	2.227 (df=14467)	2.637 (df=14468)	0.354 (df=14075)	0.284 (df=14073)	0.353 (df=14074)
F Statistic	165.1***	369.9***	161.6***	2,705***	4,184***	2,633***

Note: The regressions estimate the effect of temperature on logarithmized regional GDP p.c., regional growth, logarithmized nightlights and logarithmized gross cell production in regressions with the dummy variable Poor (1 if regional GDP/nightlights/gross cell production is below sample average; 0 otherwise) and its interaction with temperature, as well as temperature squared. Regressions are run with a subset to the Gennaioli et al. (2014), the DHS 2015 and the DHS 2005 dataset without outliers (if a region's regional GDP, growth, nightlights or gross cell production exceeds five times the sample average) with country and partly 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 A.7: Baseline regressions for the effect of temperature on regional income, regional growth, *nightlights* and *gross cell production* with control variables when accounting for country and partly time fixed effects

Dependent variable	(1) Ln_GDP_region	(2) Ln_GDP_region	(3) Ln_GDP_region	(4) Growth	(5) Growth	(6) Growth
Temperature	0.005 (0.008)	0.015* (0.008)	-0.004 (0.015)	0.022 (0.028)	-0.02 (0.028)	0.015 (0.051)
Poor		-0.343*** (0.086)			0.126 (0.385)	
temperature x Poor		-0.013** (0.007)			0.047 (0.029)	
Temperature²			0.0003 (0.0005)			0.0003 (0.002)
Landlockedcountry	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Landlockedregion	-0.126*** (0.041)	-0.110*** (0.038)	-0.118*** (0.04)	-0.079 (0.11)	-0.098 (0.11)	-0.072 (0.118)
dist_gg	-0.00000* (0.00000)	-0.0000 (0.00000)	-0.00000* (0.00000)	-0.00000 (0.00000)	-0.00000 (0.00000)	-0.00000 (0.00000)
km_length_coast	-0.00000 (0.00000)	-0.00000 (0.00000)	-0.00000 (0.00000)	0.00001 (0.00001)	0.00001 (0.00001)	0.00001 (0.00002)
nbr	-0.081*** (0.025)	-0.083*** (0.021)	-0.082*** (0.025)	0.218 (0.23)	0.213 (0.227)	0.218 (0.229)
nbr_nr	0.043* (0.022)	0.044** (0.021)	0.045** (0.02)	-0.196 (0.154)	-0.194 (0.15)	-0.194 (0.156)
Latitude	0.018** (0.009)	0.017* (0.009)	0.018** (0.009)	-0.036** (0.015)	-0.036** (0.017)	-0.036** (0.015)
Area_sqkm	0.00000** (0.00000)	0.00000** (0.00000)	0.00000** (0.00000)	-0.00000 (0.00000)	-0.00000 (0.00000)	-0.00000 (0.00000)
Malaria_ecology	0.03 (0.021)	0.028 (0.018)	0.027 (0.02)	0.019 (0.045)	0.016 (0.046)	0.016 (0.049)
Ln_Cum_Oil_Gas_Prod	1.371 (2.236)	1.672 (1.682)	1.203 (2.22)	9.046 (9.739)	8.114 (9.859)	8.953 (9.42)
Ln_Pop_density	-0.0003 (0.016)	0.001 (0.015)	0.003 (0.016)	-0.06 (0.074)	-0.059 (0.075)	-0.057 (0.065)
CapitalisinRegion	0.335*** (0.049)	0.282*** (0.044)	0.329*** (0.047)	0.319 (0.217)	0.385* (0.221)	0.315 (0.209)
Ln_GDP_country	0.905*** (0.104)	0.736*** (0.091)	0.906*** (0.103)	-11.071*** (2.299)	-9.906*** (1.947)	-11.099*** (2.349)
YearsofEducation	0.166*** (0.026)	0.148*** (0.025)	0.166*** (0.026)	-0.105 (0.092)	-0.09 (0.093)	-0.105 (0.089)
Country FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	NO	NO	NO
Observations	7500	7500	7500	1505	1505	1505
R2	0.918	0.927	0.918	0.64	0.642	0.64
Residual Std. Error	0.333 (df=7366)	0.314 (df=7364)	0.333 (df=7365)	1.699 (df=1411)	1.695 (df=1409)	1.7 (df=1410)
F Statistic	616.9***	691.5***	613.1***	26.92***	26.57***	26.62***

Note: The regressions estimate the effect of temperature on logarithmized regional GDP p.c., regional growth, logarithmized nightlights and logarithmized gross cell production in regressions with the dummy variable Poor (1 if regional GDP/nightlights/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 Gennaioli et al. (2014), the DHS 2015 and the DHS 2005 dataset with country and partly 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 A.7 continued: Baseline regressions for the effect of temperature on regional income, regional growth, *nightlights* and *gross cell production* with control variables when accounting for country and partly time fixed effects

Dependent variable	(7) Ln_nightlights	(8) Ln_nightlights	(9) Ln_nightlights	(10) Ln_GCP	(11) Ln_GCP	(12) Ln_GCP
Temperature	0.036 (0.049)	0.028 (0.077)	0.455 (0.333)	-0.011 (0.013)	-0.065 (0.044)	0.041 (0.044)
Poor		-1.389 (1.786)			-2.308* (1.328)	
temperature x Poor		0.01 (0.064)			0.062 (0.047)	
Temperature²			-0.01 (0.008)			-0.001 (0.001)
Latitude	-0.032 (0.037)	-0.028 (0.035)	-0.028 (0.038)	-0.033** (0.016)	-0.021* (0.012)	-0.032** (0.016)
All_Population_Count	0.00000*** (0.00000)	0.00000*** (0.00000)	0.00000*** (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)	
Aridity	-0.016 (0.018)	-0.014 (0.018)	-0.014 (0.017)	-0.003 (0.01)	-0.003 (0.009)	
drought_episodes	0.050* (0.03)	0.042 (0.032)	0.051* (0.03)	-0.012 (0.01)	-0.009 (0.009)	-0.012 (0.01)
Enhanced_Vegetation_Index	-0.0002** (0.0001)	-0.0002* (0.0001)	-0.0002** (0.0001)	0.00001 (0.00003)	0.00003 (0.00003)	
Frost_Days	0.151 (0.894)	0.19 (0.873)	0.337 (0.945)	0.249 (0.228)	0.219 (0.177)	
global_human_footprint	0.141*** (0.005)	0.132*** (0.008)	0.140*** (0.005)	0.002* (0.001)	0.002** (0.001)	0.002* (0.001)
growing_season_length	0.019 (0.078)	0.015 (0.076)	0.025 (0.08)	-0.03 (0.032)	-0.024 (0.03)	-0.029 (0.032)
Irrigation	0.057*** (0.014)	0.056*** (0.012)	0.057*** (0.014)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
ITN_Coverage	0.908 (0.589)	1.244* (0.638)	0.942 (0.576)	-0.550* (0.284)	-0.575* (0.311)	-0.563** (0.274)
Malaria_Incidence	-6.267* (3.779)	-5.965* (3.56)	-6.302* (3.81)	-0.078 (0.561)	0.03 (0.534)	-0.09 (0.559)
Malaria_Prevalence	2.077 (3.195)	2.016 (3.143)	1.952 (3.19)	-0.019 (0.486)	-0.121 (0.467)	-0.023 (0.487)
PET	-0.319 (0.441)	-0.256 (0.421)	-0.296 (0.44)	-0.057 (0.068)	-0.06 (0.065)	-0.053 (0.066)
proximity_to_national_borders	-0.00000 (0.00000)	-0.00000 (0.00000)	-0.00000 (0.00000)	0.00000 (0.00000)	-0.00000 (0.00000)	0.00000 (0.00000)
Proximity_to_Protected_Areas	0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)	-0.00000 (0.00000)	-0.00000 (0.00000)	-0.00000 (0.00000)
proximity_to_water	0.00000*** (0.00000)	0.00000*** (0.00000)	0.00000*** (0.00000)	-0.00000 (0.00000)	-0.00000 (0.00000)	-0.00000 (0.00000)
Rainfall	0.0005* (0.0003)	0.0004 (0.0003)	0.0005* (0.0003)	0.0002* (0.0001)	0.0001 (0.0001)	0.0002* (0.0001)
Slope	-0.055 (0.056)	-0.057 (0.053)	-0.055 (0.056)	-0.02 (0.017)	-0.014 (0.013)	-0.019 (0.017)
Wet_Days	0.03 (0.078)	0.039 (0.076)	0.018 (0.076)	-0.013 (0.02)	-0.002 (0.02)	-0.014 (0.021)
Country FE	YES	YES	YES	YES	YES	YES
Time FE	NO	NO	NO	NO	NO	NO
Observations	5231	5231	5231	5218	5218	5218
R2	0.619	0.625	0.619	0.763	0.804	0.764
Residual Std. Error	1.969	1.952	1.967	0.325	0.296	0.325
F Statistic	(df=5186) 191.1***	(df=5184) 188.0***	(df=5185) 187.2***	(df=5177) 417.8***	(df=5175) 504.6***	(df=5176) 408.1***

Note: The regressions estimate the effect of temperature on logarithmized regional GDP p.c., regional growth, logarithmized nightlights and logarithmized gross cell production in regressions with the dummy variable Poor (1 if regional GDP/nightlights/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 Gennaioli et al. (2014), the DHS 2015 and the DHS 2005 dataset with country and partly 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 A.8: Baseline regression with country-level temperature and income data from Gennaioli et al. (2014) when accounting for country and time fixed effects in order to compare results with Burke et al. (2015,2018)

Dependent variable	(1) Ln GDP region
Temperature	0.351* (0.185)
Temperature²	-0.007 (0.026)
Country FE	YES
Time FE	YES
Observations	487
R2	0.98
Residual Std. Error	0.189 (df=358)
F Statistic	133.8***

Note: The regressions estimate the effect of temperature and temperature squared on logarithmized regional GDP p.c.. Regressions are run with country-level data (country averages) from Gennaioli et al. (2014) 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.